Housing Capital and Intergenerational Mobility in the United States*

Ariel Binder† Max Risch‡ John Voorheis§

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Abstract

Housing represents the most important capital asset for most U.S. families. Despite substantial analysis of the intergenerational mobility of income, large gaps in our knowledge of the distribution of housing assets and their transmission over time remain, as housing is generally not reflected by income flows. Using novel linked data that combines survey responses with administrative tax data and information on ownership and valuation from property tax records for over 3.4 million families, we provide new evidence on the intergenerational transmission of housing capital. We find that housing capital is more persistent across generations than labor income. We document important disparities between average housing outcomes for White and Black children. These difference persist even conditional on parent rank in the distribution of housing assets, with the gap growing throughout the parental housing capital distribution. A decomposition shows that average differences in children's labor market outcomes associated with parental assets explain about half of the observed intergenerational persistence (a "labor income channel"), and that there is also a substantial "direct channel" — conditional on children having the same earnings, children of parents with more housing assets have more assets themselves on average. The direct channel is also important for explaining the intergenerational gap in outcomes of Black and White children. Finally, we present quasi-experimental evidence that local housing supply constraints help explain spatial differences in intergenerational persistence across US counties. Our results establish the importance of housing markets, both independently from and jointly with labor markets, in shaping the intergenerational persistence of economic resources.

JEL codes: E24, O18, R31, D31

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†Center for Economic Studies, U.S. Census Bureau

‡Tepper School of Business, Carnegie Mellon University

§Center for Economic Studies, U.S. Census Bureau

1. Introduction

Homeownership is widely considered a key marker of economic success in America. According to the 2022 Survey of Income and Program Participation, the median rented household had a net wealth of $\$9,000$, while the median owned household had a net wealth of $\$400,000$, 60% of which was held in housing.[1] Homeownership is a key source of collateral that can back investments in children and other assets (Lovenheim, 2011; Wold et al., 2023). In turn, higher home values reflect exposure to more-desirable neighborhoods, higher quality schools, better environmental conditions and other amenities which shape economic well-being and its transmission across generations (Chetty et al., 2014; Chetty and Hendren, 2018a; Colmer and Voorheis, 2020).

Despite the likely importance of housing for generational wealth, detailed measurement of intergenerational housing outcomes in the United States has been constrained by lack of available data. While the intergenerational mobility (IGM) of income has been the subject of a massive literature (see reviews by Black and Devereux, 2011; Mogstad and Torsvik, 2023; Deutscher and Mazumder, 2023), housing is not typically reflected in income flows. In this paper, we leverage a dataset that links income tax records, household surveys, and property ownership and valuation records for over 3.4 million families to generate new evidence on the relationship between parent and child housing capital in the contemporary U.S. Beyond the fact that housing is a primary capital asset, we view housing as an illustrative opportunity to study wealth transmission exactly because it is largely not captured by income flows. By observing both sources of information, we can analyze joint and independent relationships between housing capital and human capital mobility. We moreover show that our results generalize to a proxy measure of total capital wealth that is available in our data.

Our dataset enables us to observe parental housing capital in the year 2000, when most parents were in their late 40s, and their children's outcomes circa 2021, when they were aged 35-43. We use tax filing records to construct intergenerational linkages of parent and child

[1] https://www2.census.gov/library/publications/2024/demo/p70br-202.pdf.

housing and income information. Relative to Chetty et al. (2014), our sample of children is 9 years older, and the ages of the parents and children are more closely aligned, which is important given the lumpy accumulation of housing capital. We implement a simple weighting estimator based on predicted homeownership rates of our sample children at ages 45-49 to fully align parent and child ages.[2]

Our analysis proceeds in three parts. We start by establishing descriptive patterns on the IGM of housing capital. We use the rank-rank framework popularized in the IGM of income literature, but build in flexibility to non-parametrically account for the masses of parents and children who do not own a home. These explorations yield three main findings. First, housing capital is more persistent across generations than labor income. We find a rank-rank slope in total income of 0.35, similar to that previously found using tax records (e.g. Chetty et al., 2014, 2020), and find that this slope drops to 0.29 when we focus solely on labor income. In contrast, we estimate a housing capital rank-rank slope of 0.43.[3] When we condition on both parent and child owning property, the rank-rank slope rises to 0.58.

Second, Black-White disparities in the IGM of housing capital follow different patterns from that of income. Consistent with Chetty et al. (2020), we find similar income rank-rank slopes between Black and White families.[4] On the other hand, we find differential persistence in housing capital between Black and White families, with White families showing substantially more intergenerational persistence and Black families experiencing stronger downward mobility, even at the top of the parental distribution. While the average gap in housing capital between Black and White children raised by the parent homeowners at the bottom of the distribution is only 5 ranks, the gap among children raised by parents at the top of the distribution is more than 20 ranks. Using various methods to impute plausible counterfactual housing values, we show that if Black children owned houses at the same

[2]Because this is only a slight extrapolation from our observed ages, our results are robust across different weighting assumptions.

[3]This degree of persistence is notable given that most parents are still alive when we measure child housing capital, so our results are not driven by the transfer of estates.

[4]The intercept disparity is around 12 ranks, and this baseline disparity changes little throughout the parental income distribution.

rate as White children (conditional on parental housing), average ranks of Black and White children would be similar in the bottom half of the parental housing distribution, and the extreme gap at the top of the distribution would close by about half.

Third, like income, housing capital IGM varies substantially across U.S. counties, but the spatial patterns of this variation are distinct across the two measures. Using absolute mobility (i.e. the intercept in the rank-rank model) as a benchmark for comparison, we find a cross-county correlation between income IGM and housing IGM of 0.63. The differences in these spatial patterns are visible in choropleth maps, which show that absolute housing capital intergenerational mobility is substantially larger than income mobility in both large coastal metros such as Boston and San Francisco as well as large parts of the southeast. In contrast, we do not see larger persistence in housing capital in locations where income persistence is high, such as the in the South. Instead, we see that there is larger housing asset persistence in locations where there is relatively more income mobility, such as coastal urban areas, potentially reflecting the differential ability to accumulate assets conditional on income.

In the second part of the analysis, we use our link between housing asset and income information to investigate the relationship between the IGM of housing and human capital and to provide a richer understanding of the IGM of parent and child resources in the U.S. more broadly. We specify a simple model of intergenerational capital accumulation that generates a decomposition of the housing capital rank-rank slope into three channels. First, a "labor income" channel allows parental resources to augment the earning potential of children, and these labor income flows yield capital holdings. Second, a "savings/investment" channel allows parental resources to influence the *rate* at which labor income is converted into housing capital. Finally, a "direct channel" allows parental resources to directly affect child housing capital for a given level of labor income—for example through bequests, inter vivos transfers, providing collateral, or by increasing financial literacy.

We perform the decomposition using a simultaneous equation model. The estimates indi-

cate that the intergenerational persistence of housing capital occurs almost entirely through the labor income and direct channels. Both are important, and the direct channel (0.254) is slightly larger in magnitude than the labor income channel (0.173). While the labor income channel acts primarily by raising child homeownership rates, the direct channel acts primarily by raising home values conditional on ownership. By including parent income into the analysis, we show that the direct channel operates through parent assets rather than parent earnings, while the labor income channel is similarly associated with parent earnings and assets.[5] In addition, we show that while equalizing child labor market earnings would greatly reduce the Black-White housing gap at the bottom of the parental distribution, differences in average outcomes for Black and White children grow throughout the parental distribution even conditional on child earnings, due to differences in the IG correlation of assets (the direct channel).[6]

Taken together, the analysis shows that children of parents with more resources earn more income and consequently have more assets, but also that there is a substantive independent predictive role of parent assets. Even conditional on children earning the same amount, children of wealthier parents have significantly more assets on average. We test the robustness of this implication using a capitalization method to estimate the total wealth rank of parents and children, and find very similar intergenerational patterns.

In the final section, we examine the role of local housing markets in shaping housing capital mobility. We leverage granular estimates of housing supply elasticities in metro areas (Baum-Snow and Han, 2024) combined with observed cohort variation in our dataset to construct a difference-in-difference design at the county level. In the post-Great-Recession epoch of expanding demand for housing, our approach identifies differential price shocks across counties by interacting the national quantity change with the county-specific slope of

[5]That is, parent earnings and assets both are important determinants of child labor earnings, but, conditional on child labor earnings, parent earnings do not shift children up that asset distribution while parent assets do.

[6]Thus, among children raised by the richest parents, only 35% of the racial gap in housing capital attainment is explained by labor income, but 60% of the Black-White Gap is attributable to income.

the supply curve as measured in 2001.[7] Relative to older cohorts, younger cohorts were more exposed to these price shocks. We control for county fixed effects, and also allow mobility to trend arbitrarily across cohorts according to geographic, population, and parental housing variables as observed in 2000, to proxy for demand shocks that might be correlated with baseline housing supply.

We find that housing supply constraints importantly shaped housing capital IGM during this recent housing expansion. Net of controls, a change in baseline housing supply from $1SD$ below to $1SD$ above the median is associated with a relative increase in absolute mobility from 2010-2021 of 4.6 rank points, and a decline in the rank-rank slope of 3.6 rank points. These effects are 36% and 25%, respectively, of twice the cross-county standard deviation observed in our 2021 dataset. We also find a non-linear pattern of effects, whereby marginal housing supply expansions in the most inelastic areas return substantial mobility gains, while further housing supply expansions beyond the mean exert no detectable effects.

Taken together, our analyses paint a richer picture of intergenerational mobility than has been possible with income measures alone. Our findings suggest that (housing) capital markets independently shape economic resources and their transmission across generations, beyond what is implied by labor income. Moreover, capital and labor-market processes interact, with parental financial capital shaping child financial capital accumulation through its effects on child labor income.

1.1. Contributions to the literature

Our investigation enriches three strands of literature. First, we offer new large-scale estimates of capital wealth persistence in the U.S. Our headline rank-rank slope of 0.43 for housing capital and capitalized wealth is similar to the 0.39 net-wealth estimate of Pfeffer and Killewald (2017) in PSID data, despite differences in sample composition and wealth

[7] As shown by Howard and Liebersohn (2021), population increased between 2000 and 2018 by about the same amount in inelastic as in elastic areas, suggesting that the instrumented price shocks that we generate are similar on average to the actual price shocks experienced at the county level.

concept.[8] Similar to Charles and Hurst (2003), we find labor income and asset ownership to be primary channels of wealth transmission, but we place greater emphasis on ownership and direct transmission in our context.[9] Gilraine et al. (2023) and Benetton et al. (2022) provide specific evidence of human-capital and direct effects of parental housing capital, which we generalize in our decomposition framework. While one limitation of our analysis is the absence of mortgage debt, our measures of housing capital, labor, and non-labor income analogize to a "lifetime resources" measure, which Black et al. (2023) has argued is more predictive of child outcomes than net wealth.

Second, our work sheds light on sources of racial disparities in wealth and intergenerational mobility. Previous studies have attributed much of the cross-sectional racial wealth gap to labor income differences (e.g., Barsky et al., 2002; Sabelhaus and Thompson, 2023; Derenoncourt et al., 2023). In our intergenerational context, we find the labor income channel to be important in explaining disparities among Black and White children growing up in poor families, but increasingly unimportant in richer families. While recent work has revealed differential returns in the housing market conditional on ownership (Killewald and Bryan, 2016; Avenancio-León and Howard, 2022; Kermani and Wong, 2021; Box-Couillard and Christensen, 2024), our findings point to the primary importance of ownership gaps. (Ownership gaps have also been emphasized by Killewald and Bryan (2016, 2018).) In general, our work complements existing literature on racial mobility gaps in income, which often focuses on human capital channels (Bhattacharya and Mazumder, 2011; Davis and Mazumder, 2018; Chetty et al., 2020; Collins and Wanamaker, 2022; Derenoncourt, 2022; Binder et al., 2022a).

Third, our housing supply analysis broadens the scope of the "childhood exposure" literature which examines the impacts of neighborhoods on human capital formation and adulthood income (Chetty and Hendren, 2018a,b). Our study is the first we have seen to link

[8] In contrast, Fagereng et al. (2020) estimate a much flatter rank-rank slope in net wealth, and a rank-rank slope of around 0.3 in financial wealth, in Norwegian administrative data.

[9] See Feiveson and Sabelhaus (2018) for an involved discussion on the latter using measures of transfers in the SCF.

housing supply constraints to intergenerational processes, suggesting that the decline in housing affordability since the Great Recession has created more intergenerational wealth persistence and shaped regional inequality. This finding connects intergenerational mobility literature to recent urban economics literature that has evaluated the consequences of housing supply constraints for local prices and aggregate housing market phenomena (e.g., Howard and Liebersohn, 2021; Pennington, 2021; Hilber and Mense, 2021; Asquith et al., 2023; Baum-Snow, 2023; Mense, 2025).

2. Data

We leverage the Census Bureau's data linkage infrastructure to develop a sample of families containing children (generation g) and their parents (generation $g-1$). Such a sample requires i) parent-child links; ii) information on parental housing assets and income; and iii) information on children's adulthood levels of housing assets and income.

2.1. Intergenerational data sources and sample construction

We use the 2000 Census Long Form (2KLF) as a primary source of the first two pieces of information. The Long Form sampled 1 in 6 U.S. households during the year 2000, collecting information on household and family structure, sociodemographic variables, and family income sources.[10] It also provides housing asset information: whether the reference person owns the given housing unit, and if so, the reference person's estimate of the current market value of the home. We associate these households to their children using relationship identifiers. The 2KLF data contain unique person numbers called Protected Information Keys (PIKs), which facilitate the linkage of de-identified personal information across different household surveys and administrative records (Layne et al., 2014).

Because we require a set of individuals who can reliably be linked to parents from 2KLF household rosters, *and* who were old enough by the year 2021 to own a home, we consider

[10]The Census Long Form was the precursor to the American Community Survey (ACS).

all 2KLF individuals aged 14-16 who were children of reference persons. The average child in our 2KLF sample was 36 years old in 2021. To increase the sample size, particularly to include children observed at older ages, we supplement the 2KLF sample with additional samples containing older children, which we draw from the Census Databank.[11] The Databank contains sociodemographic and annual taxable-income information on everyone who filed a federal income tax return in each tax year during 1994-5 and 1998-2021, as well as selected prior years. The Databank includes the PIKs of all dependents claimed by each filer beginning with the 1994 tax year, which allows researchers to very closely approximate parent-child links with claimer-dependent links (e.g. Chetty et al., 2020).

First, we consider all dependents aged 14-16 in the 1994 Databank year whose primary or spousal claimer was *also* a sampled householder in the 2KLF. The average dependent in this sample was 42 years old in 2021. We supplement the sample further with an analogous Databank sample based on the 1998 year.[12] Our final sample includes 3.4 million parent-child pairs, with children born in 1978-86 and aged 39.0 on average in 2021, and parents aged 46.3 on average[13] in 2000 when we measure their housing assets. We construct this main sample for children of all races, however we will focus on non-Hispanic Black and non-Hispanic White children in some subsequent analyses.

2.2. Child housing asset measurement

To measure homeownership rates and housing asset levels in our sample of children, we leverage 2019-2021 administrative records on the universe of parcels in the US on which property taxes are paid. Commercial data providers aggregate and standardize these records

[11] This archive contains a commingled set of federal tax return, Social Security birth-record, and Decennial Census information, and is available for research use based on a partnership between Census and the Opportunity Insights initiative.

[12] Ideally we would have used the 1997 year to create a fully non-overlapping set of birth cohorts with the 1994 and 2000 years, but Census never received 1996 or 1997 data from the Internal Revenue Service (IRS). Although not all families file taxes in every tax year, we verified that including the 1995 and 1999 years would barely raise our sample size. This is due to i) the narrow age range of the dependents we need to consider, and ii) the child tax credit, which provides a strong incentive for claimers to file taxes. Gee et al. (2024) demonstrates the near-universal coverage of children on U.S. tax returns.

[13] With a standard deviation of 7.6 years.

across thousands of local taxing jurisdictions, and Census has a repository of files from prior contracts that support household survey production.[14] We use data acquired by the Census Bureau from one such commercial vendor(Black Knight, Incorporated, BK hereafter) for this study.[15]

Measuring ownership. Property assessment files contain the parcel owner(s)' name(s) as of the most recent assessment, which usually occurs in the year prior to the vintage year.[16] Deed files record the most-recent, or in some cases a longer history, of transfers of ownership of the parcel. We passed these files through Census's record-linkage system, which parsed name and address strings into PIKs. For a given parcel in a given year, we assigned the owner as the owner listed on the most-recent assessment, or as the buyer listed on the most-recent deed transfer if the parcel was not found in the assessment records. We link children in the intergenerational sample to these ownership records, which provides the number of properties owned by each sample child in each of 2019-2021.

Measuring property valuations. We use the Automated Valuation Model (AVM) files, which record predicted market values for each property in the given vintage year. These predictions come from a hedonic model that takes into account recent sales of similar properties in similar locations as the property in question.[17]

In a final step, we collapse the short panel of 2019-2021 information into a single ownership and a single asset holdings observation for each individual. This observation usually reflects 2021 holdings, subject to minor editing that we describe in Appendix A.2.[18] We note that the asset concepts we derive from the BK records cover all property holdings, not just those

[14] Binder et al. (2022b) provide further information and illustrate a high degree of comparability in coverage and in parcel-level characteristics between commercial providers.

[15] Black Knight has subsequently been acquired by Intercontinental Exchange, which continues to make similar data available.

[16] In most other cases, the assessment year matches the vintage year or occurs two years prior to the vintage year.

[17] These valuations are nonmissing for the vast majority of parcel-years—where they are missing, we nearly always observe the most-recent assessed value for property taxation purposes (assessment file), the most-recent sold value (deed file), or both. Accordingly, we estimate a flexible imputation model that predicts market value on the basis of this information. Appendix A.1 provides the details.

[18] We also show in that Appendix section that property valuations align reasonably well with ACS owners' estimated valuations of their residential property.

tied to the individual's residence. As an example, roughly 8% of all children in the sample and 15% of all owners own multiple properties. A corollary of this is that individuals who rent their residence but remotely own a property will show up as owners in administrative data but not in survey data.

However, our data contain two limitations. First, properties indirectly owned by business entities do not have valid names and so are not assigned PIKs, and we lack the data necessary to assign these businesses to their final owner(s). Therefore, we focus on a concept of "personal," as opposed to "business," property holdings for the parent and child generations. Second, we do not have a reliable source of mortgage loan data currently, which necessitates a focus on gross assets as our main concept of housing wealth.[19] In Section 5.5, we show robustness of our main descriptive results on housing wealth to a total wealth measure that we derive from capitalizing income flows on the tax records á la Saez and Zucman (2016); Piketty et al. (2018) and Smith et al. (2022).

2.3. Income measurement

To consider relationships between income and wealth, we use information from the 2KLF and household tax returns to construct a composite rank measure of childhood family income (CFI). We replicate the "tax-unit" concept of family income introduced by Chetty et al. (2014). Based on how adjusted gross income (AGI) is summarized on federal tax returns, this is the sum of the primary filer's personal income and that of their legal co-residing spouse if one exists. To smooth out transitory income variation, we average across three years. For parents, we average two years of tax return information with 2KLF reported tax-unit income (the sum of reference person's and partner's personal incomes from the 2KLF).[20] To measure adulthood income of the children, we use AGI information from their 2018, 2019,

[19] To the degree that gross assets better reflect lifetime assets, this may be the desired concept. Additionally, this aligns the parent and child assets concepts.

[20] Following Chetty et al. (2014), we drop negative incomes before constructing averages, as these usually reflect transitory accounting choices of business owners who have high permanent incomes and asset holdings.

and 2021 tax returns.[21] We average these observations together, omitting negatives and then constructing ranks *within* child birth cohort.[22] We detail the averaging and income ranks in Appendix A.6.

3. Analytical Approach: Rank-Rank Relationships

Our main approach to measuring the intergenerational persistence of housing assets is a rank-rank analysis. Housing is particularly conducive to a rank-rank specification because i) there are masses of non-owners in each generation which would not be incorporated in log transformations; ii) housing assets are highly skewed at the very top, and we want the analysis to reflect the intergenerational relationship throughout the distribution; and iii) the 2KLF data on parental housing assets translates better into ranks than levels.[23]

3.1. Assigning ranks

Rather than arbitrarily rank those who own no housing assets, we reduce noise by assigning non-owners a common rank of $(1-x)/2$, where x is the property ownership rate in the sample for a given generation. We then rank owners from $1-x+1/N$ up to 1 by asset value. This specification preserves population mean and median ranks of 0.5.

For the parent generation, the 2KLF elicited valuations of owned residences in 25 categorical bins, which results in 26 possible parental wealth ranks including the renters. Just as is done for renters, we assign owner ranks based on the midpoint of each bin. For example, if 5% of parents own homes in the lowest value bin, these individuals get assigned a rank of $1-x+.05/2$.

[21] We exclude 2020 due to anomalous earnings and unearned income processes associated with the COVID-19 pandemic.

[22] A small percentage of children did not file taxes during any of these 3 years and are defaulted to having the bottom income rank.

[23] Typical household surveys only contain information on residential ownership, but not on remote ownership. While the exclusion of remote ownership information compromises measurement of housing assets in levels, we believe it is of little consequence for inferring ranks. In the context of our BK data on children housing assets, we ran a test where we excluded multiple property ownership and reassigned ranks on the basis of the *maximum*-valued property (if any property is owned) instead of the *total* value of all owned properties. The correlation between these two rank measurements was almost one.

Following the income mobility literature, our aim is to measure mobility, and its potential differences across subgroups, in the full U.S. population. Accordingly, we define one rank measure at the population level, and use this measure both in full-population analyses and in investigations of differential rank-rank relationships across race or geographic subgroups.

3.2. Empirical specification

The parental ownership rate in our sample is approximately 78%. This implies that children of renters are assigned a parental rank of 0.11, the child of the poorest owner is assigned a parental rank of 0.22, and the child of the $(0.11/0.78)^{th}$ percentile owner is assigned a parental rank of 0.33. Were we to specify a linear-in-ranks expectation function, this would force a constant linear relationship across these 3 groups. This is likely too restrictive: for example, as shown in Appendix Table D.2, parent renters have higher average income than the poorest owners.[24] On the other hand, parental income increases monotonically with housing asset rank in the population of owners. We therefore relax the linear model by assigning children of renters their own intercept:

$$W_i^g = \alpha + \beta W_i^{g-1} + \delta \mathbf{1}\{\text{renter}_i^{g-1}\} + u_i^g, \tag{1}$$

where W_i^{g-1} is child i's parental housing asset rank, $\mathbf{1}\{\text{renter}_i^{g-1}\}$ is an indicator for the parent renting their residence, and u_i^g captures idiosyncratic determinants of child i's housing rank.

We define the following relationships:

- *Absolute Mobility (α)*: average rank of children with worst-off owners;
- *Relative Mobility (β)*: gain in child rank associated with a one-rank gain in parent rank;
- *Renter Mobility (δ)*: rank difference between children of renters and the lowest value owners.

[24] Parent renters also have a much higher standard deviation of income, \$49,770, relative to \$26,850 for homeowners at the bottom of the distribution.

Relative mobility (β) is defined over parent owners, estimated as $\hat{\beta}$ from Eq. (1). We define α and δ in terms of the lowest value observed parental owner, who has a rank of 0.22. That is, we estimate relative mobility as $\tilde{\alpha} = \hat{\alpha} + 0.22 \cdot \hat{\beta}$ and renter mobility as $\tilde{\delta} = \hat{\delta} - 0.11 \cdot \hat{\beta}$.

3.3. Weighting

We begin with a base weight bw_g that is equivalent to the parent household of child g's sampling weight in the 2KLF. We then make two modifications to the base weights.

Imperfect record linkage. The PIK assignment algorithm works best when the record of Personally Identifiable Information contains Social Security Number and/or (full name, location, date of birth). Because the property records contain only (full name, location), some records were not assigned a valid owner PIK. We show in Appendix A.3 that the PIK'd administrative records slightly understate the individual homeownership rate inferred from survey data.

We address this issue as follows: let x_{ACS^*} define the individual homeownership rate inferred from survey data.[25] This yields the following adjusted weight:

$$aw_i^g = bw_i^g \times \begin{cases} \frac{1-x_{ACS^*}}{1-x_{BK}} & \text{if child } i \text{ is not a BK owner} \\ \frac{x_{ACS^*}}{x_{BK}} & \text{if child } i \text{ is a BK owner.} \end{cases} \tag{2}$$

That is, we slightly up-weight the observed owners and down-weight the observed non-owners to replicate this survey-derived benchmark. To capture the intergenerational heterogeneity that is of interest, we iterate this procedure across 550 sample cells defined by (White, Black, Hispanic, Asian, Other) $\times$ (parent renter, 10 deciles of parental owners) $\times$ (10 deciles of parental income).[26]

[25] Specifically, denote the residential property ownership share as x and the population share of residential renters who remotely own property as r. Using the 2018 SIPP, we estimate both of these objects and define the adjustment factor $a_{SIPP} = \frac{x_{SIPP}+r_{SIPP}}{x_{SIPP}}$. Because we cannot observe r in the larger ACS sample, we estimate the population ownership rate as the product of the observed ACS residential ownership rate with the SIPP adjustment factor: $x_{ACS^*} = x_{ACS} \cdot a_{SIPP}$.

[26] In doing so, we estimate x_{ACS} in each of the 550 cells, and allow a_{SIPP} to vary across the 5 racial-ethnic groups, to construct a cell-specific estimate of x_{ACS*}.

Effectively, this weighting adjustment uses owners assigned owner PIKs to represent owners not assigned owner PIKs, conditional on parental background information. This amounts to a "conditional missing at random" assumption. This assumption is not unreasonable: among the children in our sample who showed up as homeowners in 2018-2021 ACS data, we found that after conditioning on parental background, there was very little difference in average home value between ACS owners who were and ACS owners who were not matched to a BK owner record.[27]

Life-Cycle adjustment. Our sample children (parents) have a mean age of 39 (47) when we measure their housing assets. As shown in Figure 1, the life-cycle profile of homeownership is still substantially upward-sloping at age 39. We benefit from measuring housing wealth near the plateau in life-cycle ownership rates for two related reasons. First, we wish to make statements about "lifetime" asset holdings, which is the relevant object in standard models of household consumption and investment decisions. Second, issues of interpretation can arise in studying intergenerational wealth processes when comparisons are made between parents and children of different ages (Charles and Hurst (2003), Boserup et al. (2017)).

Accordingly, we further re-weight the sample to target a set of age 45-49 ownership rates. Because the residential ownership rate in our sample cohorts converged with that of prior Gen-X cohorts by age 40 (see Figure 1), we use the Gen-X cohorts as the basis for our target ownership rates.[28] These cohorts are too old to be linked to parental wealth and income records, so we can only observe average target ownership rates by racial group. We address this by translating the vector of subgroup ownership rates observed in our sample upward by a vector that hits the average race-specific target while preserving relative ownership rates

[27]To be conservative, we relaxed this assumption with an additional adjustment to the weights that we describe in Appendix A.4. In essence: if, in subgroup $g-1$, ACS owners who show up in the BK data own more expensive properties than ACS owners those who do not, this implies that the *observed* set of BK owners of type $g-1$ is richer than the *true* set. Accordingly, we should up-weight the relatively poorer owners of type $g-1$ and down-weight the relatively richer owners of type $g-1$. As it turned out, this adjustment exerted virtually no effect on the results, which further supports the conditional missing at random property of the data.

[28]Specifically, we consider those born in 1970-76, who were aged 45-49 in the 2019-2021 ACS. Just as for the base weight adjustment, we adjust the residential ownership rates inferred from this ACS sample into property ownership rates by applying adjustment factors estimated from the SIPP. See note 25 above.

between subgroups observed in the oldest birth cohort.[29]

Appendix A.5 provides the formal assumption behind this translation, and shows robustness of key findings to plausible alternative translations. It also reports supplementary figures that provide further motivation for our life-cycle adjustments.

4. Intergenerational Mobility of Housing Wealth

4.1. Intergenerational Mobility of Housing Assets in the U.S.

Figure 2 shows our main estimates of the intergenerational mobility in housing wealth in the U.S., based on our weighted estimates of (1). The navy blue dots show the average child rank conditional on parent rank, the light blue dashed line shows the median child rank for parents of a given rank and the red and green dashed lines show the 25th and 75th percentile child rank conditional on parent rank, respectively. Focusing first on the average rank-rank relationship, we see that the relationship is highly linear conditional on parent ownership. We find a β parameter of 0.427. This represents a substantively higher persistence in housing asset rank than for income which has a β of 0.347, as shown in Appendix Figure D.8.[30] We also see a non-linearity at the bottom of the parental distribution. Children of parent renters have similar average ranks as those of parents at the bottom of the home value distribution. On average, children with parents at the bottom of the homeownership distribution are in the 36.5^{th} percentile of their distribution ($\alpha = 36.5$), and children of parent renters are 1.74 ranks higher on average ($\delta = 1.74$). Appendix Table D.2 shows that average income for parent renters is higher than that for parents with low-value houses and that median

[29] For example, suppose there are two equal-sized subgroups, one with a 58% ownership rate and one with a 50% ownership rate. Between age 39 and age 47, the population ownership rate increased from 54% to 62%. Moreover, suppose that the oldest cohort of subgroup 1 attained a 62% ownership rate while the oldest cohort of subgroup 2 attained a 52% ownership rate. Our procedure dictates setting subgroup 1's age-47 ownership rate to $0.58 + 0.08 \cdot 0.62/0.57 = 66.7\%$ and subgroup 2's age-47 ownership rate to $0.50 + 0.08 \cdot 0.52/0.57 = 57.3\%$. Notice that these two rates average out to the age-47 population ownership rate of 62%.

[30] Our rank-rank income relationship is very similar to that estimated in Chetty et al. (2020). The data used are from the same source, though for a different time period, so this is unsurprising.

incomes are very similar.[31]

The quantiles provide further context. In the top 5% of parental housing assets, the median child rank is substantively higher than the mean—half of children are in the top 20% of the housing wealth distribution. The 75th percentile shows that 25% of children with parents in the top 5% are in the top 5% of the distribution. Perhaps most striking is the pattern for the 25th percentile. Through most of the distribution the 25th percentile is well below the mean rank, at the top of the distribution the 25th percentile quickly approaches the mean. Besides the intergenerational persistence, this highlights another channel of intergenerational relationship of resources—children of the wealthiest parents are much less likely to move down the distribution. This pattern also holds for income, but to a slightly lesser degree (Appendix Figure D.8).

Further, we can separately explore how the IG persistence is associated with i) child homeownership rates increasing with parent housing assets and ii) child home values increasing conditional on ownership. Appendix Figure D.4 displays these relationships. Panel A shows that the probability of ownership increases relatively smoothly with parent housing, though the increase is somewhat faster at the bottom of the parent distribution. Among parent homeowners, child rank conditional on ownership increases linearly with parent rank. These margins highlight an important feature for children of parent renters. The probability of child ownership is substantially lower among parent renters than for children with parents at the bottom of the home value distribution, but conditional on ownership the average rank is quite high, matching those at the median of the parental distribution. Appendix Table D.2 implies that parent renters are a much more heterogeneous group than parents at the bottom of the ownership distribution. The average income for parent renters is higher while

[31] Appendix Table D.7 shows the association between the δ parameter and parent and child characteristics. Across various controls, including controlling for child income and location, children of parent renters are on average between two ranks above and two ranks below that of parents at the bottom of the ownership distribution. Taken together, on average children of parent renters have very similar homeownership to children of parents at the bottom of the housing distribution, while movements up the parental distribution are correlated with relatively large increases in average child outcomes. We also see that conditioning on parent location, the estimated δ flips signs — within parent commuting zone (CZ), children of parent renters are about one rank lower than children of parent with the lowest value homes.

the medians are similar; the standard deviation of parent income for parent renters is $49,770 compared to $26,850 for parent owners at the bottom of the asset distribution.

We combine these relationships and decompose the rank-rank slope into the portion attributable to increasing child homeownership rates and increasing child home values (Figure 3). In the bottom portion of the parent housing distribution, most of child average gains with increased parental rank come from higher probabilities of homeownership. The share from home values increase throughout the parental distribution and in the top third of the parental distribution most of the persistence comes from increases in average home values.

4.2. Intergenerational Racial Gaps in Housing Wealth

Figure 4 shows the rank-rank relationship in housing assets separately for Black and White families. Intergenerational persistence of housing is much stronger for White than for Black households. The β parameters are 0.425 and 0.260 for White and Black families, respectively. The α parameters show that White households experience substantially higher "absolute" mobility in housing. The differences are even larger for parent renters. All of the nonlinearity at the bottom of the distribution is driven by White households, whereas Black families see an approximately linear relationship throughout the distribution.

This pattern contrasts somewhat to the IG income relationship documented in Chetty et al. (2020) or using these data (Appendix Figure D.8), which display similar intergenerational slopes for Black and White families. For housing, the average gap in child outcomes, conditional on parent assets, grows across the parental distribution. For parents in the 25th percentile in the housing distribution, White children are approximately 5 ranks higher than Black children on average, at the 75th percentile the gap grows to 15 ranks, and at the very top the gap is almost 20 ranks. Even for Black families at the top of the distribution, their children are relatively likely to be in the bottom half of the distribution—this reflects large differential downward mobility between Black and White families, particularly at the top of the distribution.

Cross-sectional differences in homeownership rates between Black and White families is well documented. Panel A of Figure 5 shows the probability of children owning a home for parents in different parts of the housing distribution separately for Black and White families, displaying large conditional disparities on homeownership rates. Children from Black households in the top 10% of the parental distribution are less likely to own a home than children of white parents in the 30^{th} percentile of the distribution.

Given this, we explore the roles of extensive margin homeownership relative to the intensive margin of asset value (the value of the home conditional on ownership) in explaining the Black-White IG gaps. We conduct simulations where we equalize the homeownership rates of Black and White children conditional on parent assets. To do so, we must assume the value of homes of the newly simulated Black homeowners. In the first exercise, we assume that the simulated homeowners have housing assets equal to average housing assets for the observed Black homeowners with parents in that rank (Panel B of Figure 5).[32] If we assign equal ownership rates at the observed gap in asset values conditional on parent rank, the patterns in intergenerational housing assets become much similar between Black and White families. Throughout the majority of the parental distribution, child outcomes would be very similar with some divergence remaining at the very top. This reflects the fact that, conditional on owning a home and parental rank, the gaps in child housing assets are relatively small compared to the unconditional gaps, as shown in Appendix Figure D.5.

This exercise does not account for selection in the observed data. If observed Black homeowners are positively selected, an policy that moved toward equalization of ownership rates would not result in asset values of new homeowners equal to those of observed homeowners, but would instead provide opportunities lower in the current distribution. Therefore, we use various methods to impute property values for counterfactual Black homeowners, which we describe in Appendix A.8. In the first approach, we capitalize observed rent payments of

[32]That is, we assign Black children with parents in rank Y the same homeownership rate as White children with parents in rank Y. The simulated new Black homeowners within rank Y are assigned the average housing assets of the observed Black homeowners within rank Y.

Black children in our sample who we observe as renters in matched ACS records. The results of this exercise are shown in Panel C. Appendix Figure D.7 presents alternative approaches including estimating the value of first homes conditional on observables using observed first-time purchases in our data (Panel A), and assigning marginal homeowners the 25th and 10th percentile of the observed distribution conditional on parent rank (Panels B and C). Together, these exercises suggest that if homeownership rates were equalized, average ranks of Black and White children would be roughly the same in the bottom half of the parental distribution, but that for Black and White children of parents at the top of the housing distribution there would likely remain substantial conditional gaps in housing values.

Finally, we descriptively explore the parent and child characteristics that drive Black-White gaps in housing. Appendix Tables D.9 and D.10 show how estimated intergenerational parameters and raw gaps in housing assets and ownership depend on various parent and child characteristics. The first column of Appendix Tables D.9 shows the difference in parameters depicted in Figure 4. Differences in observed parental characteristics do not explain very much of the observed gaps.[33] Columns (7)-(11) investigates how the gaps are associated with differences in child outcomes, conditional on parent housing rank. Differences in child location do not explain the observed gaps. Controlling for child income explains relatively little of the β-gap — as parental assets increase, White children have significantly higher assets then Black children, even if they earn the same amount of income. We investigate these patterns in a more structured way in Section 5. When controlling for the full set parent and child controls (column (12)), there remains a large β-gap unexplained by any of these characteristics.[34]

Appendix Table D.10 complements this by showing average differences in housing assets and homeownership rates. The average differences are shown in column (1). Controlling for parent housing assets reduces the asset gap by about 47% and the ownership rate gap by

[33] Parent location accounts for a portion of the α-gap, but does nothing to attenuate the β-gap.

[34] Differences in parent and child location and child characteristics, including location and income, only explain about half of the δ-gap.

about 32%. Adding information on parent income, marital status and location reduces the asset gap by 57.5% and the ownership rate gap by 51.4%.

4.3. Regional Variation in Intergenerational Mobility

In addition to developing new facts about the intergenerational transmission of housing capital for the country as a whole, we can also examine how this transmission varies across space. To examine these patterns, we estimate county-level α, δ, and β statistics in a two-part process. First, we directly estimate these parameters from the microdata; then, because these estimates can be quite noisy for small counties, we apply a standard area-level small area estimation method (Faye-Herriot regression) which smooths the direct estimates.[35] To visualize the geographic distribution of county-level housing capital mobility, we produce a series of choropleth maps.

Figure 6 maps our key housing capital mobility parameters for our pooled sample across race groups. The two measures of upward mobility – α and δ, representing the predicted housing wealth rank for individuals born to the worst-off homeowner parents and the differential predicted to renter vs. owner parents respectively – show broadly similar patterns. Broad stretches of the southeast, Appalachia, many parts of Indian country (such as the region in northwest New Mexico and northeast Arizona containing the Navajo and Hopi lands) and many "Rust Belt" areas such as Detroit, MI and Cleveland, OH show markedly lower levels of absolute housing wealth mobility. Conversely, large, high cost coastal metro areas (San Francisco, New York, Boston) and a broad swath of California, the Mountain West and Pacific Northwest show substantially higher absolute mobility. Patterns for the relative mobility measure β are less stark, but a high-to-low mobility gradient from northwest to southeast still roughly prevails.

We can then contrast these geographic patterns with the patterns in income mobility

[35] This smoothing has a shrinkage property such that as the number of observations underlying the direct estimates goes to zero, the Faye-Herriot estimate converges to the estimate for some larger geography (in our case, commuting zones, or groups of similarly sized commuting zones chosen to meet Census Bureau disclosure avoidance guidelines). For data quality reasons, we omit counties with fewer than 10 underlying microdata observations.

documented in Chetty et al. (2014) and Chetty et al. (2020). Figure D.10 reproduces the geographic distribution parameters which capture absolute (α) and relative (β) income mobility. Some patterns appear reasonably concordant across the two measures: higher absolute mobility in the Great Plains, and lower mobility in large parts of the South and Appalachia. However, beneath these relative patterns within mobility concept lie substantial differences.

Figure 7 shows the geographic variation in the *difference* between housing capital and income mobility concepts, e.g. each county's housing α (β) minus its income α (β). Here we observe interesting differences: absolute income mobility is substantially lower than housing capital mobility in large parts of the southeast, and in many large coastal metros (such as Boston and Los Angeles). Differences in relative mobility show fewer broad regional patterns; there is generally more dispersion in housing mobility within region than for income mobility, which shows very strong regional patterns. Broadly, we do not see larger persistence in housing capital in locations where income persistence is high, such as the in the South. Instead, we see that there is larger housing asset persistence in locations where there is relatively more income mobility, such as coastal urban areas, potentially reflecting the differential ability to accumulate assets conditional on income.

5. Intergenerational Mobility of Resources: Income, Wealth and Mechanisms

Given the different patterns in mobility in income vs. housing capital, in this section we further explore what the intergenerational mobility of housing assets documented in the previous section imply about the IGM of parent and child resources in the U.S. more broadly. To do so, we leverage the link with administrative tax records to explore the joint relationship between income and housing. We analyze whether housing rank is simply a proxy for income rank and the degree to which it provides further information about the intergenerational persistence of resources, which is imperfectly proxied by income. We show that housing has an important contribution to the intergenerational persistence of resources, independent of

what is measured using income flows.

5.1. Mobility of Wealth v. Income

In this section we discuss the relationship between estimating in the intergenerational transmission of resources using income and wealth. Most studies the U.S. have focused on the IGM of income because of data availability and because it is correlated with well-being and economic parameters of interest like returns to human capital. Yet, while income is related to resources or well-being more broadly defined, it may only be a noisy measure of parent or child resources — either because it is transitory relative to lifetime wealth or because it does not capture all relevant inputs to a concept of total resources. Wealth is generally believed to be a better and more stable measure of resources and well-being (Wolff (2017), Piketty (2014)).

In Appendix B, we present a simple statistical framework for how to interpret IGM relationships when parent and child *total resources* are intergeneratoinally linked. In the framework, wealth has various components with different rates of return, and income represents the realized flow returns to the stock of wealth. The analysis shows that if parent and child total resources are intergenerationally linked and individuals have heterogeneous asset compositions, i) estimated income-income relationships will generally understate the true relationships between parent and child total resources as income is a noisy proxy for total resources, and ii) the reduced-form estimate of the IGM of income will overstate the role of parent income in predicting child income when parent wealth is omitted.

In particular, we note that housing, the most important asset for most households in the U.S. through most of the distribution, produces no regular income flows meaning that it will effectively not be reflected in income measures, though housing could affect child income and assets. Variation in housing assets across parents would create a relationship where income is a noisy proxy for parent resources and the IGM of income coefficient would understate the true intergenerational persistence of resources. Similarly, if some parents earn only labor

income and other families earn a combination of labor and capital income (e.g., dividends from equities), and child outcomes are also a function of the wealth underlying the dividend income, then we would expect the IGM coefficient on total income to be larger than that on labor income alone.

We leverage our unique combination of data to flexibly estimate the joint relationship between parent and child income and housing assets using a specification of the form:

$$Y_i^g = \alpha_i + \beta_1 Y_i^{g-1} + \beta_2 H_i^{g-1} + e_i^g, \tag{3}$$

where Y_i^g and Y_i^{g-1} are parent and child positions in the income distribution, respectively, and we additionally include parent housing rank as a right-hand-side variable. Appendix Table D.11 shows the regression coefficients and Figure 8 shows the non-parametric rank-rank relationships.

Including housing assets substantially attenuates the income-income slope, and shows a large independent role of housing assets in explaining child income. Figure 8 shows approximately linear relationships between parent and child income controlling for parent housing wealth; parent housing rank shifts children up the distribution at any level of income on average.[36] The size of the bubbles represent the relative population weights for children. Parent housing and income rank are highly correlated, yet there is substantial variation in parent housing conditional on income in the middle of the distribution, and this variation is meaningfully correlated with child outcomes.

This implies that for many families in the middle of the distribution parent income apparently substantively mis-measures household resources, and conditional on parent income, kids from families with more housing wealth earn substantially more on average than those whose parents have similar income but less wealth. This demonstrates an independent role of parent housing assets in explaining average child outcomes. Section 4 discusses that the

[36] Appendix Table D.11 shows that an interaction term between parent income and housing assets is very small implying an approximately linear relationship between each conditional on the other.

rank-rank slope of housing assets is steeper than that for income. Appendix Figure D.9 and Table D.5 display that the rank-rank slope for labor income show less persistence than the slopes for total income or housing assets. Along with the joint relationships discussed here, these patterns strongly suggest that parent and child resources are intergenerationally linked, beyond income flows, and therefore housing assets (and capital assets more generally) have an independent role in explaining intergenerational persistence in resources in the U.S.[37]

5.2. A simultaneous equation model of intergenerational resource transmission

Building on the previous discussion, and leveraging our unique combination of data, we expand the reduced form model of the relationship between parent and child resources. Take generation g's lifetime budget constraint as:

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

Where lifetime consumption c_g plus the amount of resources transferred to the next generation b_g must equal lifetime earnings, Y_g, some share of which is saved at rate s_g and earns average returns r, plus any inherited wealth from the previous generation b_{g-1}.

From this static capital accumulation framework, we start by assuming reduced form relationships between parent resources and components in the child's budget constraint. Children imperfectly inherit productivity/human capital from parents as a function of parent resources (W_{g-1}), which produces labor income (Y_g). This could be from parent inputs into the human capital development of children, material or otherwise.[38] Children use their own

[37] Housing assets are only one source of resources mis-measurement when using parent income as a proxy for parent resources, but housing is the most important capital asset across the majority of the parent distribution and therefore likely the most consequential for understanding the independent role of assets in explaining IGM of total resources. Appendix Table D.2 shows that non-labor sources of capital income are rare across most of the parental distribution and particularly concentrated at the very top. Pensions are the other important source of wealth throughout the distribution, but pension assets (and rank in the pension asset distribution) are likely highly correlated with, and therefore largely captured by, labor earnings.

[38] For example, this could include material inputs such as private schooling or tutors, computers, college costs, or it could include non-material inputs such as time spent teaching children, entrance to the education or employment networks (ex, legacy or nepotism), or transmission of preferences over labor market earnings or careers. In this way, productivity/human capital are being defined from a realized and rewarded in the

earnings to accumulate wealth, but may also have additional wealth as a function of their parents' resources. This could be from a direct inheritance b_{g-1} or parental resources could affect children's saving rates through transmission of preferences for, or knowledge about, savings opportunities.

Now, children's current stock of wealth can be written as a reduced form function of child earnings and parent wealth given by:

$$W_g = f(Y_g, W_{g-1}) = (1+r)\bar{\eta}Y_g + (1+r)\theta_s(Y_g \times W_{g-1}) + \alpha_b W_{g-1} + e_g$$

where $(1+r)\bar{\eta}$ is the average gross rate of return on child earnings independent of parent resources and $(1+r)\theta_s$ is the differential rate of return on child earnings for children of parents with different amounts for resources.[39]

This leads to a simultaneous equation model that can be represented by the regressions:

$$Y_i^g = \lambda W_i^{g-1} + u_i^g \tag{s1}$$

$$W_i^g = \alpha_y Y_i^g + \alpha_b W_i^{g-1} + \alpha_s(Y_i^g \times W_i^{g-1}) + \epsilon_i^g \tag{s2}$$

where the first equation (s1) represents the relationship between parent resources and child earnings and the second equation (s2) is the relationship between child resources, child earnings and parent resources. The coefficient α_y represents the average increase in child assets as child earnings increases, independent of parent wealth.

If children have more assets than predicted by their earnings alone because of parental wealth then α_b and/or α_s will be greater than zero; α_b represents the degree to which parent assets shift children up the asset distribution conditional on (or at all levels of) child earnings, and α_s represents the degree to which children of wealthier parents accumulate more assets for a given increase in their earnings than children of less wealthy parents.[40]

market standpoint, not a potential or ability standpoint.

[39] A more complete derivation is presented in Appendix C

[40] The reduced-form parameter, α_s, will reflect differences in savings rates as a function of parent resources

If parent resources only affect child resources through child earning ability, then $\lambda > 0$ and $\alpha_y > 0$ and $\alpha_b = \alpha_s = 0$; conditional on observing child earnings parent resources have no further association with child assets. But, if children with higher wealth parents have more assets than children with lower wealth on average, even conditional on having the same earnings, α_b and/or α_s will be greater than zero. Because we have information on parent and child earnings and assets, we can separately estimate these reduced form parameters.

5.3. Labor Income and Direct Channels of Intergenerational Mobility

Putting this framework in the simultaneous equation terminology, the direct effect of parent assets on child assets is α_b, or the degree to which higher parent assets are associated with higher child assets, conditional on child income. We call this this "direct channel." The indirect effect is $\lambda \times \alpha_y$, the degree to which children of wealthier parents earn more and use the higher earnings to acquire more assets. We refer to this as the "labor income channel." Finally, we call α_s the "propensity to save" channel, or the differential relationship between child earnings and assets due to parents having more assets. In this simultaneous equation framework, the direct channel, labor income channel and propensity to save channel decompose the reduced-form slope parameter from a regression of child assets on parent assets, or β from Equation (1).

We estimate the simultaneous equation model represented by Equations (s1) and (s2) using rank-rank regressions of child earnings on parent assets and child housing assets on child earnings and parent assets, respectively.[41] We find empirically that on average parent resources have important labor income and direct channels, and that the "propensity to save" channel is less important for explaining intergenerational persistence.

Figure 9, Panel A shows the simple decomposition of the the rank-rank relationship

(θ_s), but would also encompass any differences in rates of return realized by children of parents with more resources, conditional on their income.

[41] The rank-rank specifications, for example, imply that α_y represents the rate at which moving up the earnings distribution is associated with moving up the housing distribution. The interaction coefficient, α_s, is the differential rate by which increases in child earnings rank are associated with increases in housing rank for parents higher in the parent asset distribution.

between parent and child housing into direct and labor income channels, excluding the interaction term; the associated coefficients are reported in column 1 of Appendix Table D.12. This model implies that approximately 60% of the rank-rank slope is from the direct channel and the remaining 40% is from the labor income channel. While differences in labor market outcomes associated with parent assets are important for determining average child assets, there is also a substantial direct channel — even conditional on children having the same earnings, children of parents with more housing assets have more assets themselves on average.

In Panel B, we include the "propensity to save" channel in the decomposition of the rank-rank slope. We see that this channel only accounts for a very small share of rank-rank slope, about 6.8%. This means that as children move up the earnings distribution they move up the housing distribution at similar rates regardless of parent assets. An interpretation is that children of wealthier parents do not have differential preferences for investing in housing as they move up the earnings distribution. Yet, they do have substantially more housing at all levels of earnings as displayed by the large remaining direct channel, clearly underscoring the independent role of parent assets in determining child assets.[42]

Next we assess how direct and labor income channels are associated with the increases in child ownership rates and child home values across the parent distribution. Panel C of Figure 9 shows that the increases in homeownership rates across the parent distribution are almost fully associated with the fact that children of high-asset-parents earn more income (the labor income channel). On the other hand, conditional on children earning the same amount, children of wealthier parents have substantially more valuable homes (the direct channel).

These results also provide insight into the difference in average outcomes between children of parent renters and parents with low housing assets, δ (Appendix Table D.13). If it weren't for the propensity to save channel, the rank-rank slope would be near linear across the entire

[42]The propensity to save channel is conceptually a mix of the labor income channel (a function of increased child earnings) and a direct channel (higher assets conditional on earnings).

parent distribution, including for parent renters. The main reason that children of parent renters have more housing on average than children of parents with low housing assets is that as they move up the earnings distribution, they move up the housing distribution much faster.[43] Appendix Figure D.4 shows the entire δ gap is due to substantially higher average home values conditional on owning a home among children of renters, while the ownership rates for children of parent renters are lower than those of parents with low housing assets. The direct-indirect decomposition shows that this is mostly from the direct channel, implying that the propensity to save channel is not a result of children of renters differentially increasing the probability of owning a home as they earn more, but instead, when their earnings increase they purchase more valuable houses. Together, this is consistent with children of renters having differential preferences, which may also be reflected in the fact that the sign on δ flips when controlling for parental or child location (Appendix Table D.7), which may be correlated with preferences and the value of houses conditional on ownership.

Finally, we include parent income rank, in addition to parent housing rank in the simultaneous equations.[44] First we add parent labor earnings rank (Table D.12, col. 5 and Figure D.11 Panel A). The labor income channels are broadly similar, but there is almost no direct channel of parent earnings (0.0286) while the direct channel on housing is barely attenuated (0.241). Conditional on having the same earnings, children of higher earning parents do not have substantially more housing assets, but children of parents with more assets do. Next, we include parent total income rank i.e., including capital and private business income in addition to labor income. The labor income channels are still broadly similar. The direct channel associated with parent income is no longer trivial (0.070), and the direct channel of parent housing is moderately attenuated (0.207), though still accounting for 48.5% of the rank-rank slope. Together this implies i) the direct and labor income channels of parent housing assets are to some degree a proxy for parent non-housing resources; ii) for the

[43] Only a small part is associated with the fact that children of parent renters earn more on average (the labor income channel).

[44] Concretely, we add parent income rank to the right hand sides of Equations (s1) and (s2) allowing for labor income and direct channels of parent income independent of parent assets.

most part, this is from the association with parent capital income rather than parent labor earnings; and iii) even after conditioning on parent income there is a large direct channel of parent housing.

Taken together, the simultaneous equation analysis shows that i) unsurprisingly, children of parents with more resources earn more income and consequently have more assets, but ii) there is also a substantive independent role of parent assets in predicting child assets – even conditional on children earning the same amount, children of wealthier parents have more significantly more assets on average.

5.4. Direct and Labor Income Channels and the Black-White IG Gap

We also use this framework to investigate the Black-White IGM gaps in housing. Similarly, we decompose the difference in the average housing ranks of children of Black and White families across the parental asset distribution into the portion attributable to differences in child earnings and differences in housing assets conditional on children having the same earnings. The main decomposition is presented in Figure 10 Panel A. The gap in absolute mobility (α) is driven by the labor income channel; for children of parents at the bottom of the distribution, Black-White gaps in housing are fully associated with the Black-White differences in labor market earnings. But, almost the entire difference in IG persistence is driven by direct channels. If child labor market outcomes were equalized conditional on parent assets, there would still be a growing gap between the assets of Black and White children across the parental distribution. At the top of the parental distribution, only about 35% of the Black-White asset gap is explained by differences in child labor market earnings.[45]

Panel B decomposes the direct and labor income channels into differences in home values and homeownership rates. As discussed in Section 4.2, the majority of the gaps in absolute mobility and IG persistence are related to differential homeownership rates. This decompo-

[45]Appendix Tables D.14 and D.15 show the decomposition of the rank-rank slope separately for Black and White families, confirming that the labor income channels are rather similar across groups, so the large slope differential is due to the direct channel. Further, we see that for Black families, differences in labor market earnings across the parental distribution fully account for differences in homeownership rates across the distribution.

sition shows that this is a function of both direct and labor income channels. Equalizing child average earnings conditional on parent assets would close most of the ownership gap at the bottom of the parental asset distribution, but only about half of the ownership gap in the top half of the distribution. In other words, even conditional on Black and White children having the same earnings, there are large gaps in homeownership rates across the distribution.[46]

Appendix Figure D.14 shows the implications of adding parent income rank and child non-labor income into the decomposition. After accounting for parent housing, parent income explains little Black-White IG gap (Panel A). While the majority of the gap in absolute mobility is explained by differences in child labor earnings, Panel B shows that a portion of the difference in persistence is explained by differential average non-labor income between Black and White children for the same level of parent housing assets, though important direct channels of parent housing assets remain. Together, this implies that i) equalizing child labor market earnings would greatly reduce the gap in absolute mobility, thereby largely closing the racial gap at the bottom of the parental distribution, but ii) differences in average outcomes for Black and White children grow throughout the parental distribution, associated with differences in the IG correlation of assets and capital income.

5.5. The role of parental assets, a robustness check using capitalized wealth

The previous analyses show that parental housing assets have an independent role determining child outcomes, in addition to income. We propose that this is because it is an asset that is not represented in income flows and the relationship between child total resources and parent resources may be a function of wealth, not only income. Housing is the most important capital asset through the majority of the income distribution, so it should be a strong proxy for wealth rank independent of income rank. Yet, people may accumulate wealth in various ways, investing in housing may mean substitution away from other assets and not owning

[46]For most of the distribution, the difference in home values is associated with differential child earnings (labor income channel), though a growing part of the home value gap comes from the direct channel at the top of the parental distribution.

a home can provide opportunities to accumulate other assets. Because housing has a large extensive margin component, it may be a lumpy measure of assets — as we have shown, measurement is relatively sensitive to timing because purchases of housing imply important re-ranking while income ranks are more stable over time even as average income increases.

To understand how sensitive our interpretations of the role of parent assets for child outcomes are, we provide estimates of intergenerational mobility of total wealth using a capitalization method. That is, we create estimates of parent and child total wealth starting from income flows and using estimated average rates of return to map flows back to their underlying stocks. For observed income source y_i, we assign underlying wealth for that source, $w_i = y_i/r_i$. We do so using the capitalization factors provided by Piketty et al. (2018) (PSZ) for fixed-income assets and corporate equities, capitalizing interest and dividend income respectively.[47] For pension wealth, we use the method from Smith et al. (2022) (SZZ), applying age-dependent multipliers to labor and retirement income. For housing wealth, we use our direct estimates from the micro data. Summing these components gives an estimate of total wealth, and we rank parents and children by their respective wealth distributions. Appendix A.9 provides details of the capitalization method.

While there is uncertainty and debate about how to estimate wealth using capitalization methods,[48] we believe it provides a useful estimate in our context for a few reasons: i) we focus on rank-rank relationships so we do not need to get the dollar amount of wealth right, just the relative ranking between individuals, which is a much lower bar, ii) much of the debate is about time trends where different policies or macro trends can affect the relationships between observed income flows and wealth — we only need to do the ranking in the cross section, i.e., rank parents relative to each other correctly and children relative to each other, iii) the large majority of the debate and the sensitivity to methods is at the very top of the distribution, above the top 1%. While the very top is critical to get level

[47] Distributional tables are updated to 2022 available on Gabriel Zucman's website: https://gabriel-zucman.eu/usdina/.

[48] See, for example, Kopczuk (2015), Bricker et al. (2016), Saez and Zucman (2016), Smith et al. (2022).

estimates and full distributional statistics correct, our primary focus is not the very top of the distribution so re-rankings within the top 1% would not affect our measures.

First, we estimate rank-rank IGM parameter using capitalized wealth (Appendix Figure D.15). The rank-rank relationship is fairly linear and has a very similar slope to that for housing, 0.43. The estimated rank-rank wealth relationship shows substantially more IG perseverance than using income alone. When using capitalized wealth, the slope is quite linear through the bottom of the parent distribution. This supports that many parent renters have non-housing wealth and that the children of these parents have higher wealth on average.[49,50] Appendix Figure D.16 shows the relationships separately for Black and White families. Similar to housing, there is a significant β-gap, for White families $\beta = 0.424$ and for Black families $\beta = 0.335$, so the conditional gap widens at the top of the parental distribution. While there is substantial downward mobility among Black families even at the top of the parental distribution, White families have high persistence and the children of the wealthiest White parents are highly insulated from downward mobility.

Next we decompose the rank-rank slope using the simultaneous equation model (Appendix Figures D.18 and D.19). The results are similar to those using housing assets. The magnitudes of the direct and labor income channels are similar. Conditional on children having the same labor earnings, those with wealthier parents have substantially more wealth on average. Decomposing parent wealth into labor (pension) and non-labor (housing and financial assets) wealth, the labor income channel is similar across sources, while the direct channel is almost exclusively from non-labor wealth. As parents move up these distributions, children's average labor market outcomes increase similarly, but conditional on child earnings, more parent capital wealth is associated with higher average child wealth, whereas once we condition on child earnings parent labor wealth provides little additional information

[49] That is, the children with renter parents that re-rank up the distribution using the capitalization method also re-rank up the child distribution on average.

[50] Further, the capitalization method is less sensitive to the life-cycle adjustment; the IGM estimate without the LCA weights is only moderately attenuated and remains significantly higher than the slope for income (Appendix Figure D.17). This supports that the raw housing ranks, before life-cycle adjustments, underestimate persistence.

about child wealth.[51] Finally, we continue to see that the Black-White gap in intergeneraional persistence is almost exclusively driven by the direct channel of parental wealth.[52]

Together, these analyses support the interpretation that intergenerational persistence in total resources is stronger than that of income, and that capital wealth has an important role for understanding intergenerational mobility independent of labor market outcomes or income flows more generally.

6. The Housing Supply Channel of Intergenerational Mobility

In the previous section we showed that parental housing assets are important for explaining child outcomes, independent of income. In Section 4.3, we showed considerable geographic variation in housing wealth mobility. The income mobility literature has pointed to the importance of various local exposures in shaping human capital formation and adulthood earnings. While these exposures indirectly influence asset holdings as well, we see that earnings do not sufficiently explain housing asset mobility or its geographic variation. Accordingly, we extend the local exposure literature by examining how local housing markets affect housing asset mobility.

As shown in Appendix Figure D.20, house prices grew slightly slower than prices of other goods and median personal income from 1987-1998. Thereafter, house prices considerably outpaced the other two series, coinciding with our sample cohorts reaching peak home-buying ages. At the same time, concern has risen over housing shortages, restrictive zoning and permitting, and construction costs (e.g., Gyourko and Molloy, 2015; Baum-Snow, 2023). These features vary considerably across local areas, suggesting local variation in exposure to price growth during the post-Great-Recession period. We leverage this variation in a

[51] Non-surprisingly, housing is an important part of this direct channel given its importance as the largest non-pension asset.

[52] The similarity of these results to the housing results is not surprising given that housing, along with pension wealth, is the most important asset throughout most of the parent wealth distribution. Pension wealth is a function of labor earnings, the most important income source through most of the distribution, which means that income ranks closely approximate pension wealth ranks. Similarly, housing ranks closely approximate non-labor wealth. See Appendix Table D.2.

difference-in-difference design.

6.1. Housing supply data

We obtain information on housing supply elasticities from Baum-Snow and Han (2024). These authors combine micro-geographic information on city features (e.g., land availability, zoning restrictions, and distance from city center) with housing transactions data to model the responsiveness of housing units to demand-driven price shocks and estimate housing supply elasticities in 2001 and 2011 for every residential tract in U.S. metro areas. They find considerable variation in housing supply elasticities across city aggregates (as in Saiz (2010), Gorback and Keys (2020)) and across census tract.

We merge Baum-Snow and Han's public-use data package onto our micro dataset according to parental location as measured in the 2KLF.[53] Our dataset covers the approximately 800 counties located in U.S. metro areas. We denote county c's housing unit supply elasticity in 2001 as γ_c, where $\gamma = \frac{d\ln(Q)}{d\ln(P)}$. The population-weighted empirical distribution ranges from 0.1 to 0.8, with a mean (median) of 0.36 (0.32) and a standard deviation of 0.17.

6.2. Empirical framework

Motivating example. Consider two hypothetical counties. County 1 has a housing supply elasticity of $\gamma_1 = 0.2$, while county 2 is more elastic, with $\gamma_2 = 0.4$. These supply curves are fixed over time. Suppose we observe two birth cohorts of data, cohort b and cohort q, where cohort q is younger. A *common demand shock* requires the addition of 10 log points more units in each county between the two cohorts.

Consider a mobility statistic m, which we estimate separately by birth cohort and county. The reduced-form mobility response to being exposed to the more-elastic county is given by the difference-in-difference estimate

$$r = (m_{2,q} - m_{2,b}) - (m_{1,q} - m_{1,b}).$$

[53] As we lack sufficient sample size for tract-level analysis, we aggregate their tract-level elasticities up to the county level using the aggregation method they propose in their Equation (21).

We can rescale this into a *price semi-elasticity of mobility* by dividing the reduced-form estimate by the implied difference in price growth:

$$s = s(r, d\ln(Q), \gamma_1, \gamma_2) = \frac{r}{\frac{d\ln(Q)}{\gamma_2} - \frac{d\ln(Q)}{\gamma_1}}. \tag{4}$$

In this case, $d\ln(Q) = 0.1$, $\gamma_2 = 0.4$, and $\gamma_1 = 0.2$, which yields a semi-elasticity of $s = -4 \cdot r$. Hence, if the more-elastic county experienced a relative decline in β of .025 (i.e. 2.5 rank points), then $s = .1$. This implies that a 10-log-point increase in price raises intergenerational persistence by 1 rank point.

Difference-in-difference regression framework. In practice, we observe many counties, potentially experiencing different demand and supply shocks over the period of interest. We proceed by generalizing rank-rank specification (1) into a difference-in-difference estimator. We model the housing asset rank of child i, who grew up in county c, and was born in year b, as follows:

$$\begin{aligned} W^g_{icb} \quad = \quad & \left(\alpha + \alpha_f' \mathbf{F_b} + \alpha_\gamma \gamma_c + \alpha_x' \mathbf{X_c F_b}\right) + \alpha_{DiD} \gamma_c b \; + \\ & W_i^{g-1} \cdot \left(\left(\beta + \beta_f' \mathbf{F_b} + \beta_\gamma \gamma_c + \beta_x' \mathbf{X_c F_b}\right) + \beta_{DiD} \gamma_c b\right) \; + \\ & \mathbf{1}\{renter_i^{g-1}\} \cdot \left(\left(\delta + \delta_f' \mathbf{F_b} + \delta_\gamma \gamma_c + \delta_x' \mathbf{X_c F_b}\right) + \delta_{DiD} \gamma_c b\right). \end{aligned} \tag{5}$$

The first column of parameters represent the 3-parameter specification in terms of absolute mobility (α), relative mobility (β), and renter mobility (δ). The second set of parameters interacts these mobility effects with a suite of birth-cohort fixed effects $\mathbf{F_b}$ to allow for national birth-cohort trends in mobility. The third set of parameters allows mobility to vary by the baseline housing supply elasticity γ_c. This allows more-elastic counties to have different mobility levels than less-elastic counties, independent of the price increases to which our cohorts were exposed.[54] The fourth set of parameters allows mobility to *trend* differently

[54] We implement a more-robust version of $\alpha_\gamma \gamma_c$ by specifying a full suite of county fixed effects. That is, we allow baseline housing asset rank to vary arbitrarily across counties instead of fixing the relationship to be parametric with respect to the housing supply elasticity.

across birth cohorts according to a set of initial county characteristics $\mathbf{X_c}$. The final set contains our response parameters of interest: how mobility varies with γ_c interacted with a linear trend in birth year b.[55] Because the distribution of γ_c is non-monotonic and highly skewed, with some negative and very small values, we specify a cubic or quartic in γ_c, which flexibly allows non-constant responses of mobility to γ_c across the γ_c distribution.

Identifying assumption. Our design is akin to a *shift-share instrument*, in that we interact the local supply elasticity with the national change in quantity demand to form a predicted price change at the local level. We wish to interpret the DiD effects as mobility responses to differential cross-cohort price shocks generated by predetermined differences in housing supply—due e.g. to variation in available land, land-use restrictions, distance from a central business district, and markets for construction labor and materials. This interpretation is valid if, after conditioning on controls $\mathbf{X_c}$, there is no systematic correlation between baseline housing supply elasticity and subsequent local housing market shocks (Goldsmith-Pinkham et al., 2020). These controls include: a suite of Census division fixed effects, the 2001-2011 *change* in the housing supply elasticity, the county-level rate of parental homeownership and average home value, and a "superstar county" dummy.[56]

It is instructive to note that certain local demand shocks do not compromise our inferences. For example, if national demographic trends raise demand for housing, resulting in more population density in inelastic counties, and population density produces agglomeration effects or neighborhood amenities, we consider these responses as part of the "treatment" of living in a less-elastic county. One could also imagine the reverse scenario, in which disamenities due to congestion arise in less-elastic counties, endogenously shifting demand toward more-elastic counties.

[55]The linear trend increases efficiency and ease of interpretation, but we recover quantitatively similar results if we instead specify a full set of birth cohort fixed effects.

[56]This is a county with a 2000 population in the top 3 percent of the national distribution of counties according to the 2000 Census, which roughly equates to being in the top decile of our metro sample of counties.

6.3. Main results

Appendix Table D.16 presents estimates from each of 12 different specifications of Equation (5).[57] Each estimate is the response of the cohort trend in mobility to an increase in γ_c from $-1SD$ to $+1SD$ relative to the population median. The estimates are quantitatively similar across all 12 specifications and are statistically significant in nearly all of them.

Table 2 summarizes the main results by presenting the median effects across the 12 specifications.[58] Averaged across ages 25-38, the national housing stock increased by 6.05 log points between the 1978 and 1986 birth cohorts, so we set $d\ln(Q) = .0605$ to calculate price semi-elasticities of form (4).[59] Given this, the specified increase in γ_c implies a price decline of 27.2 log points.[60] Row 1 shows that this is associated with a 2.6-rank decline in the rank-rank slope of housing assets, or a price semi-elasticity of around 0.1—a 1-rank-point rise in relative mobility per 10-log-point decline in price.

This response is economically significant. Between the first half of 2010 and the end of 2021, the national housing stock increased by 8.2 log points. Extrapolating our shift-share instrument onto this housing expansion implies a relative price decline of 38.0 log points, which in turn produces a 3.6-rank differential in relative mobility between the inelastic and elastic counties. As shown in the last column of the table, this effect is one-quarter of the observed cross-county differential in our sample.

Applying the same analysis to absolute (α) and renter (δ) mobility, we find a price semi-elasticity of around $-.12$ for α and about 0.10 for δ. This implies that the outcomes

[57] These specifications result from the interaction of 3 choices: i) the polynomial order of γ_c (cubic, quartic); ii) whether we multiply the regression weights by the inverse standard error of γ_c to further adjust for small-area uncertainty; and iii) the set of trend controls. In all cases we allow our baseline mobility measures (α, β, δ) to vary with birth cohort fixed effects interacted with a full suite of Census division dummies $\mathbf{F_{d(c)}}$ and with the 2001-2011 *change* in γ_c. We then layer on interactions with county-average parental housing characteristics in 2000 (i.e. the rate of parental homeownership and the average home value, which we summarize as $\overline{\mathbf{H^{g-1}}}_{\mathbf{c}}$), or with a "superstar" county dummy $S(c)$.

[58] These effects are quite close in magnitude to the "cubic, weighted" specification with the full set of trend controls, which is also our *a priori* preferred specification.

[59] Source: Census Bureau Population and Housing Unit Estimates: https://www.census.gov/programs-surveys/popest.html.

[60] That is, $d\ln(p_c) = \frac{.0605}{.491} - \frac{.0605}{.153} = -.272$.

of children raised by the worst-off owners improve when housing supply expands, while the prospects of children raised by renters do not change much.[61] Scaled in terms of the 2010-2021 housing expansion, elastic counties experienced a 4.6-rank gain in absolute mobility relative to inelastic counties. This effect is over one-third of the observed cross-county differential in our sample. This is a large effect, suggesting that the recent decline in housing affordability has importantly shaped intergenerational inequality and its spatial variation.

6.4. Heterogeneity

We now analyze heterogeneity in the reduced-form mobility response across race and housing-market characteristics. Appendix Table D.17 presents the full results; we summarize them in Figure 11. We estimate much larger mobility responses for Black families than for White families. While an increase in γ_c from $1SD$ below to $1SD$ above the median increases the cross-cohort trend in White families' absolute mobility by 3.2 rank points, the increase for Black families is 6.3 rank points. Moreover, the decrease in the White (Black) rank-rank slope is 2.9 (14.9) rank points. In sum, the the quasi-experiment raises the prospects of "poorest-owner" White (Black) children by 2.6 (3.0) rank points,[62] while it changes the prospects of the "richest-owner" White (Black) children by 0.3 (-8.6) rank points. This suggests that housing supply expansions widen the average Black-White mobility gap by widening the gap in relative mobility.

As previously discussed, there is reason to expect non-constant responses of mobility across the γ_c distribution, due to the inversion of the elasticity in the price instrument. Accordingly, we use our flexible non-linear specification to estimate marginal effects of housing supply changes at different points in the distribution.[63] Figure 12 presents the results, overlayed with a histogram of housing supply elasticity exposure. The graphs on the top present

[61] The 1.2-rank gain in everyone's housing assets is offset by the 1-rank loss experienced by children of renters relative to children of owners.

[62] I.e. $3.2 - 0.22 \cdot 2.9$ versus $6.3 - 0.22 \cdot 14.9$. We also find little change in the Black-White mobility gap among children of renters.

[63] Cut points for the heterogeneity analysis are $-1.5SD$ to $-1SD$, $-1SD$ to $-0.5SD$, $-0.5SD$ to $+0.5SD$, and $+0.5SD$ to $+2SD$ relative to the mean county elasticity.

reduced-form mobility responses for each of β and α, while the graphs on the bottom rescale these estimates into price semi-elasticities.

For both relative and absolute mobility, we observe strong mobility gains of over 3 rank points among the most inelastic counties. These gains then decay to zero as we move toward more elastic counties. When we convert these estimates in terms of a given change in price, the mobility gains are strong up through the mean of the distribution, with semi-elasticities of around 0.14. These results indicate that adding supply to the tightest markets has the largest mobility returns both because price is sensitive to marginal supply expansions and because the per-price mobility response is strong in these markets. These results are not simply due to markets with higher baseline prices experiencing systematic demand shocks, since we control for an interaction between average parental home value and birth-cohort fixed effects. Also, Figure 11 shows similar mobility responses across low- and high-price areas.

7. Conclusion

Our analysis highlights the central role of housing capital in shaping intergenerational economic mobility in the United States. Using linked administrative and survey data on over 3.4 million families, we find that housing wealth is more persistent across generations than income and that this persistence is shaped both by labor market outcomes and the direct transmission of assets. The geographic patterns in housing capital persistence differ substantially from patterns in intergenerational income mobility. Importantly, we identify significant racial disparities in intergenerational housing outcomes that cannot be fully explained by income alone. Furthermore, we show that local housing supply constraints significantly affect the extent of housing capital mobility across regions. These findings underscore the importance of considering housing markets, alongside labor markets, in understanding and addressing the long-term transmission of economic inequality.

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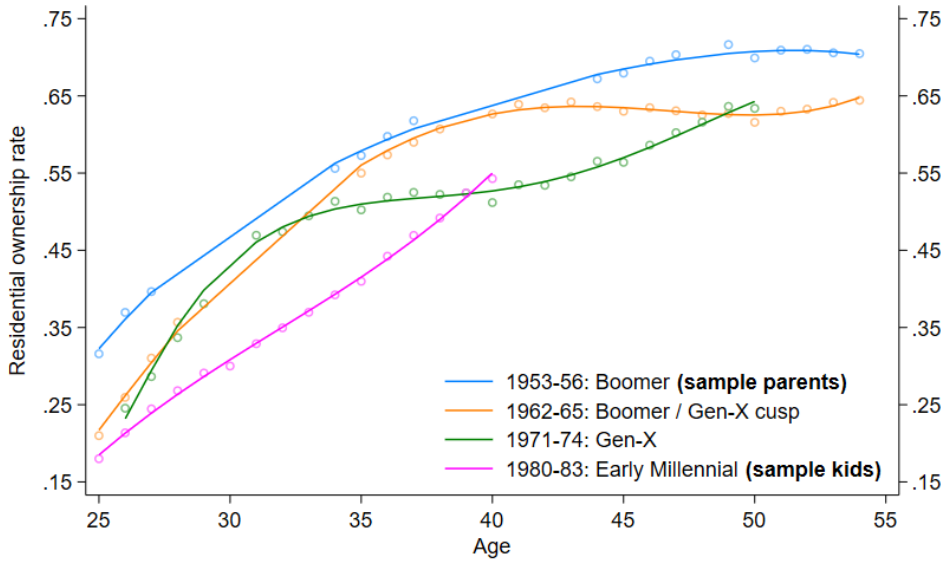
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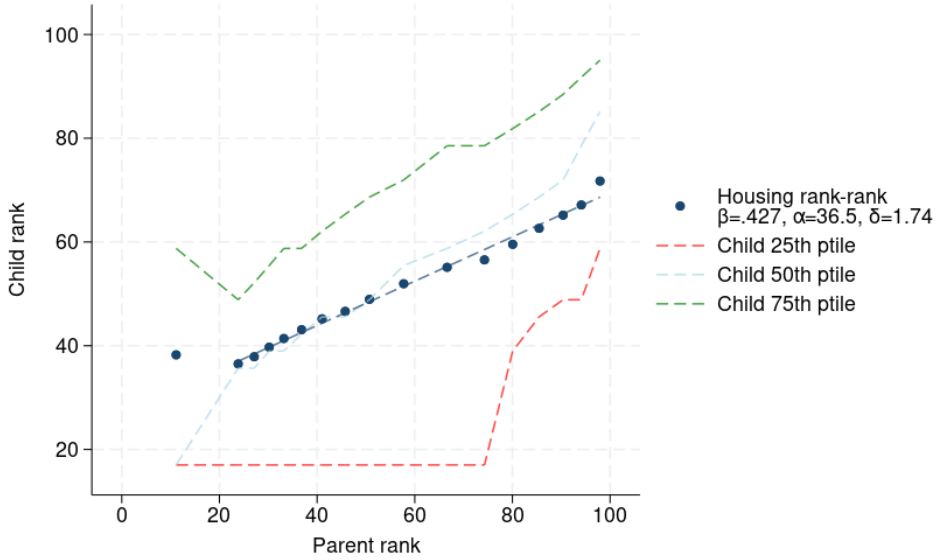
Figures and Tables

Figure 1: Age-Ownership Profiles in Selected Birth Cohorts



Source: 1980-2000 Long Form and 2005-2022 American Community Survey public-use files.
Notes: The lines plot residential ownership rates as a function of age for each of 4 selected birth-cohort groups. Residential ownership is defined as being the reference person or spouse in a housing unit that is owned (as opposed to rented). Note, the sample is restricted to individuals born in the United States.

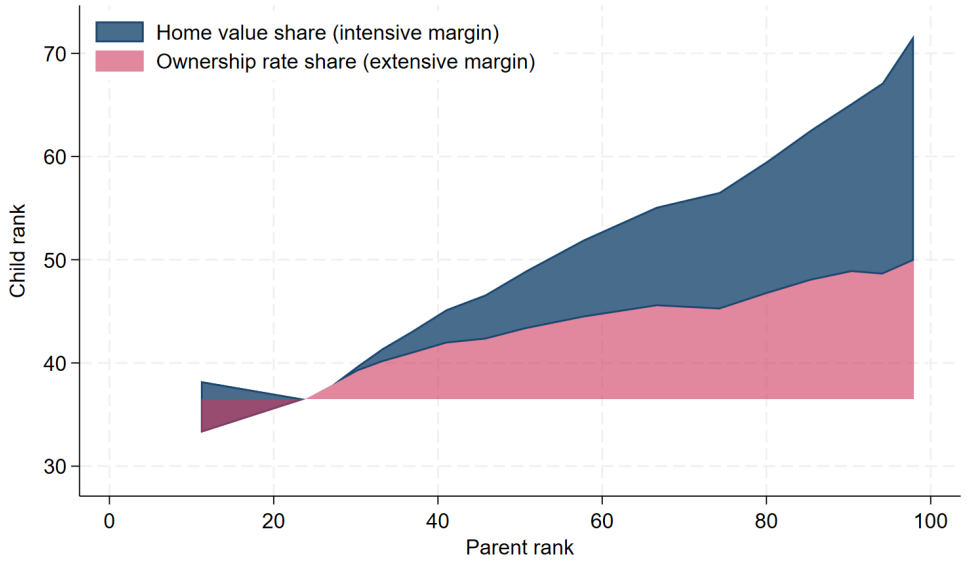
Figure 2: Intergenerational Mobility of Housing Assets - Rank-Rank relationship



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Note: This figures shows the rank-rank relationship of housing assets. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is the linear rank-rank slope (β). Percentiles of the child housing rank distribution conditional on parent rank are also shown. α is the average child rank for children of parent homeowners at the bottom of the home value distribution and δ is the difference in the average child rank between children of parent renters and parents in the bottom of the housing value distribution.

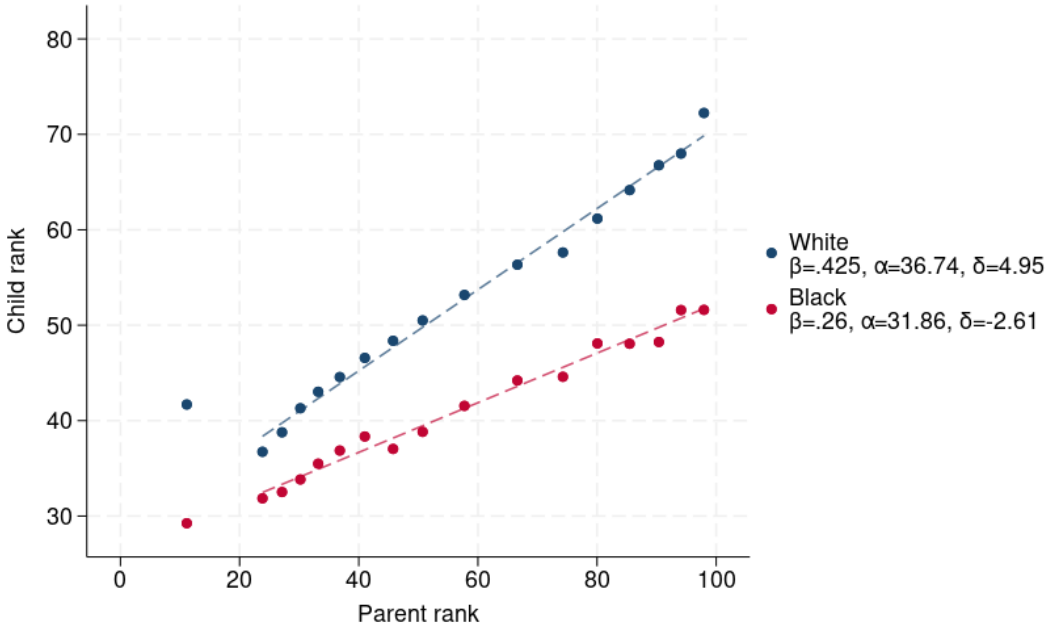
Figure 3: Decomposition - homeownership rate v. home value



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Note: This figure decomposes the rank-rank slope in housing assets into the portions attributable to increasing child homeownership rates across the parent distribution ("extensive margin") and the portion attributable to increasing home values conditional on ownership across the parent distribution ("intensive margin"). We describe the decomposition in Appendix A.7.

Figure 4: Intergenerational Mobility of Housing Assets by Race

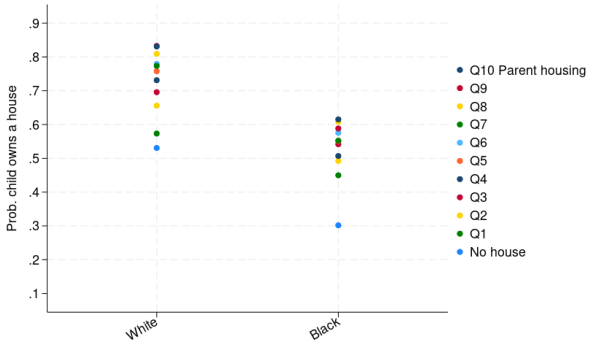


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

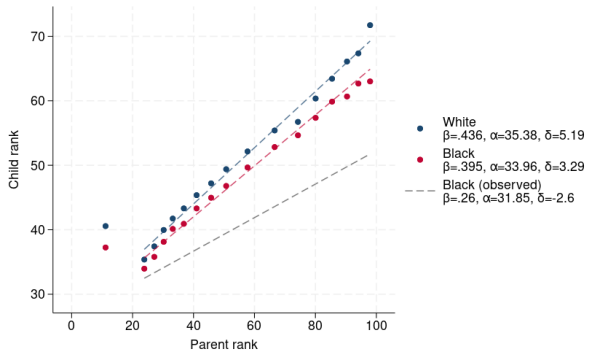
Note: This figure shows the rank-rank relationship of housing assets separately for Black and White Families. Dots represent the average child ranks conditional on parent rank and dashed lines show the linear rank-rank slopes (β); α is the average child rank for children of parent homeowners in the bottom of the home value distribution and δ is the difference in the average child rank between children of parent renters and parents in the bottom of the housing value distribution. Ranks are defined at the population level.

Figure 5: Homeownership and Black-White IGM Gaps

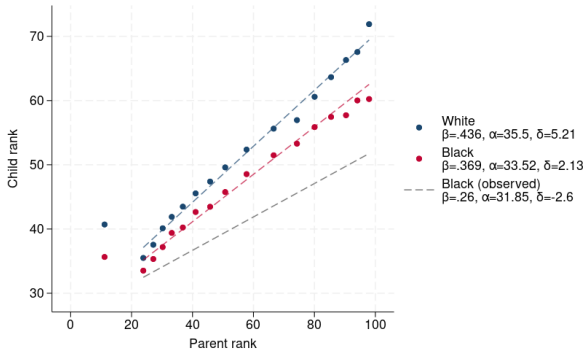
(a) Ownership probabilities by race



(b) Counterfactual ownership rates



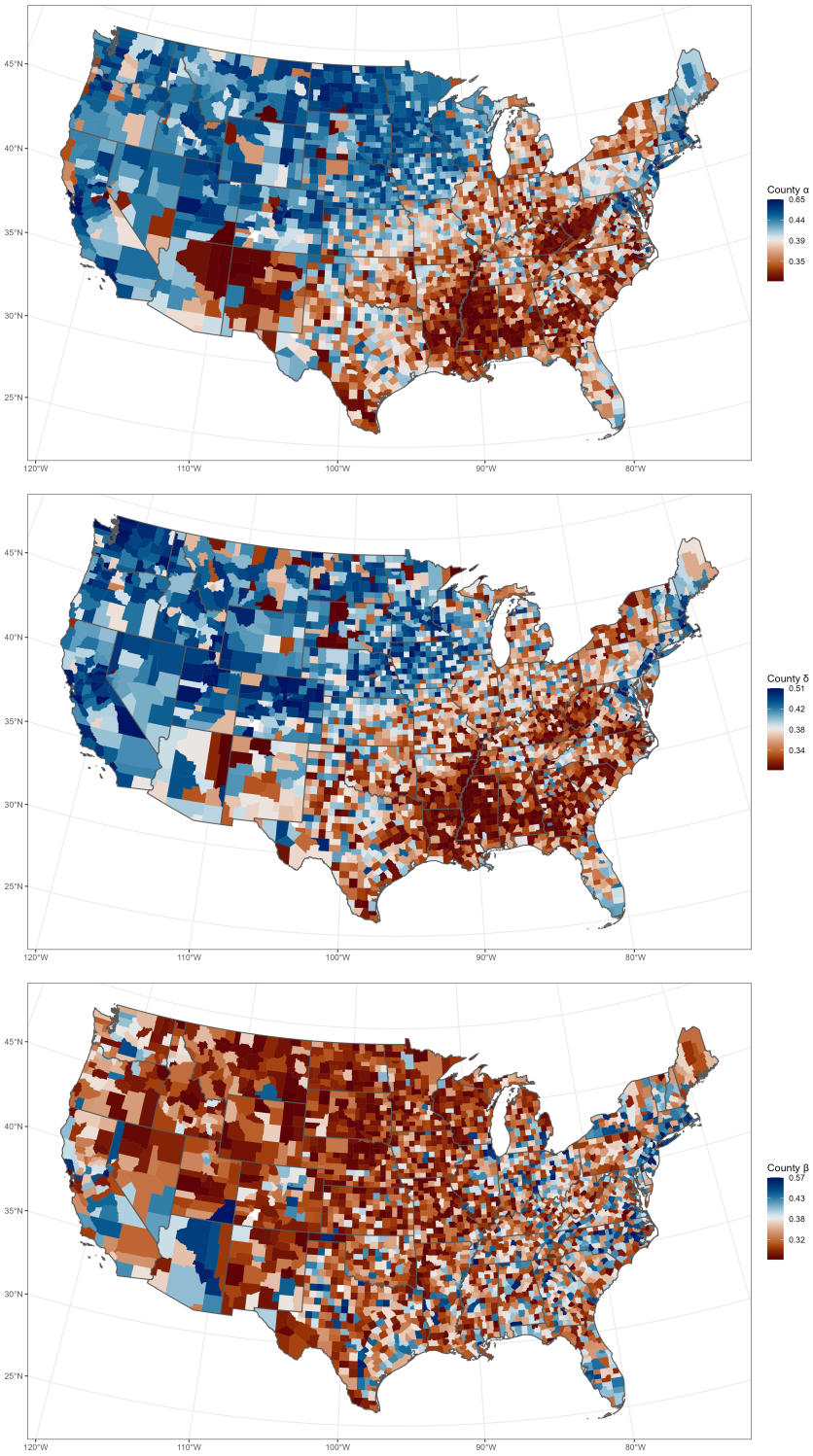
(c) Counterfactual ownership - capitalized rent



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Note: Panel A shows child homeownership rates across deciles of the parent housing asset distribution, separately for Black and White families. Panel B shows counterfactual rank-rank slopes for a simulation where the homeownership rates of Black children are equalized to those of White children within parent rank bins, and housing assets of the new marginal Black homeowners are assumed to equal the observed average housing assets for Black homeowners within each parental bin, as described in Appendix Section A.8.3. Panel C shows another counterfactual exercise where Black and White child homeownership rates are equalized, but the new marginal Black homeowners have are assigned estimated home values according to a capitalization approach of observed rent payments, as described in Appendix Section A.8.1. For both, ranks are redefined for the population after the simulations and the corresponding rank-rank relationships for Black and White families are shown, as is the observed Black rank-rank relationship for reference (gray dashed line).

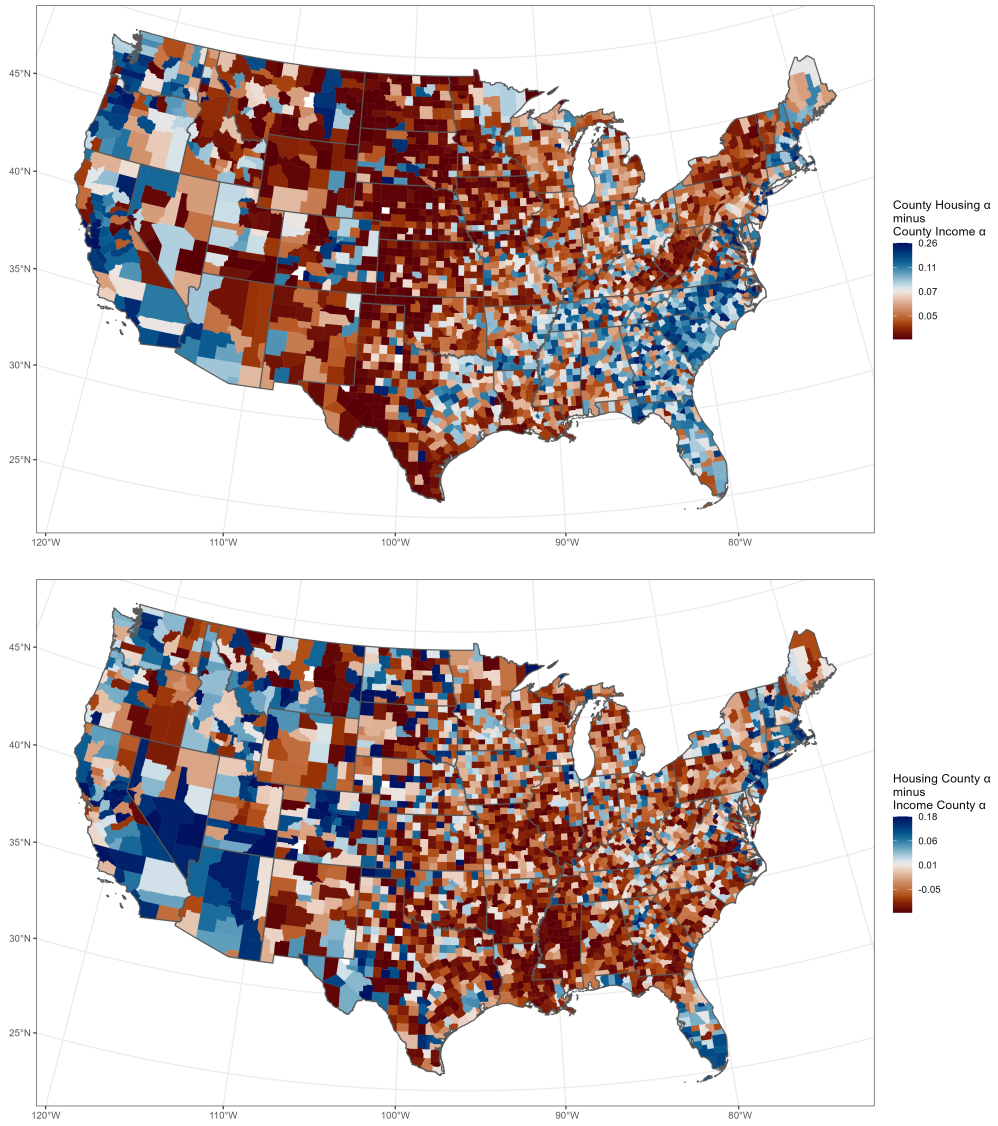
Figure 6: Geographic Distribution of Housing Capital Mobility, α, δ and β Parameters



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Notes: Each subfigure is a county-level choropleth map of the estimates of the α, δ and β (absolute housing capital mobility for the children of the poorest owners, the difference in absolute mobility between renter and owner children, and relative mobility for owner children respectively). These county-level estimates are produced using a Faye-Herriot small area estimation model.

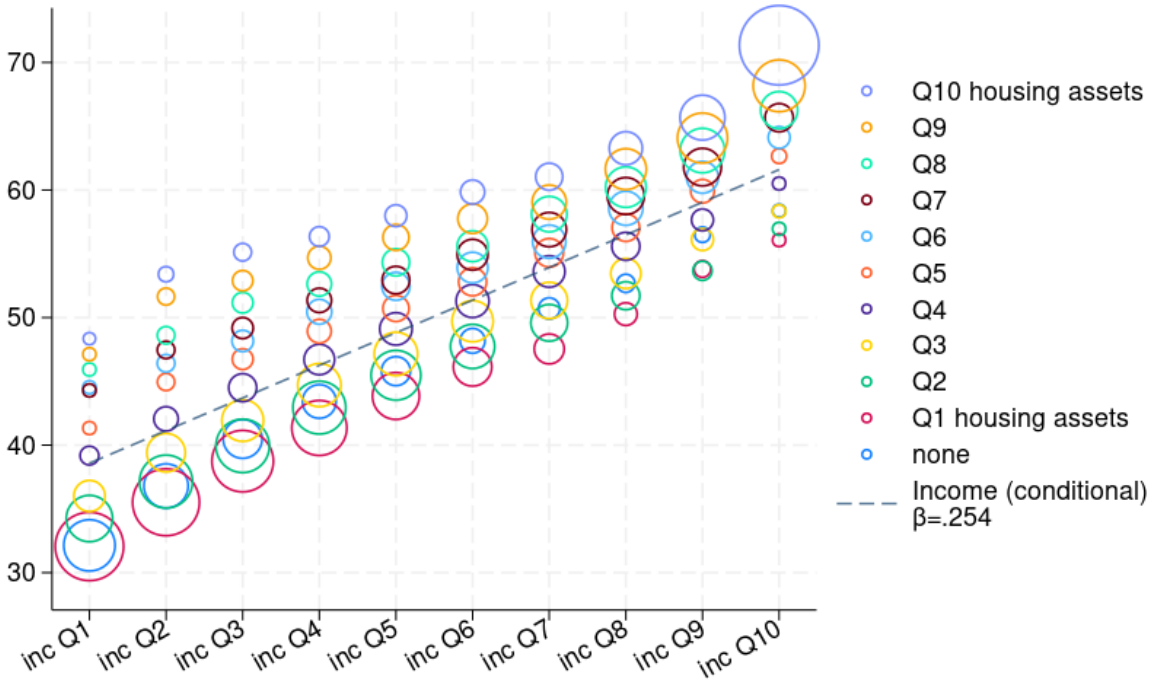
Figure 7: Contrasting the Geographic Distribution of Income Mobility and Housing Capital Mobility



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank and Chetty et al. (2014)

Notes: The top subfigure is a county-level choropleth map of the county-level differences in the small area estimate of housing capital absolute mobility and the relevant estimate of absolute income mobility from Chetty et al. (2014). The bottom subfigure similarly shows a county-level choropleth map of the county-level differences in the small area estimate of housing capital relative mobility and the relevant estimate of relative income mobility from Chetty et al. (2014).

Figure 8: Child income and parent income and housing assets

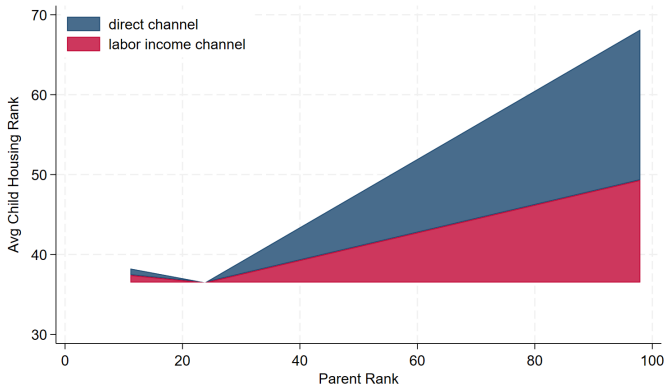


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

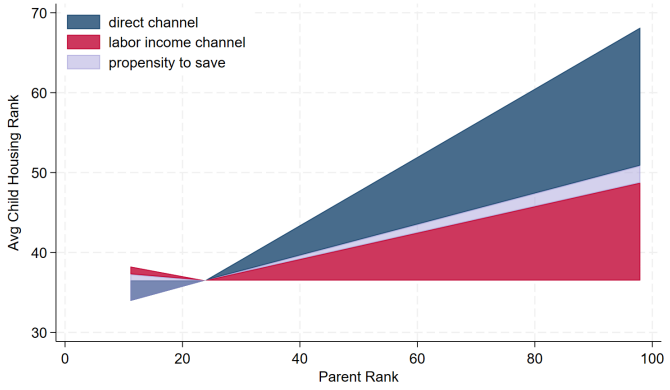
Note: This figure shows the non-parametric relationship between child income rank and parent income and housing asset ranks. Each bubble represents the average child income rank (y-axis) conditional on the decile of parent income (x-axis) and parent housing asset ranks (series of bubbles, defined by color). The size of each bubble represents the relative population of children in each cell. The "none" series is for children of parent renters, "Q1 housing assets" are parents in the bottom 10% of assets conditional on homeownership and "Q10 housing assets" are parents in the top decile of housing assets conditional on ownership. The dashed line represents the income rank-rank slope after conditioning on parent housing rank.

Figure 9: Decomposition of Housing Asset Slope - Labor Income and Direct Channels

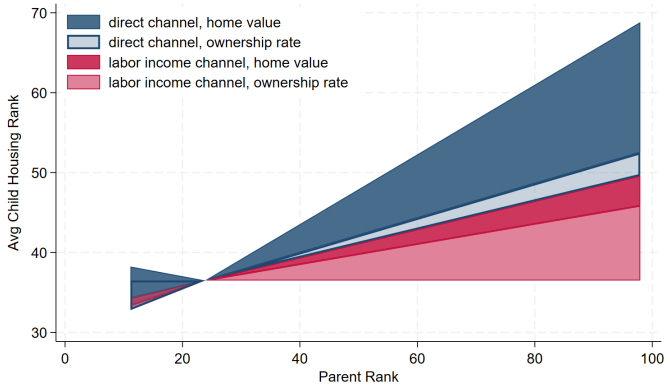
(a) Direct and Labor Income Channels



(b) Including the "propensity to save" channel



(c) Home value v. homeownership

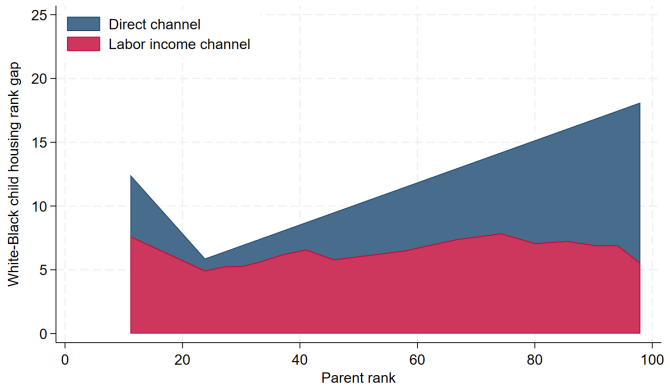


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

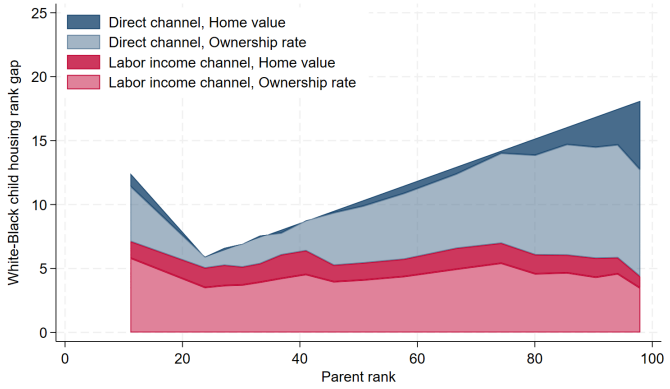
Note: Panel A shows a decomposition of the population rank-rank slope of housing assets into the direct and labor income channels as derived from simultaneous equations (s1) and (s2), and described in Section 5.2. The red area represents the share associated with the labor income channel, i.e. the increase in child assets across the parent distribution due to the fact that children of wealthier parents earn more income. The blue is the direct channel, i.e. conditional on children earning the same amount, the increase in child assets due to having wealthier parents. Panel B shows the direct channel, labor income channel and the "propensity to save" channel — the interaction effect between child earnings and parent housing assets. Panel C shows a further decomposition of the direct and labor income channels into the shares associated with increasing child home values and increasing ownership rates across the parental distribution.

Figure 10: Direct and Labor Income Channels - Decomposition of Black-White IG gaps

(a) Direct v. Labor Income Channels

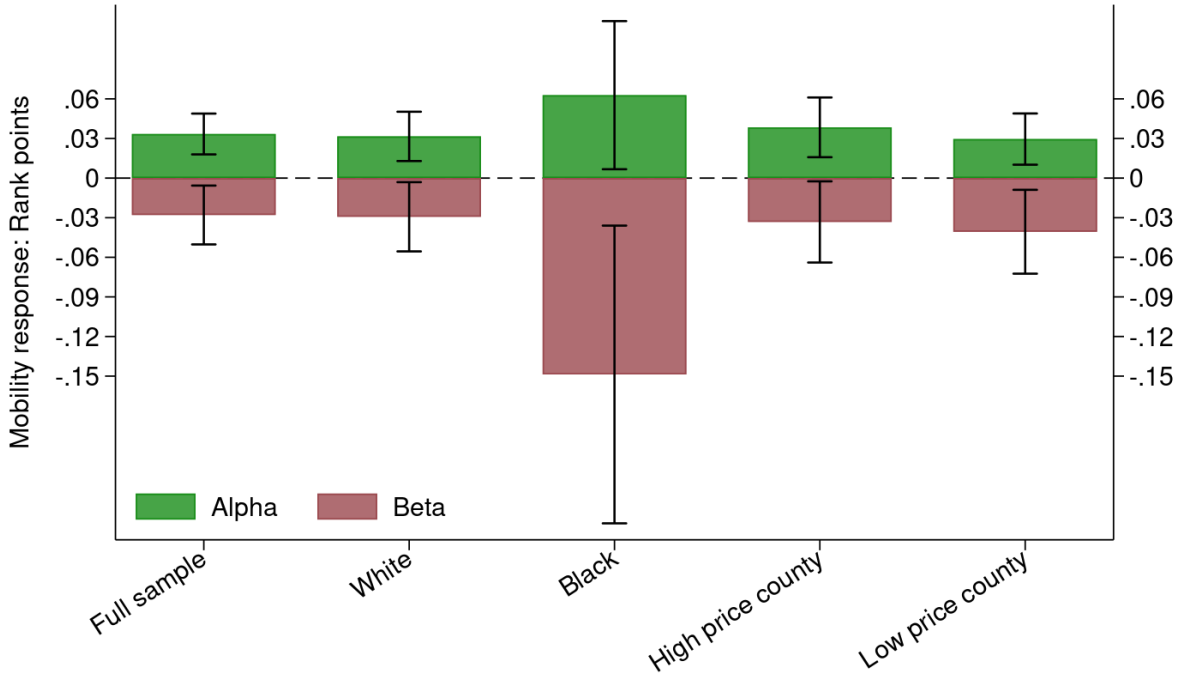


(b) Home value v. ownership rate



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figure shows a decomposition of the gap in Black and White child average housing ranks across the parent distribution, decomposed into direct and labor income channels. The labor income channel is the difference in average Black and White child ranks that is associated with Black and White children having different earnings conditional on parent rank. The direct channel is the remaining gap in child housing ranks, conditional on Black and White children having the same earnings within parent rank. Panel B further decomposes the direct and labor income channels into the portion associated with differences in child home values and child ownership rates across the parental distribution.

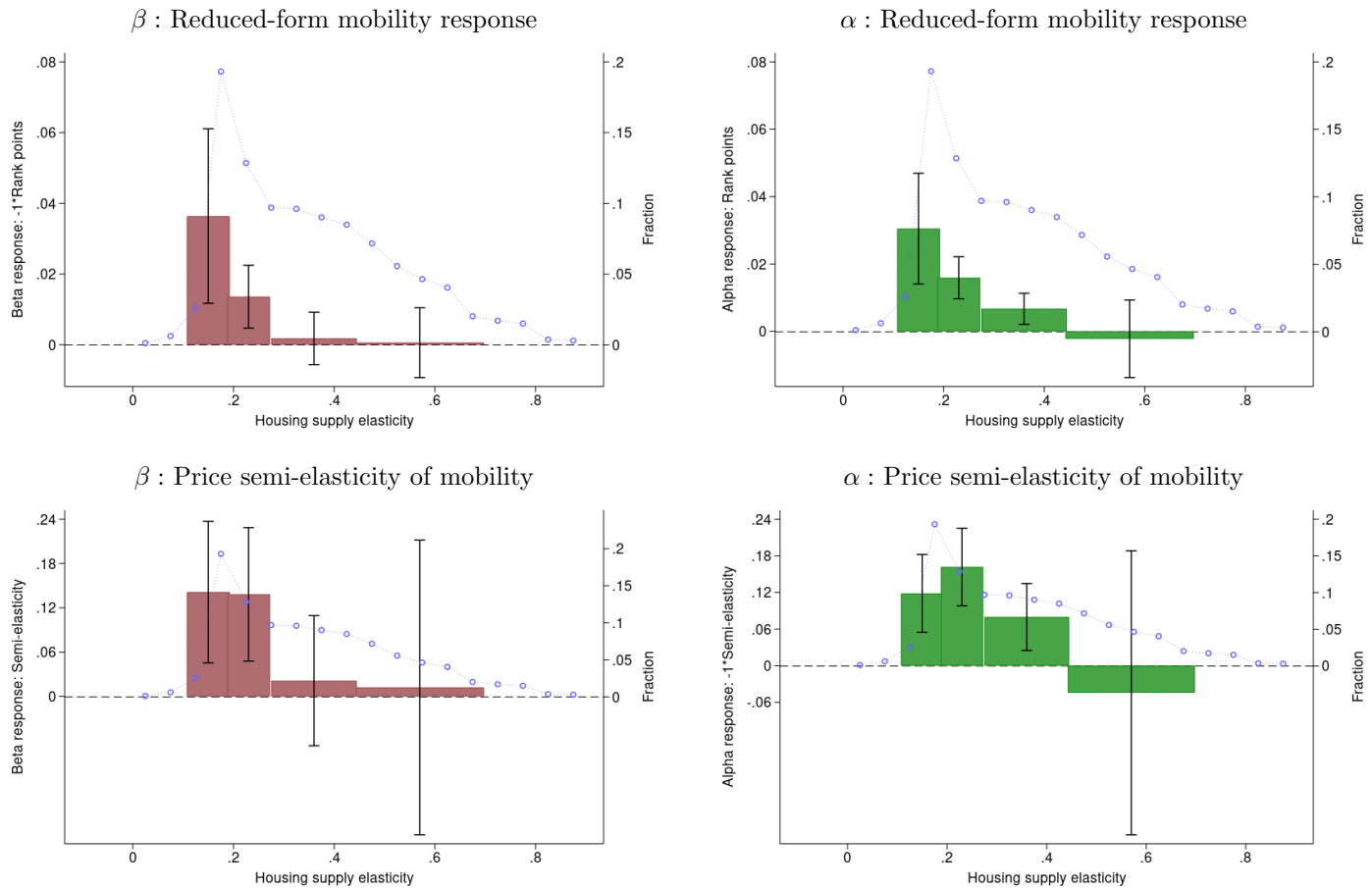
Figure 11: Heterogeneity in Mobility Effects of a $2SD$ Change in Local Housing Supply



Source: Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Notes: Green (maroon) bars correspond to main effects on α (β) by subgroup. "High (Low) price county" denotes counties with average parental home value in 2000 above (below) the unweighted 60^{th} percentile in our metro sample. These effects come from the "cubic, weighted" specifications presented in Appendix Table D.17. 90% confidence intervals are overlaid on the bars as whisker plots.

Figure 12: Heterogeneity in Mobility Responses across the Housing Supply Elasticity Distribution



Source: Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Notes: Each bar corresponds to the estimated mobility response to a change in the baseline housing supply elasticity from the x-coordinate of the left end of the bar to the x-coordinate of the right end of the bar. Estimates are signed such that a positive estimate means more mobility (i.e. higher α and lower β). 90% confidence intervals are overlaid on the bars as whisker plots. In each graph, the blue histogram is the population distribution of baseline (2001) housing supply elasticity exposure, plotted on the right y-axis.

Table 1: Summary statistics

	Full sample	Black families	White families
Parent characteristics			
Ownership rate	0.78	0.56	0.84
Housing assets	299,046	132,620	341,598
Housing assets (median)	224,580	76,830	265,950
Income	104,664	58,949	118,487
Labor earnings	79,156	46,273	90,190
Number in household	3.8	3.7	3.7
Workers in household	2.9	2.6	3.0
White	0.71	0	1
Black	0.12	1	0
Hispanic	0.11	0	0
Asian	0.03	0	0
Other race/ethnicity	0.02	0	0
Child characteristics			
Ownership rates	0.66	0.43	0.72
Housing assets	331,300	143,800	363,100
Housing assets (median)	220,000	0	257,000
Housing assets | own	497,400	338,100	492,700
Income	96,000	41,560	108,200
Labor earnings	79,310	39,090	88,110

Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Notes: This table shows summary statistics for the parents and children in our sample of over 3.4 million families. The statistics are averages unless otherwise stated. Parent and child income and assets are in 2021 dollars, and we use the S&P CoreLogic Case-Schiller U.S. National Home Price Index (CSUSHPINSA) for bringing parent housing assets to 2021 values. Population weights are used for parent statistics and child non-housing statistics. Life-cycle adjusted (LCA) weights are used for child housing assets and ownership rates.

Table 2: Effects of Price Changes Induced by $2SD$ Change in Local Housing Supply on Intergenerational Mobility of Housing Assets

	Median DiD effect	As a semi-elasticity	Scaled by $\Delta \ln \overline{p_c} = 0.380$	2· cross-county SD	Standardized effect
β	-.026	0.096	0.036	0.146	24.9%
	(.013)	(.048)	(.018)	–	(12.4%)
α	0.033	-.121	-.046	0.128	36.0%
	(.009)	(.033)	(.013)	–	(9.8%)
δ	-.026	0.096	0.036	0.102	35.6%
	(.010)	(.037)	(.014)	–	(13.7%)

Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Notes: The intergenerational mobility responses reported in the first column are the changes in the 1978-86 cohort trends that result from being exposed to a housing supply elasticity $1SD$ above the median relative to $1SD$ below the median. These responses are the median responses extracted from the 12 specifications tested in Appendix Table D.16. The second column divides these responses by the instrumented 27.2 log-point decrease in price to obtain a price semi-elasticity. The third column scales the semi-elasticities by 0.380, which is the instrumented price decrease in the more-elastic county applied to the entire 2010-2021 housing expansion. See Sections 6.2 and 6.3 for further detail. The final column expresses these scaled responses in terms of twice the observed cross-county standard deviation in mobility. For example, the scaled response of β to a 2-standard-deviation increase in the housing supply elasticity is one-quarter of the observed 2-standard-deviation range of β.

A. Appendix: Data and methodology details

A.1. Imputing missing valuations

Our data linkage effort captures properties owned by the 3.4 million children in our sample. Some housing observations have missing AVM valuations; for the vast majority of these cases we observe either the assessed property value, the value associated with the most-recent transfer of ownership of the property, or both. We use this information to impute the AVM valuation according to the following flexible model:

- 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.
- Repeat for all counties.

This procedure captures the reality that different local jurisdictions have different assessment policies, such as assessing the property at different percentages of market valuation (i.e. AVM value), considering or ignoring certain improvements made to the structure and land beyond the original build, or imposing a varying maximum rate at which the assessed value is allowed to grow.[64] Moreover, the model accounts for the time since the last assessment or sale, to account for the fact that properties not recently assessed or sold will, ceteris

[64]For example, the State of Michigan began capping the property tax assessment growth rate in 1994 to be no greater than the inflation rate (Skidmore et al., 2010). On the other hand, New York State law—with the exceptions of New York City and Nassau County—directs municipalities to assess properties at a common percentage of predicted market value, but does not require this percentage to be identical across municipalities: https://www.tax.ny.gov/research/property/assess/reassessment/fairassessments.htm.

paribus, have lower assessed/last-sale values. Finally, the model allows the relationship between (transacted value, transaction year) and current AVM value to vary according to the current year. This captures county-specific, contemporaneous shocks to market valuations.

To avoid a degenerate model, we require at least 10 regression observations to estimate the model for the given county-concept cell. Due to the combination of missing AVM valuations and small counties in our sample, at the end of this process, a small share of properties in our data still have a missing valuation. Accordingly, in a final step, we iterate across U.S. states and regress log AVM valuation on vintage year fixed effects plus a wide set of family characteristics: race effects, parental income quintile effects, a linear effect in parental income rank, parental housing asset decile effects, kid filing status effects (i.e. single, married filing separately, married filing jointly), and kid income quintile effects. We impute remaining missing property valuations in the given state as fitted values from the state-specific model.

A.2. Collapsing 2019-2021 asset data into one snapshot

Our goal is to use the 2019-2021 short panel of information on children's housing assets to approximate "permanent" asset holdings throughout adult life. Effectively, rather than *averaging* asset values across the panel, as is often done in the income literature to smooth out transitory variations, we do something closer to taking the *2021* asset value in the panel. This aligns with the fact that, other than a temporary dip in 2020, house prices increased consistently over this period, and this is also a period during which vastly more children went from being non-owners to owners than the reverse.

Accordingly, we assign a child observed to own no more than 1 property during each of the 3 years the 2021 observed asset value, or the maximum observed asset value if no properties were owned in 2021. For multiple property owners, we impose some further editing, given that unedited rates of multiple ownership were non-trivially higher than benchmarks we constructed in SIPP and SCF data. We reasoned that this may stem from an individual selling a property and buying another within a short time frame (especially across two

different jurisdictions), but being listed as the owner or buyer on both due to the timing of record updates. Thus, we require an individual to own multiple properties in *each* of 2020 and 2021 to count in our data as a multiple owner. When this condition holds, we assign them the cumulated 2021 values of any property owned in *both* 2020 and 2021, and exclude the value of any property owned in only one of those years. That is, an individual who owns the same single property in 2020 and 2021, and owns at least one other property for only one of those years, is assigned the 2021 value of the single property.

The rare set of individuals who own multiple properties in at least one of the years in the panel, but do not own any of the same properties in each of 2020 and 2021, are treated identically to single owners. That is, they are assigned their 2021 asset holdings, or the maximum assets observed during the 2019-2021 period if they do not own any property in 2021. Our assignment of asset holdings to kids who transition *out* of homeownership during our sample window assumes that in 2021 they possess the assets they sold off in 2019 or 2020. While this may not fully be true in the event of foreclosure, this subgroup is small enough to exert no real effect on the main results.

A.3. Overview of record-linkage bias

To examine this bias, we merged residential ownership and valuation information from children sampled by the 2018-2021 ACS onto our main sample. Appendix Table A.1 presents ownership confusion matrices for 2020 and 2021 ACS respondents. Averaging the numbers across these matricres, we note much more agreement than disagreement: approximately 82.4% of the mass is on-diagonal. However, the off-diagonal mass is not evenly distributed, with 5.0% more cases corresponding to (ACS owner, BK non-owner) than the converse. That is, 6.3% of ACS respondents owned a BK property but were coded as a non-owner based on their ACS information, while the converse was true for 11.3% of respondents.

Some off-diagonal mass should be expected due to the difference in concepts and timing. For example, anyone who is not the reference person or spouse in an owner-occupied ACS

residence gets an ACS ownership value of 0. (The survey instrument directs the homeowner to fill out the survey as the reference person.) However, some of these individuals may own remote property, or even the residence in question in cases where the owner or spouse of owner did not respond to the ACS as the reference person. On the other hand, the 2021 BK files tend to record ownership as of 2020, so a 2021 ACS respondent who just bought their first home may not yet show up on the administrative records. Nonetheless, the nontrivial degree of *mismatch* indicated to us a modest under-count of owners in the administrative records.

Table A.1: Ownership rates reported in ACS v. Black Knight data

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.

A.4. Intensive margin weighting adjustment to address record-linkage bias

To specify this adjustment, it is necessary to define some terms. Begin by considering the distribution function of property holdings that exists among the children in our sample universe that own at least one property. Label this function $F(v)$. Consider two conditional distribution functions: $F_1(v) = A(v \mid \text{Owner exists in the BK owner records})$ and $F_0(v) = A(v \mid \text{Owner is missing from BK owner records})$. By considering the children who showed up as residential homeowners in the 2018-2021 ACS, we observe a sample from each conditional distribution, with analogous empirical distribution functions A_1 and A_0 and respective sizes N_1 and N_0.

Consider a sequence of Q uniformly-spaced quantiles, $q_1, \ldots, q_Q$, of A_1. That is, $A_1(q_n) -$

$A_1(q_{n-1}) = 1/Q$. Some simple algebra yields:

$$A(q_n) - A(q_{n-1}) = \frac{N_1/Q + N_0(A_0(q_n) - A_0(q_{n-1}))}{N_1 + N_0}.$$

This identity relates the probability density of "censored owners", i.e., property owners who showed up as such in the BK records, to the probability density of all owners, all in terms of objects we observe in the ACS subsample. We apply the analogy principle to this identity: that is, we assume that the quantile-specific relationship between A_1 and A_0 that we observe in the set of ACS owners holds for the entire universe of U.S. owners:

Assumption: Consider a sequence of Q quantiles $p_1, \ldots, p_Q$ of the observed BK valuation distribution. Then, $\frac{N_1/Q+N_0(A_0(q_n)-A_0(q_{n-1}))}{N_1+N_0}$ is an unbiased estimate of $F(p_n) - F(p_{n-1})$.

This assumption dictates the following further adjustment to the adjusted weights aw_g, which are specified in the main text as equation (2):

$$iw_g = aw_g \cdot \frac{N_1/Q + N_0(A_0(q_n) - A_0(q_{n-1}))}{N_1 + N_0} \tag{A.1}$$

if kid g is a BK owner with housing assets in the $[n-1, n)$ quantile range. We label this as iw_g to denote that it is an "intensive margin" adjustment that applies only to observed BK owners.

Just as for the initial adjustment to the ownership rates, we perform this adjustment separately within each of the 550 parental-background subgroups defined by the interaction of race-ethnicity, parental housing wealth, and parental income. Overall, approximately 120,000 of the children in our sample showed up in the 2018-2021 ACS as homeowners, and we partition this set into 550 subgroups of varying sizes. Accordingly, we allow the choice of the number of quantiles Q to dynamically scale with subgroup size. Specifically, we set $Q = \lfloor N^{g-1}/15 \rfloor - 1$ where N^{g-1} is the number of BK owners belonging to subgroup $g-1$. For example, if $N^{g-1} = 64$, then $Q = 3$, which implies that we split the subgroup at the 25^{th}, 50^{th}, and 75^{th} percentiles into four quartiles with 16 observations per quartile. For a

few small groups with $N^{g-1} < 30$, we do not implement the intensive margin adjustment procedure.

A.5. Weighting to address life-cycle bias

A.5.1. Main weighting specification

As discussed in the main text, our life-cycle weighting adjustment involves up-weighting observed owners and down-weighting observed non-owners to rescale sample rates of property ownership from their age-39 observed values to age-47 target values. This involves two main assumptions.

Assumption: each racial-ethnic group's target ownership rate equals the rate observed in the Gen-X cohorts at ages 45-49. We estimate these rates directly from ACS and SIPP data. Specifically, we use 2019-2021 ACS data on individuals aged 45-49 to compute race-specific target residential ownership rates t_{ACS}. We then use 2018 SIPP data on individuals with this age range to estimate the inverse proportion of total property owners who are residential owners, i.e. $\tilde{a}_{SIPP} = \frac{t_{SIPP}+r_{SIPP}}{t_{SIPP}}$, where r is the share of individuals who rent their residence but remotely own property. Finally, we construct our target individual property ownership rate as $t_{ACS^*} = t_{ACS} \cdot \tilde{a}_{SIPP}$, for each racial-ethnic group.

To state our second assumption, let $\Delta_{ACS^*} = t_{ACS^*} - x_{ACS^*}$, i.e., the observed change in the given racial-ethnic group's individual ownership rate between ages 39 and 47. We can re-express this identity as follows:

$$t_{ACS^*} = x_{ACS^*} + \Delta_{ACS^*} \times \frac{x^{oldest}_{ACS*}}{x^{oldest}_{ACS^*}},$$

where x^{oldest}_{ACS*} is the individual property ownership rate observed in the oldest children in our sample—i.e. children born in 1978, who are ages 42-43 when we record their ownership rates.

Assumption: for a given parental wealth×income subgroup $g-1$,

$$t^{g-1}_{ACS^*} = x^{g-1}_{ACS^*} + \Delta_{ACS^*} \times \frac{x^{g-1,oldest}_{ACS^*}}{x^{oldest}_{ACS^*}}. \tag{A.2}$$

We call this an "oldest-cohort proportional" assumption. That is, the higher a subgroup $g-1$'s oldest cohort's ownership rate is relative to the group-average oldest cohort's ownership rate, the higher is the constant by which we translate the $g-1$'s overall sample ownership rate. Put another way, subgroup-specific target ownership rates are assigned by adding the difference between the group target ownership rate and the group observed rate (Δ_{ACS^*}) on to each subgroup's observed rate, but then scaling this constant up or down according to relative ownership rates between subgroups that were observed in the 1978 cohort.

We iterate this procedure across all parental resource subgroups within a racial-ethnic group, and then again across racial-ethnic groups.

With subgroup-specific target ownership rates in hand, the following life-cycle weighting adjustment results:

$$lcaw_g = \begin{cases} aw_g \cdot \frac{1-t_{ACS^*}^{g-1}}{1-x_{ACS^*}^{g-1}} & \text{if kid } g \text{ is not a BK owner} \\ iw_g \cdot \frac{t_{ACS^*}^{g-1}}{x_{ACS^*}^{g-1}} & \text{if kid } g \text{ is a BK owner.} \end{cases} \tag{A.3}$$

The rest of this section provides further background motivation for the life-cycle adjustment and shows robustness of key intergenerational statistics to plausible alternative life-cycle weighting specifications.

A.5.2. Further motivation for life-cycle weights

This subsection shows the importance of the age at which children are observed for measurement of the IG relationship of housing assets. To do so, we compare two cohort groups capturing the youngest and the oldest children in our sample: children born in 1985-86 versus those born in 1978-79. The former group is ages 35-36 when we measure their asset holdings in 2021, while the latter group is ages 42-43.

Panel A of Appendix Figure A.1 compares the rank-rank housing asset relationship between these two cohort groups, reporting estimates of α and β in each group. We observe the rank-rank slope steepening considerably, from 0.28 to 0.34, as children age, while absolute

mobility falls by two rank points. That is, as children age closer to their eventual plateau in life-cycle ownership rates, intergenerational persistence increases.

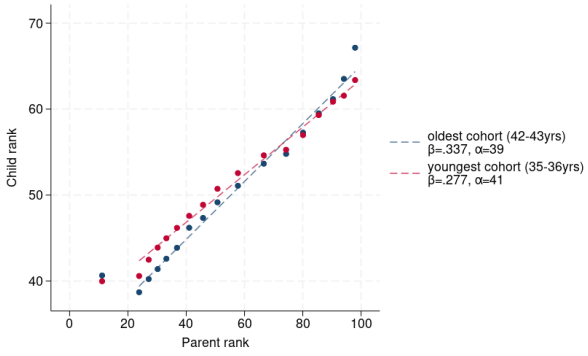
In contrast, Appendix Figure A.2 shows that we do not observe this pattern for income. While age-related measurement error in lifetime income rank is also a concern, research suggests that this is small by age 35, which is the age of our youngest cohort (Mazumder, 2016). The facts that i) our Millennial cohorts have low but rapidly-increasing ownership rates throughout their 30s and ii) asset rank jumps discontinuously on first ownership—suggest that age-related measurement error is more problematic in our setting.

Panel B of Appendix Figure A.1 indicates that this problem arises due to the extensive margin of ownership. It limits the sample to children who own property and shows similar rank-rank relationships across age. This suggests a simple strategy to address bias from having observed a set of immature housing portfolios is to model the mature ownership rate on the data. This strategy is reflected in the life-cycle-adjusted weights of form (A.3). Effectively, the distribution of assets conditional on ownership does not appear to change much as children age from their mid-30s into their 40s, only the probability of ownership.

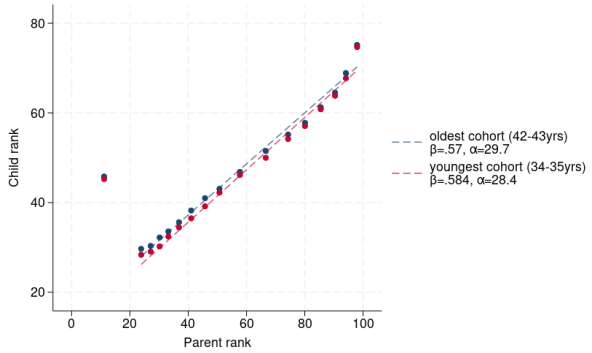
Panel C plots individual homeownership rates as a function of parental housing asset rank in our two comparison cohorts and also shows the plot of the life-cycle adjusted (LCA) rates. We can see the slope of the profile somewhat steepen between youngest and oldest cohort, suggesting that children from wealthier families (particularly the wealthiest) are a bit likelier to age into homeownership between the ages of 35 and 43. The LCA profile, presented in green, allows the youngest cohort's profile to have some influence, but is weighted toward the profile of the oldest cohort. In effect, the LCA profile is a level upward shift of the oldest cohort's profile. It is important to recognize that even this level upward shift increases the degree of intergenerational persistence. Because children from wealthier families buy higher-valued homes (Panel B), their rank in the housing asset distribution increases by more when they first a purchase a home. As a consequence, when the homeownership rate increases by P percentage points across all subgroups, the rank-rank slope of housing assets steepens.

Figure A.1: Rank-rank relationships of housing wealth, by child cohort

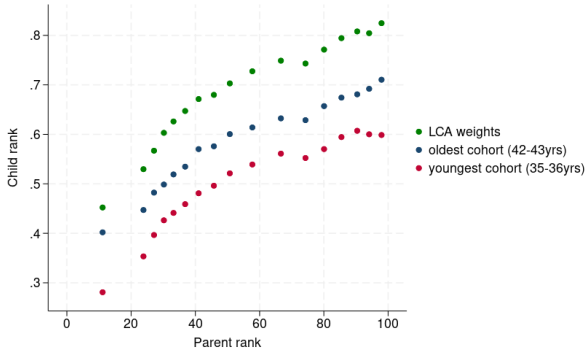
(a) Rank-rank relationships, young v. old



(b) Conditional on child homeownership



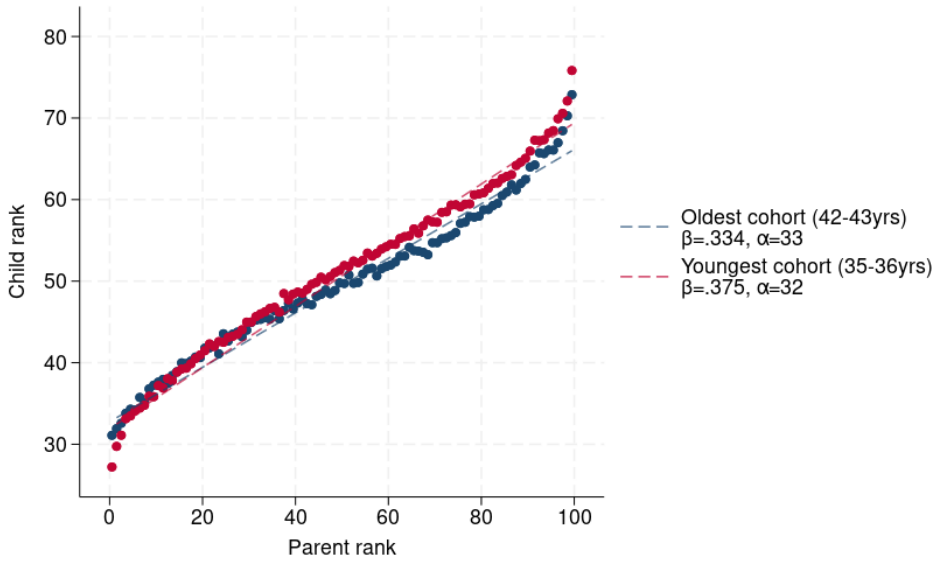
(c) Homeownership rates



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Note: This figure shows the rank-rank relationship of housing assets. Dots represent the average child ranks conditional on parent rank and dashed lines are the linear rank-rank slope (β); α is the average child rank for children of parents in the bottom of the home value distribution. Panel (a) shows rank-rank relationships for the oldest (blue) and youngest (red) children in our sample. Panel (b) shows rank-rank relationships among child homeowners (i.e. child ranks are assigned among the subset of child homeowners). Panel (c) shows child homeownership rates across the parental distribution for the youngest and oldest cohorts, and for the full sample using the life-cycle adjusted (LCA) weights.

Figure A.2: Rank-rank relationships of income, different child cohorts



This figure shows non-parametric rank-rank intergenerational relationships between child and parent income. Income is defined as average adjusted gross income (AGI) over three years. Panel A shows results for the full sample. Dots represent the average child ranks conditional on parent rank and the dashed line is the linear rank-rank slope (β). The series in blue shows the rank-rank relationship for the oldest cohort of children in the sample, and the red series shows the relationship for the youngest cohort.

A.5.3. Robustness to alternative weighting specifications

To close this section, we demonstrate that other plausible methods of translating observed subgroup ownership rates up into targeted life-cycle adjusted rates return extremely similar rank-rank profiles of housing assets. This involves drop-in replacing the oldest-cohort proportional assumption stated above with an alternative assumption. We consider:

Alternative Assumption 1: for a given parental wealth×income subgroup $g-1$,

$$t^{g-1}_{ACS^*} = x^{g-1}_{ACS^*} + \Delta_{ACS^*} \times \frac{(x^{oldest} - x^{youngest})^{g-1}_{ACS*}}{(x^{oldest} - x^{youngest})_{ACS*}}. \tag{A.4}$$

Alternative Assumption 2: for a given parental wealth×income subgroup $g-1$,

$$t^{g-1}_{ACS^*} = x^{g-1}_{ACS^*} + \Delta_{ACS^*} \times \frac{(x^{oldest}/x^{youngest})^{g-1}_{ACS*}}{(x^{oldest}/x^{youngest})_{ACS*}}. \tag{A.5}$$

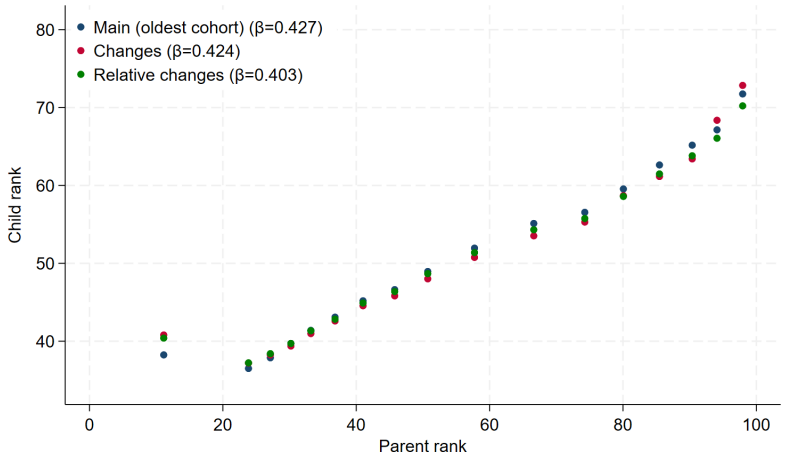
Thus, instead of translating a given subgroup's ownership rate upward by an amount

that is proportional to the oldest cohort's observed ownership rate in that subgroup, Alternative Assumption 1 bases the translation on the observed *change* in the ownership rate between youngest and oldest cohorts. Alternative Assumption 2 bases the translation on the observed *ratio* of the oldest-cohort to youngest-cohort ownership rate. One can refer to these alternatives as a "change proportional" (Alternative 1) or a "relative-change proportional" (Alternative 2) assumption. Thus, consider two alternative subgroups that have identical ownership rates in the full sample and identical oldest-cohort ownership rates. However, one subgroup had a constant ownership rate across cohorts whereas the other subgroup experienced large ownership growth across cohorts. The baseline assumption would assign these two subgroups the same LCA ownership rate, effectively assuming that the rapid growth in the second subgroup was a transitory "age-in" phenomenon that leveled off by age 43. On the other hand, the alternative assumption would extrapolate the second subgroup's inter-cohort growth into a higher LCA ownership rate for that subgroup.

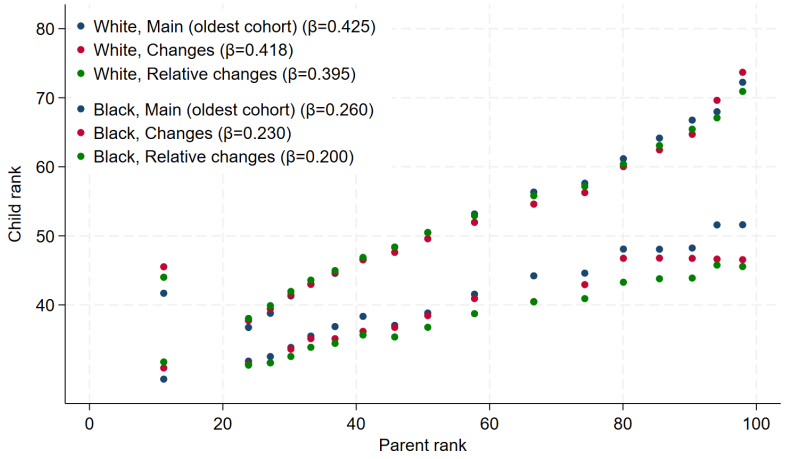
It is not obvious which assumption is closer to the truth. Fortunately, Figure A.3, Panel A indicates that the population profile of children housing assets as a function of parental housing assets is extremely insensitive across these alternatives. Panel B also shows that the assumptions are almost completely inconsequential for the difference in intergenerational profiles between White and Black families. In sum, while the preceding subsection indicates that it is important to make a life-cycle adjustment to observed ownership rates, these results suggest that how exactly one implements the adjustment does not matter.

Figure A.3: Rank-rank relationships - robustness to LCA

(a) Full sample



(b) Black and White families



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figure shows rank-rank housing asset relationships using various methods of constructing life-cycle adjusted (LCA) weights. The blue series shows rank-rank relationships using the main LCA weights described in Appendix Section A.5.1 and used in the main analysis. The red series "Changes" uses Alternative Assumption 1 and the green series "Relative changes" uses Alternative Assumption 2 as described in Appendix Section A.5.3. Panel A shows rank-rank relationships for the full sample. Panel B shows the relationships separately for Black and White families.

A.6. Income measurement and ranking

To consider relationships between income and wealth, we use the 2KLF and Databank to construct a composite rank measure of childhood family income (CFI). We replicate the

"tax-unit" concept of family income introduced by Chetty et al. (2014). Based on how adjusted gross income (AGI) is summarized on federal tax returns, this is the sum of the primary filer's personal income and that of their legal co-residing spouse if one exists. To smooth out transitory income variation,as well as differences in income measurement across sources, we average two years of AGI information in the Databank together with the sum of reference person's and partner's personal incomes from the 2KLF.[65] For the 2KLF sample, we consider the householder's AGI from the 1999 and 2001 tax years along with the 2KLF tax-unit income concept. For the 1994 (1998) Databank sample, we consider 1994 and 1995 (1998 and 1999) AGI information along with 2KLF tax-unit income. *Within* each sample (i.e. to adjust for cohort effects), we average these three years of childhood family income (CFI) together and then construct a national CFI rank measure based on the averaged value.

To measure adulthood income of the children, we consider AGI information from their 2018, 2019, and 2021 tax returns.[66] We average these observations together, omitting negatives and then constructing ranks *within* child birth cohort.[67]

A.7. Extensive-Intensive margin decomposition of rank-rank housing slope

In Figure 3, we decompose the observed rank-rank housing slope into the portions associated with changes in child homeownership rates (extensive margin) and changes in home value conditional on ownership (intensive margin) as parent asset rank increases. To do so we use the decomposition of the change in average housing rank:

$$\begin{aligned}\Delta H &= (AP + A^r(1-P)) - (A_0P_0 + A^r(1-P_0)) \\ &= \underbrace{\Delta P(A_o - A^r)}_{Extensive} + \underbrace{\Delta A * P}_{Intensive} + \Delta A \Delta P\end{aligned}$$

were H average child housing rank, A is average housing value conditional on ownership at a given parent rank and A_0 is the average value at the lower parent rank, A^r is the average

[65] Following Chetty et al. (2014), we drop negative incomes before constructing averages, as these usually reflect transitory accounting choices of business owners who have high permanent incomes and asset holdings.

[66] We exclude 2020 due to anomalous earnings and unearned income processes associated with the COVID-19 pandemic.

[67] A small percentage of children did not file taxes during these 3 years and are defaulted to having the bottom income rank.

rank of child renters, and P and P_0 are the probability of ownership at a given and previous parental rank, respectively.

The first term represents the portion of the increase in average home value across the parent distribution associated with the extensive margin of homeownership (i.e. if the ownership rate changed as observed, but housing value conditional on ownership remained fixed). Note, this accounts for the fact that increasing the probability of ownership will move people from renters to owners. The second terms represents the intensive margin, or the change in home value conditional on ownership keeping the probability of ownership fixed. The third term is the covariance between the changes asset value and ownership rates. We arbitrarily split this evenly between the intensive and extensive margins.

To allow for nonlinearities across the parental distribution, we do the decomposition separately between deciles of the parental distribution. That is, we do the decomposition separately over changes between each parental decile evaluated at the mean within each decile.

A.8. Assigning counterfactual home values to marginal Black owners

As mentioned in the main text, we offer various decompositions of the Black-White gap in child housing asset rank (conditional on parents') into the extensive versus intensive margins. The extensive margin measures the portion of the mobility gap due to differential probabilities of child homeownership conditional on parental assets, while the intensive margin is the residual—i.e. the portion due to differential property values conditional on ownership and parental assets.

To perform these decompositions, we iterate through each parental housing asset status and bring Black children's ownership rate up to White children's ownership rate by assigning counterfactual home values to a marginal set of Black renters. We group all parental renters into their own bin, and then aggregate the 25 different home value bins elicited on the 2000 Long Form survey into 16 bins, with the goal of equalizing bin sizes. In practice, the

aggregated bins vary slightly in size, but each contain roughly 4.9% of parents, with the remaining 22% occupying the parental renter bin.

Our baseline decomposition assigns counterfactual home values to Black renters by pulling from the observed distribution of Black children's home values (conditional on parental asset status), but this assumes that observed renters have the same set of opportunities in the housing market as observed owners. This is likely unrealistic, and is also hard to align to a specific policy that increases Black ownership rates. Below, we specify two alternative methods for assigning counterfactual home values to the marginal set of Black renters.

A.8.1. Capitalizing rental payments

We link children in our dataset to 2016-2021 ACS records using the PIK identifiers, and consider those who appeared in the ACS in a home that is being rented. We envision a policy that transfers the rental unit from the landlord to the renter at the fair market price. We infer this price by capitalizing observed monthly rental payments R according to a standard user cost of capital formula:

$$R = \frac{P \cdot (a - h)}{12} \tag{A.6}$$

where P is the unit price, h is the annual appreciation rate, and a is the annual rate of return associated with an alternative use of funds. Based on historical stock and housing market performance, we set $a - h = .05$. After rearranging terms, this yields $P = 240 \cdot R$.

This simple equation assumes away property taxation, capital depreciation, and risk aversion. Property taxation in the United States is quite low—around 1% on average—while capital depreciation and risk aversion point in opposite directions. That is, maintenance and upkeep costs would effectively lower h and therefore P, and to the extent that stock returns are more volatile than housing returns, a risk-averse investor would be willing to pay a higher P to lower the variance of expected returns.

A.8.2. Renter → "starter home" transitions

Our linkage to the ACS gives us a subsample of children who were renters in 2016-2019, but then showed up as owners in BK data circa 2021. This allows us to model a "starter home" purchase in terms of prior observed rent and parental background variables. Accordingly, we envision a policy in which marginal Black renters are offered down-payment or other assistance to purchase a starter home. We model the price of this home by regressing log BK housing assets on a quadratic in log ACS rent, race fixed effects, parental housing asset bin fixed effects, and parental income vigintile fixed effects. We then predict housing assets for ACS renters in 2018-2021 who are *not* observed to own any property in the BK data.

A.8.3. Simulation approach

For each counterfactual:

- For each parental housing asset bin b:
  - Use the empirical distribution of capitalized rents or predicted starter home values to compute the 5^{th}, 20^{th}, 50^{th}, 80^{th}, and 95^{th} percentiles for Black individuals.
  - Compute the percentage p_b of Black children who do not currently own homes that need to be assigned homes to equalize the homeownership rate with White children. Randomly assign that mass of children.
  - For each child to receive a counterfactual home, assign them a counterfactual value by randomly drawing one of the above percentiles with corresponding probabilities $(.10, .20, .40, .20, .10)$.
- Iterate across all parental housing bins.
- Construct new population housing asset ranks for the *entire sample* of children.
- Create counterfactual rank-rank plots for Black and for White children.

A.9. Capitalization method

We estimate total wealth ranks using a combination of the Black Knight data and individual tax data. We estimate total wealth for each individual as the sum of assets from public equities, fixed interest assets, defined contribution pension assets and housing assets.

For corporate equity we capitalize dividend income using the capitalization factors from Piketty et al. (2018) (PSZ).[68] We capitalize income flows by year and average over three years, for both children and parents. For fixed-income assets, we capitalize interest income using PSZ capitalization, capitalizing by year and averaging over three years. For pension assets, we use the method from Smith et al. (2022) (SZZ) where we apply age specific capitalization factors to labor earnings and retirement income using the formula:

$$\hat{W}_{it}^{pens} = \theta^{pens,a}(\beta^{pens,wage,a} \times y_{it}^{wage}) + (1-\theta)(\beta^{pens,pen,a} \times y_{it}^{pen})$$

. Where $\theta^{pens,a}$ is an age specific weight on current labor earnings (y_{it}^{wage}) relative to retirement income (y_{it}^{pen}), and $\beta^{pens,wage,a}$ and $\beta^{pens,pen,a}$ are age specific capitalization factors for labor earnings and pension income, respectively. For individuals less than 45 years old, $\theta^{pens,a}$=0.94, $\beta^{pens,wage,a}$=1.1 and $\beta^{pens,pen,a}$=112.8; for individuals between 45 and 60 years old $\theta^{pens,a}$=0.85, $\beta^{pens,wage,a}$=3.4 and $\beta^{pens,pen,a}$=75.3.[69]

For child housing assets we use the housing values derived from the Black Knight data directly. For parent housing assets we use the self reported housing values from the Census Long Form directly then add capitalized rental payments from the income tax returns using PSZ capitalization factors. We add the capitalized rental payments for parents because the Census Long Form asks about the value of the primary residence, but not about other properties which may be rented. For the children, we include the value of all properties, including potential rental properties, so this will already be incorporated in the Black Knight

[68] Distributional tables are updated to 2022 available on Gabriel Zucman's website: https://gabriel-zucman.eu/usdina/.

[69] See SZZ appendix O.2 for details on how the parameters and age cutoffs were chosen.

values.

We calculate total wealth for parents and children and the sum of their corporate equity, fixed-income assets, pension assets and housing assets. We then rank parents and children by their positions in the wealth distribution using population weights and using LCA weights.

B. Statistical Framework: Intergenerational Mobility of Total Resources

We present a simple statistical framework for how to interpret income IGM relationships when parent and child *total resources* are intergeneratoinally linked. Say that child wealth W_g is a reduced form relationship of parent wealth W_{g-1}, governed by parameter β,

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

Assume that all we observe is parent and child income, but we are interested the relationship between parent and child total resources, β.

Wealth has various components each with different rates of return that give rise to income flows. $W = \sum_k w_k$ and observed income $Y = \sum_k r_k w_k$. In the very special case $r_k = r$ for all k then $Y = rW$ and a regression of Y_k on Y_p would identify β. In the more realistic case of varying rates of returns, the identification depends on assumptions about the composition of assets. In particular, we note that housing, the most important asset for most households in the U.S. through most of the distribution, produces no regular income flows to the rate of return on housing will effectively be zero, meaning that it will not be reflected in income measures. Generally, let $Y_i = W_i \sum_k a_{i,k} r_k = W_i \tilde{r}_i$ for all individuals i, where $a_{i,k}$ is the share of assets held as in category k. Then

$$\frac{Y_g}{\tilde{r}_g} = \beta \frac{Y_{g-1}}{\tilde{r}_{g-1}} + u_g$$

In the special case that everyone holds the same mix of assets, $\tilde{r}$ is constant and β is recovered. In the more general case, the composition of assets and average rates of return may be individual specific and may be correlated with the parents and child wealth distributions, in which case an income-income regression would include an omitted variable ($\tilde{r}_{g-1}$) and potentially non-classical measurement error in child resources through $\tilde{r}_g$, which will bias the estimate.

The model the bias, let $Y_i = rW_i + \eta_i$ where η_i represents the idiosyncratic individual relationship between income and wealth relative to a population average rate of return r on wealth. Concretely, η_i can be thought of as the degree to which the income of individual i overstates the relationship between income and wealth relative to average. In a rank-rank regression, this is the degree to which the income rank overstates the wealth rank. This gives the income-income relationship of:

$$Y_g = \beta(Y_{g-1} - \eta_{g-1}) + \eta_g + ru_g, \tag{B.7}$$

Bias is introduced by using income as a noisy proxy for wealth for parents and children. The η_{g-1} is directly related to Y_{g-1}, which leads to an underestimate of the true β. Using child income as a proxy for child wealth can lead to further bias. It is most likely that η_g is negatively correlated with parent income leading to further downward bias; on average, higher income parents will have kids with whose income understates their wealth more — for example, higher income parents have children with more housing assets or higher shares of their income from interest or dividends.

In this formulation, child income is a function of both parent income and wealth. Substituting for η_{g-1} in Equation (B.7), we have

$$\begin{aligned} Y_g &= \alpha_1 Y_{g-1} - \alpha_2 \eta_{g-1} + \eta_g + ru_g \\ &= \alpha_1 Y_{g-1} - \alpha_2 (Y_{g-1} - rW_{g-1}) + \eta_g + ru_g \\ &= \gamma_1 Y_{g-1} + \gamma_2 W_{g-1} + \eta_g + ru_g. \end{aligned}$$

Therefore, wealth is an omitted variable for the true IGM of income and the income IGM coefficient will be overstated relative to the true relationship when wealth is omitted.[70]

[70]The parameter η_g represents the degree to which the outcome, child income rank, overstates the wealth rank. This will reflects the potential omitted variable bias for recovering the full IG correlation between parent and child resources when using child income rank as the outcome of interest, even when including income and wealth as explanatory variables. In general, η_k will be negatively correlated with parent wealth as, for example, if children of wealthier parents also have a larger share of assets not reflected (housing)

Together, if the true model of intergenerational mobility is one of total parent and child resources and individuals have different asset compositions, i) the income IGM relationship alone will understate true intergenerational persistence of resources, and ii) the reduced-form IGM of income parameter will overstate the true role of parent income in predicting child income when parent wealth is omitted.

C. Simultaneous Equation Model of Intergenerational Mobility of Resources

Take generation g's lifetime budget constraint as:

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

Where lifetime consumption c_g plus the amount of resources transferred to the next generation b_g must equal lifetime earnings, Y_g, some share of which is saved at rate s_g and earns average returns r, plus any inherited wealth from the previous generation b_{g-1}.

From this static capital accumulation framework, we start by assuming children imperfectly inherit productivity/human capital from parents as a function of parent resources. This could be from parent inputs into the human capital development of children, material or otherwise. The reduced from relationship can be modeled as follows:

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

where W_{g-1} is a measure of parent resources, β is a linear relationship between parent resources and child labor market outcomes and u_g is the child's idiosyncratic component independent of parent resources.

Children use their own earnings to accumulate wealth, but may also have additional

or less reflected (dividends, capital gains) in income flows. Or see the relationship, $Y_g = rW_g + \eta_g$, so $W_g = (Y_g - \eta_g)/r = \beta W_{g-1} + u_k$. To recover the full IG relationship, we would need to include information on child wealth.

wealth (above the average conditional on their earned income) as a function of their parents' resources. This could be from a direct inheritance b_{g-1} or parental resources could affect children's saving rates through transmission of preferences for, or knowledge about, savings opportunities. These reduced form relationships could be given as follows:

$$b_{g-1} = f(W_{g-1}) = \alpha_b W_{g-1} + \epsilon_g$$

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

where α_b is the average share of parent resources transferred to children, ϵ_g is an idiosyncratic component of child wealth independent of child income or parent wealth, θ_s is the association between parental wealth and child savings rates and ν_g is the idiosyncratic component of the savings rate independent of parent wealth, with mean $\bar{\eta}$.

Now children's current stock of wealth can be written as a reduced form function of child earnings and parent wealth given by:

$$\begin{aligned} W_g = f(Y_g, W_{g-1}) &= (1+r)s_g Y_g + b_{g-1} \\ &= (1+r)(\theta_s W_{g-1} + \nu_g)Y_g + \alpha_b W_{g-1} + \epsilon_g \\ &= (1+r)\bar{\eta} Y_g + (1+r)\theta_s (Y_g \times W_{g-1}) + \alpha_b W_{g-1} + e_g \end{aligned}$$

where $(1+r)\bar{\eta}$ is the average gross rate of return on child earnings independent of parent resources and $(1+r)\theta_s$ is the differential rate of return on child earnings for children of parents with different amounts for resources. This leads to a simultaneous equation model that can be represented by the regressions:

$$Y_i^g = \lambda W_i^{g-1} + u_i^g \tag{A.s1}$$

$$W_i^g = \alpha_y Y_i^g + \alpha_b W_i^{g-1} + \alpha_s (Y_i^g \times W_i^{g-1}) + \epsilon_i^g \tag{A.s2}$$

where the first equation (A.s1) represents the relationship between parent resources and child earnings and the second equation (A.s2) is the relationship between child resources, child

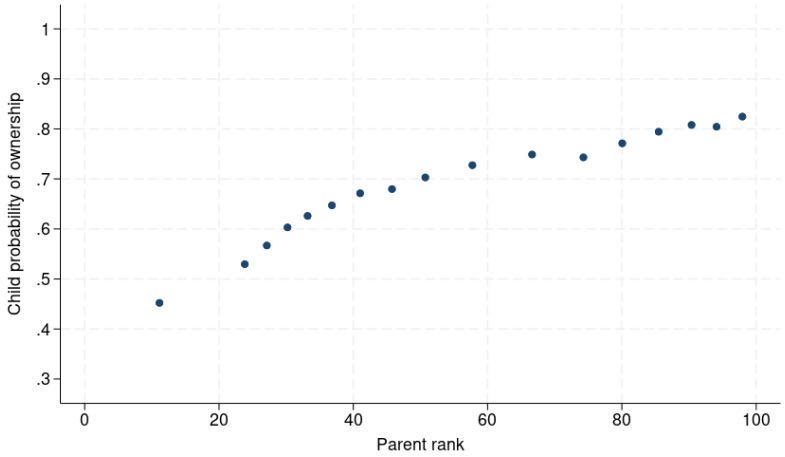
earnings and parent resources. The coefficient α_y represents the average increase in child assets as child earnings increases, independent of parent wealth.

D. Additional Tables and Figures

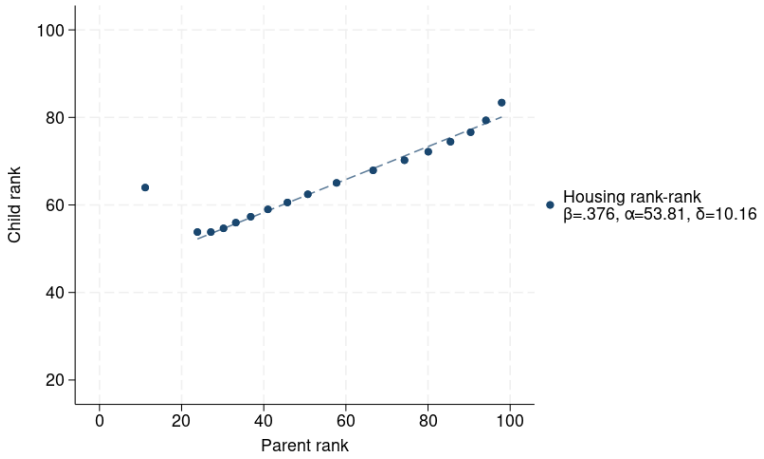
D.1. Appendix Figures

Figure D.4: IGM Housing Relationships - Extensive and Intensive Margins

(a) Probability of homeownership by parent rank



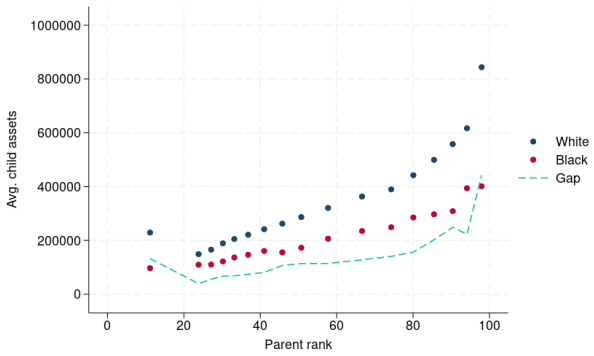
(b) Home value conditional on ownership by parent rank



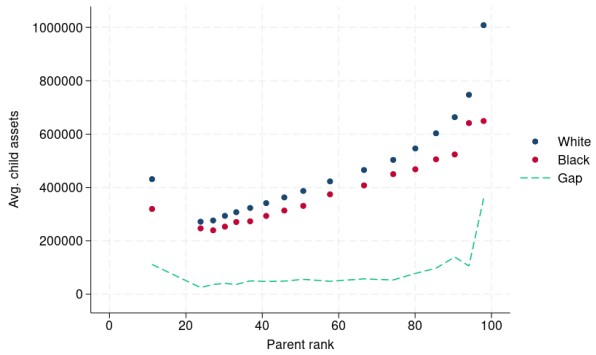
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: Panel A of this figure shows the non-parametric relationship between child homeownership rates and parental housing asset rank. Panel B shows average child asset value ranks conditional on ownership (i.e. among the subset of child homeowners) across the parental housing asset distribution. Dots represent the average child ranks conditional on parent rank and dashed lines show the linear rank-rank slopes (β); α is the average child rank for children of parents in the bottom of the home value distribution and δ is the difference in the average child rank between children of parent renters and parents in the bottom of the housing value distribution.

Figure D.5: Average child assets by parent rank and race

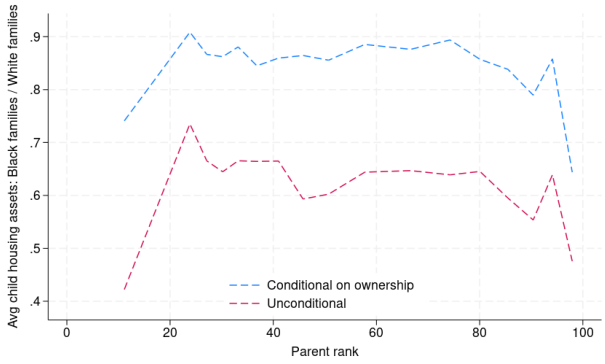
(a) Unconditional housing asset values



(b) Housing asset values conditional on ownership



(c) Relative gaps in housing asset values

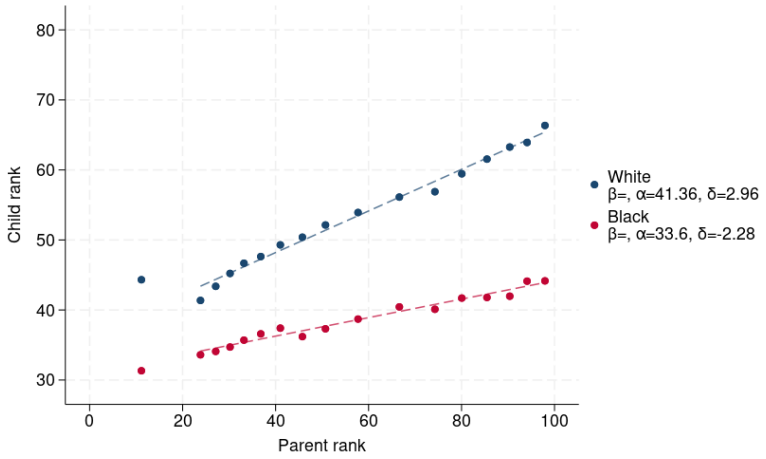


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

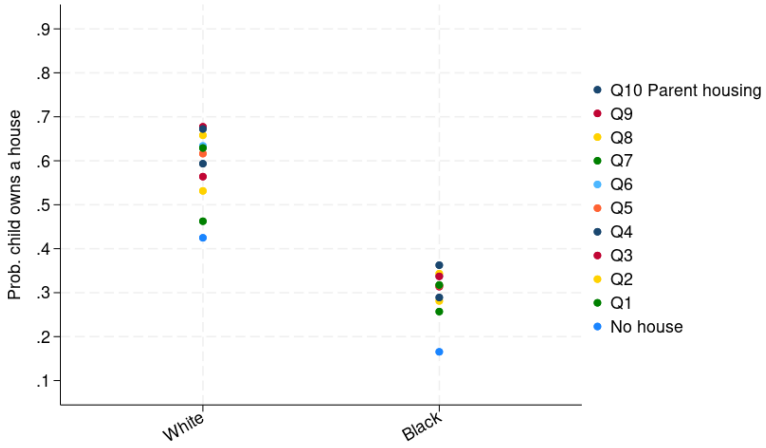
Note: This figure shows average housing assets for children of Black and White families, conditional on parental asset rank. Panel A shows the the raw averages across all White and Black children; the dashed line represents the average White-Black gap at each parental rank. Panel B shows the averages for the White and Black children conditional on homeownership (i.e. among the subsets of homeowners). Panel C represents relative differences, showing the average assets of Black children over those for White children at each parental rank.

Figure D.6: Rank-rank housing assets by race - no LCA weights

(a) Rank-rank slopes



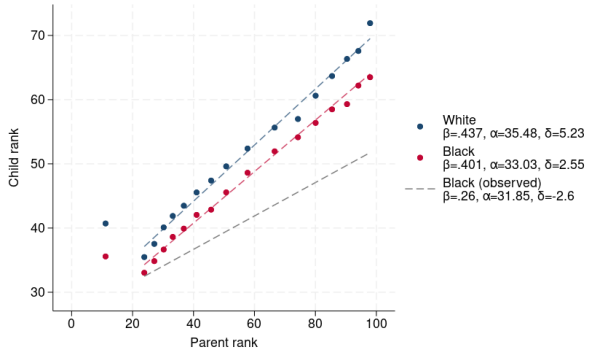
(b) Child homeownership probabilities by parent asset rank



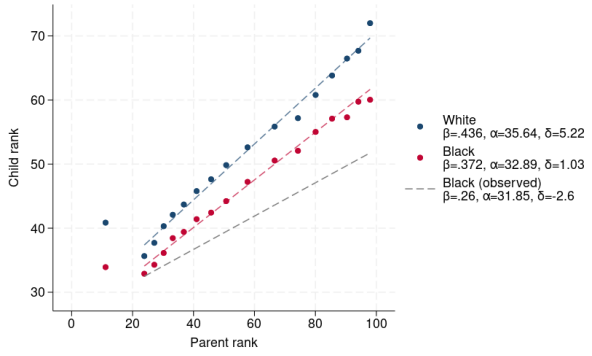
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figure compares intergenerational mobility of housing assets between Black and White families, using population weights rather than the main life-cycle adjusted (LCA) weights. Panel A shows the rank-rank relationship of housing assets separately for Black and White families. Dots represent the average child ranks conditional on parent rank and dashed lines show the linear rank-rank slopes (β); α is the average child rank for children of parents in the bottom of the home value distribution and δ is the difference in the average child rank between children of parent renters and parents in the bottom of the housing value distribution. Ranks are defined at the population level. Panel B shows child homeownership rates across deciles of the parent housing asset distribution, separately for Black and White families.

Figure D.7: Counterfactual Black ownership rates and home values

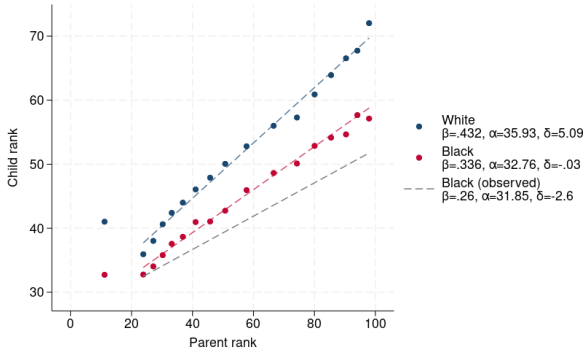
(a) Home values estimated using first-time owners



(b) Home values at 25^{th} ptile White value



(c) Home values at 10^{th} ptile White value

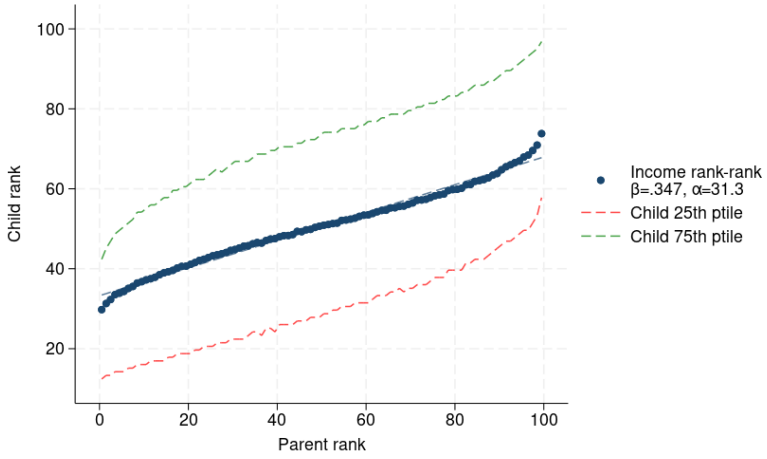


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

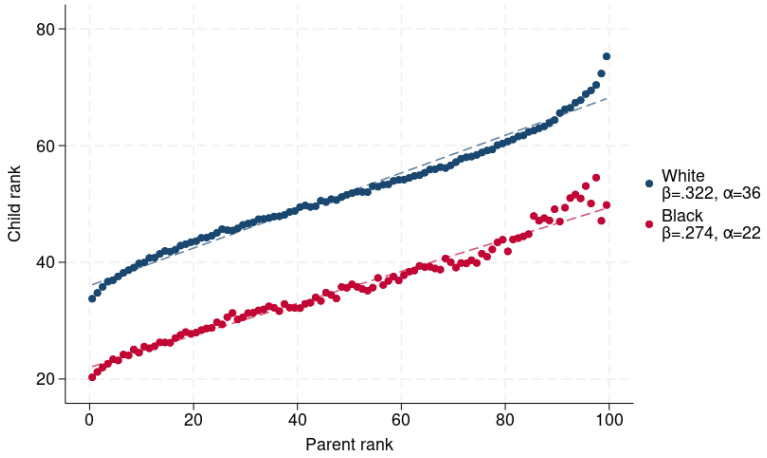
Note: This figure shows counterfactual rank-rank slopes for simulations where the homeownership rates of Black children are equalized to those of White children within parent rank bins. Panel A shows relationships from a counterfactual exercise where Black and White child homeownership rates are equalized, but the new marginal Black homeowners have are assigned estimated home values based on a regression model using first time home buyers observed in a matched ACS sample, as described in Appendix Section A.8.2. Panels B and C equalize homeownership rates across the parental distribution and assign new marginal Black homeowners the observed 25^{th} and 10^{th} percentiles of housing asset values among Black homeowners within each parental asset bin, respectively, as described in Appendix Section A.8.3. For all exercises, ranks are redefined for the population after the simulations and the corresponding rank-rank relationships for Black and White families are shown, as is the observed Black rank-rank relationship (grey dashed line).

Figure D.8: Income Rank-Rank IGM Relationships

(a) Income rank-rank



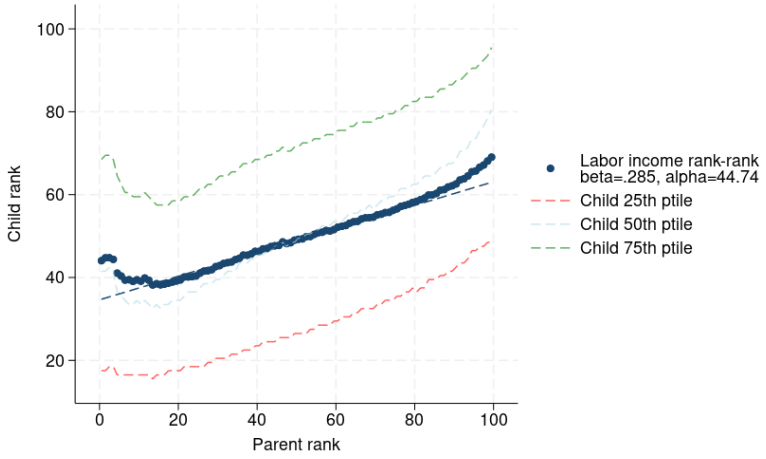
(b) White v. Black families



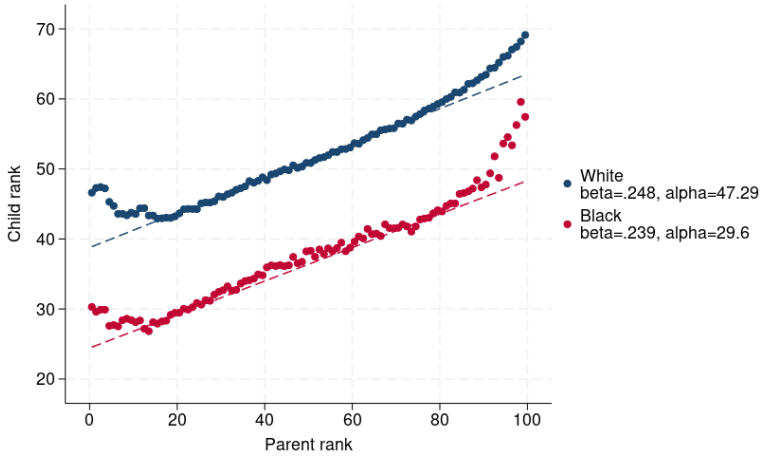
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figure shows non-parametric rank-rank intergenerational relationships between child and parent income. Income is defined as average adjusted gross income (AGI) over three years. Panel A shows results for the full sample. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is the linear rank-rank slope (β). Percentiles of the child income rank distribution conditional on parent rank are also shown. α is the average child rank for children of parents at the bottom of the income distribution (the intercept in a regression of child rank on parent rank). Panel B shows the rank-rank relationships separately for Black and White families.

Figure D.9: IGM Rank-Rank Relationships of Labor Earnings

(a) Labor income rank-rank

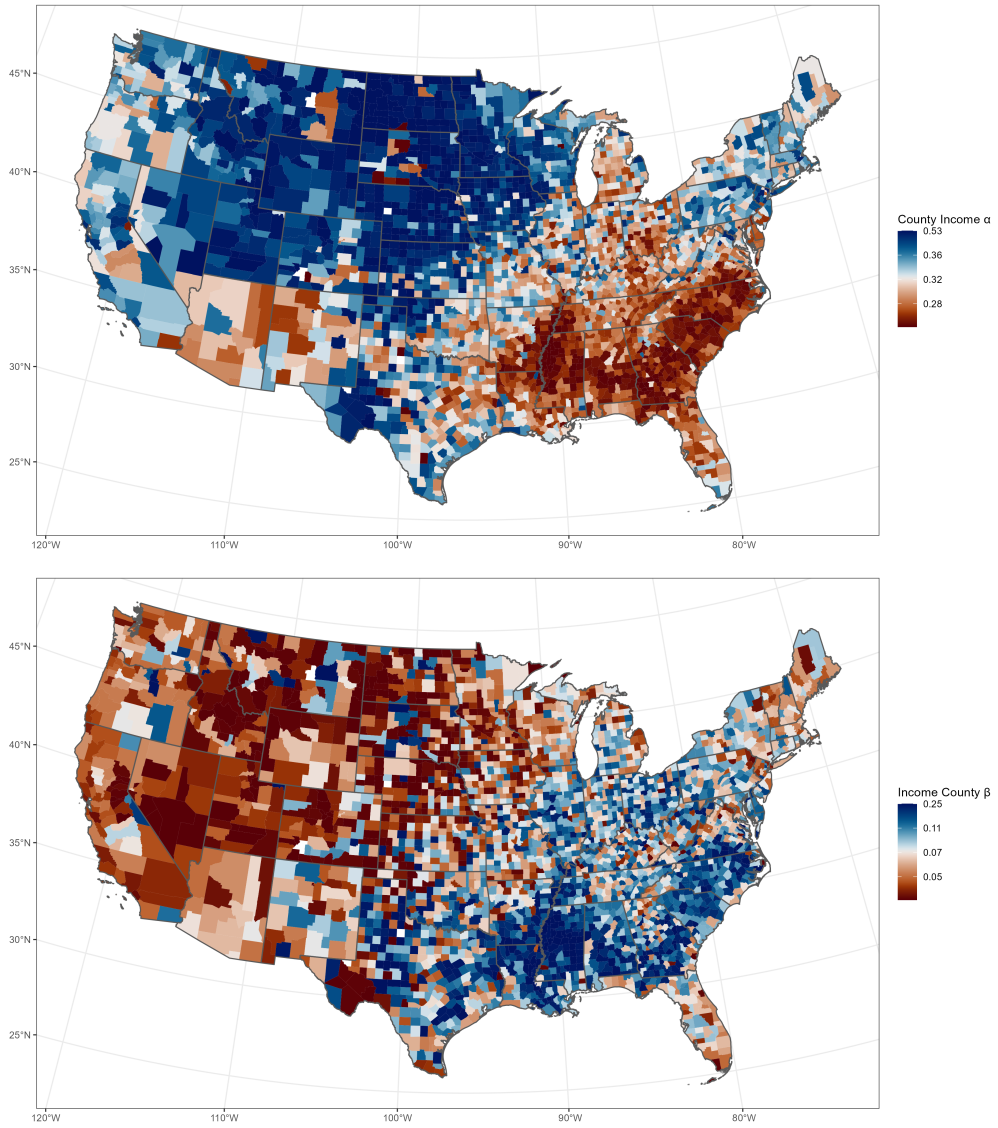


(b) White v. Black families



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figure shows non-parametric rank-rank intergenerational relationships between child and parent labor earnings. Labor earnings are defined as average total annual W-2 wage and salary income over three years. Panel A shows results for the full sample. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is the linear rank-rank slope (β). Percentiles of the child labor earnings rank distribution conditional on parent rank are also shown. α is the average child rank for children of parents at the bottom of the income distribution (the intercept in a regression of child rank on parent rank). Panel B shows the rank-rank relationships separately for Black and White families.

Figure D.10: Geographic Distribution of Income Mobility, α and β Parameters

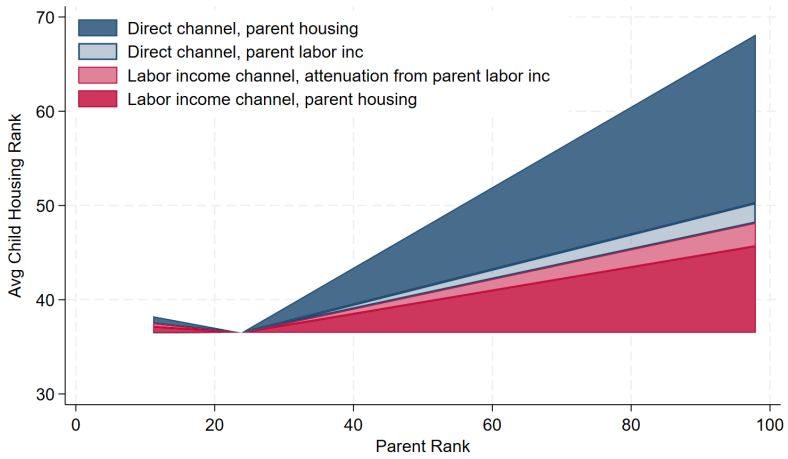


Source: Chetty et al. (2014)

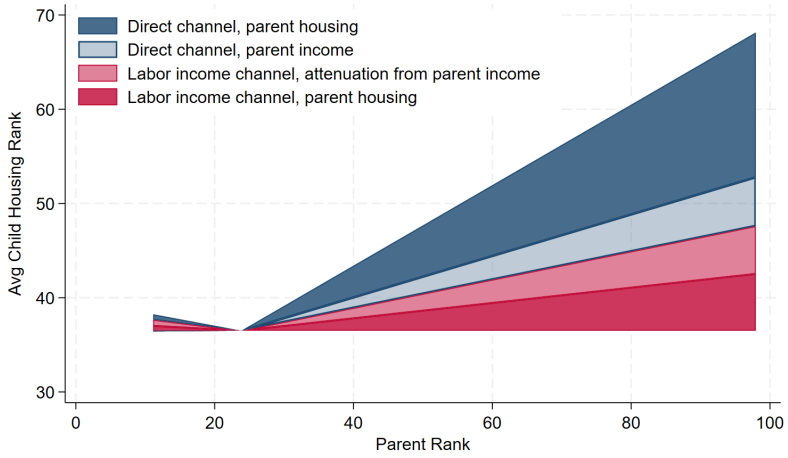
Notes: Each subfigure is a county-level choropleth map of absolute and relative intergenerational income mobility, reproduced from Chetty et al. (2014).

Figure D.11: Direct and Labor Income Channels - Adding Parent Income

(a) Including parent labor income



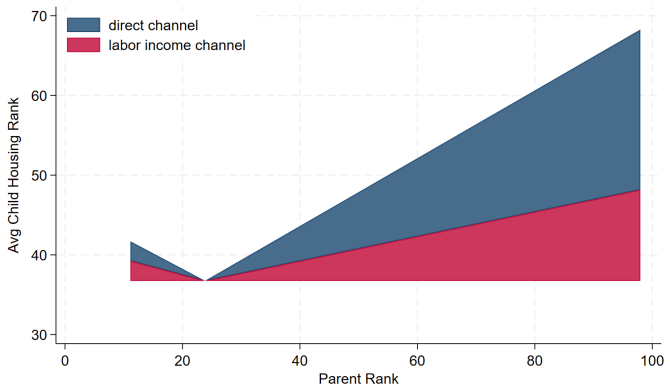
(b) Including parent total income



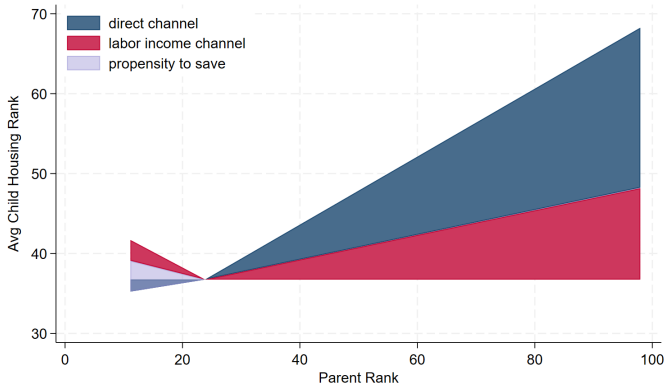
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: Panel A shows a decomposition of the population rank-rank slope of housing assets into the direct and labor income channels. The direct and labor income channels are derived from simultaneous equations (s1) and (s2), and described in Section 5.2. Panel A shows results after adding parent labor income rank to the simultaneous equations. Panel (B) shows results after adding parent total income (adjusted gross income, or AGI) rank to the simultaneous equation models. The red areas represents the share associated with the labor income channel, i.e. the increase in child assets across the parent distribution due to the fact that children of wealthier parents earn more income. The blue areas represent the direct channel, i.e. conditional on children earning the same amount, the increase in child assets due to having wealthier parents.

Figure D.12: Labor Income and Direct Channels - White Families

(a) Direct v. labor income channels



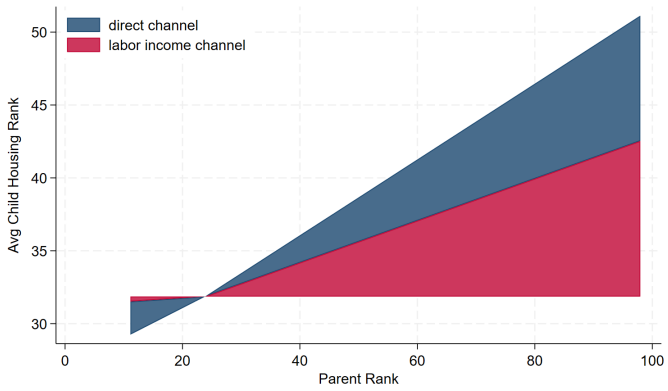
(b) Including the "propensity to save" channel



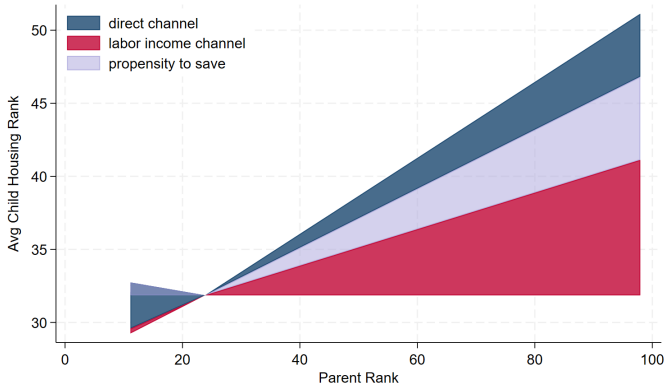
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: Panel A shows a decomposition of the population rank-rank slope of housing assets into the direct and labor income channels. The direct and labor income channels are derived from simultaneous equations (s1) and (s2), and described in Section 5.2. The red area represents the share associated with the labor income channel, i.e. the increase in child assets across the parent distribution due to the fact that children of wealthier parents earn more income. The blue is the direct channel, i.e. conditional on children earning the same amount, the increase in child assets due to having wealthier parents. Panel B shows the direct channel, labor income channel and the "propensity to save" channel — the interaction effect between child earnings and parent housing assets.

Figure D.13: Labor Income and Direct Channels - Black Families

(a) Direct v. labor income channels



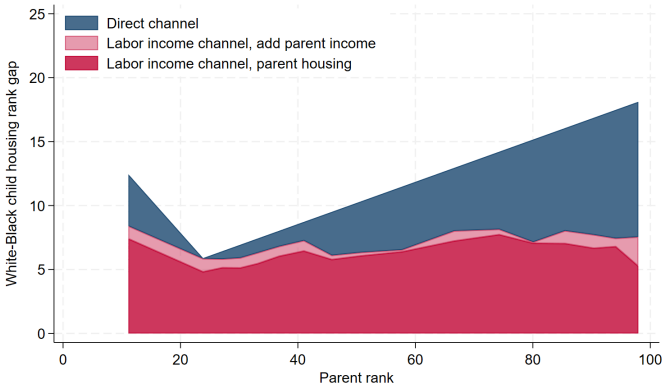
(b) Including the "propensity to save" channel



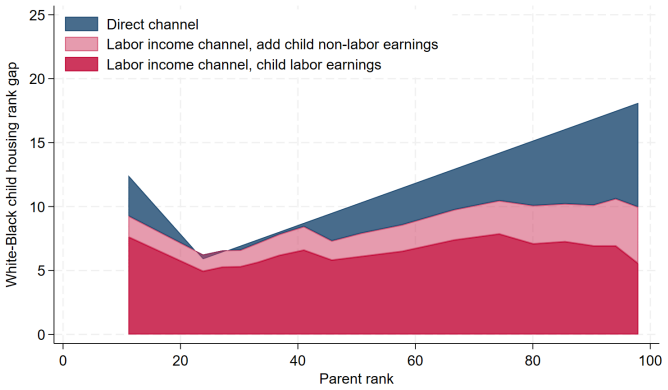
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: Panel A shows a decomposition of the population rank-rank slope of housing assets into the direct and labor income channels. The direct and labor income channels are derived from simultaneous equations (s1) and (s2), and described in Section 5.2. The red area represents the share associated with the labor income channel, i.e. the increase in child assets across the parent distribution due to the fact that children of wealthier parents earn more income. The blue is the direct channel, i.e. conditional on children earning the same amount, the increase in child assets due to having wealthier parents. Panel B shows the direct channel, labor income channel and the "propensity to save" channel — the interaction effect between child earnings and parent housing assets.

Figure D.14: Further Direct and Labor Income Channel Decompositions of Black-White IG gaps

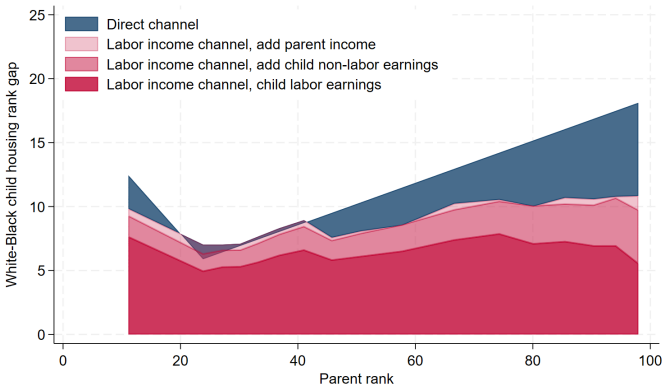
(a) Add parent income to decomposition



(b) Role of child total income relative to labor income



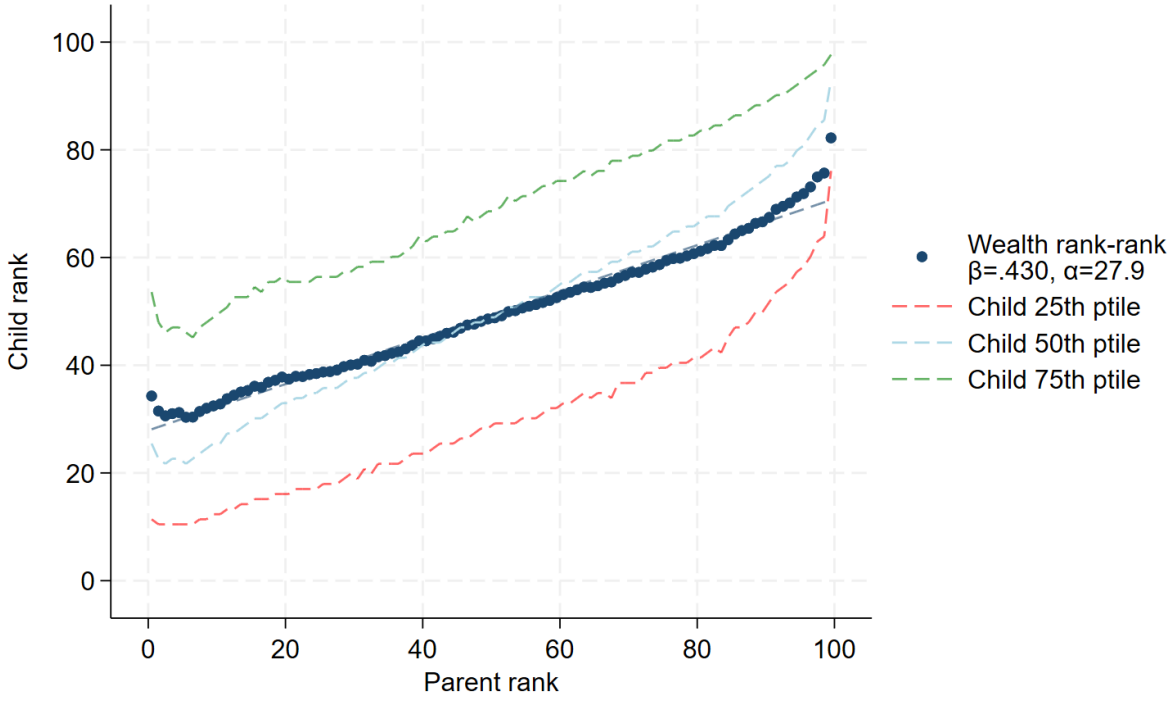
(c) Child total income and parent income



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Note: This figure shows a decomposition of the gap in Black and White child average housing ranks across the parent distribution, decomposed into direct and labor income channels. The labor income channel shows the difference in Black and White ranks associated with Black and White children having different earnings conditional on parent rank. The direct channel shows the remaining gap in child housing ranks, conditional on Black and White children having the same earnings within parent rank. Panel (a) adds controls for parent income rank. Panel (b) shows the additional amount of the gap explained when conditioning on child total income, as opposed to only child labor income. Panel (c) includes parent labor income and uses child total income.

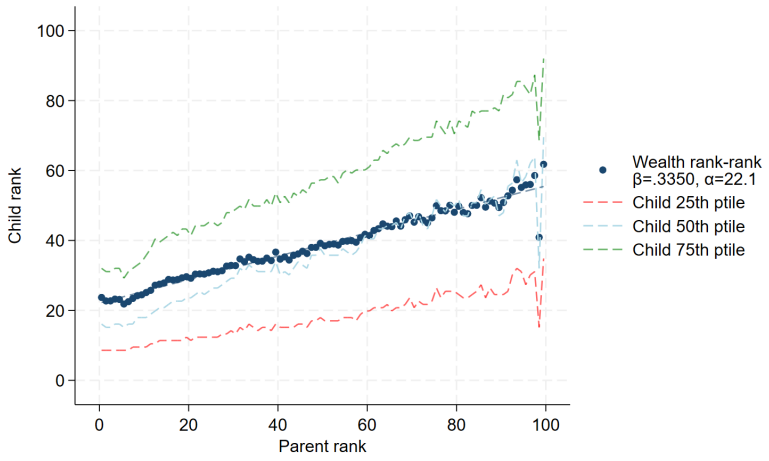
Figure D.15: Rank-rank IGM - Capitalized wealth



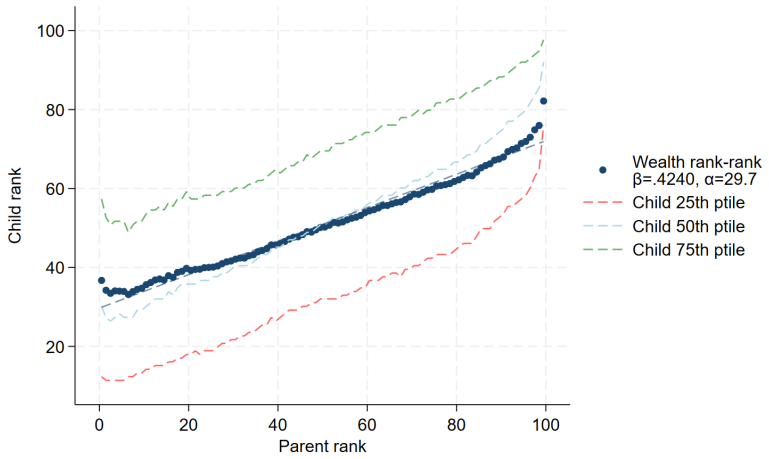
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figures shows the rank-rank relationship of child and parent capitalized wealth. The capitalization method is described in Section 5.5 and Appendix A.9. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is the linear rank-rank slope (β). Percentiles of the child wealth rank distribution conditional on parent rank are also shown. α is the average child rank for children of parents in the bottom of the wealth distribution (the intercept in a regression of child rank on parent rank).

Figure D.16: Rank-rank IGM - Capitalized wealth, by Race

(a) Black families

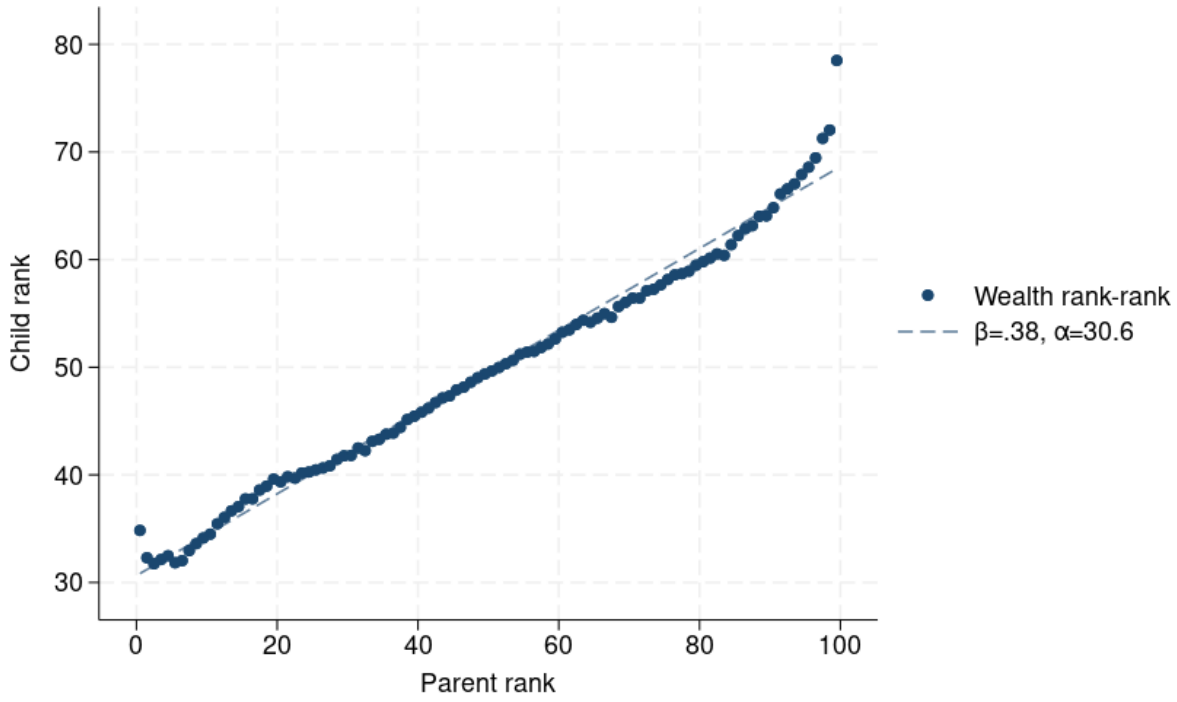


(b) White families



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figures shows the rank-rank relationship of child and parent capitalized wealth, separately for Black and White families. The capitalization method is described in Section 5.5 and Appendix A.9. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is the linear rank-rank slope (β). Percentiles of the child wealth rank distribution conditional on parent rank are also shown. α is the average child rank for children of parents in the bottom of the wealth distribution (the intercept in a regression of child rank on parent rank).

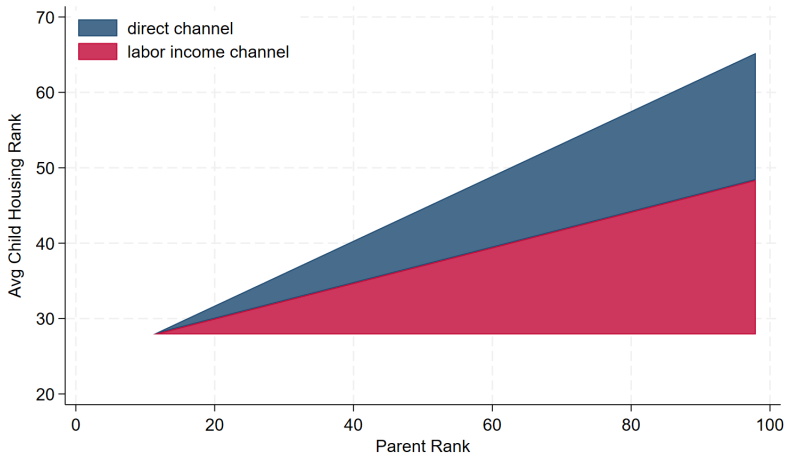
Figure D.17: Rank-rank IGM - Capitalized wealth - No LCA weights



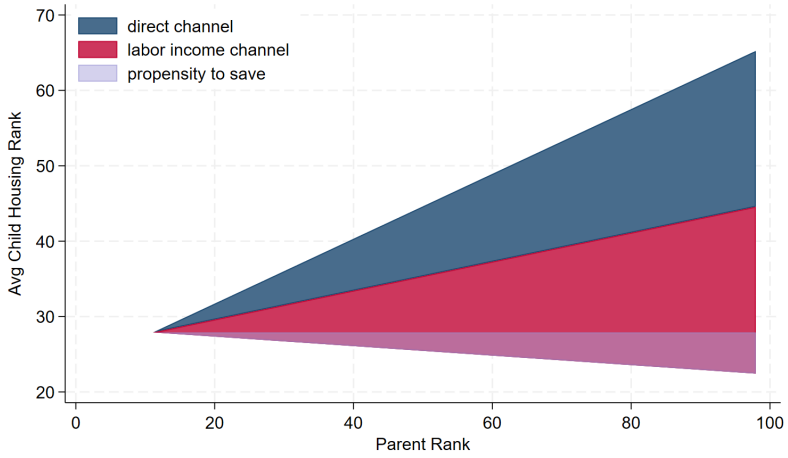
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figures shows the rank-rank relationship of child and parent capitalized wealth, using population weights rather than the main life-cycle adjusted (LCA) weights. The capitalization method is described in Section 5.5 and Appendix A.9. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is the linear rank-rank slope (β).

Figure D.18: Capitalized wealth - Direct and labor income channels

(a) Direct v. Labor income channels



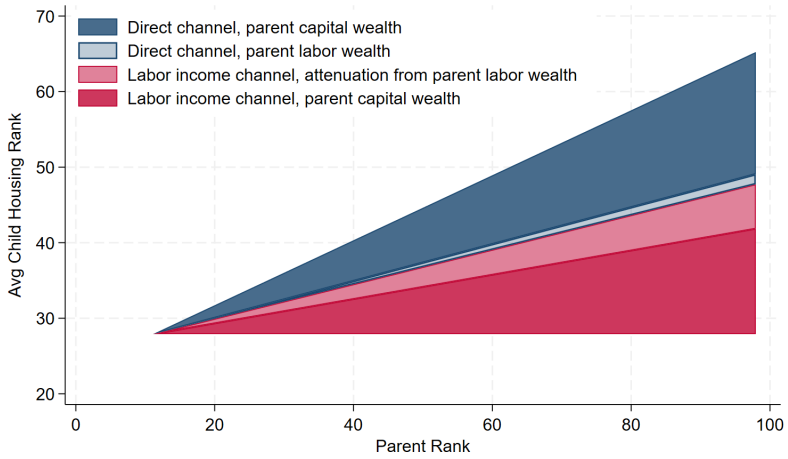
(b) Including the "propensity to save" channel



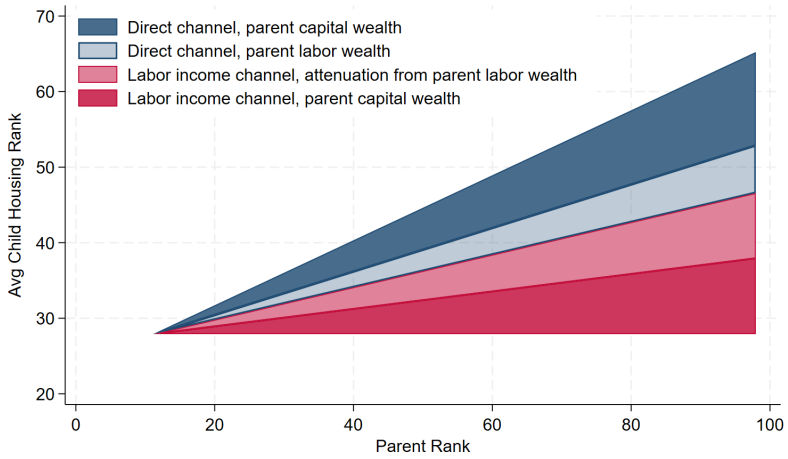
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: Panel A shows a decomposition of the population rank-rank slope of capitalized assets into the direct and labor income channels. The capitalization method is described in Section 5.5 and Appendix A.9. The direct and labor income channels are derived from simultaneous equations (s1) and (s2), and described in Section 5.2. The red area represents the share associated with the labor income channel, i.e. the increase in child assets across the parent distribution due to the fact that children of wealthier parents earn more income. The blue is the direct channel, i.e. conditional on children earning the same amount, the increase in child assets due to having wealthier parents. Panel B shows the direct channel, labor income channel and the "propensity to save" channel — the interaction effect between child earnings and parent housing assets.

Figure D.19: Capitalized wealth - Direct and labor income channels by source

(a) Parent pension v. non-pension "capital" wealth

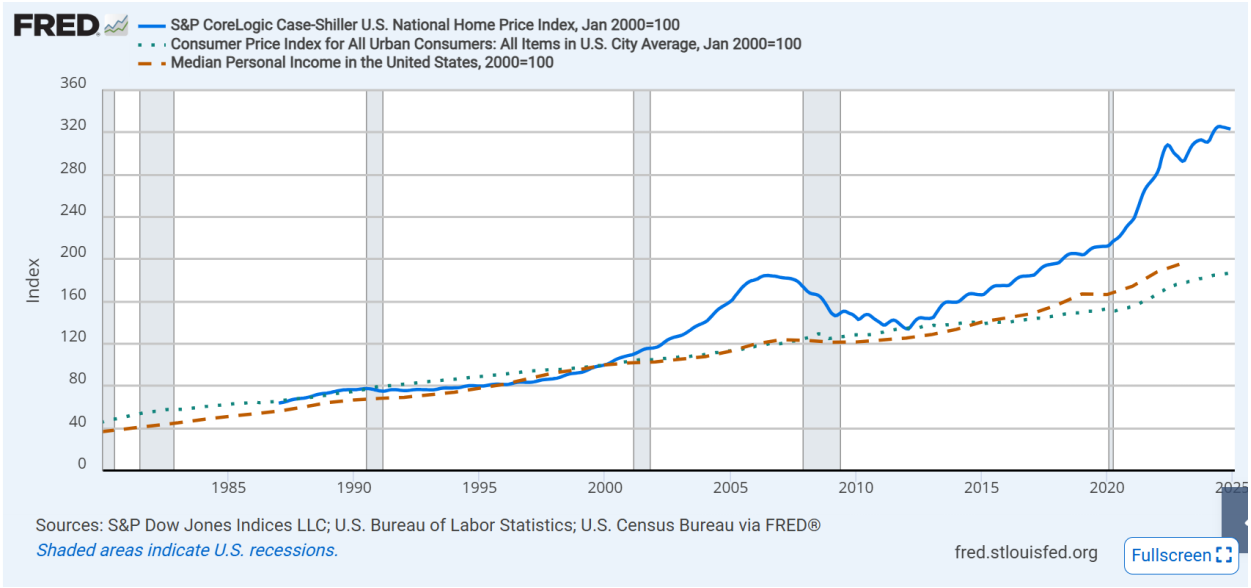


(b) Parent housing v. non-housing wealth



Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figure shows a decomposition of the population rank-rank slope of capitalized assets into the direct and labor income channels. The capitalization method is described in Section 5.5 and Appendix A.9. The direct and labor income channels are derived from simultaneous equations (s1) and (s2), and described in Section 5.2. Panel A separates parent wealth into the labor wealth (pension) rank and the capital wealth (housing+fixed income assets+corporate equity) rank. Panel B separates parent wealth into housing wealth and non-housing wealth (pension+fixed income assets+corporate equity) ranks. The red areas represents the share associated with the labor income channel, i.e. the increase in child assets across the parent distribution due to the fact that children of wealthier parents earn more income. The blue areas represent the direct channel, i.e. conditional on children earning the same amount, the increase in child assets due to having wealthier parents.

Figure D.20: National Trends in Home Prices, Consumer Price Index, and Median Personal Income: 1980-2024



D.2. Appendix Tables

Table D.2: Summary statistics by parent housing rank

Parent Housing Rank (%tile)	Average Housing Assets	Income		Labor earnings		Investment income	
		mean	median	mean	median	mean	median
11	0	34,090	26,980	26,240	20,020	285	0
24	14,300	30,660	26,190	23,700	19,880	199	0
27	32,950	34,980	31,010	27,480	24,210	255	0
30	45,000	38,370	35,090	30,650	27,890	296	0
33	55,000	41,310	38,240	33,130	30,850	343	6
37	65,000	44,340	41,490	35,940	34,060	361	12
41	75,000	47,940	45,150	38,970	37,550	428	21
46	85,000	51,490	48,690	42,060	40,640	510	32
51	95,000	55,530	52,770	45,450	44,420	629	48
58	112,500	61,420	57,740	49,970	48,650	783	73
67	137,500	68,290	63,660	55,340	53,600	1,012	102
74	162,500	75,210	68,930	59,870	57,370	1,516	143
80	187,500	83,340	75,210	65,640	62,280	1,623	200
85	225,000	93,990	82,620	73,060	67,570	2,318	296
90	275,000	108,000	90,840	81,220	71,900	3,045	420
94	350,000	133,000	104,600	96,550	79,710	4,910	683
98	692,600	257,100	147,800	162,100	95,060	17,940	1,859

Notes: This table shows information about parent income across the distribution of parent housing assets. Income is adjusted gross income (AGI), Labor earnings is total W-2 wage and salary income, and Investment income is the sum of interest and dividend income. Values in 2000 dollars.

Table D.3: Rank-rank housing parameters, across weights, cohorts and race

	All Cohorts (LCA weights)	Ages 35-36	Ages 38-39	Ages 41-42	All Cohorts (no LCA)
Full Sample					
β	0.427***	0.277***	0.303***	0.337***	0.305***
	(0.0007)	(0.0017)	(0.0013)	(0.0021)	(0.0007)
α	36.5	40.58	40.27	38.69	40.05
δ	1.74	-0.61	0.25	1.96	0.16
White					
β	0.425***	0.269***	0.296***	0.328***	0.297***
	(0.0008)	(0.0019)	(0.0015)	(0.0023)	(0.0008)
α	36.74	42.00	41.48	39.96	41.36
δ	4.95	1.90	2.92	4.85	2.96
Black					
β	0.260***	0.121***	0.133***	0.152***	0.132***
	(0.0027)	(0.0050)	(0.0040)	(0.0068)	(0.0022)
α	31.86	35.11	33.39	31.92	33.6
δ	-2.61	-2.85	-1.67	-1.76	-2.28

Notes: This table shows estimate parameters from our rank-rank specification of housing intergenerational mobility (Equation (1)): β represents relative mobility, or the increase in the average child asset rank associated with a one rank increase in parent assets; α is our measure of absolute mobility, or the average rank of children of the parents homeowners at the bottom of the housing asset distribution; δ shows the average difference in outcomes for children of parent renters and parent homeowners at the bottom of the distribution, i.e. the average child rank of parent renters minus α. The parameters are shown separately for the full sample using the main life-cycle adjusted (LCA) weights, for different child cohorts, and for the full sample with population weights instead of LCA weights. Estimates are shown separately for the full sample, for White families and for Black families.

Table D.4: Rank-rank income parameters across cohorts and race

	All Cohorts	Ages 35-36	Ages 38-39	Ages 41-42
Full Sample				
β	0.358***	0.376***	0.365***	0.334***
	(0.0006)	(0.0013)	(0.0010)	(0.0016)
α	32.12	31.91	31.37	32.76
White				
β	0.322***	0.338***	0.334***	0.299***
	(0.0007)	(0.0016)	(0.0012)	(0.0019)
α	35.92	35.88	34.76	36.35
Black				
β	0.274***	0.296***	0.280***	0.253***
	(0.0017)	(0.0041)	(0.0031)	(0.0051)
α	22.00	21.96	21.65	22.00

Notes: This table shows estimate parameters from a rank-rank specification of income intergenerational mobility (i.e. Equation (1), excluding the indicator for parent renters): β represents relative mobility, or the increase in the average child income rank associated with a one rank increase in parent income; α is a measure of absolute mobility, the average rank of children of the parents at the bottom of the income distribution (the regression intercept). Income is measured as average adjusted gross income (AGI) over three years. The parameters are shown separately for the full sample and for different child cohorts. Estimates are shown separately for the full sample, for White families and for Black families. All estimates are population weighted.

Table D.5: Rank-rank parameters for labor earnings across cohorts and race

	All Cohorts	Ages 35-36	Ages 38-39	Ages 41-42
Full Sample				
β	0.286***	0.312***	0.290***	0.255***
	(0.0005)	(0.0012)	(0.0010)	(0.0015)
α	34.61	34.40	35.40	37.14
White				
β	0.248***	0.269***	0.252***	0.222***
	(0.0006)	(0.0015)	(0.0011)	(0.0017)
α	38.77	39.15	39.58	40.94
Black				
β	0.244***	0.266***	0.249***	0.216***
	(0.0015)	(0.0037)	(0.0028)	(0.0046)
α	24.43	24.30	25.24	25.96

Notes: This table shows estimate parameters from a rank-rank specification of labor earnings intergenerational mobility (i.e. Equation (1), excluding the indicator for parent renters): β represents relative mobility, or the increase in the average child labor earnings rank associated with a one rank increase in parent labor earnings; α is a measure of absolute mobility, the average rank of children of the parents at the bottom of the earnings distribution (the regression intercept). labor earnings is measured as average of total W-2 wage and salary earnings per year over three years. The parameters are shown separately for the full sample and for different child cohorts. Estimates are shown separately for the full sample, for White families and for Black families. All estimates are population weighted.

Table D.6: Black-White Differences in Housing Assets

	LCA (main)	Child Cohorts 35-36yrs	38-39yrs	41-42yrs	no LCA	B-W ownership rates equalized
Unconditional	$219,400	$194,900	$207,300	$233,700	$212,800	$151,700
Conditional on parent rank	$116,700	$113,600	$127,800	$146,500	$130,500	$48,190
Conditional on child ownership						
Unconditional	$166,800	$151,600	$160,800	$185,200	$166,100	$166,900
Conditional on parent rank	$72,460	$60,8600	$71,340	$82,080	$71,910	$74,630

Notes: This table shows the average differences in housing assets between children of White and Black families. The first row shows the unconditional difference in average assets; the second row shows the average difference conditional on parent housing asset rank; the next two rows show average differences among child homeowners. The columns show differences separately for the full sample using the main life-cycle adjusted (LCA) weights (col. 1), for different child cohorts (cols. 2-4), for the full sample with population weights instead of LCA weights (col. 5), and for the counterfactual exercise where we equalize Black and White child ownership rates within parent rank, as described in Section 4.2 and Appendix A.8.

Table D.7: Delta - various controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
δ	1.745***	1.178***	-0.964***	-0.860***	1.654***	-0.598***	-1.877***	0.615***	-1.120***	2.571***	-1.068***	-1.266***
	(0.0882)	(0.0897)	(0.0925)	(0.103)	(0.0881)	(0.104)	(0.0946)	(0.0701)	(0.0771)	(0.0795)	(0.0767)	(0.0879)
Parent Controls												
Parent income		X		X		X						X
Parent CZ			X	X		X						X
N family members					X	X						X
Child Controls												
Child location							X		X		X	X
Child income								X	X		X	X
Child married										X	X	X

Notes: This table shows estimates of the δ parameter from our rank-rank specification of housing intergenerational mobility when including controls for various parent and child characteristics. The δ estimates are the average difference in housing assets between children of parent renters and children of parent homeowners at the bottom of the asset distribution. Controls for parent characteristics are: average parent adjusted gross income (AGI); fixed effects for parent commuting zone (CZ); number of family members in parent household. Controls for child characteristics are: fixed effects for the child's county (location); average child AGI; an indicator for whether the child is married.

Table D.8: Beta - various controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
β	0.425***	0.298***	0.389***	0.254***	0.428***	0.254***	0.319***	0.222***	0.167***	0.375***	0.171***	0.134***
	(0.00071)	(0.00085)	(0.00080)	(0.00093)	(0.00072)	(0.00112)	(0.00078)	(0.00060)	(0.00066)	(0.00066)	(0.00066)	(0.00095)
Parent Controls												
Parent income		X		X		X						X
Parent CZ			X	X		X						X
N family members					X	X						X
Child Controls												
Child location							X		X		X	X
Child income								X	X		X	X
Child married										X	X	X

Notes: This table shows estimates of the β parameter from our rank-rank specification of housing intergenerational mobility (Equation (1)) when including controls for various parent and child characteristics. The β parameter represents relative mobility, or the increase in the average child asset rank associated with a one rank increase in parent assets Controls for parent characteristics are: average parent adjusted gross income (AGI); fixed effects for parent commuting zone (CZ); number of family members in parent household. Controls for child characteristics are: fixed effects for the child's county (location); average child AGI; an indicator for whether the child is married.

Table D.9: Black-White Gaps in Rank-Rank Relationships, across controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	-5.88	-4.18	-5.53	-3.60	-5.73	-3.30	-8.13	1.69	0.26	1.07	0.43	1.30
β	-0.165***	-0.168***	-0.178***	-0.183***	-0.166***	-0.185***	-0.152***	-0.132***	-0.119***	-0.164***	-0.119***	-0.133***
	(0.00273)	(0.00276)	(0.00277)	(0.00281)	(0.00273)	(0.00414)	(0.00274)	(0.00224)	(0.00229)	(0.00251)	(0.00228)	(0.00347)
δ	-7.560***	-6.531***	-7.357***	-6.276***	-7.444***	-6.239***	-6.760***	-4.402***	-3.767***	-6.865***	-3.923***	-3.845***
	(0.223)	(0.229)	(0.226)	(0.273)	(0.223)	(0.276)	(0.230)	(0.178)	(0.188)	(0.203)	(0.187)	(0.235)
Parent Controls												
Parent income		X		X		X						X
Parent CZ			X	X		X						X
N family members					X	X						X
Child Controls												
Child location							X		X		X	X
Child income								X	X		X	X
Child married										X	X	X

Notes: This table shows the average differences in the parameters from our rank-rank specification of housing intergenerational mobility (Equation (1)) between Black and White families. The tables resents estimated differences: in relative mobility (β), or the increase in the average child asset rank associated with a one rank increase in parent assets; our measure of absolute mobility (α), or the average rank of children of the parents homeowners at the bottom of the housing asset distribution; and δ, or the average difference in outcomes for children of parent renters and parent homeowners at the bottom of the asset distribution. The parameters are estimated including controls for various parent and child characteristics. Controls for parent characteristics are: average parent adjusted gross income (AGI); fixed effects for parent commuting zone (CZ); number of family members in parent household. Controls for child characteristics are: fixed effects for the child's county (location); average child AGI; an indicator for whether the child is married.

Table D.10: Black-White Gaps in Housing Assets, across controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Housing assets	-219,400***	-227,800***	-170,100***	-120,100***	-116,700***	-93,430***	-234,400***	-51,500***	-111,600***	-60,050***	-30,640***
	(809.4)	(844.3)	(912.3)	(846.2)	(802.7)	(928.6)	(846.6)	(786.8)	(824.6)	(826.8)	(980.8)
Housing assets	-166,800***	-174,600***	-140,700***	-87,370***	-72,460***	-73,670***	-179,400***	-43,080***	-109,700***	-66,810***	-41,390***
(home owners)	(1500)	(1497)	(1622)	(1528)	(1457)	(1589)	(1417)	(1343)	(1541)	(1323)	(1501)
Ownership rate	-0.294***	-0.292***	-0.222***	-0.193***	-0.201***	-0.143***	-0.297***	-0.092***	-0.147***	-0.078***	-0.037***
	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0009)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0012)
Parent Controls											
Parent CZ		X				X					X
Parent married			X			X					X
Parent income				X		X					X
Parent housing					X	X					X
Child Controls											
Child location							X			X	X
Child income								X		X	X
Child married									X	X	X

Notes: This table shows the average differences in housing assets and homeownership rates between children of Black and White families, across different controls for parent and child characteristics. The first row shows differences in average housing assets including zeros for renters. The is differences in assets among child homeowners. The third row shows differences in child homeownership rates. Controls for parent characteristics are: fixed effects for parent commuting zone (CZ); an indicator for the parents being married; average parent adjusted gross income (AGI); and parent housing asset rank (indicators for vigintile in the parent housing distribution). Controls for child characteristics are: fixed effects for the child's county (location); average child AGI; an indicator for whether the child is married.

Table D.11: Relationship Between Child Income and Parent Income and Assets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Parent housing assets	0.152***	0.162***	0.226***	0.282***	0.179***	0.213***		
	(0.0007)	(0.0012)	(0.0006)	(0.0010)	(0.0006)	(0.0011)		
Parent income	0.254***	0.264***						
	(0.0007)	(0.0011)						
Parent labor income			0.186***	0.252***			0.165***	0.212***
			(0.0006)	(0.0012)			(0.0006)	(0.0012)
Parent non-housing assets					0.241***	0.278***		
					(0.0006)	(0.0012)		
Parent non-pension assets							0.257***	0.293***
							(0.0006)	(0.0009)
Interaction		-0.0002***		-0.0012***		-0.0007***		-0.0008***
		(0.00002)		(0.00002)		(0.00002)		(0.00002)
N	3,266,000	3,266,000	3,266,000	3,266,000	3,266,000	3,266,000	3,266,000	3,266,000
R^2	0.135	0.135	0.126	0.127	0.139	0.139	0.136	0.137

Notes: This table shows estimates from rank-rank relationships between child income and parent income and/or asset ranks (Equation (3). The outcome of each regression is child rank in the income distribution. Explanatory variables are parent ranks in the income or asset distribution represented by each row. Parent and child income is defined as average adjusted gross income (AGI); parent labor income is average total W-2 wage and salary income; parent non-housing assets is capitalized parent wealth, other than housing (see Section 5.5 and Appendix A.9); parent non-pension assets is capitalized parent wealth other than pension wealth; "Interaction" represents the interaction between the two explanatory parent income/asset rank variables in the relevant column.

Table D.12: Direct and Labor Income Channel Decomposition of Rank-Rank Slope (β)

	(1) all	(2) all	(3) home value	(4) home ownership	(5) all	(6) all
Direct channel, parent housing	0.254***	0.233***	0.306***	0.00078***	0.241***	0.207***
	(0.00063)	(0.00135)	(0.00061)	(0.00001)	(0.00067)	(0.00076)
Labor income channel, parent housing	0.173***	0.165***	0.070***	0.00250***	0.124***	0.081***
	(0.00060)	(0.00054)	(0.00001)	(0.00000)	(0.00031)	(0.00013)
Propensity to save (interaction term)		0.00038***				
		(0.00002)				
Direct channel, parent labor inc					0.0286***	
					(0.00053)	
Labor income channel, parent labor inc					0.093***	
					(0.00017)	
Direct channel, parent income						0.070***
						(0.00063)
Labor income channel, parent income						0.120***
						(0.00029)
Housing Direct share	59.5%	54.5%	81.3%	23.7%	56.4%	48.5%

Notes: This table shows estimates of the "direct channel," "labor income channel," and "propensity to save" channels from the simultaneous equation model represented by Equations (s1) and (s2) and described in Section 5.2. For columns 1, 2, 5 and 6, the outcome is child housing asset rank. For column 3 the outcome is child housing asset rank subsetting to children homeowners. For column 4 the outcome is an indicator for child homeownership. In columns 1 - 4, parent housing asset rank is the only parental explanatory variable included in the equations. Column 5 shows results of a specification that adds the parent rank in the labor income (total W-2 wage and salary earnings) distribution; the specification in column 6 adds parent rank in the distribution of adjusted gross income (AGI). The final row reports the share of the rank-rank housing slope decomposition attributable to the direct channel of parental housing, for each specification.

Table D.13: Direct and Labor Income Channel Decomposition of the Gap Between Children of Parent Renters and Low Asset Parents (δ)

	(1) all	(2) all	(3) home value	(4) home ownership	(5) all	(6) all
Direct channel, parent housing	-0.810***	2.554***	-8.400***	0.0932***	-0.737***	-0.583***
	(0.0723)	(0.136)	(0.0952)	(0.0014)	(0.0722)	(0.0750)
Labor income channel, parent housing	-0.936***	-0.950***	-1.761***	-0.0158***	-0.694***	-0.595***
	(0.0201)	(0.0207)	(0.0640)	(0.0001)	(0.0119)	(0.0095)
Propensity to save (interaction term)		-0.0818***				
		(0.00281)				
Direct channel, parent labor inc					0.0634***	
					(0.00106)	
Labor income channel, parent labor inc					0.149***	
					(0.0004)	
Direct channel, parent income						0.081***
						(0.00111)
Labor income channel, parent income						0.158***
						(0.0005)
Housing Direct share	59.5%	54.5%	81.3%	23.7%	56.4%	48.5%

Notes: This table shows estimates of the decomposition of the δ parameter (the average difference in outcomes for children of parent renters relative to children of parent homeowners at the bottom of the asset distribution) into the "direct channel," "labor income channel," and "propensity to save" channels from the simultaneous equation model represented by Equations (s1) and (s2) and described in Section 5.2. For columns 1, 2, 5 and 6, the outcome is child housing asset rank. For column 3 the outcome is child housing asset rank subsetting to children homeowners. For column 4 the outcome is an indicator for child homeownership. In columns 1 - 4, parent housing asset rank is the only parental explanatory variable included in the equations. Column 5 shows results of a specification that adds the parent rank in the labor income (total W-2 wage and salary earnings) distribution; the specification in column 6 adds parent rank in the distribution of adjusted gross income (AGI). The final row reports the share of the δ decomposition attributable to the direct channel of parental housing, for each specification.

Table D.14: Direct and Labor Income Channel Decomposition of Rank-Rank Slope (β) - Black Families

	(1) all	(2) all	(3) home value	(4) home ownership	(5) all	(6) all
Direct channel, parent housing	0.116***	0.058***	0.243***	-0.00049***	0.093***	0.081***
	(0.0023)	(0.0044)	(0.0033)	(0.00005)	(0.0025)	(0.0027)
Labor income channel, parent housing	0.144***	0.125***	0.078***	0.00255***	0.082***	0.064***
	(0.00042)	(0.00032)	(0.00013)	(0.00000)	(0.00014)	(0.00025)
Propensity to save (interaction term)		0.00131***				
		(0.00008)				
Direct channel, parent labor inc					0.0445***	
					(0.0019)	
Labor income channel, parent labor inc					0.104***	
					(0.00022)	
Direct channel, parent income						0.047***
						(0.0020)
Labor income channel, parent income						0.111***
						(0.00025)
Housing Direct share	44.6%	22.4%	75.6%	-23.7%	35.8%	31.1%

Notes: This table shows estimates of the "direct channel," "labor income channel," and "propensity to save" channels from the simultaneous equation model represented by Equations (s1) and (s2) and described in Section 5.2. The estimates are for the subsample of Black families. For columns 1, 2, 5 and 6, the outcome is child housing asset rank. For column 3 the outcome is child housing asset rank subsetting to children homeowners. For column 4 the outcome is an indicator for child homeownership. In columns 1 - 4, parent housing asset rank is the only parental explanatory variable included in the equations. Column 5 shows results of a specification that adds the parent rank in the labor income (total W-2 wage and salary earnings) distribution; the specification in column 6 adds parent rank in the distribution of adjusted gross income (AGI). The final row reports the share of the rank-rank housing slope decomposition attributable to the direct channel of parental housing, for each specification.

Table D.15: Direct and Labor Income Channel Decomposition of Rank-Rank Slope (β) - White Families

	(1) all	(2) all	(3) home value	(4) home ownership	(5) all	(6) all
Direct channel, parent housing	0.271***	0.270***	0.309***	0.00089***	0.259***	0.223***
	(0.0007)	(0.0016)	(0.0007)	(0.00001)	(0.0007)	(0.0008)
Labor income channel, parent housing	0.154***	0.154***	0.064***	0.00214***	0.113***	0.073***
	(0.00048)	(0.00048)	(0.00001)	(0.00000)	(0.00026)	(0.00011)
Propensity to save (interaction term)		0.00001				
		(0.00002)				
Direct channel, parent labor inc					0.0272***	
					(0.0006)	
Labor income channel, parent labor inc					0.082***	
					(0.00014)	
Direct channel, parent income						0.073***
						(0.0007)
Labor income channel, parent income						0.109***
						(0.00024)
Housing Direct share	63.7%	63.5%	82.9%	29.4%	60.9%	52.5%

Notes: This table shows estimates of the "direct channel," "labor income channel," and "propensity to save" channels from the simultaneous equation model represented by Equations (s1) and (s2) and described in Section 5.2. The estimates are for the subsample of White families. For columns 1, 2, 5 and 6, the outcome is child housing asset rank. For column 3 the outcome is child housing asset rank subsetting to children homeowners. For column 4 the outcome is an indicator for child homeownership. In columns 1 - 4, parent housing asset rank is the only parental explanatory variable included in the equations. Column 5 shows results of a specification that adds the parent rank in the labor income (total W-2 wage and salary earnings) distribution; the specification in column 6 adds parent rank in the distribution of adjusted gross income (AGI). The final row reports the share of the rank-rank housing slope decomposition attributable to the direct channel of parental housing, for each specification.

Table D.16: Quasi-experiment: increase in baseline γ_c from $-1SD$ to $+1SD$ relative to the median

Mobility response (r.p.):	*cubic, unwtd*			*cubic, wtd*			*quartic, unwtd*			*quartic, wtd*		
1978-86 cohort trend	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
... in β (Relative)	-.025	-.030	-.024	-.030	-.031	-.026	-.022	-.027	-.020	-.026	-.027	-.020
	(.013)	(.013)	(.014)	(.013)	(.013)	(.014)	(.012)	(.013)	(.014)	(.012)	(.013)	(.014)
... in α (Absolute)	.035	.034	.027	.039	.034	.028	.034	.032	.025	.036	.032	.025
	(.009)	(.009)	(.010)	(.009)	(.009)	(.010)	(.008)	(.009)	(.010)	(.008)	(.009)	(.010)
... in δ (Renter)	-.026	-.029	-.019	-.029	-.030	-.020	-.024	-.028	-.018	-.027	-.028	-.016
	(.009)	(.010)	(.012)	(.010)	(.010)	(.012)	(.009)	(.010)	(.012)	(.009)	(.010)	(.012)
N	2.33M	2.33M	2.33M	2.33M	2.33M	2.33M	2.33M	2.33M	2.33M	2.33M	2.33M	2.33M
R^2	0.160	0.161	0.161	0.156	0.156	0.156	0.160	0.161	0.161	0.156	0.156	0.156
Change in γ	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338
Instrumented $d \ln \overline{p_c}$	-.272	-.272	-.272	-.272	-.272	-.272	-.272	-.272	-.272	-.272	-.272	-.272
$(\alpha, \beta, \delta) \cdot (1, \mathbf{F_b})$	X	X	X	X	X	X	X	X	X	X	X	X
$(\alpha, \beta, \delta) \cdot \gamma_c$	X	X	X	X	X	X	X	X	X	X	X	X
$(\alpha, \beta, \delta) \cdot \Delta\gamma_c \cdot \mathbf{F_b}$	X	X	X	X	X	X	X	X	X	X	X	X
$(\alpha, \beta, \delta) \cdot \mathbf{F'_{d(c)}} \cdot \mathbf{F_b}$	X	X	X	X	X	X	X	X	X	X	X	X
$(\alpha, \beta, \delta) \cdot \overline{\mathbf{H^{g-1}}}_\mathbf{c} \cdot \mathbf{F_b}$		X	X		X	X		X	X		X	X
$(\alpha, \beta, \delta) \cdot S(c) \cdot \mathbf{F_b}$			X			X			X			X

Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Notes: Effects are reported in rank points /100: e.g. .01 implies one rank. Robust standard errors, clustered on county, appear below point estimates in parentheses. The table reports 12 specifications, resulting from the interaction of 3 choices: i) in the polynomial order of γ_c (cubic, quartic); ii) in whether to multiply the regression weights by the inverse standard error of γ_c, provided in Baum-Snow and Han's public-use data package, to further adjust for small-area uncertainty; and iii) in the set of trend controls. In all cases we allow our baseline mobility measures (α, β, δ) to vary with birth cohort fixed effects interacted with a full suite of Census division dummies $\mathbf{F_{d(c)}}$ and with the 2001-2011 *change* in γ_c. We then layer on interactions with county-average parental housing characteristics in 2000 (i.e. the rate of parental homeownership and the average home value, which we summarize as $\overline{\mathbf{H^{g-1}}}_\mathbf{c}$), or with a "superstar" county dummy $S(c)$.

Table D.17: Quasi-experiment: increase in baseline γ_c from $-1SD$ to $+1SD$ relative to the median

Mobility response (r.p.):	*Full sample*		*White*		*Black*		*Hi price cty*		*Lo price cty*	
1978-86 cohort trend	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
... in β (Relative)	-.030	-.026	-.029	-.029	-.143	-.154	-.038	-.028	-.045	-.036
	(.013)	(.014)	(.016)	(.016)	(.064)	(.073)	(.018)	(.020)	(.020)	(.019)
... in α (Absolute)	.039	.028	.035	.028	.061	.065	.043	.034	.033	.026
	(.009)	(.010)	(.011)	(.012)	(.031)	(.038)	(.013)	(.015)	(.012)	(.012)
... in δ (Renter)	-.029	-.020	-.018	-.012	-.042	-.045	-.024	-.032	-.003	-.006
	(.010)	(.012)	(.012)	(.014)	(.027)	(.031)	(.014)	(.016)	(.014)	(.013)
N	2.33M	2.33M	1.64M	1.64M	282K	282K	1.32M	1.32M	1.01M	1.01M
R^2	0.156	0.156	0.138	0.139	0.096	0.096	0.156	0.157	0.156	0.157
Change in γ	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338	0.338
Instrumented $d \ln \overline{p_c}$	-.272	-.272	-.272	-.272	-.272	-.272	-.272	-.272	-.272	-.272
$(\alpha, \beta, \delta) \cdot (1, \mathbf{F_b})$	X	X	X	X	X	X	X	X	X	X
$(\alpha, \beta, \delta) \cdot \gamma_c$	X	X	X	X	X	X	X	X	X	X
$(\alpha, \beta, \delta) \cdot \Delta\gamma_c \cdot \mathbf{F_b}$	X	X	X	X	X	X	X	X	X	X
$(\alpha, \beta, \delta) \cdot \mathbf{F'_{d(c)}} \cdot \mathbf{F_b}$	X	X	X	X	X	X	X	X	X	X
$(\alpha, \beta, \delta) \cdot \overline{\mathbf{H^{g-1}}}_\mathbf{c} \cdot \mathbf{F_b}$		X		X		X		X		X
$(\alpha, \beta, \delta) \cdot S(c) \cdot \mathbf{F_b}$		X		X		X		X		X

Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

Notes: Effects are reported in rank points /100: e.g. .01 implies one rank. Robust standard errors, clustered on county, appear below point estimates in parentheses. The table reports estimates from the "cubic, weighted" specifications shown above in Appendix Table D.16. "Hi (Lo) price cty" denotes counties with average parental home value in 2000 above (below) the unweighted 60^{th} percentile in our metro sample. We estimate racial heterogeneity by estimating equation (5) separately for each racial group. Because our baseline specification explicitly controls for trends in mobility according to average parental home value, we capture heterogeneity in housing supply effects across price group by interacting our main DiD parameters with a price group binary variable.