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Housing Capital and Intergenerational Mobility in the United States

Ariel J. Binder
U.S. Census Bureau and IZA@LISER

Max Risch
Carnegie Mellon University

John Voorheis
U.S. Census Bureau

IZA@LISER NETWORK
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Abstract

Housing is the largest capital asset for most families. While the intergenerational mobility literature has extensively studied the income distribution, it has devoted less attention to housing, in part due to data limitations. We document 3 features of intergenerational mobility by comparing housing capital and income in a new dataset covering 3.4 million U.S. families. First, housing is more persistent across generations than earnings. Moreover, the housing gap between White and Black children grows more sharply throughout the parental resource distribution than does the earnings gap. Second, less than half of intergenerational housing persistence operates through child earnings, leaving substantial scope for direct transmissions of capital assets and knowledge. The direct channel is much weaker among Black families and can almost fully explain their greater risk of downward mobility. Third, local housing supply constraints shape spatial differences in the intergenerational mobility of housing—but not of earnings—as measured in a quasi-experimental shift-share design. Our results highlight a more rigid structure of economic resources across families than implied by income studies.

JEL classification

E24, O18, R31, D31

Keywords

housing markets, intergenerational mobility, homeownership, wealth distribution, capital, income, housing supply, racial disparities

Corresponding author

Ariel J. Binder

ariel.j.binder@census.gov

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1. Introduction

Homeownership is widely considered a marker of economic success in America. According to a 2022 U.S. Census Bureau survey, the median rented household held $9,000 of wealth, while the median owned household held $398,000, 60% of which was housing wealth.[1] Homeownership is a 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 that shape children's economic well-being (Chetty et al., 2014; Chetty and Hendren, 2018a; Colmer and Voorheis, 2020).

Despite its association with generational wealth, measurement of housing resources across multiple generations of U.S. families has been constrained by data limitations. Housing does not typically generate income flows. Thus, it is not well reflected in cross-generational datasets on income—analyses of which have come to dominate the literature on intergenerational mobility (see reviews by Black and Devereux, 2011; Mogstad and Torsvik, 2023; Deutscher and Mazumder, 2023).

Yet, there is reason to suspect that "nonhuman" capital assets like housing are more intergenerationally persistent than income. While nonhuman capital can be bought and sold directly, human capital is transferred indirectly via parental investments. Becker and Tomes (1979, 1986) theorize a structure in which poor and middle families invest all or most expendable resources in children's human capital, while rich families find it efficient to bequest nonhuman capital as well,[2] and the ratio of nonhuman to human capital rises among such families. Recent industry surveys and news articles report that children are increasingly relying on parental assistance to purchase a home, even those with "good jobs".[3]

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

[2] The marginal product of parent investment is diminishing and depends on the child's "endowment", for example, genetics, peers, learning cultures and environments, of skills and learning potential, which is imperfectly correlated across generations. This implies that in most cases, rich families are able to invest in children's human capital to the point where the marginal product of investment equals the rate of return on direct transfers of nonhuman capital.

[3] Redfin report: "Nepo-Homebuyers: Aside from Paychecks, Family Money Is the Most Common Source

As housing capital reflects a combination of inherited nonhuman capital and savings out of earned income, it is a useful measure to study intergenerational processes.

In this paper, we leverage a new dataset of property ownership and valuation records for over 3.4 million families, observed in multiple years surrounding the year 2000 and the year 2020, to document the relationship between parent and child housing resources in the contemporary United States. The data also contain linked income tax records, allowing us to investigate the joint relationship between housing capital and human capital mobility.

We conduct three empirical inquiries on this novel dataset. In the first inquiry, we characterize the joint distribution of parent and child housing capital. We find that housing capital exhibits substantially more intergenerational persistence than does labor income. Our estimate of the housing capital rank-rank slope is 0.43 – children born to parents 10 ranks higher in the housing distribution are on average 4.3 ranks higher in their housing distribution[4] – whereas, our estimate of the labor income rank-rank slope is 0.29. The rank-rank slope for total income, which includes realized capital income flows in addition to labor income, falls in between, at 0.35.[5]

We extend this inquiry to examine the Black-White gap in children's housing resources. We find that the average gap grows substantially throughout the parent housing distribution. Among children of parents at the bottom of the home value distribution, the average White child is about 5 ranks higher in the housing distribution than the average Black child; this gap grows to 20 ranks at the top of the parental distribution. In contrast, Chetty et al. (2020) report a relatively constant Black-White income gap of about 12.5 ranks across the parental income distribution (which we also find in our dataset). Using various approaches

of Young People's Down Payments", Zillow's Chief Economist: "Almost 40% of first-time home buyers seek out money from their parents", Lending Tree: "Nearly 80% of Gen Z Homeowners Had Down Payment Help — Mostly From Family", The Washington Post: "What does it take to buy a house? Increasingly, Mom and Dad"

[4]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. When we condition on both parent and child owning property, the rank-rank slope rises to 0.58.

[5]This 0.35 estimate of the rank-rank slope of total income matches prior studies of U.S. tax records, e.g. Chetty et al., 2014, 2020.

to impute counterfactual housing values, we provide robust evidence that the racial housing gaps we document are largely driven by disparities in homeownership rates rather than in home values among owners.

The second inquiry leverages our linkage between housing and income information. We use a simple capital transmission framework to specify a decomposition of the housing rank-rank slope into three channels. A "labor income" channel captures that children of parents with more housing assets earn more on average and therefore accumulate more housing capital. This channel accounts for 40% of the observed intergenerational persistence. A "direct" channel allows parental housing to affect child housing conditional on child earnings, through the direct transmission of resources such as assets or financial knowledge. This channel accounts for 54% of the rank-rank slope—i.e., even among children with the same earnings, those of parents with more assets hold significantly more housing assets themselves. Finally, a "savings/investment" channel allows children of parents with more housing assets to allocate more of their earnings toward housing. This channel explains only 6% of the rank-rank slope—as children earn more, they accumulate housing at roughly the same rate, regardless of parental housing assets. Together, these results suggest that much of the intergenerational persistence in housing capital is explained by factors outside the labor market, such as direct transfers of resources or market opportunities.

Applying this analysis to racial disparities, we find that differences in average labor market outcomes explain most of the Black-White housing gap at the bottom of the parental housing distribution. On the other hand, the direct channel explains most of the large Black-White housing gap at the top of the parental housing distribution; even conditional on Black and White children earning the same amount large gaps in housing assets remain.

We interpret the results as showing that nonhuman capital plays an important role in shaping intergenerational resource persistence, independent of labor market factors. Although these conclusions are based on observing housing assets only, as a robustness check, we also consider a measure of total capital resources. We do this by applying capitalization factors to the detailed capital income flows we observe in the tax records (as in Saez and Zucman, 2016; Smith et al., 2022), and adding the result to housing capital. Using this total resources measure, we estimate very similar aggregate intergenerational persistence (rank-rank slope of 0.43), a large direct channel, and similar patterns of racial disparities. This confirmation is not surprising given that housing is the dominant asset for most households outside of the top 1%.

Our final inquiry leverages the mass and geographic coverage of our dataset to examine the intergenerational mobility of housing resources in local markets. Like income, we find that housing mobility varies considerably across U.S. counties. However, the spatial patterns are distinct: we estimate a cross-county correlation between housing and income rank-rank slopes of 0.41. This suggests that local neighborhood factors shape housing persistence as well as income persistence, but that the sets of factors affecting each outcome are distinct.

To examine the role of local housing markets more precisely, we leverage granular estimates of housing supply elasticities (Baum-Snow and Han, 2024) combined with observed cohort variation to construct a difference-in-difference design. Our approach identifies differential price shocks from the post-Great-Recession housing boom by interacting the national quantity change with the county-specific slope of the supply curve as measured in 2001. 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 within counties according to geographic, population, and average parental housing outcomes as observed in 2000. These proxy for systematic demand shocks that might be correlated with baseline housing supply.

We show that being exposed to more elastic counties during the recent housing boom is associated with higher average homeownership rates, but without any evident association with labor income. Net of controls, we find that children differentially exposed to elastic counties saw more average upward mobility in housing resources and lower intergenerational persistence than did children more-exposed to inelastic counties.[6] We show that these effects primarily operate through the ownership margin, i.e. by reducing the gap in homeownership between children from poorer versus richer families.

Taken together, our findings indicate that economic resources are more concentrated across generations than has been implied by income studies and that housing capital, and capital market opportunities, play an important independent role in shaping the distribution of economic resources and their transmission across generations.

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 United States. Our headline rank-rank slope of 0.43 for housing capital and capitalized wealth is similar to the net-wealth estimate of Pfeffer and Killewald (2017) in PSID data.[7] Similar to Charles and Hurst (2003), we find labor income and asset ownership to be important channels of wealth transmission, although we place greater emphasis on ownership and direct transmission channels.[8] Gilraine et al. (2023), Benetton et al. (2022) and Daysal et al. (2023) provide evidence of specific mechanisms related to human-capital and direct effects of parental housing capital, which we generalize in our decomposition framework. Additionally, our focus on housing asset values, labor and non-labor income analogize to "lifetime resources" measures, 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. 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). We find

[6] Concretely, being exposed to an inelastic county ($1SD$ below median) relative to an elastic county ($1SD$ above median) is associated with 4.7 rank point lower housing for children at the bottom of the parental housing distribution, and an increase in the rank-rank slope of 3.8 rank points. These effects are 37% and 26%, respectively, of twice the cross-county standard deviation observed in our 2021 dataset.

[7] 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.

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

the labor income channel to be important in explaining housing 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, along with Killewald and Bryan (2016, 2018), point to the primary importance of ownership rates in explaining the intergenerational gap in housing resources between Black and White children.[9]

Third, our housing supply analysis broadens the scope of the "childhood exposure" literature, which examines the impacts of neighborhoods on human capital formation and income (Chetty and Hendren, 2018a,b). Our study is the first we have seen to link 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 on housing supply constraints and their consequences for prices and residential sorting (e.g., Paciorek, 2013; Howard and Liebersohn, 2021; Pennington, 2021; Hilber and Mense, 2021; Asquith et al., 2023; Baum-Snow, 2023; Mense, 2025).

2. Data

To analyze the intergenerational relationship of housing capital, we leverage the Census Bureau's data linkage infrastructure to construct a sample of families that includes children (generation g) and their parents (generation $g-1$). For the analysis we require 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.

[9] 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).

2.1. Intergenerational Data Sources and Sample Construction

We use the 2000 Census Long Form (2KLF) as a primary source of parent-child links and information on parent housing assets. The Long Form sampled 1 in 6 U.S. households during the year 2000, collecting information on household and family structure, sociodemographic characteristics, and family income sources. It also elicited whether the reference person owned the given housing unit and, if so, their estimate of the value of the home. We associate reference persons to their children using relationship identifiers. To observe children who were old enough to own a home by the year 2021, we restrict the 2KLF sample to children aged 14-16. These children were aged 35-37 in 2021.

Given the ages at which recent cohorts purchase homes (Figure 1), we supplement the 2KLF sample with samples containing older cohorts, which we draw from the Census Databank. The Databank records sociodemographic and annual income information on everyone who filed a federal income tax return during 1994-2022 (excluding 1996-7). It also contains unique, de-identified person numbers called Protected Information Keys (PIKs), which allow researchers to closely approximate parent-child links with claimer-dependent links (e.g. Chetty et al., 2020). From the Databank, we draw all dependent children aged 14-16 in tax year 1994 or 1998 whose claimer was also sampled in the 2KLF, and recover information on claimers' housing assets from their 2KLF records.

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 in 2000 when we measure their housing assets.

2.2. Child Housing Asset Measurement

To measure homeownership and housing assets in our sample of children, we leverage a set of administrative records from 2019-2021 on the universe of parcels in the U.S. on which property taxes are paid. Commercial data providers standardize these records across thousands of local taxing jurisdictions, and Census has a repository of files from prior contracts that support household survey production.[10] We use data from Black Knight, Incorporated (BK hereafter) for this study.

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. Deed files record the recent 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 then link these PIK'd records to the set of children described above.

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 given property.[11] In a final step, we collapse the short panel of 2019-2021 information into a single observation for each individual. This observation usually reflects 2021 holdings, subject to minor editing that we describe in Appendix A.2.

We want to focus on a long-run, or permanent, concept of housing capital. Our preferred measure of this concept in our dataset is gross assets, consistent with Black et al. (2023) and Boserup et al. (2017) who argue for a gross "lifetime resources" concept rather than net wealth to study intergenerational inequality. This is further informed by a simulation exercise that we provide in Appendix B. We derive a simple formula for the long-run value of housing capital in terms of three parameters—the home value appreciation rate, the mortgage interest rate, and the opportunity cost of capital—and two observed values—the current asset value and the "downpayment rate" (i.e. equity-to-value ratio). We obtain

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

[11] 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.

information on the latter by linking a large subsample of owners in our data to mortgage-balance information from their IRS tax Form 1098 records. We show that the rank-rank relationship in gross housing assets closely approximates the long-run rank-rank relationship under a wide range of parameter values, while the rank-rank relationship in net wealth compares far less favorably.[12] These results also are consistent with the fact that the vast majority of U.S. homeowners hold no mortgage debt by age 65.

Finally, we note that a limitation of these data is that properties indirectly owned by business entities do not have valid names to be directly assigned to 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.

2.3. Income Measurement

We use information from the 2KLF and federal tax returns to construct measures of family income. Our primary income measure is adjusted gross income (AGI), which 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 the analogous income concept from the 2KLF (i.e. the sum of reference person's and partner's personal incomes).[13] For children, we average AGI information across 2018, 2019, and 2021 tax returns.[14] We then construct ranks from these average income measures, ranking children *within* birth cohort.[15] For our measure of labor income, we use total wage and salary earnings as reported on tax returns.

Table 1 records some basic summary statistics of our final sample.

[12] The main implication of the framework is that when the child downpayment rate is relatively constant across the parent housing distribution, the gross asset value is a very good proxy for the long-run value in intergenerational rank-rank regressions. We show evidence of this constant relationship in Appendix Figure B.4.

[13] 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.

[14] We exclude 2020 due to anomalous earnings processes associated with the COVID-19 pandemic.

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

3. Analytical Approach: Rank-Rank Relationships

We use a rank-rank specification to measure intergenerational relationships in housing capital. Housing is particularly conducive to this specification because i) there are masses of non-owners in each generation which would not be incorporated in log transformations, and ii) housing assets are highly skewed at the very top, and we want the analysis to reflect the intergenerational relationship throughout the distribution.

3.1. Assigning Ranks

We assign 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 home valuations in 25 categorical bins, which results in 26 possible parental ranks including 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 $1 - x + .05/2$.

Our aim is to measure mobility 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 mobility 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 parent homeowner at the bottom of the value distribution is assigned a parental rank of 0.22, and the child of the owner at the $14.1^{st} = (0.11/0.78)$ percentile of the value distribution is assigned a parental rank of 0.33. Were we to specify a linear-in-ranks function, this would force a linear relationship across these 3 groups. This is likely too restrictive: for example, as shown in Appendix Table F.3, parent renters have higher average incomes than the owners at the bottom of the value distribution, and may differ in other unobserved ways. 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. From Equation (1) we define the following relationships:

- *Absolute Mobility (α)*: average rank of children raised by poorest 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 those of poorest owners.

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

3.3. Weighting

We begin with a base weight bw_i^g that is equivalent to the parent household of child i'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, as discussed further in Appendix A.3.

We address this issue as follows: let x_{ACS^*} define the population individual homeownership rate inferred from survey data, using the American Community Survey (ACS), and x_{BK}

be the observed rate in the Black Knight data. We define 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 owners observed through the BK linkage 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) × (parent renter, 10 deciles of parental owners) × (10 deciles of parental income).[16]

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 little difference in average home value between those who were and those who were not matched to a BK owner record.[17]

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 for the sample children, whereas it is about at its plateau for the sample parents. We benefit from measuring housing wealth near the plateau in life-cycle ownership rates for two reasons. First, we wish to make statements about "lifetime" holdings, which is the relevant object in standard models of household decision-making. 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 a set of age 45-49 target ownership rates.

[16] In doing so, we estimate x_{ACS*} in each of the 550 cells; further detail is provided in Appendix A.3.

[17] To be conservative, we relaxed this assumption with an additional adjustment to the weights that we describe in Appendix A.4. This adjustment exerted no discernible affect on our main results.

Because the population ownership rate in our observed "Millennial" cohorts converged with that of Gen-X cohorts by age 40 (see Figure 1), we use these cohorts as the basis for our targets. Appendix A.5 describes a natural scaling assumption that generates subgroup-specific weights based on population target ownership rates (which we allow to vary by race), and shows robustness of key facts in the data to plausible alternative scalings.[18]

4. Intergenerational Persistence of Housing Capital

Figure 2 presents estimates of the population relationships between parental and child housing capital. The navy blue dots plot average child rank as a function of parent rank, the light blue dashed line shows the median child rank, and the red and green dashed lines show the 25th and 75th percentile child ranks, respectively. The average relationship is approximately linear across the distribution of parent owners.

We estimate a β parameter of 0.427,[19] which reflects higher intergenerational persistence than total income or labor earnings. Our estimated rank-rank slope for total income is 0.347, shown in Appendix Figure F.9 and Table F.4 (see also Chetty et al., 2020). Moreover, when we focus on labor earnings alone, the rank-rank slope drops to 0.286 (Appendix Figure F.10).

Further, the quantiles show a qualitative change in the distribution of child outcomes at the top of the parent housing distribution. Through most of the parent distribution, the median child housing rank is very near the mean. At the top of the distribution children are disproportionately less likely to experience downward mobility. Among children born to parents in the top 5% of the, over half end-up in the top 20% of housing distribution and 25% end-up in the top the top 5%.[20]

[18] At the time of this writing, the 2024 public-use ACS data had recently been released, which enabled us to measure the ownership rate for the oldest cohort in our sample (1978) at age 46. The ownership rate was 0.634, which is close to, but slightly higher than, the Gen-X rate at that age shown in Figure 1. Rates by racial group were also quite close but slightly higher than their benchmarks. This indicates that our target ownership rates are reasonable if not conservative.

[19] Children born to homeowners 10 ranks higher in the housing distribution are on average 4.3 ranks higher in their housing distribution.

[20] This pattern holds for income and earnings as well, but to a lesser degree (Appendix Figures F.9 and F.10).

Finally, on average children of parent renters are slightly higher in the housing distribution than those of homeowners at the bottom of the value distribution (a $\tilde{\delta}$ of 1.74 ranks). Parent renters are a relatively diverse group, with higher average income than those at the bottom of the distribution and a much higher standard deviation of income (Appendix Table F.3). This is reflected in the divergence in the quantiles of child outcomes among parent renters. Appendix Table F.5 shows that the higher average income explains a portion of positive $\tilde{\delta}$, but location is the key influence. Among children growing up in the same commuting zone, children of renters are, instead, about one rank lower in the housing distribution on average.

4.1. Ownership Versus Intensive Margin

We next explore how intergenerational housing persistence is associated with i) child homeownership rates (the extensive margin) and ii) child home values conditional on ownership (the intensive margin). Figure 3 shows a decomposition of the rank-rank slope into the portions attributable to each component. (See Appendix A.6 for methodological details.) In the bottom portion of the parent owner distribution, an increase in parental housing rank affects child housing rank primarily by increasing the probability of child homeownership. The share of child housing gains generated by the intensive margin of home value rises throughout the distribution; in the top third, the intensive margin is the dominant channel of intergenerational housing persistence.

Figure F.6 shows that children of parent homeowners have notably higher homeownership rates than children of renters, however, conditional on owning a home children of renters own substantially more valuable homes on average. The left side of Figure 3 shows how these opposing forces generate $\tilde{\delta}$. The bottom pink portion shows the negative wedge in renter mobility created by lower ownership rates, but this is more than offset by the higher average home values conditional on ownership, represented by the blue portion.

4.2. Black-White Housing Mobility Gaps

Figure 4 shows the average rank-rank plot of housing capital separately for non-Hispanic Black and for non-Hispanic White families. We see a substantially higher rank-rank slope for White families than for Black families ($\beta_{White} = 0.425$ while $\beta_{Black} = 0.260$). This results in a widening of the gap in average outcomes between Black and White children across the parental distribution. At the bottom of the parental home value distribution, the gap between children of White and Black families is 5 ranks; the gap grows to about 20 ranks at the top. While there is high persistence and buffering against downward mobility at the top of the distribution for White families, Black families are exposed to strong downward mobility even at the top of the parental distribution.[21] Focusing on parent renters, we see that the positive $\tilde{\delta}$ is attributable to White families, whereas Black children of renters' average housing housing rank is a downward linear extrapolation of the rank-rank slope among Black children of owners.

These patterns contrast with racial differences in income mobility, which we show in Appendix Figure F.9. (See also Chetty et al., 2020.) The Black-White income gap changes little across the distribution of parental income, staying between 13 and 16 ranks. We estimate an income rank-rank slope of 0.322 for White families and 0.274 for Black families.[22] Compared to income, the gap in housing capital is relatively small at the bottom of the parental distribution, but grows to be substantially larger at the top. Together, this shows particularly strong intergenerational persistence in housing capital among White families, as compared to income or to housing for Black families.

We next shed light on the roles of ownership versus intensive margins in racial housing gaps. Panel A of Figure 5 shows the probability of child homeownership by race for each

[21] Appendix Figure F.11 shows the rank-rank relationships with quantiles of child outcomes separately for Black and White families. We also assess how various controls affect estimates of racial gaps in housing mobility parameters in Appendix Tables F.7 and F.8. They change little with controls for location or childhood family structure. We explore the role of income in detail in the Section 5.

[22] It appears that the slight difference in slopes is driven by capital income; rank-rank slopes of labor income are virtually identical between Black and White families (Appendix Figure F.10).

decile of the parental housing distribution and for parent renters. We observe large racial disparities in ownership rates, ranging from around 13 percentage points among children of bottom-decile owners to over 20 percentage points among children of top-decile owners and among children of renters. Black children of top-decile owners are less likely to own homes than White children of second-decile owners.

Given this, we conduct simulations where we remove the gaps in child homeownership rates and assess how much of the total Black-White gap this would close. First, we scale-up the ownership rates for Black children to equal those of White children, conditional on parent housing rank. Then, we must assign counterfactual home values to the new marginal Black homeowners. In the first exercise, we assume that new Black homeowners have the same average housing capital as the observed Black homeowners within each bin of parental housing capital. As shown in Panel B, this counterfactual exercise closes the large majority of the observed racial gap in child housing assets at each parental housing rank. This reflects Appendix Figure F.7, which shows that conditional on owning a home, the average Black-White gap in child housing assets is relatively small throughout the parental housing distribution (except for the extreme top). Unconditional gaps, however, are much larger.

This exercise does not account for selection into homeownership. If observed Black homeowners are positively selected, a policy that equalized Black-White ownership rates might disproportionately provide opportunities to Black children at lower values than the existing pool of owners. Accordingly, we model property values for counterfactual Black homeowners under various assumptions, which we describe in more detail in Appendix A.7. In our preferred approach, we capitalize rent payments of Black children in our sample who we observe as renters in matched ACS records. This could be interpreted as a policy in which landlords transfer properties to tenants at an estimated fair market value. Panel C shows that this counterfactual also closes the majority of the racial gap in child housing rank throughout the parental housing distribution, although significant gaps remain at the top of the distribution and among children of renters.

Appendix Figure F.8 presents alternative approaches, including estimating the value of first homes based on observed renter-to-owner transitions and assigning marginal homeowners the 25^{th} percentile of the observed distribution of Black children's home values conditional on parent rank. Together, the analysis shows that differences in homeownership rates are a major driver of the observed Black-White gaps.

5. The Roles of Income and Direct Transfers in Capital Persistence

In this section we examine the joint relationship between income and housing capital. A goal is to explore what the intergenerational relationships of housing capital implies about the intergenerational transmission of economic resources more broadly. We adopt two related perspectives. First, we conceive of income as a noisy proxy for total resources in an intergenerational regression, with unobserved capital generating omitted variable bias. Second, we derive a simple empirical model from a Becker-Tomes-style setup. The model relates parental resources to child resources partially through its effect on child earnings. Our linked data on housing capital, capital income, and labor income allows us to assess both perspectives. We find strong empirical support for both.

5.1. Parental Assets as an Omitted Variable in an Income-Income Model

Most prior research on intergenerational mobility has focused on income. While income is correlated with total economic resources, this correlation is imperfect for at least the following reasons: i) income may vary in composition between earnings and capital income across families, and thus obscure variation in the holding of capital assets; ii) income does not capture the possession or transfer of unrealized assets; iii) income does not capture savings. Prominent observers have argued that wealth is a better measure of economic well-being than income (e.g. Piketty, 2014; Wolff, 2017).

Appendix C presents a statistical framework that formalizes i) and ii). Total wealth comprises a portfolio of assets with different rates of return. Income is the sum of flow returns to these assets. If portfolio composition is heterogeneous in the cross-section, and this heterogeneity is correlated across generations, then a regression of child income on parent income will 1) likely understate the true degree of persistence in economic resources, and 2) overstate the influence of parent income by omitting information on capital assets. In particular, housing is the most important capital asset for most U.S. families, yet it produces no regular income flows so it will not be reflected in income measures.

We have a dataset that contains this usually-unobserved correlate of economic well-being. This enables us to estimate:

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

where Y_i^g and Y_i^{g-1} are parent and child positions in the income distribution, respectively, and we include parent housing rank on the right-hand side. Appendix Table F.9 reports the regression coefficients and Figure 6 shows a non-parametric illustration.

Figure 6 shows that although parent housing and income are highly correlated on average, there is substantial variation in parent housing capital conditional on income, particularly in the middle of the income distribution. Further, this variation is strongly associated with child outcomes. As such, including housing capital in the income model attenuates the income slope by around 10 ranks while parental housing resources shift children up the income distribution by about 15 ranks at each parental income level. As the housing coefficient is larger than the attenuation of the income coefficient, moving from the bottom to the top of the joint parental income and housing distribution is associated with a larger increase in average child incomes than is moving from the bottom to the top of the unconditional income distribution.[23] An implication is that income alone does not fully capture parent resources and that parental capital assets play an independent role in explaining child outcomes.

[23] The sum of housing and income coefficients is 0.406 (Appendix Table F.9), while the income slope in the absence of parental housing is 0.347. This table also shows the interaction term between parent income and housing assets is very small implying an approximately linear conditional relationships.

5.2. A Simple Model of Intergenerational Capital Transmission

Next, we develop a simple capital accumulation framework to add more structure to the joint intergenerational relationships between income and capital assets. Take generation g's lifetime budget constraint as:

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

Lifetime consumption, c_g, plus the amount of resources transferred to the next generation through human capital investments (b_g^{HC}) or non-human capital transfers (b_g^K), 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}^K. We summarize lifetime resources as W_g.

As in Becker and Tomes (1979, 1986), we assume parents make investments in child human capital and potentially bequest non-human capital as well. Randomness in child endowments and labor-market circumstances generates a positive but imperfect relationship between parent resources, W_{g-1}, and child earnings, $Y_g(b_{g-1}^{HC})$. Children use their earnings to accumulate capital. They also accumulate additional capital as a function of parental resources, through direct transfers or the influence of parental resources on children's savings rates and portfolio choices.[24]

Modeling these reduced form relationships (see Appendix D) 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 (s1) is the relationship between parent resources and child earnings and (s2) is the

[24] That is, we model child labor market earnings as a noisy reduced-form function of parent wealth, $Y_g = \lambda W_{g-1} + u_g$, transfers of non-human capital as a function of parent wealth, $b_{g-1}^K = \alpha_b W_{g-1} + e_g$, and child saving decisions to be a function of parent wealth, $s_g = \theta_s W_{g-1} + \eta_g$. See details in Appendix D.

relationship between child resources, child earnings and parent resources.

This model allows parental resources to affect children's via three channels. First, a "labor income" channel, given by $\lambda \times \alpha_y$, allows parental assets to indirectly shape children's assets via their effect on children's labor-market success. If children have more assets than predicted by their earnings in a way that is correlated with parental assets, then α_b and/or α_s will be greater than zero. The "direct" channel, α_b, allows parental assets to shift children up the asset distribution independent of child earnings. Finally, α_s, or the "savings/investment" channel, allows children of wealthier parents to accumulate more assets for a given increase in their earnings than children of less wealthy parents. This encompasses both differences in savings rates and differences to returns on those savings as a function of parental assets.

5.3. Decomposing the Housing Asset Rank-Rank Slope

Figure 7, Panel A shows a simple decomposition of the rank-rank relationship between parent and child housing capital into direct and labor income channels; the associated coefficients are reported in column 1 of Appendix Table F.10.[25] Both channels are important. Children of parents with more housing assets earn more on average and therefore accumulate more housing capital; this labor income channel accounts for approximately 40% of the rank-rank slope. Yet, 60% is from the direct channel – even conditional on having the same earnings, children of parents with more housing assets have more assets themselves on average. This indicates that while the labor market is an important mediating channel, much of the intergenerational persistence in housing capital appears to be explained by factors outside the labor market, such as direct transfers of resources, preferences, and/or market opportunities.

In Panel B, we include the interaction term between parental assets and child earnings, i.e. the "savings/investment" channel, to the decomposition. We see that this channel only accounts for a 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

[25]Concretely, we estimate the simultaneous OLS regressions where W_g and W_{g-1} are child and parent housing capital rank, respectively, and Y_g is child labor income rank. This admits a decomposition of the average rank-rank relationships given by Eq. (1).

regardless of parent assets. An interpretation is that children of high-asset parents do not have differential preferences for, or returns to, 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, which underscores the independent role of parent assets in determining child assets.[26]

Panel C of Figure 7 shows that the increase in child homeownership rates across the parental distribution is almost fully associated with the labor income channel, whereas the intensive margin of home value is largely explained by the direct channel. In other words, on average children with similar labor earnings have similar probabilities of owning a home regardless of parent housing assets, however those with higher-asset parents own substantially more valuable homes.[27]

These results also shed light on the difference in average housing outcomes between children of parent renters and children of parents with low housing assets, i.e., $\tilde{\delta}$. First, even conditional on earnings, children of homeowners have substantially higher homeownership rates, as shown by the negative direct channel of ownership among parent renters (Panel C). Second, the relatively high average housing rank among children of renters is driven by the savings/investment channel (Panel B). Low-earning children of renters have substantially less housing capital than low-earning children of homeowners. The reason children of renters have more housing on average is that as earnings rise, they move up the housing distribution faster. As implied by Figure 3, this operates almost entirely through the intensive margin: as earnings rise homeownership rates increase at similar rates as elsewhere in the parental housing distribution, but conditional home values rise significantly faster for children of renters.[28]

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[26]Direct transfers can be anything that shifts children up the housing distribution independent of their earnings, including transfers of tangible capital, knowledge or other implicit or explicit financial support.

[27]With the discussion of Figure 3 (Section 4.1), this implies that the labor income channel is more important at the bottom of the parental distribution, whereas the direct channel becomes more important at the top.

[28]This adds more context to the discussion in Section 4.1; renters are a more heterogeneous group than the rest of the distribution after conditioning on housing assets, and there is a subset of children of renters that have high labor earnings and disproportionately high value homes.

Finally, to consider a fuller picture of parental resources, we include parent income in addition to parent housing in the simultaneous equation model.[29] We start by considering parental earnings (Table F.10, col. 5 and Figure F.12 Panel A). There is almost no direct channel of parent earnings (0.0286) while the direct channel on housing is barely attenuated (0.241). Thus, conditional on having the similar earnings, children of higher-earning parents do not have substantially more housing assets, but children of parents with more assets do. When we consider parental total income, not just labor earnings (Figure F.12 Panel B), 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), although it still accounts for almost half the rank-rank slope. This implies that the direct channel of parent housing assets is to some degree a proxy for parent non-housing resources, but this is associated with parental capital income as opposed to labor income.

Together, the analyses show that children of parents with more housing capital earn more income on average, but that there is also a large independent role of parent assets in predicting child housing assets even after accounting for child earnings. The small savings/investment channel suggests that the persistence of housing resources across generations is driven by direct channels as opposed to preferences to save in housing.

5.4. Implications for the Black-White Gap in Housing Mobility

Now, we decompose the Black-White differences in children's average housing rank across the parental housing distribution into the portions attributable to differences in child earnings (labor income channel) and differences in parental housing assets conditional on children having the same earnings (direct channel). The main decomposition is presented in Figure 8 Panel A. The gap in absolute mobility (α) is almost completely explained by the labor income channel; conditional on child earnings, housing outcomes are similar for Black and White children near the bottom of the parental distribution. On the other hand, almost the entire

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

racial difference in the persistence of housing across generations is driven by direct channels. Therefore, even conditional on having similar labor market outcomes, there are large racial gaps in housing capital at the top of the parent distribution.[30] Earnings differences also explain most, but not all, of the racial gap in renter mobility.

Panel B decomposes the direct and labor income channels into differences in home values and homeownership rates. As discussed in Section 4.2, most of the gaps in both absolute mobility and intergenerational persistence are related to differential homeownership rates. The decomposition shows that this is a function of both direct and labor income channels. Differences in child earnings largely explain the ownership gaps at the bottom of the parental distribution, but large ownership gaps remain at the top even conditional on earnings.[31]

5.5. Robustness Analysis with a Capitalized Measure of Total Resources

In the preceding sections we interpret the strong intergenerational persistence of housing capital and the independent role of parent housing capital in predicting child outcomes through a lens of the intergenerational transmission of capital assets and economic resources more broadly. Housing is the most important capital asset through the majority of the wealth distribution, so it should be a strong proxy for lifetime wealth rank independent of income rank.[32] Yet, families may accumulate wealth in different ways. Investing in housing may mean substitution away from other assets.

To understand how sensitive our interpretations are to the focus on housing, we provide estimates of intergenerational mobility of total capital resources using capitalization methods. 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

[30] Appendix Tables F.12 and F.13 show the decomposition of the rank-rank slope separately for Black and White families.

[31] Including parent income in addition to housing explains very little of the gap (Appendix Figure F.15).

[32] Piketty et al. (2018) show that housing and pensions are the largest wealth components for the bottom 90% of the wealth distribution. This is also true in our measure described below (Appendix Table F.14).

assets, corporate equities, and private business assets.[33] For pension wealth, we use the method from Smith et al. (2022) (SZZ), applying age-dependent multipliers to labor and retirement income. For housing assets, we use our direct estimates from the micro data. Summing these components gives an estimate of total gross wealth, and we rank parents and children by their respective wealth distributions.

While there is uncertainty and debate about how to estimate wealth using capitalization methods,[34] we believe it provides a useful measure 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, 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 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 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 a rank-rank β parameter using capitalized wealth (Appendix Figure F.16). The rank-rank relationship is quite linear and has a very similar slope to that for housing capital, 0.43. The slope remains quite linear through the bottom of the parent distribution. This implies that the parent renters with relatively high non-housing assets are those with children that have relatively high assets as well. Appendix Figure F.17 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.

[33] For fixed-income assets we capitalize taxable and non-taxable interest, for corporate equities we capitalize dividends and capital gains, for private business assets we capitalize sole proprietor, partnership and S-corporation income using the distributional tables updated to 2022 available on Gabriel Zucman's website: https://gabriel-zucman.eu/usdina/. Appendix A.8 provides details of the capitalization method.

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

Next, we decompose the rank-rank slope using the simultaneous equation model (Appendix Figures F.18 and F.19). The results are similar to those using housing assets. There is an important labor income channel, but conditional on children having the same labor earnings, those with wealthier parents have substantially more wealth on average through the direct channel. Decomposing parent wealth into labor (pension) and non-labor (housing and financial assets) wealth, the direct channel is almost exclusively from non-labor wealth. 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 about child wealth.[35]

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

6. The Housing Supply Channel of Intergenerational Persistence

In the previous section we show that parental housing assets are important for explaining child resources, independent of parent or child incomes. Prior literature has shown considerable cross-area variation in the intergenerational mobility of income, and the importance of local exposures in shaping child human capital (see Chyn and Katz, 2021 for a review). In this section, we extend the local exposure literature to a nonhuman capital context. We examine how asset price shocks, plausibly generated by varying supply constraints, shaped the intergenerational mobility of housing capital during the recent housing boom in the U.S.

[35]The similarity to the results using housing capital alone is not surprising given that housing and pensions are the most important assets through most of the distribution. Appendix Table F.14 shows the composition of capitalized wealth across the distribution. Housing assets closely approximate total non-pension wealth through most of the distribution. Pension wealth is a function of labor earnings so income ranks closely approximate pension ranks.

6.1. Geographic Variation in Housing Persistence

We begin by documenting that, like income, housing mobility varies considerably across U.S. counties.[36] Figure 9, Panel A displays a choropleth map of the county-level distribution of the housing rank-rank slope. Panel B displays an analogous map for income, based on public data drawn from Chetty et al. (2014). While there are some similarities between the two maps, such as high degrees of intergenerational persistence throughout the Southeast and Mid-Atlantic, the spatial patterns are noticeably different. The cross-county correlation between housing and income rank-rank slopes is 0.41. Figure 10 maps the geographic distribution of the difference between housing β and income β. We note that housing persistence exceeds income persistence in a variety of large urban areas, such as: New York City and surrounding counties, Los Angeles, Chicago, Houston, Phoenix, Dallas/Fort Worth, Seattle, Boston, DC, Miami, Atlanta, Charlotte, San Diego, San Antonio, Minneapolis, Denver, Las Vegas, and the Philadelphia suburbs. On the other hand, income persistence exceeds housing persistence throughout lower-population areas in the South.

6.2. Housing Supply Data

As shown in Appendix Figure F.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. The recent period coincides with when our sample cohorts were purchasing homes. Concern has risen over housing shortages, restrictive zoning and permitting, and construction costs (e.g., Gyourko and Molloy, 2015; Baum-Snow, 2023). We leverage geographic variation in these factors in a difference-in-difference design to examine how recent changes in housing affordability have shaped intergenerational mobility of housing resources.

We obtain information on housing supply elasticities from Baum-Snow and Han (2024), who estimate housing supply elasticities in 2001 and 2011 for every residential tract in U.S. metro areas.[37] They find considerable variation in housing supply elasticities across

[36] Further details of the cross-area analysis can be found in Appendix E.

[37] These authors combine micro-geographic information on city features (e.g., land availability, zoning

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.[38] 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.

6.3. 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 population shock requires the addition of 10 log points more units in each county between the two cohorts. As observed by Howard and Liebersohn (2021, 2025), U.S. population and housing quantity has grown about the same in more- versus less-elastic places since 2000.

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

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

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

restrictions, and distance from city center) with housing transactions data to model the responsiveness of housing units to demand-driven price shocks

[38] 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).

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. 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:

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

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 average mobility levels than less-elastic counties.[39] The fourth set of parameters allows mobility to trend differently across birth cohorts according to a set of initial county characteristics $\mathbf{X_c}$. The final set contains our parameters of interest: how mobility varies with γ_c interacted with a linear trend in birth year b.[40]

As shown in the denominator of equation (4), the response of log price is linear in the change in the *inverse* housing supply elasticity. This suggests specifying (5) in terms of $1/\gamma_c$. We opted not do so because there are a few negative values of γ_c in the data and a few more values very close to zero, creating a non-monotonic and highly skewed distribution. Instead, we specify a cubic or quartic in γ_c, which flexibly allows non-constant responses of mobility

[39] 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.

[40] 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.

to γ_c across the γ_c distribution.

Identifying assumption. Our design is akin to a shift-share instrument. We wish to interpret the DiD effects as mobility responses to differential cross-cohort price shocks generated by predetermined differences in housing supply — e.g. due 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: Census division fixed effects, the 2001-2011 change in the housing supply elasticities, the county-level rate of parental homeownership and average home value, and a large county dummy.[41]

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.

6.4. Main Results

We start by estimating the average effects of exposure to a more-elastic county on child outcomes.[42] These effects are listed in the first row of Table 2. Each estimate is the response of the cross-cohort trend in the outcome to an increase in γ_c from from $-1SD$ to $+1SD$ relative to the population median. In all columns we control for county fixed effects and allow the average child outcome to trend across cohorts arbitrarily according to Census division dummies ($\mathbf{F_{d(c)}}$) and to the 2001-2011 change in the supply elasticity ($\boldsymbol{\Delta}\gamma_\mathbf{c}$). In the even-numbered columns we further control for differential outcome trends by county-level

[41] This is a county with a 2000 population in the top 3% 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.

[42] This involves omitting the interactions with parental resources from Equation (5), i.e. omitting the bottom two rows of parameters.

parental ownership rate and home value ($\overline{\mathbf{H^{g-1}}_{\mathbf{c}}}$), and a large county dummy ($\mathbf{S(c)}$).

On average, exposure to more elastic counties has no significant association with children's average labor income rank (cols. 1,2), but increases children's average housing rank (cols. 3,4) through an increased probability of homeownership (cols. 5,6). An rise in average homeownership rates could exacerbate (reduce) intergenerational persistence if the homeownership rates disproportionately rise at the top (bottom) of the parental housing distribution; there could be no resulting effect on mobility if the ownership rate increases are uncorrelated with parent assets.

The next three rows of the table report the implications for intergenerational mobility. We continue to estimate null effects on labor income. In contrast, we document strong effects on absolute mobility of housing outcomes. We find that exposure to a more-elastic county improved the average housing rank (ownership probability) of a child raised by parents at the bottom of the housing distribution by 2.8 to 3.4 rank points (4.1 to 4.4 percentage points). Exposure to more-elastic supply also lessened intergenerational persistence: the housing rank-rank slope fell by 2.6 to 3.1 rank points, and the association between parental housing and child ownership fell by 3.7 percentage points. We also detect significant declines in renter mobility. These results imply an equalizing effect of looser housing supply during the recent housing expansion. Children from the bottom of the distribution were likelier to be drawn into homeownership, resulting in significant gains in housing rank and narrowing the gap between children from the bottom and the top of the distribution. The absence of effects on average earnings or earnings mobility suggest that spurious labor-market shocks or income-based residential sorting are unlikely explanations.

Proceeding with housing rank as our main outcome of interest, Appendix Table F.15 probes robustness by presenting estimates from each of 12 different specifications of Equation (5).[43] The estimates are quantitatively similar across all 12 specifications and are statistically

[43] 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 cohort trend controls.

significant in nearly all of them.

Table 3 summarizes by presenting the median effects across the 12 specifications and converting them into estimated price semi-elasticities.[44] 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).[45] Given this, the specified increase in γ_c implies a price decline of 27.2 log points ($d\ln(p_c) = \frac{.0605}{.32+.17} - \frac{.0605}{.32-.17} = -.272$). 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 official end of the Great Recession and the end of 2021, the national housing stock increased by 8.47 log points.[46] Extrapolating our shift-share instrument onto this housing expansion implies a relative price decline of 39.2 log points, which in turn produces a 3.7-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 -0.12 for α and about 0.10 for δ. This implies that the outcomes 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.[47] Scaled in terms of the 2010-2021 housing expansion, elastic counties experienced a 4.7-rank gain in absolute mobility relative to inelastic counties. This effect is over one-third of the observed cross-county differential in our sample, suggesting that the uneven spatial decline in housing affordability has importantly shaped intergenerational inequality and its spatial variation.

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

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

[46] Source: https://fred.stlouisfed.org/series/ETOTALUSQ176N

[47] For children of renters, the relative 1.2-rank gain in absolute mobility is effectively offset by the 1-rank loss experienced by children of renters relative to children of owners.

6.5. Heterogeneity

Appendix Table F.16 presents heterogeneity results by race and by average county house price in 2000 (above / below the median). We estimate slightly larger mobility responses for White families than the population-average responses, while we estimate small and statistically insignificant responses for Black families. This suggests that a housing supply expansion in an area with racial heterogeneity would widen the racial gap in absolute mobility, while shrinking 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. Figure 11 presents the results, overlaid on a histogram of housing supply elasticity exposure. The graphs on the top present 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. The 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, Appendix Table F.16 shows similar mobility responses across low- and high-price areas.

7. Conclusion

Housing is the primary capital asset for most households in the United States, and is widely viewed as a key stepping stone to wealth accumulation and financial stability. While its role in creating generational wealth is well recognized, far less is known about the intergenerational transmission of housing capital, largely due to data limitations. This paper documents the intergenerational transmission of housing capital using a new dataset linking property ownership and valuation records to survey and income tax data for over 3.4 million families.

First, we show that housing capital is substantially more persistent across generations than labor earnings or total income, with a rank–rank slope of 0.43 compared to 0.29 for labor income. This persistence differs sharply by race. White families exhibit high persistence and limited downward mobility at the top of the parental housing capital distribution, while Black families experience lower persistence driven by substantial downward mobility at the top. As a result, the Black–White gap in child housing outcomes widens across the parental distribution, from about 5 ranks at the bottom to 20 ranks at the top. These gaps are driven primarily by differences in homeownership rates rather than in home values conditional on ownership.

Second, we leverage the link between housing capital and income information to study the joint determination of earnings and housing outcomes. Using a simple capital transmission framework, we decompose the housing rank–rank slope into a labor income channel, which allows parental assets to indirectly shape children's assets via their effect on children's labor market success, and a direct channel, which captures the affect of parental housing capital on children's housing capital conditional on child earnings. While the labor market is an important mediating force, most of the observed persistence in housing capital appears to arise from factors outside the labor market, such as direct transfers of assets or provision of opportunities.

Motivated by these findings, we examine the role of local housing markets in shaping intergenerational mobility. This extends the "neighborhood exposure" literature, which has largely focused on human capital, by considering variation in exposure to housing markets—the primary capital market for most households. Leveraging variation in local housing supply elasticities, we find that exposure to more elastic housing markets increases upward mobility and weakens intergenerational persistence in housing capital. These effects operate primarily through the homeownership margin: more elastic supply reduces the gap in homeownership rates between children from high- and low-asset families. This suggests that housing supply constraints do more than raise prices, they reinforce the transmission of advantage by limiting access to homeownership.

Taken together, these results highlight the central role of housing in shaping intergenerational mobility in the United States. They suggest that equalizing opportunity requires attention to economic factors beyond labor markets. While policy discussions of mobility have largely emphasized human capital and labor market access, our findings point to housing market opportunities, and the constraints that limit them, as fundamental and underappreciated determinants of whether economic advantage persists across generations.

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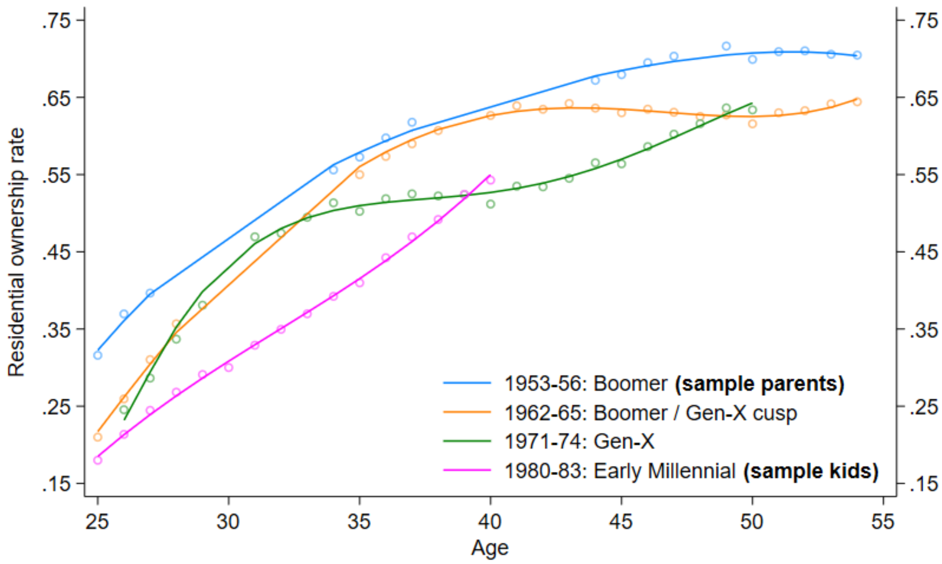
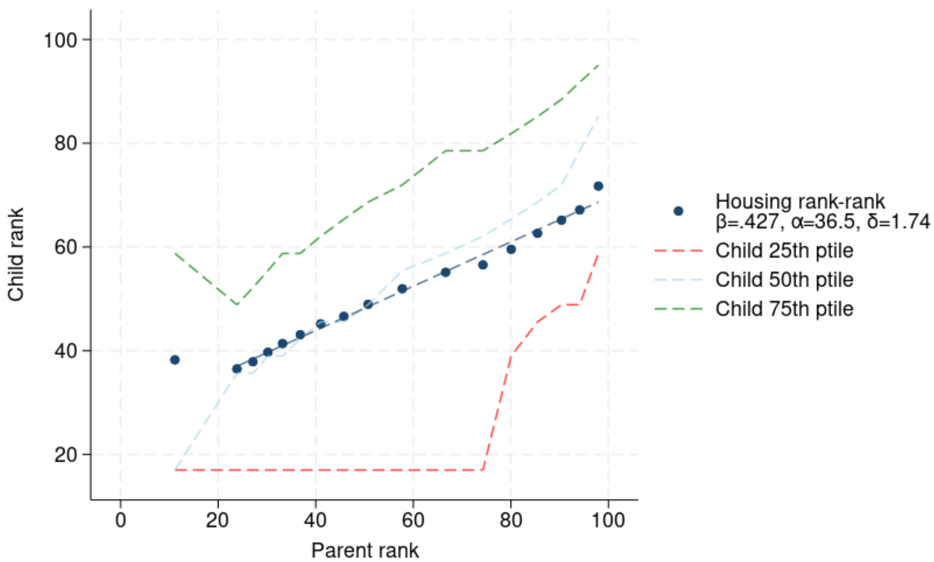
Figures and Tables

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.

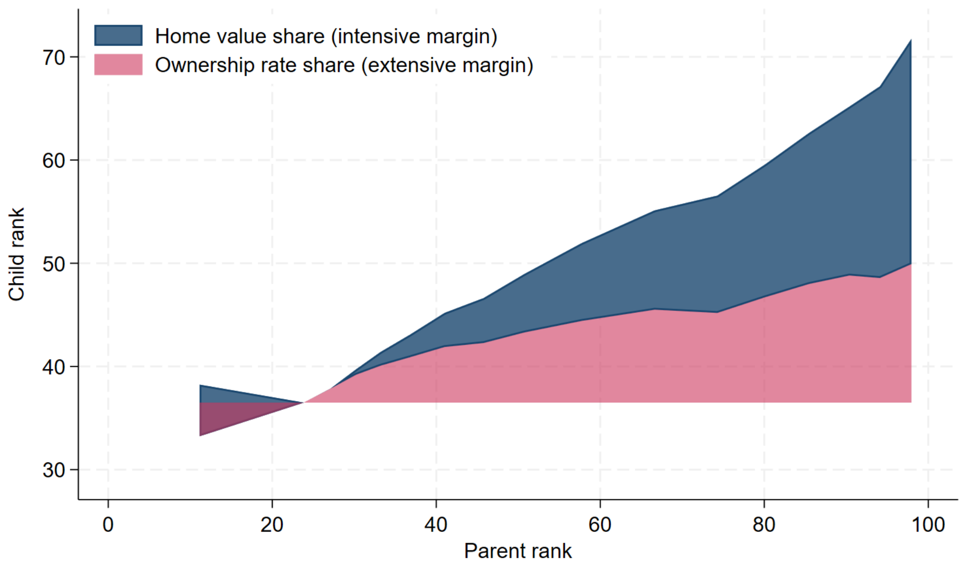
Figure 2: Intergenerational Mobility of Housing Assets - Rank-Rank Relationship



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.

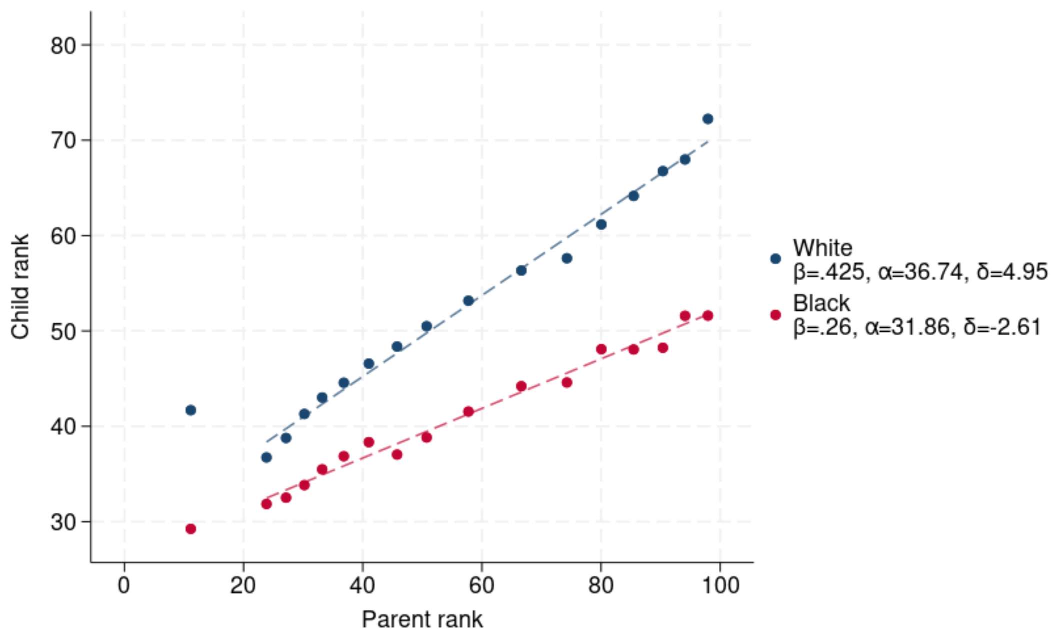
Figure 3: Decomposition – Homeownership Rate v. Home Value



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.6.

Figure 4: Intergenerational Mobility of Housing Assets by Race

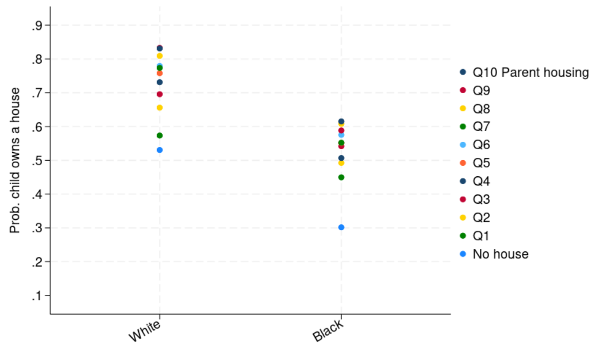


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

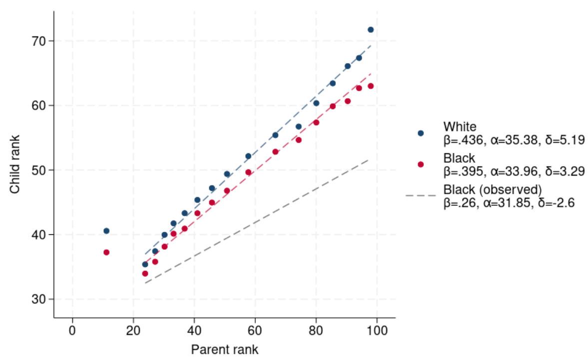
Note: This figure shows the rank-rank relationship of housing assets separately for Black and White Families. Dots represent the average child ranks conditional on parent rank and dashed lines show the linear rank-rank slopes (β); α is the average child rank for children of parent homeowners in the bottom 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

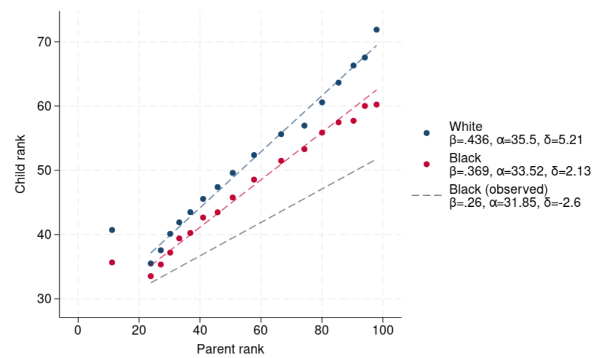
(a) Ownership probabilities by race



(b) Counterfactual ownership rates



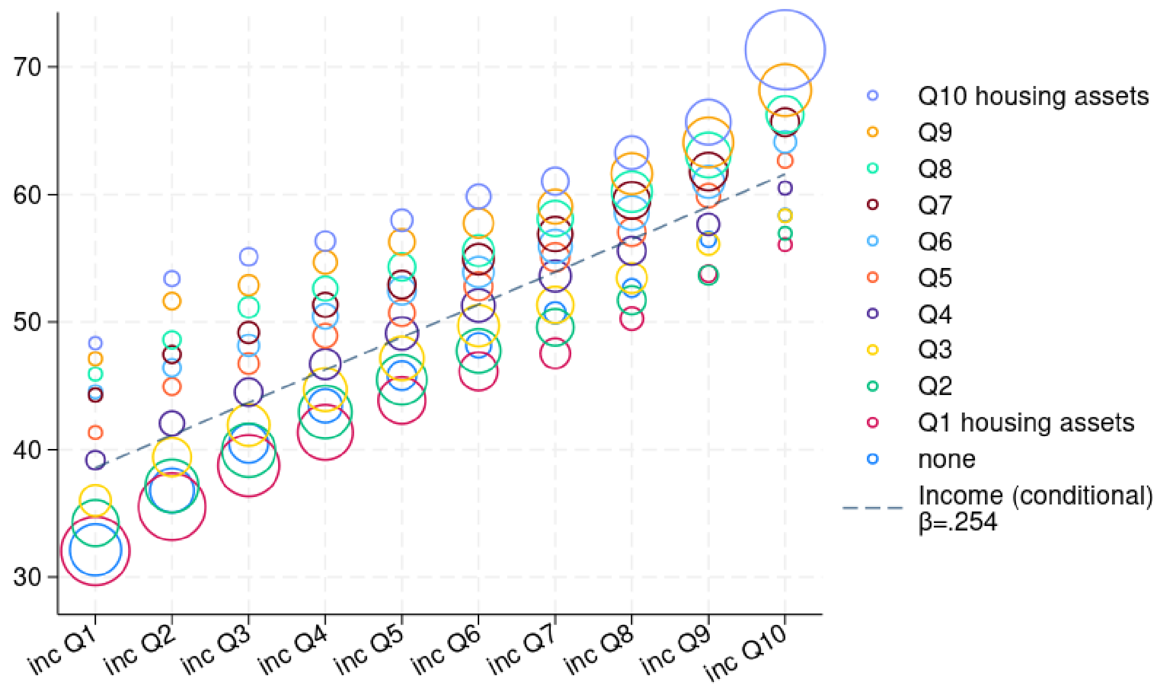
(c) Counterfactual ownership - capitalized rent



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.7.3. 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.7.1. 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: Child Income and Parent Income and Housing Assets

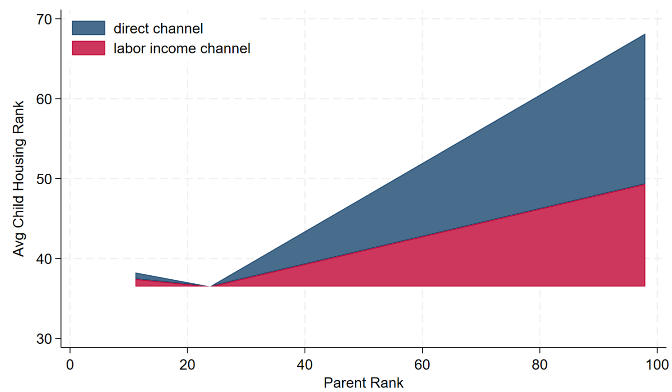


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

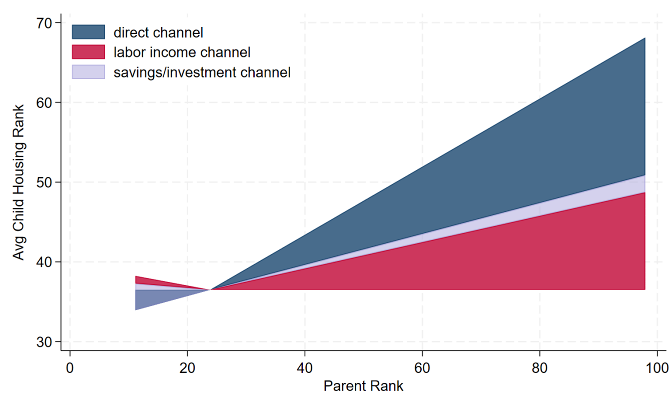
Note: This figure shows the non-parametric relationship between child income rank and parent income and housing asset ranks. Each bubble represents the average child income rank (y-axis) conditional on the decile of parent income (x-axis) and parent housing asset ranks (series of bubbles, defined by 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 7: Decomposition of Housing Asset Slope - Labor Income and Direct Channels

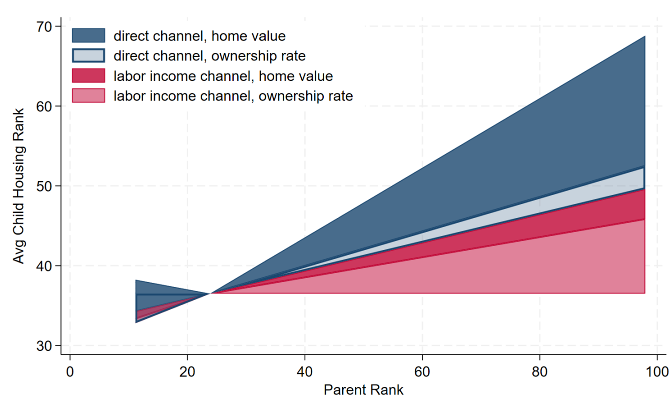
(a) Direct and labor income channels



(b) Including the “savings/investment” channel



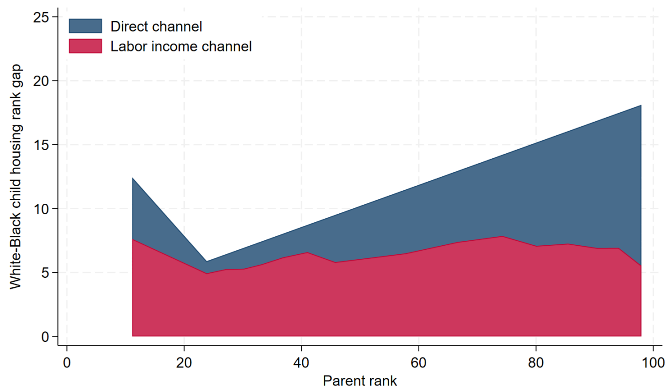
(c) Home value v. homeownership



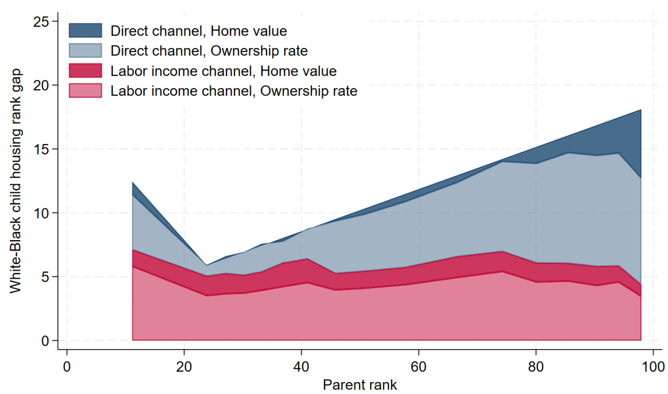
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: Panel A shows a decomposition of the population rank-rank slope of housing assets into the direct and labor income channels as derived from simultaneous equations (s1) 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 “savings/investment” 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 8: Direct and Labor Income Channels - Decomposition of Black-White IG Gaps

(a) Direct v. labor income channels



(b) Home value v. ownership rate

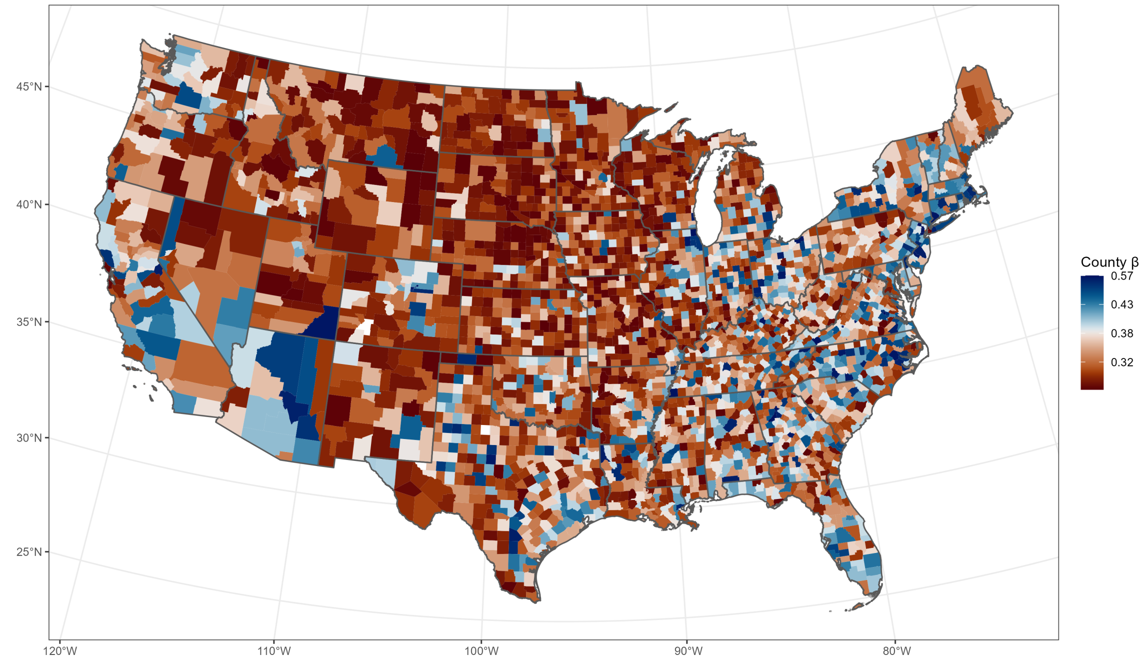


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

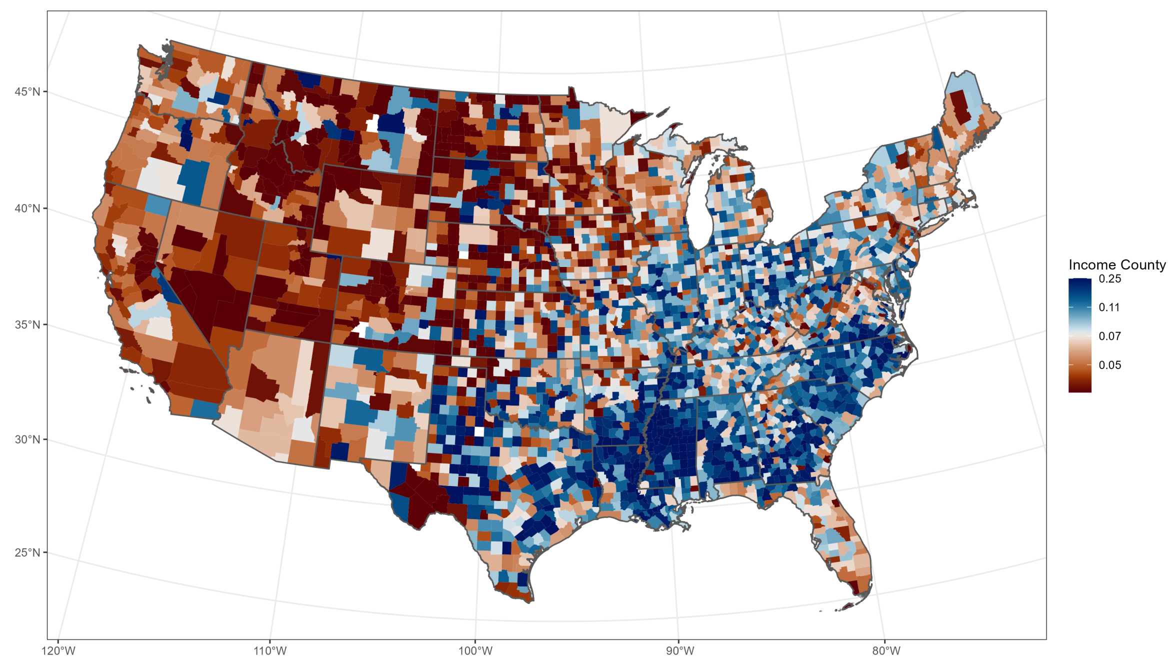
Note: This figure shows a decomposition of the gap in Black and White child average housing ranks across the parent distribution, decomposed into direct and labor income channels. The labor income channel is the difference in average Black and White child ranks that is associated with Black and White 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 9: Geographic Distribution of Intergenerational Persistence in Economic Resources

(a) Housing capital



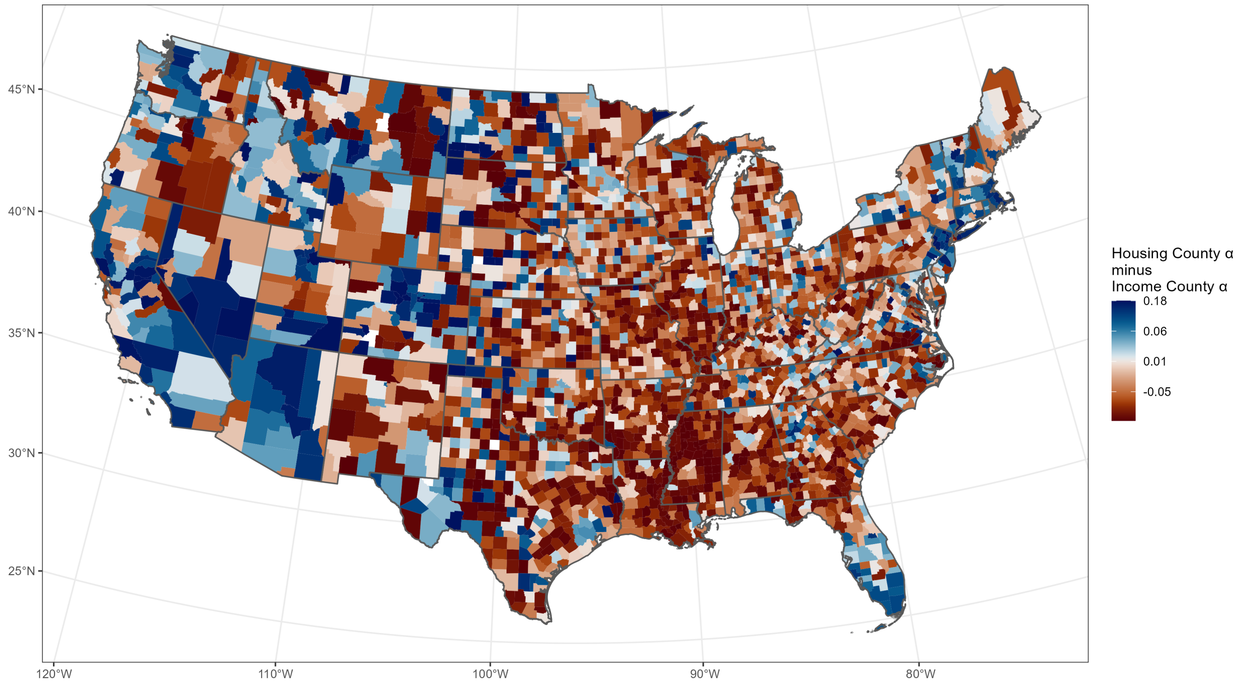
(b) Income



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

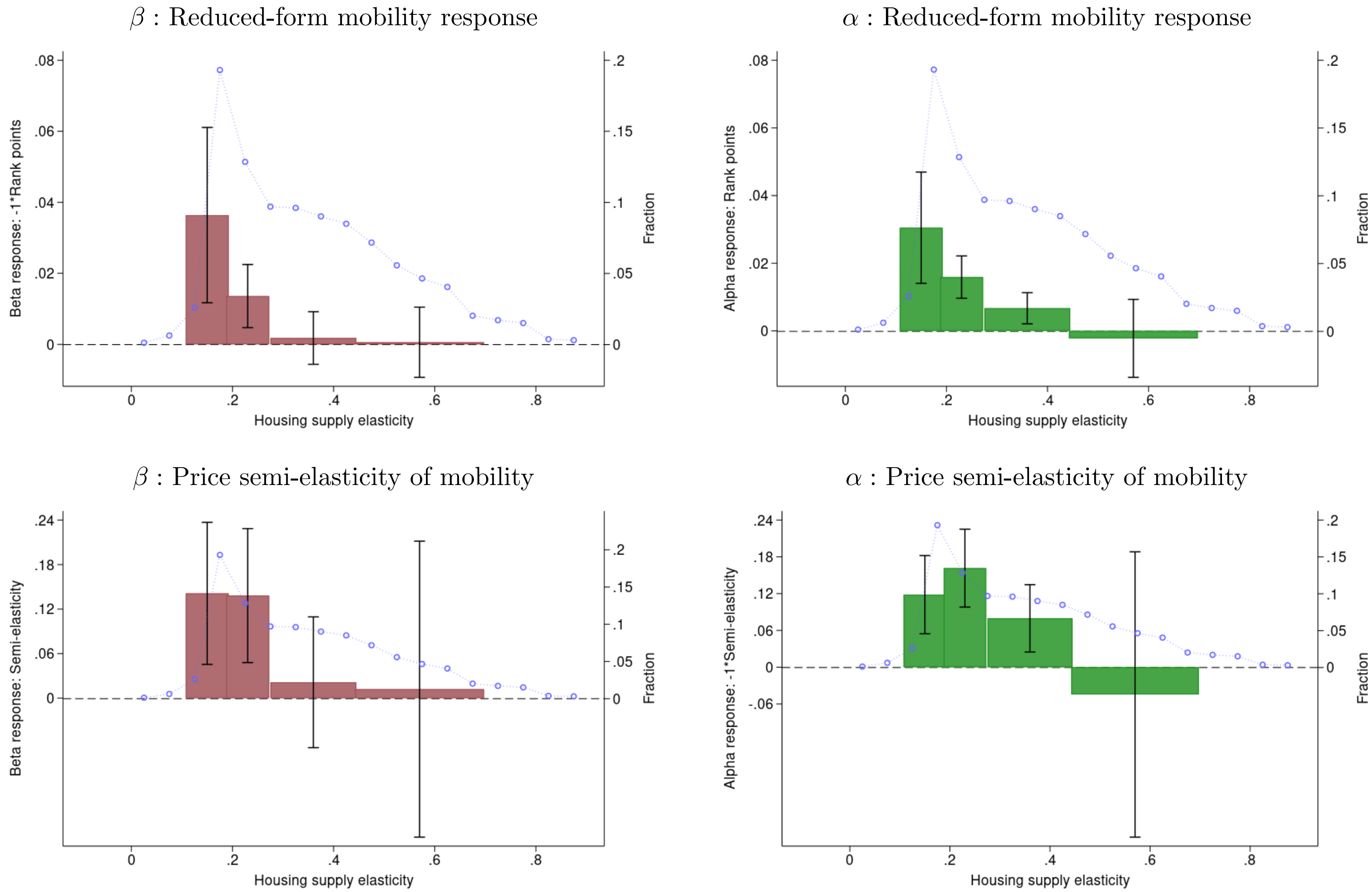
Notes: Each subfigure is a county-level choropleth map of the rank-rank slope of economic resources. The top subfigure considers housing capital in our dataset: we estimate equation (1) separately for each county and then smooth the county-level estimates according to a Faye-Herriot small area estimation model. See Section 6.1 for further detail. The bottom subfigure considers income as reported in dataset constructed by Chetty et al. (2014).

Figure 10: Contrasting the Geographic Distribution of Housing and Income Persistence



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: County-level choropleth map of difference between the housing and income rank-rank slopes reported in the preceding figure.

Figure 11: 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. These 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. 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
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: Quasi-Experiment: Increase in γ_c from $-1SD$ to $+1SD$ Relative to the Median

	Labor rank		*Housing rank*		*Pr(own)*		*Housing rank | own*	
1978-86 cohort trend	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
. . . in avg outcome	0.006	0.004	0.013***	0.010**	0.017***	0.014***	0.002	0.000
	(.004)	(.005)	(.004)	(.005)	(.006)	(.007)	(.003)	(.003)
. . . in β (Relative)	0.008	0.004	-.031**	-.026*	-.037*	-.037	-.016	-.006
	(.009)	(.011)	(.013)	(.014)	(.022)	(.023)	(.012)	(.013)
. . . in α (Absolute)	0.000	0.001	0.034***	0.028***	0.044***	0.041***	0.014	0.005
	(.007)	(.006)	(.009)	(.010)	(.016)	(.018)	(.009)	(.010)
. . . in δ (Renter)	—	—	-.030***	-.020*	-.049***	-.034	-.013	-.005
	—	—	(.010)	(.012)	(.019)	(.021)	(.009)	(.011)
N	2.33M	2.33M	2.33M	2.33M	2.33M	2.33M	1.13M	1.13M
R^2	0.117	0.117	0.156	0.156	0.105	0.105	0.289	0.289
Change in γ	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
$(\alpha,\beta,\delta)\cdot(1,\mathbf{F_b})$	X	X	X	X	X	X	X	X
$(\alpha,\beta,\delta)\cdot\gamma_c$	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
$(\alpha,\beta,\delta)\cdot\mathbf{F}'_{\mathbf{d(c)}}\cdot\mathbf{F_b}$	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
$(\alpha,\beta,\delta)\cdot S(c)\cdot\mathbf{F_b}$		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 or percentage points /100: e.g. .01 implies one rank, or one percentage point. Robust standard errors, clustered on county, appear below point estimates in parentheses. The first row omits the interaction of the treatment (i.e. birth cohort trend interacted with baseline γ_c) with parental housing variables in regression equation (5): i.e. it reports how exposure to less price growth due to more-elastic housing supply affects the average child outcome. The next three rows show the mobility effects of the treatment that result from estimation of (5) as specified in the text. R^2 values reported in the table apply to this mobility regression. For the average-effect regression, they are (respectively for each outcome): .034, .058, .037, .223.

Table 3: 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 $\Delta \ln \overline{p_c} = -0.392$	$2\cdot$ cross-county SD	Standardized effect
β	-.026**	0.096**	-.038**	0.146	26.0%**
	(.013)	(.048)	(.019)	–	(13.0%)
α	0.033***	-.121***	.047***	0.128	36.7%***
	(.009)	(.033)	(.013)	–	(10.1%)
δ	-.026***	0.096***	-.038***	0.102	37.3%***
	(.010)	(.037)	(.015)	–	(14.7%)

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 F.15. 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 0.392, which is the instrumented price decrease in the more-elastic county applied to the entire 2010-2021 housing expansion. See Sections 6.3 and 6.4 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.[48] 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

[48] 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.

As discussed in Section 3.3, we address this imperfect record linkage as follows: let x_{ACS^*} define the population individual homeownership rate inferred from survey data, using the American Community Survey (ACS). 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: $x_{ACS^*} = x_{ACS} \cdot a_{SIPP}$. We then define the following adjusted weight:

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

We up-weight the owners observed through the BK linkage and down-weight the observed non-owners to replicate this survey-derived benchmark. To capture the intergenerational heterogeneity that is of interest, we estimate x_{ACS} in each of the 550 sample cells defined by (White, Black, Hispanic, Asian, Other) $\times$ (parent renter, 10 deciles of parental owners) $\times$ (10 deciles of parental income), and allow a_{SIPP} to vary across the 5 racial-ethnic groups, to construct a cell-specific estimate of x_{ACS*}.

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 (A.1):

$$iw_g = aw_g \cdot \frac{N_1/Q + N_0(A_0(q_n) - A_0(q_{n-1}))}{N_1 + N_0} \tag{A.2}$$

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.

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.

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 $g-1$,

$$t^{g-1}_{ACS^*} = x^{g-1}_{ACS^*} + \Delta_{ACS^*} \times \frac{x^{g-1,oldest}_{ACS^*}}{x^{oldest}_{ACS^*}}. \tag{A.3}$$

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:

$$lcaw_g = \begin{cases} aw_g \cdot \frac{1-t^{g-1}_{ACS^*}}{1-x^{g-1}_{ACS^*}} & \text{if kid } g \text{ is not a BK owner} \\ iw_g \cdot \frac{t^{g-1}_{ACS^*}}{x^{g-1}_{ACS^*}} & \text{if kid } g \text{ is a BK owner.} \end{cases} \tag{A.4}$$

As an illustrative example, suppose there are two equal-sized subgroups, one with a 58% ownership rate and one with a 50% ownership rate. Each subgroup contains a set of cohorts with average age of 39. 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%.

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.4). 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.

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 $g-1$,

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

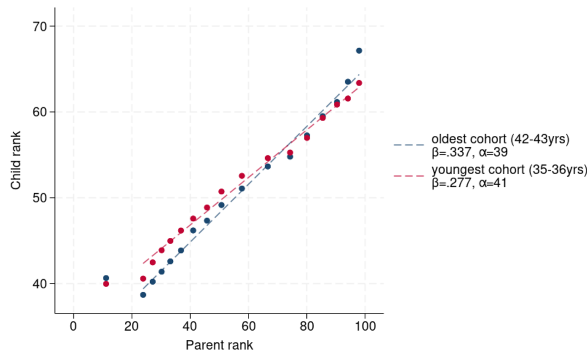
Alternative Assumption 2: for a given parental wealth×income subgroup $g-1$,

$$t^{g-1}_{ACS^*} = x^{g-1}_{ACS^*} + \Delta_{ACS^*} \times \frac{(x^{oldest}/x^{youngest})^{g-1}_{ACS*}}{(x^{oldest}/x^{youngest})_{ACS*}}. \tag{A.6}$$

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

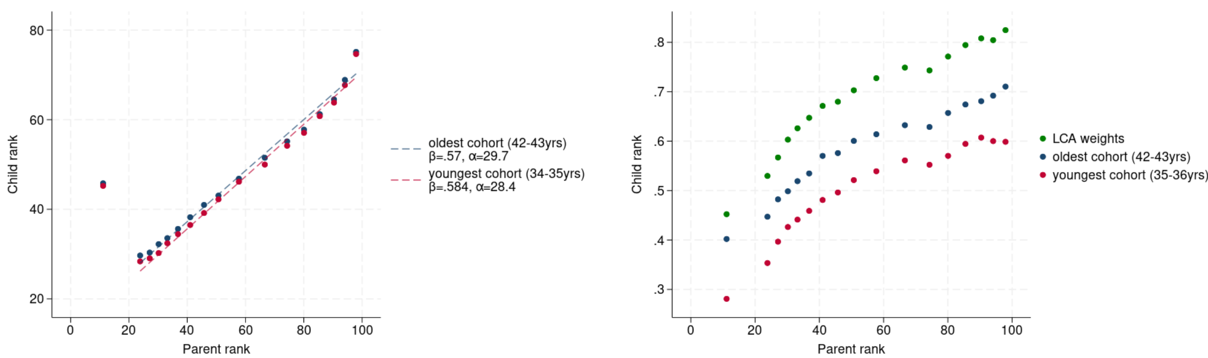
Figure A.1: Rank-rank relationships of housing wealth, by child cohort

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



(b) Conditional on child homeownership

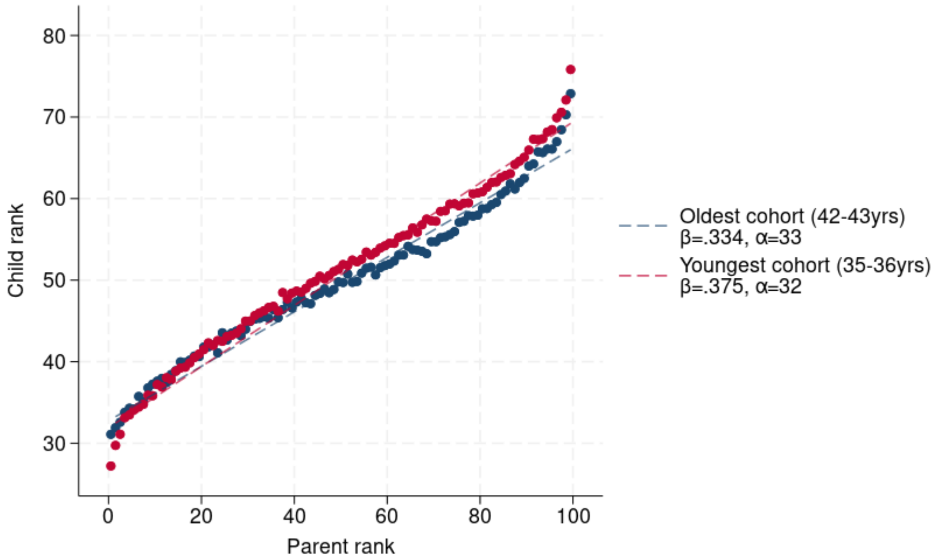
(c) Homeownership rates



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.

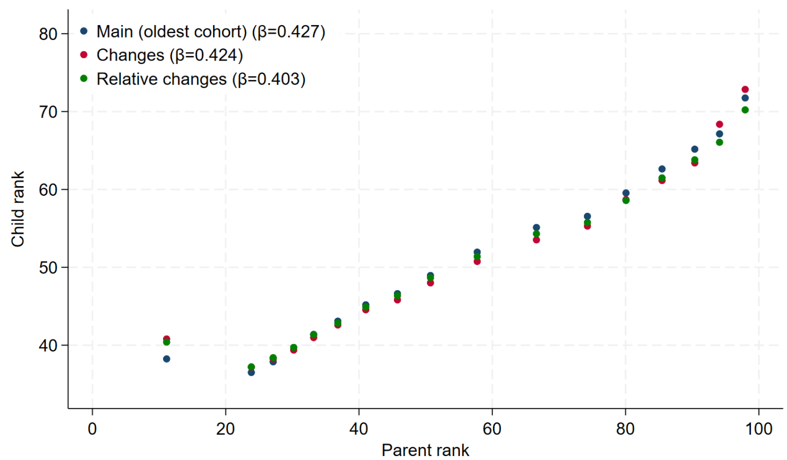
alternatives as a "change proportional" (Alternative 1) or a "relative-change proportional" (Alternative 2) assumption. Thus, consider two alternative subgroups that have identical ownership rates in the full sample and identical oldest-cohort ownership rates. However, one subgroup had a constant ownership 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.

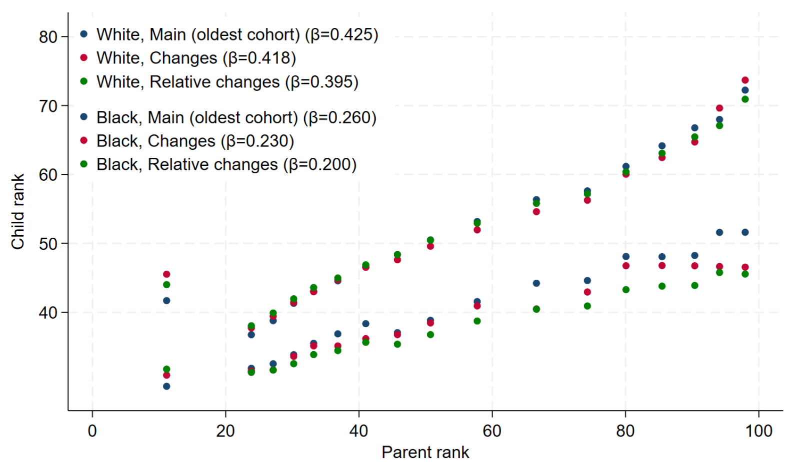
Finally, we assume that child homeownership will follow patterns similar to the previous generations. This could be conservative. At the time of this writing, the 2024 public-use ACS data had recently been released, which enabled us to measure the ownership rate for the oldest cohort in our sample (1978) at age 46. The ownership rate was 0.634, which is close to, but slightly higher than, the Gen-X rate at that age shown in Figure 1. Rates by racial group were also quite close but slightly higher than their benchmarks. If, instead, we assume that the homeownership rates reach those of the parent generation at ages 45-49 (by race) to create LCA weights, we estimate a rank-rank coefficient of $\beta = 0.486$ (s.e.=0.0007). In the plausible case that we are underestimating the homeownership rates of our cohorts of children, we are likely also underestimating the degree of intergenerational persistence in housing capital.

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.

Table A.2: Rank-rank parameters of housing and income mobility by child cohort

	All Cohorts	Ages 35-36	Ages 38-39	Ages 41-42
Housing Capital				
β	0.427***	0.277***	0.303***	0.337***
	(0.0007)	(0.0017)	(0.0013)	(0.0021)
α	36.5	40.58	40.27	38.69
δ	1.74	-0.61	0.25	1.96
Total Income				
β	0.347***	0.369***	0.357***	0.327***
	(0.0005)	(0.0013)	(0.0010)	(0.0015)
α	33.26	32.71	32.21	33.5
Housing Capital by Race				
White				
β	0.425***	0.269***	0.296***	0.328***
	(0.0008)	(0.0019)	(0.0015)	(0.0023)
α	36.74	42.00	41.48	39.96
δ	4.95	1.90	2.92	4.85
Black				
β	0.260***	0.121***	0.133***	0.152***
	(0.0027)	(0.0050)	(0.0040)	(0.0068)
α	31.86	35.11	33.39	31.92
δ	-2.61	-2.85	-1.67	-1.76

Notes: This table shows estimate parameters from our rank-rank specification of intergenerational mobility (Equation (1)). For the Housing Capital estimates: 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. For income intergenerational mobility we use 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). Total 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 defined by age in 2021.

A.6. 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 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.7. 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.7.1. 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:

$$R = \frac{P \cdot (a - h)}{12} \tag{A.7}$$

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.7.2. 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.7.3. 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.8. 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 corporate equities, fixed interest assets, private businesses, defined contribution pension assets and housing assets.

For corporate equity we capitalize dividend income and capital gains; for fixed-income assets, we capitalize taxable and non-taxable interest income separately; for private business assets we capitalize each of sole proprietorship income, partnership income and S-corporation income. For each income source, we capitalize income flows by year using the capitalization factors from Piketty et al. (2018) (PSZ) and average over three years, for both children and parents.[49] 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,

[49]Distributional tables are updated to 2022 available on Gabriel Zucman's website: https://gabriel-zucman.eu/usdina/. Interest, dividends and capital gains information come from Form 1040; sole proprietorship income comes from Form 1040, Schedule C; partnership and S-corporation income come from Schedule K-1 associated with Form 1065 and 1120-S, respectively.

$\theta^{pens,a}$=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.[50,51]

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 values.[52]

We calculate total wealth for parents and children and the sum of their corporate equity, fixed-income assets, private business 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. Appendix Table F.14 shows the composition of children total capitalized wealth by source, across the distribution of wealth.

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

[51]We also test the robustness to using the fair market value of IRA assets as reported on Form 5498 directly for our measure of pension wealth, then making an adjustment for "miscellaneous income" as in the PSZ tables. Again, the results are very similar using this method.

[52]We test the robustness of adding capitalized rental income to children total assets as well, to potentially account for rental properties held through private businesses. All results are extremely similar when adding child capitalized rental assets.

B. Gross Housing Wealth as a Measure of Long-Run Housing Wealth

Here we set-up a simple framework to analyze the conditions under which rank-rank relationships between parent and child gross or net housing wealth better approximate the rank-rank relationships in long-run housing wealth. We define long-run wealth as the wealth accumulation from the purchase of the home, net of the costs associated with the purchase. Current gross and net housing wealth are functions of the asset value and the downpayment/loan amount, and long-run housing wealth is modeled as a function of three rate parameters: i) the growth in the gross home value, ii) the mortgage rate, and iii) opportunity cost of the purchase of the home and the mortgage payments.

In our data, we can observe child gross housing wealth (assessed current home value) across the parental housing distribution and child equity shares (current equity / gross value) across the parental distribution. We show that given these observed relationships, for most realistic ranges of the above parameters the intergenerational relationship between parent and child gross housing wealth is a very good proxy for the intergenerational relationship of long-run housing wealth.

B.1. Framework

Defining parameters:

- W^T = long-run net wealth accumulated from the home as of year T
- H = purchase price of the home
- d = the down payment rate, or the share of the purchase price paid as a down payment
- g = the annual gross growth rate of the house value
- r = the interest rate on the mortgage
- k = the opportunity cost of capital invested in homeownership

Then we can define the quantities E_0 as the initial equity in the home, so $E_0 = dH$, and the initial loan amount as $L_0 = H(1-d)$. We can formulate the annual mortgage payment associated with a fixed-rate mortgage as

$$M = L_0 \cdot \frac{r}{1-(1+r)^{-n}}$$

where n is the pre-determined term length.

The opportunity cost of the mortgage payments will be

$$OC_T = \sum_{t=1}^{T} M(1+k)^{T-t}$$

This can be approximated at time T as

$$OC_T = M \cdot \frac{(1+k)^T - 1}{k}$$

Then we can state wealth at time T as:

$$W^T = H(1+g)^T - E_0(1+k)^T - M\frac{(1+k)^T - 1}{k} \tag{B.8}$$

Now, define $m = \frac{r}{1-(1+r)^{-n}}$ and define $X = \frac{(1+k)^T - 1}{k}$. Then

$$\begin{aligned} W^T &= H(1+g)^T - E_0(1+k)^T - (1-d)HmX \\ &= \underbrace{\left((1+g)^T - mX\right)}_{\alpha} H + \underbrace{\left(mX - (1+k)^T\right)}_{\beta} E_0 \end{aligned} \tag{B.9}$$

so long-run wealth is a reduced form function of current gross and net housing wealth and α and β, which are functions only of the rate parameters. To model the relationship between child housing wealth concepts and parent housing, we can differentiate B.9 with respect to parent housing P. Recharacterizing E_0 as dH, we get:

$$\frac{dW^T}{dP} = \alpha\frac{dH}{dP} + \beta\frac{dE_0}{dP} \tag{B.10}$$

Or, reformulating E_0 as dH to isolate gross wealth and debt:

$$\frac{dW^T}{dP} = (\alpha + d\beta)\frac{dH}{dP} + \beta\frac{dd}{dP} \tag{B.11}$$

so we now have a simple model of the relationship between parent housing and child long-run housing wealth as a function of our observed relationships between child gross housing and parent housing and child downpayment rates and parental housing, and the rate parameters.

Some relationships of note:

- If $r = k$ then $\beta = 0$ and W^T is only a function of H. Then the correlation between long-run wealth and parent housing may be stronger or weaker than that of current child gross housing and parent assets depending on if $\alpha \gtreqless 1$. When considering rank-rank relationships, the rank-rank relationship between parents housing and child long-run wealth and child current gross wealth will be the same.

- If $r < k$ then $\beta < 0$. Conditional on gross housing wealth, more equity or a higher down payment reduces long-run housing wealth because the opportunity cost of the downpayment is large relative to that of the larger mortgage payments associated a lower downpayent.
  - If $g > k$, then $|\alpha| > |\beta|$, so long-run wealth is more strongly correlated with gross wealth H than net equity E_0. The related association between the rank-rank relationships will depend on the sign and magnitude of dd/dP. If $dd/dP \approx 0$, the relationship between parent housing and child H is a near perfect proxy for the relationship between parent housing and long-run child wealth. If dd/dP is relatively large and negative (positive) then the relationship between parent housing and child H understates (overstates) the relationship between parent housing and long-run child housing wealth.

- If $r > k$ then $\beta > 0$. Conditional on gross housing wealth, more equity or a higher down payment increases long-run housing wealth because the opportunity cost of larger mortgage payments is larger than that of a larger downpayment.
  - If $g > r$, then $\alpha > \beta$, so long-run wealth is more strongly correlated with gross wealth H than net equity E_0, and the rank-rank relationships depend on dd/dP. If $dd/dP \approx 0$, the relationship between parent housing and child H is a near perfect proxy for the relationship between parent housing and long-run child wealth. If dd/dP is relatively large and negative (positive) then the relationship between

parent housing and child H overstates (understates) the relationship between parent housing and long-run child housing wealth.

B.2. Empirical relationships and simulation

The analysis above implies that if the child downpayment rate approximately constant across the parent housing distribution (dd/dP near zero), the rank-rank relationship between parent housing and child gross housing assets should be a near perfect proxy for the relationship between parent housing and child long-run housing wealth. In this section, we first show that the child downpayment rate is, indeed, very flat across the parent housing distribution. Second, to empirically assess how "near zero" this trend is, we use Eq. (B.8) to simulate child long-run housing wealth for ranges of realistic rate parameters. We show that because of the empirical distribution of downpayment rates, for reasonable ranges of the parameter values intergenerational persistence of long-run housing wealth very closely mirrors the rank-rank relationships in gross housing wealth documented throughout the main text.

Figure B.4 shows average child downpayment rates across the parent housing distribution among child homeowners. The mean downpayment rate and the distribution of downpayment rates are very similar across the parent distribution. Using an OLS regression of downpayment rate on parent hosuing rank, the estimated coefficient is -0.0003 (s.e.=0.00002), which is very small and negative.

The small coefficient implies that child gross housing wealth is likely a better proxy for long-run wealth than net housing wealth would be. A question is how "near zero" this is, that is how much might the gross housing relationship over or understate the long-run wealth relationship in a rank-rank specification. To assess this, we now use a range of realistic parameter values to simulate children's long-run housing wealth (associated with their observed gross wealth and debt). For a given set of parameters, we simulate long-run wealth using Eq. (B.8) above. Then, we rank children in the simulated distribution of long-run wealth and estimate rank-rank intergenerational regressions of the form used throughout the main text. Figure B.5 shows the results of this exercise.

Each point shows the estimated relative mobility (β) coefficient for child simulated long-run housing wealth. The dashed lines represents our estimate of β from the main text using our preferred gross wealth concept and the β estimate from the rank-rank relationship of net housing wealth. Across the y-axis are different combinations of rate parameters (r, k, g). As a benchmark, we set the mortgage rate $r = 4\%$, which is roughly the average rate on a 30 year fixed rate mortgage in the period the children were purchasing houses.[53] We note that k represents the effective opportunity cost of capital; if the alternative use would be to invest in capital markets it could be some combination of the safe rate of return and the return to corporate equities, if a (potentially large) portion would be used to pay rent this portion would have a zero-to-low rate of return, bringing down the effective opportunity cost. As we vary g and k, we see that for reasonable ranges the simulated rank-rank relationships in long-run housing wealth are very close to the estimated rank-rank relationship in gross housing wealth.[54] The estimated rank-rank relationship of net housing wealth is 0.228 (s.e.=0.0007), which dramatically understates the persistence of long-run wealth.[55]

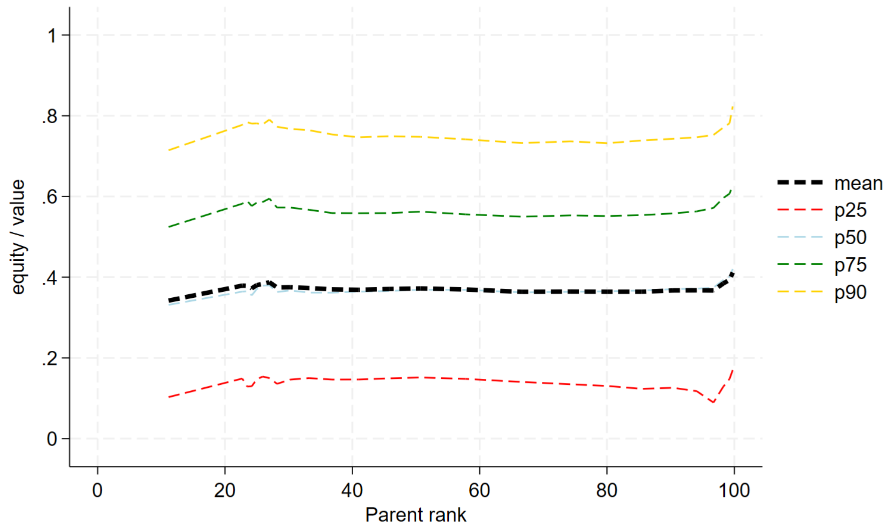
Given these relationships, we conclude, first, that gross housing wealth is the appropriate proxy for long-run housing wealth, and, second, that the observed rank-rank relationships in gross housing rank are reasonably interpreted as vary good quantitative estimates of long-run wealth relationships.

[53] We also set $T = n = 30$, so our definition of long-run is 30 years, after a 30 year mortgage is paid off.

[54] As predicted by the framework, given that the estimated average relationship between downpayment rates and parent housing is negative, in cases where $r > k$, the gross housing wealth estimate slightly overstates the long-run housing estimate, and in cases where $r < k$, the gross housing estimate slightly understates the long-run housing relationship.

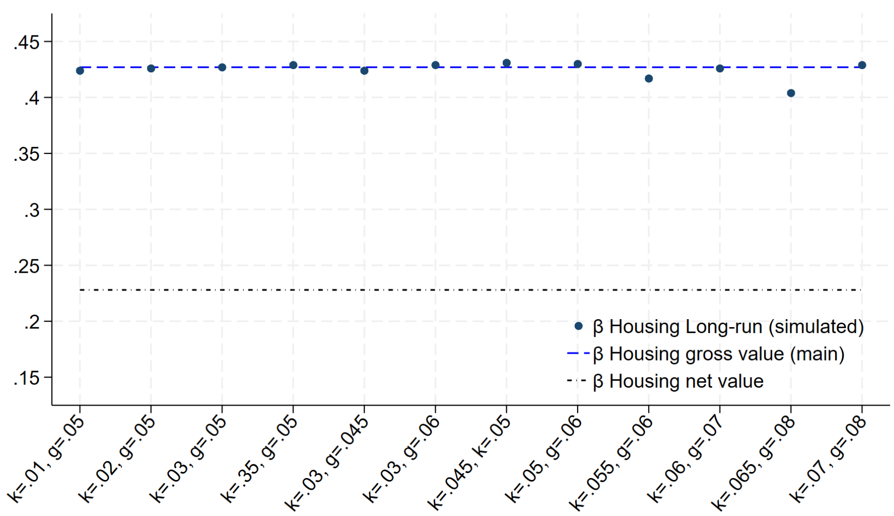
[55] Note, if $dd/dP = 0$ because everyone deterministically pays the same downpayment rate (say 20%), then rank-rank regressions of child gross and net housing wealth would give identical slopes. But, if the downpayment rate, d, is a random variable around a mean that is constant across the parent distribution, then estimated $\widehat{dE_0/dP} < \widehat{dH/dP}$ because E_0 is a function of both H and d, so there is additional variation attenuating the strength of the relationship. In this case, dH/dP is the correct proxy for dW^T/dP.

Figure B.4: Downpayment rate across parent housing distribution



Note: This figure shows the child "downpayment rate" (equity/value) across the parent housing distribution. The average is slighly under 40% throughout the distribution. The 25^{th}, 50^{th}, 75^{th}, 90^{th} percentile downpayment rates are also shown.

Figure B.5: Rank-rank slopes for simulated long-run housing values



Note: This figure shows the rank-rank slopes associated with the simulated long-run housing values using various combinations of parameters. In each simulation, the mortgage interest rate is 4%. Across the y-axis are combinations of the housing value appreciation rate, g, and the effective opportunity cost of capital, k. The coefficients of the associated rank-rank slopes (β from Eq. (1)) are the navy series of dots. The β estimates from our main rank-rank specification using gross housing value and from a rank-rank regression using net housing wealth are shown for reference.

C. 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 intergenerationally 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:

$$Y_g = \beta(Y_{g-1} - \eta_{g-1}) + \eta_g + ru_g, \tag{C.12}$$

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 (C.12), 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.[56]

[56]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.

D. Simultaneous Equation Model of Intergenerational Mobility of Resources

Take generation g's lifetime budget constraint as:

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

Lifetime consumption, c_g, plus the amount of resources transferred to the next generation through human capital investments (b_g^{HC}) or non-human capital transfers (b_g^K), 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}^K. Child labor market returns are a noisy function of parents' human capital investments, $Y_g(b_{g-1}^{HC})$.

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

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.

independent of parent resources.

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

E. Mapping Intergenerational Housing Wealth Mobility Across Counties

We have provide extensive analysis of intergenerational mobility at the national level. It is also desirable to examine how these measures vary at lower levels of geography. To do this, we first produce direct estimates of the regression equations above for each childhood county of residence, calculating α, β and δ, plus their associated standard errors. As these direct estimates can be noisy and pose disclosure risk in small counties, we employ a second modeling step. This involves Faye-Herriot small-area estimation regressions, which have a shrinkage property such that as the number of observations in a county direct estimate declines, the Faye-Herriot estimate converges to the direct estimate for some larger nested geography. In our case, we use the commuting zone containing the given county, or a group of commuting zones with a total population of at least 500,000 (which satisfies Census Bureau disclosure rules).

This approach has the double virtue of minimizing risk of unintentional disclosure of microdata in small counties, while also increasing the signal to noise ratio in such counties. However, to avoid the de-facto imputation of a commuting-zone estimate to a tiny and potentially unrepresentative county within that larger geography, we suppress estimates for counties with less than 20 parent-child pairs in our sample. We make these small-area estimates available to researchers on the Census Bureau's website.

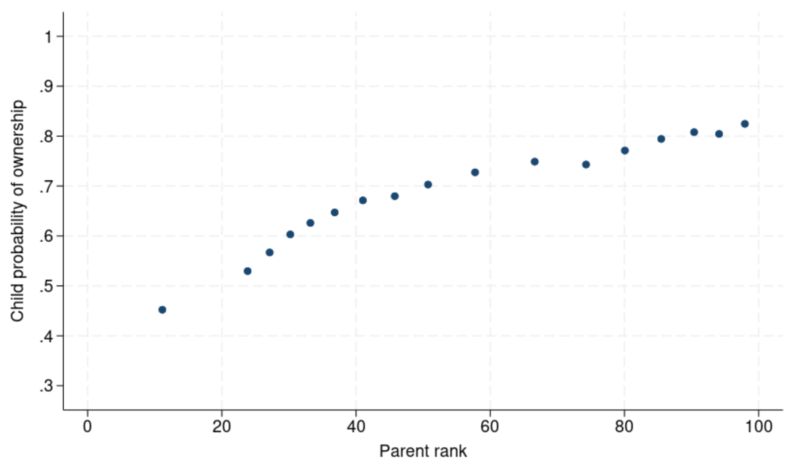
We are now in a position to visualize and describe patterns in intergenerational mobility across space, contrasting how these patterns differ across resource measures. For the purposes of this exercise, we will generate a series of choropleth maps, showing the distribution of housing wealth and income mobility measures across counties on a color scale from warm colors (low α or δ or high β, corresponding to lower levels of absolute/relative mobility) to cool colors (high α or δ or low β, corresponding to higher levels of absolute/relative mobility). Choropleth maps of counties can sometimes be misleading, as counties as a unit are mostly similar in size in terms of area but highly variable in terms of population (as an extreme example, Loving County, TX has a population under 100, while Los Angeles County, CA has a population over 10 million). This can lead to the mistaken visual inference, upweighting the characteristics of lower population, rural areas (which take up more area on a map) and downweighting the characteristics of higher population urban areas (which take up relatively less area). To address this, we map percentiles of the county-level mobility distribution, weighted by the county's sample size in our underlying microdata in each map. This ensures that the midpoint of the color scale corresponds to the mobility experience of the median child in our underlying data – and that warmer colors correspond to lower mobility than this median child, and cooler colors higher mobility.

F. Additional Tables and Figures

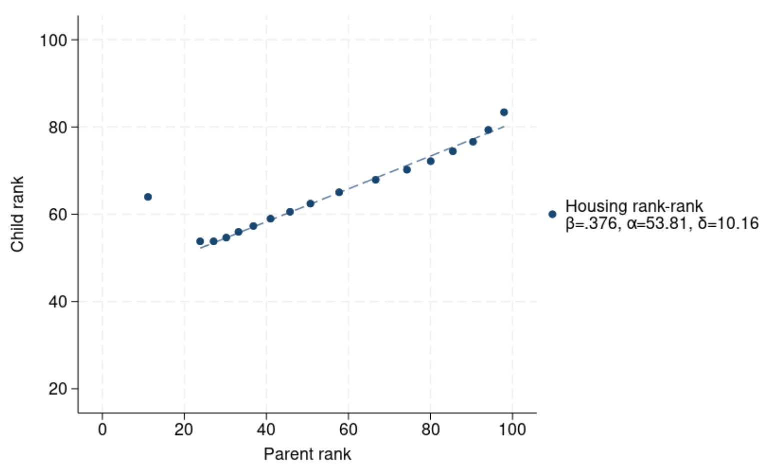
F.1. Appendix Figures

Figure F.6: IGM Housing Relationships - Extensive and Intensive Margins

(a) Probability of homeownership by parent rank



(b) Home value conditional on ownership by parent rank

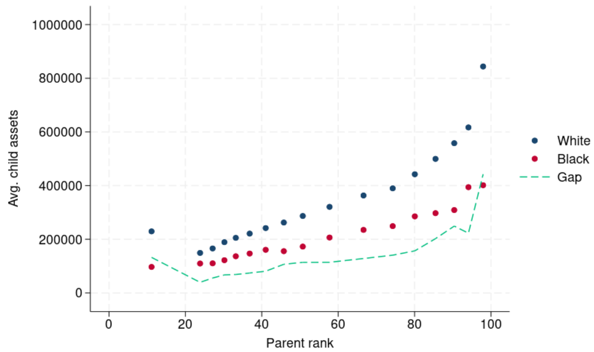


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

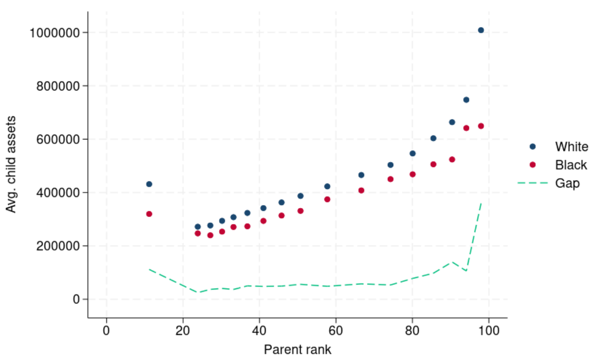
Note: Panel A of this figure shows the non-parametric relationship between child homeownership rates and parental housing asset rank. Panel B shows average child asset value ranks conditional on ownership (i.e. among the subset of child homeowners) across the parental housing asset distribution. Dots 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 F.7: Average child assets by parent rank and race

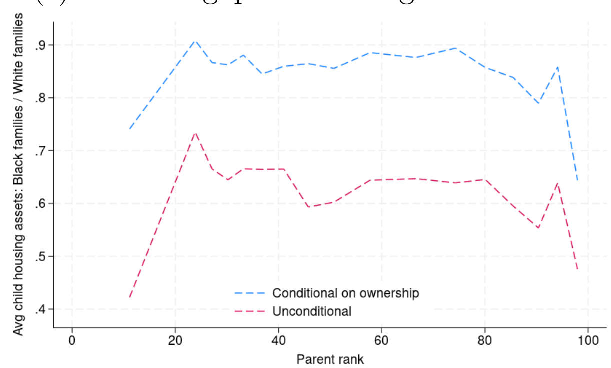
(a) Unconditional housing asset values



(b) Housing asset values conditional on ownership



(c) Relative gaps in housing asset values

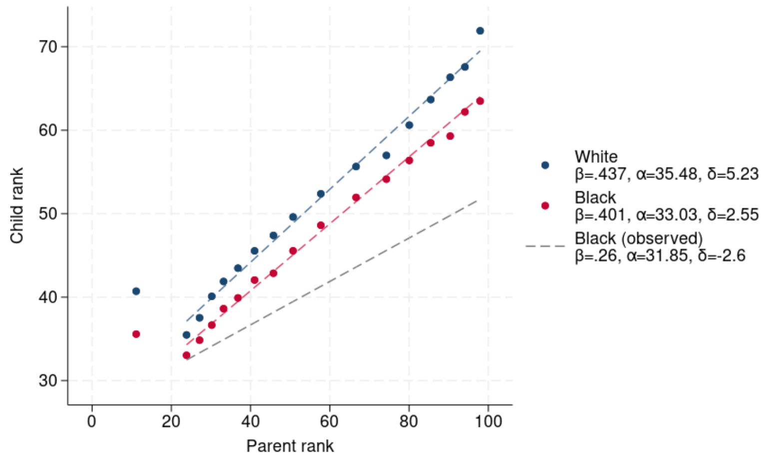


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

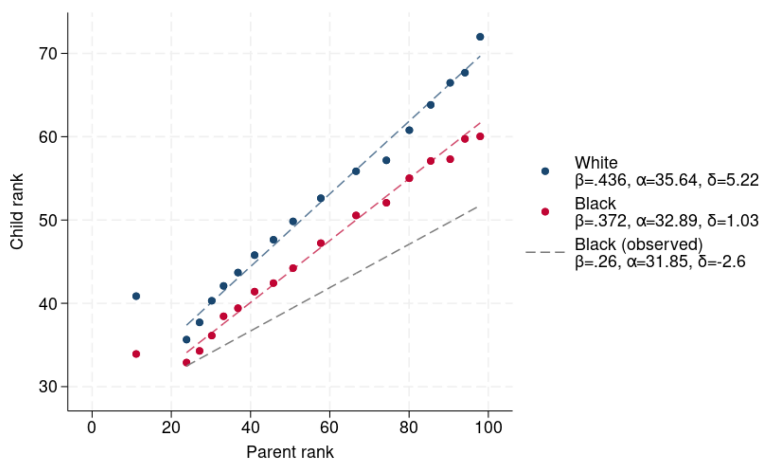
Note: This figure shows average housing assets for children of Black and White families, conditional on parental asset rank. Panel A shows the the raw averages across all White and Black children; the dashed line represents the average White-Black gap at each parental rank. Panel B shows the averages 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 F.8: Counterfactual Black ownership rates and home values

(a) Home values estimated using first-time owners



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

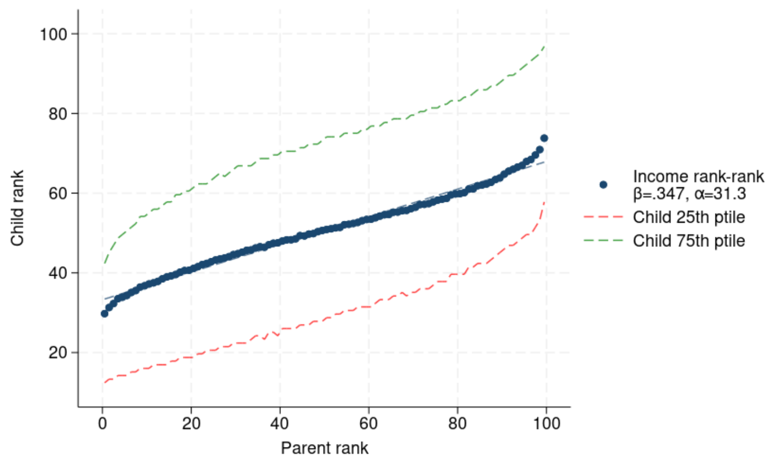


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

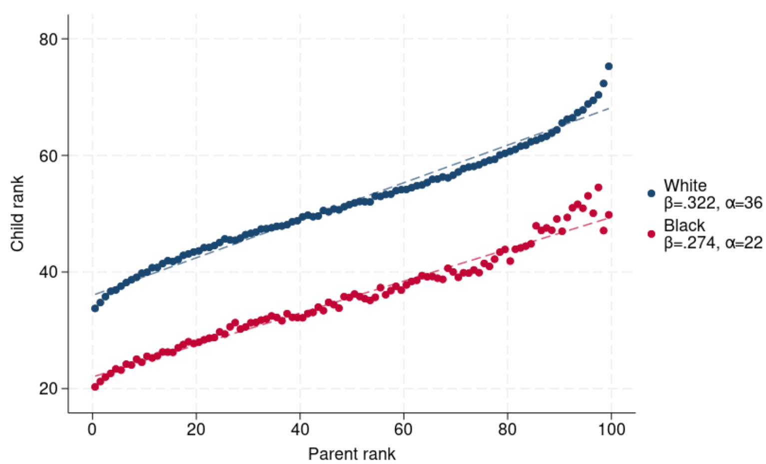
Note: This figure shows counterfactual rank-rank slopes for simulations where the homeownership rates of Black children are equalized to those of White children within parent rank bins. Panel A shows relationships from a counterfactual exercise where Black and White child homeownership rates are equalized, 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.7.2. Panels B equalizes homeownership rates across the parental distribution and assign new marginal Black homeowners the observed 25^{th} percentile of housing asset values among observed Black homeowners within each parental asset bin, as described in Appendix Section A.7.3. 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 F.9: Income Rank-Rank IGM Relationships

(a) Income rank-rank



(b) White v. Black families

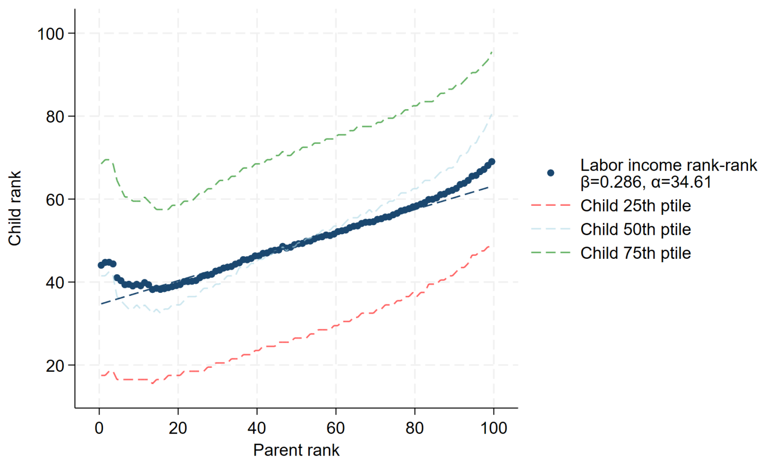


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

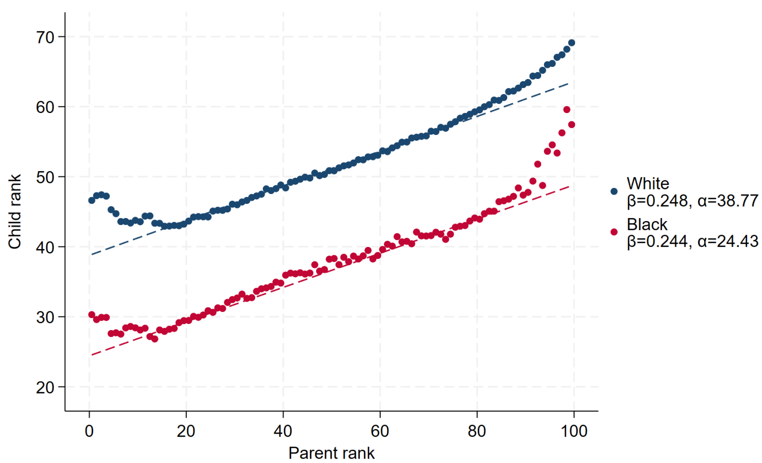
Note: This figure shows non-parametric rank-rank intergenerational relationships between child and parent income. Income is defined as average adjusted gross income (AGI) over three years. Panel A shows results for the full sample. Blue dots represent the average child ranks conditional on parent rank; 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 F.10: IGM Rank-Rank Relationships of Labor Earnings

(a) Labor income rank-rank



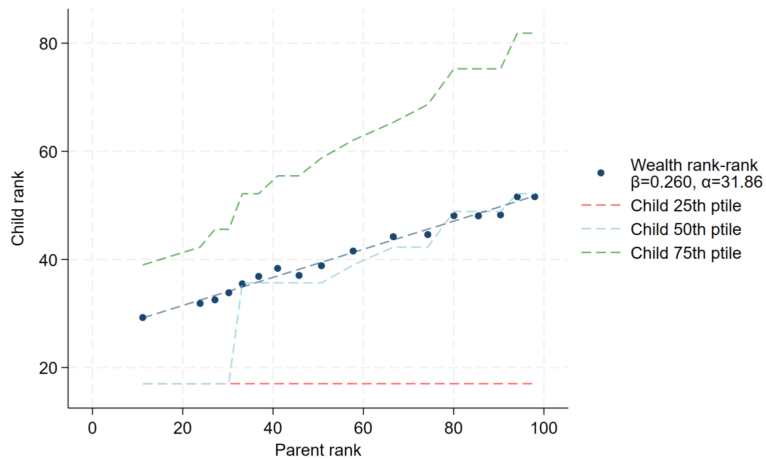
(b) White v. Black families



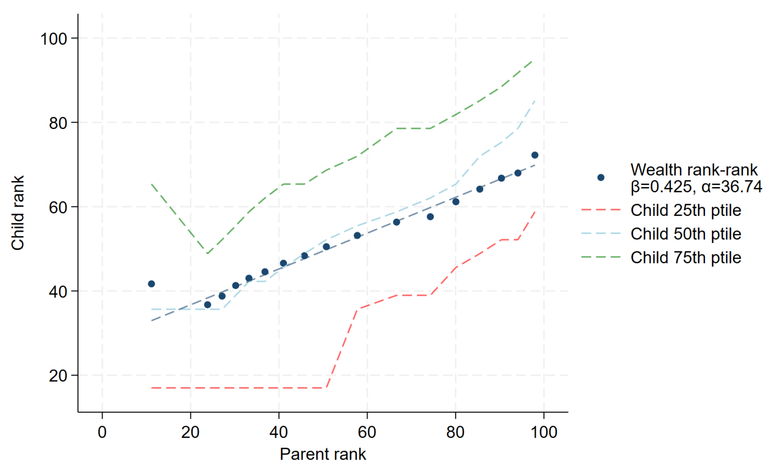
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figure shows non-parametric rank-rank intergenerational relationships between child and parent labor earnings. Labor earnings are defined as average total annual 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 F.11: IGM Rank-Rank Relationships of Housing Capital, by Race

(a) Black families



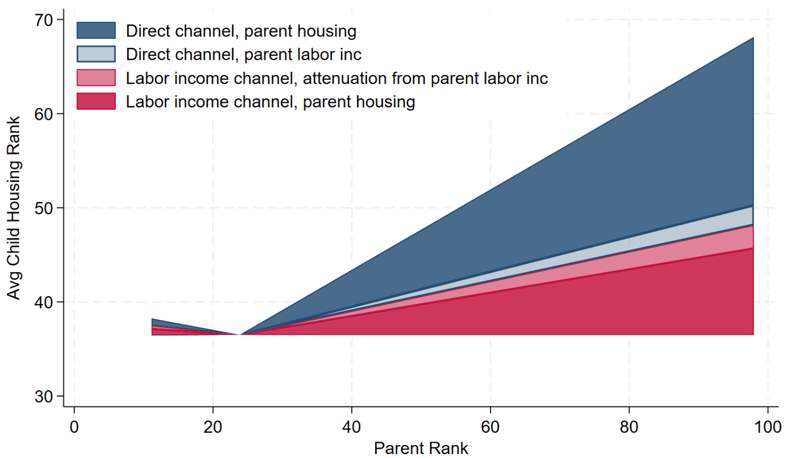
(b) White families



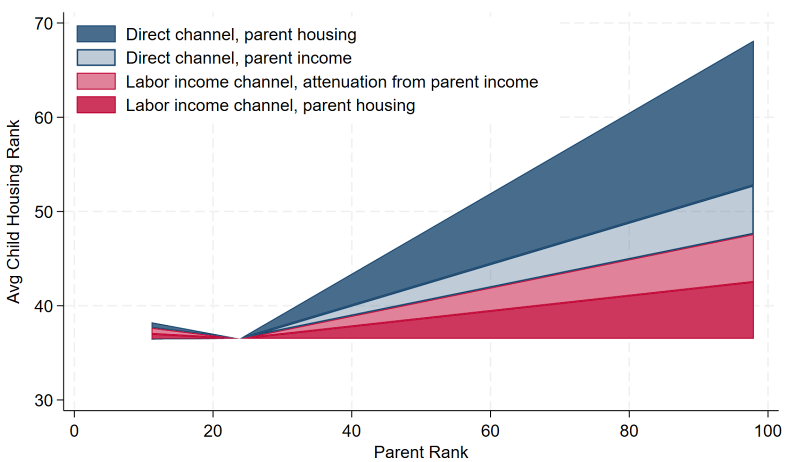
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: This figures shows the rank-rank relationship of child and parent housing, separately for Black and White families. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is the linear rank-rank slope (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 average child rank between children of parent renters and parents at the bottom fo teh housing value disribution. Percentiles of the child wealth rank distribution conditional on parent rank are also shown.

Figure F.12: Direct and Labor Income Channels - Adding Parent Income

(a) Including parent labor income



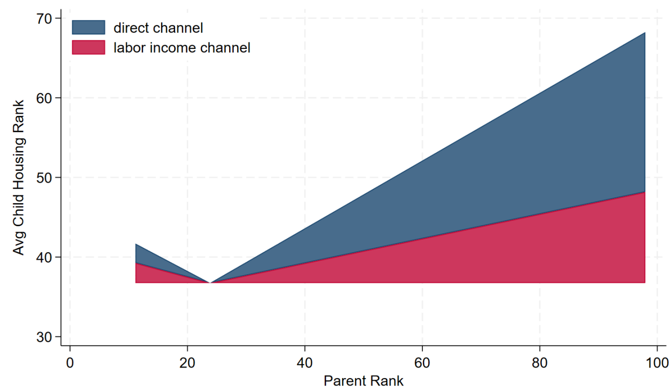
(b) Including parent total income



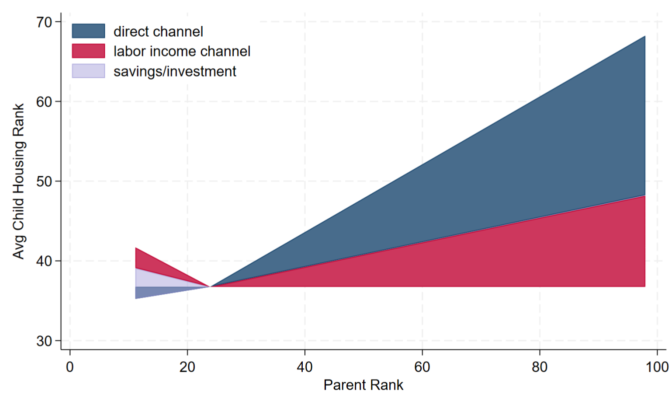
Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.
Note: Panel A shows a decomposition of the population rank-rank slope of housing assets into the direct and labor income channels. The direct and labor income channels are derived 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 F.13: Labor Income and Direct Channels - White Families

(a) Direct v. labor income channels



(b) Including the "savings/investment" channel

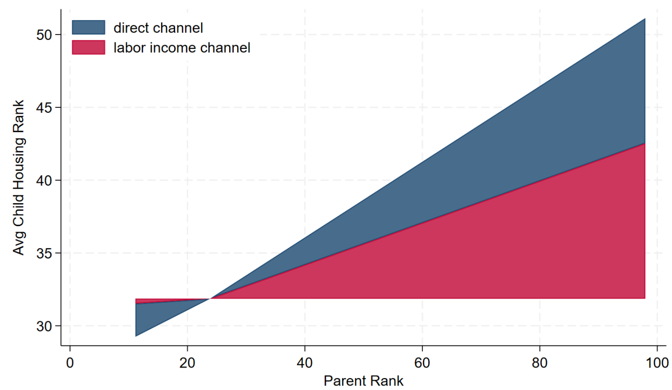


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

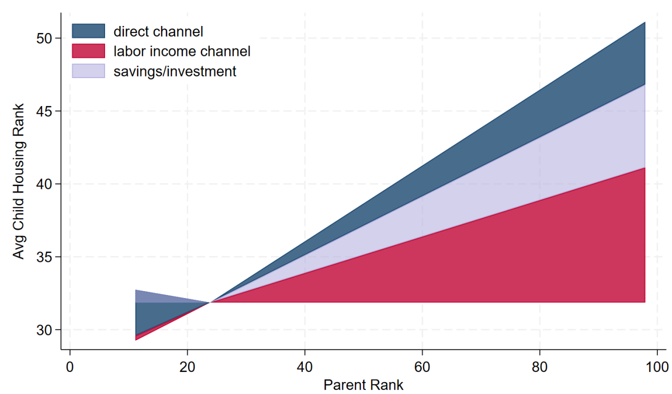
Note: Panel A shows a decomposition of the population rank-rank slope of housing assets into the direct and labor income channels. The direct and labor income channels are derived from simultaneous equations (s1) and (s2), and described in Section 5.2. The red area represents the share associated with 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 "savings/investment" channel — the interaction effect between child earnings and parent housing assets.

Figure F.14: Labor Income and Direct Channels - Black Families

(a) Direct v. labor income channels



(b) Including the "savings/investment" channel

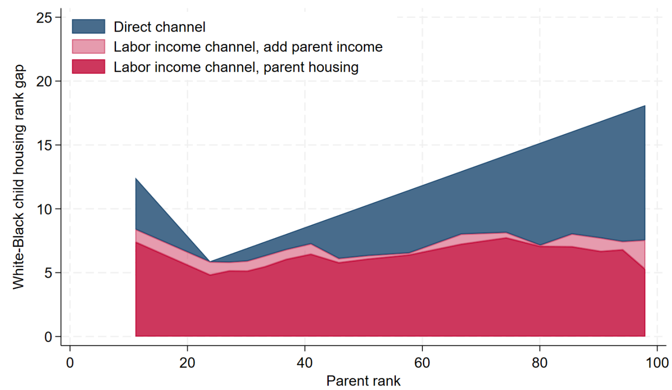


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

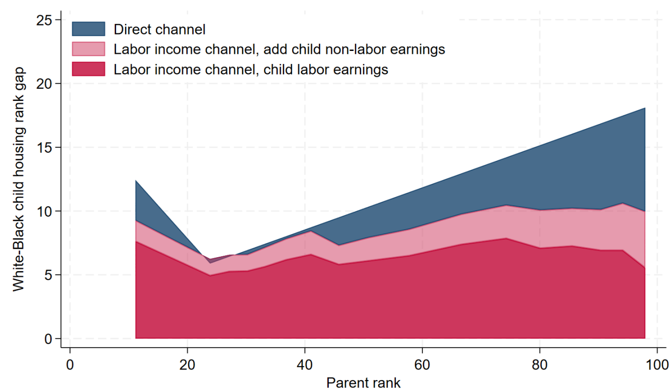
Note: Panel A shows a decomposition of the population rank-rank slope of housing assets into the direct and labor income channels. The direct and labor income channels are derived from simultaneous equations (s1) and (s2), and described in Section 5.2. The red area represents the share associated with 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 "savings/investment" channel — the interaction effect between child earnings and parent housing assets.

Figure F.15: Further Direct and Labor Income Channel Decompositions of Black-White IG gaps

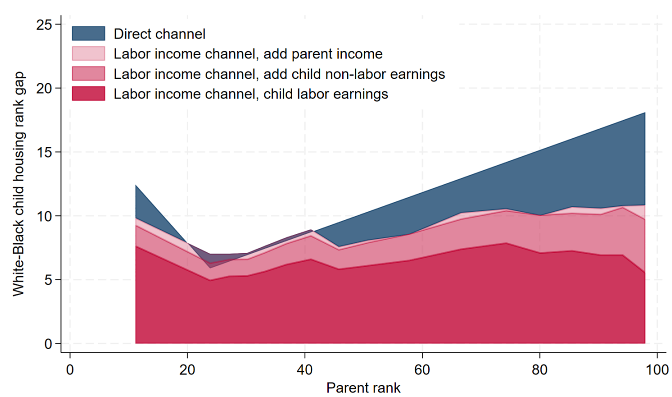
(a) Add parent income to decomposition



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

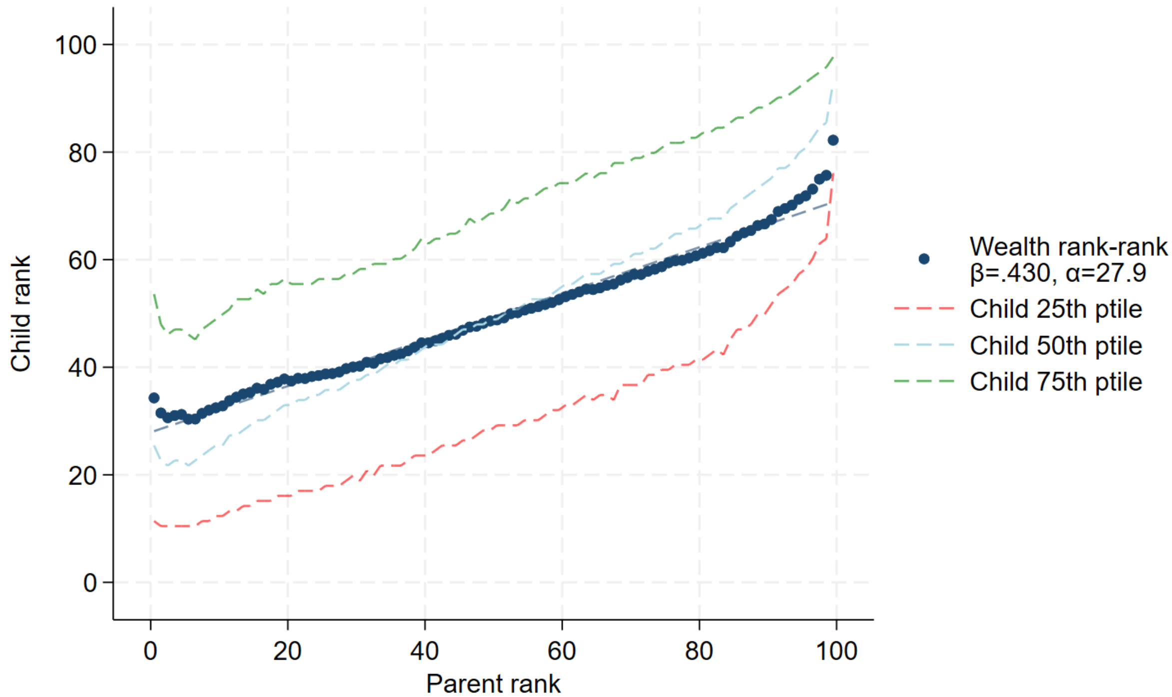


(c) Child total income and parent income



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 F.16: Rank-rank IGM - Capitalized wealth

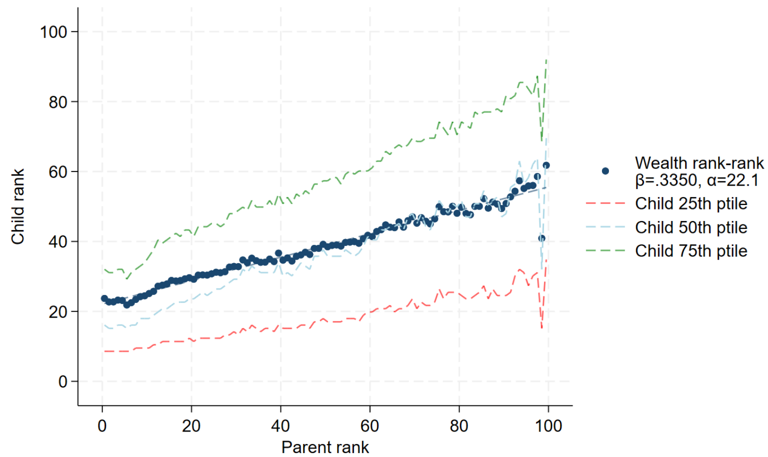


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

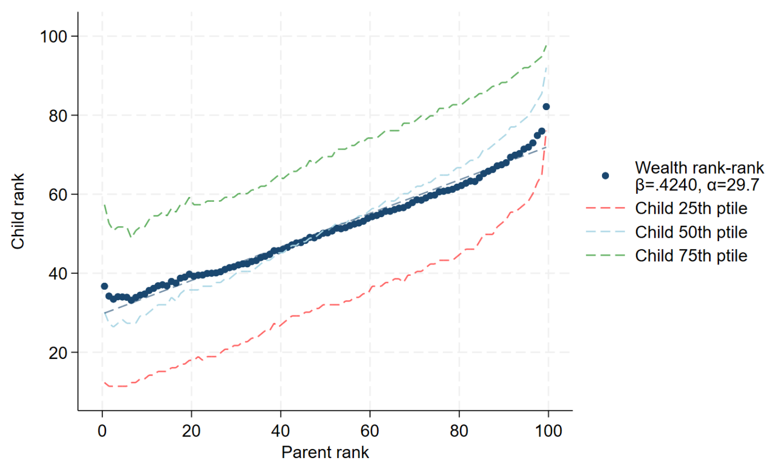
Note: This figures shows the rank-rank relationship of child and parent capitalized wealth. The capitalization method is described in Section 5.5 and Appendix A.8. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is the linear rank-rank slope (β). Percentiles 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 F.17: Rank-rank IGM - Capitalized wealth, by Race

(a) Black families



(b) White families

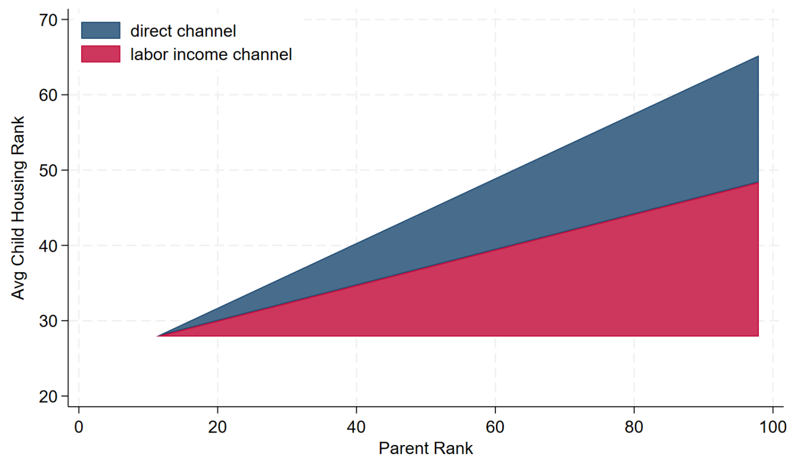


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

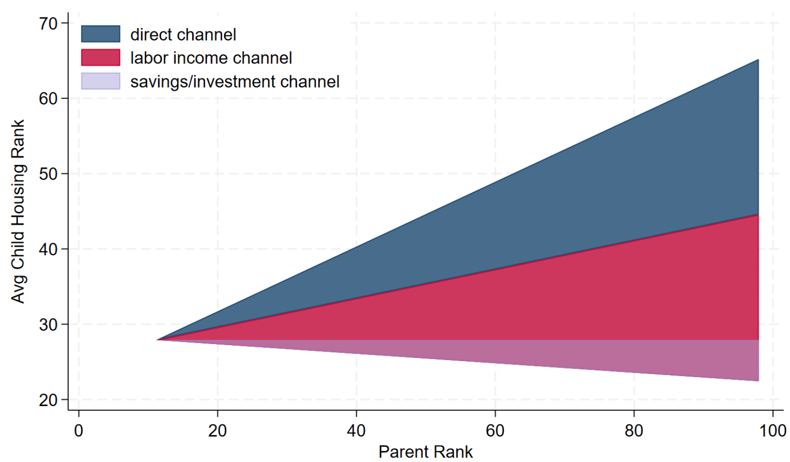
Note: This figures shows the rank-rank relationship of child and parent capitalized wealth, separately for Black and White families. The capitalization method is described in Section 5.5 and Appendix A.8. Blue dots represent the average child ranks conditional on parent rank; the blue dashed line is 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 F.18: Capitalized wealth - Direct and labor income channels

(a) Direct v. Labor income channels



(b) Including the "savings/investment" channel

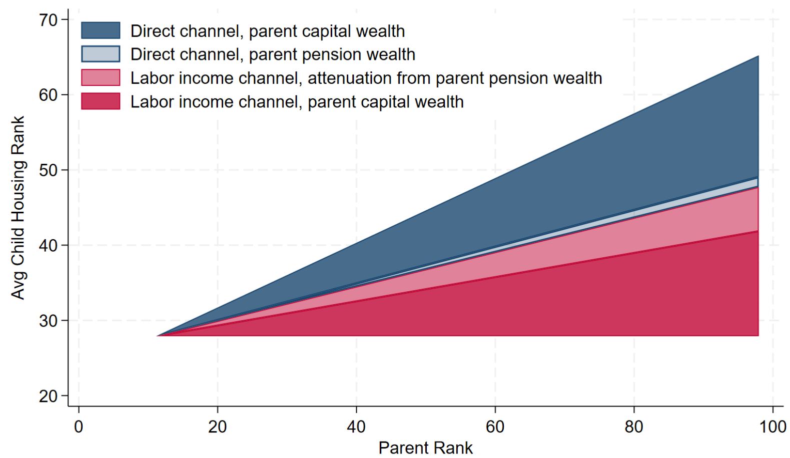


Source: 2019-2021 Black Knight property tax and deed records linked to 2000 Census Long Form and 1994 and 1998 Census Databank.

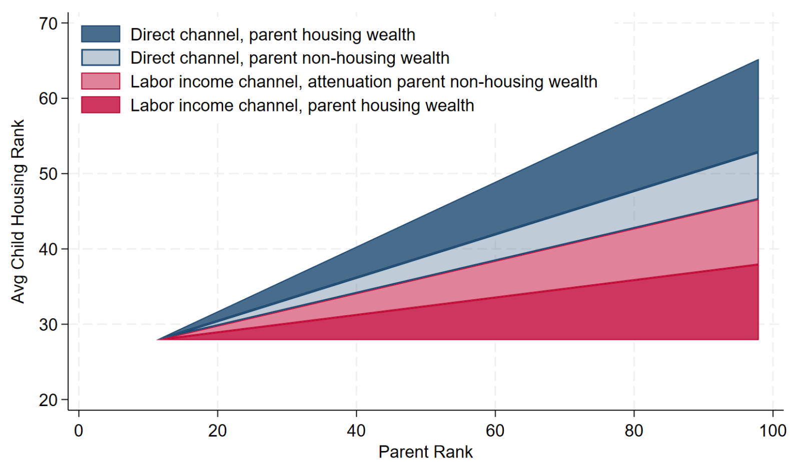
Note: Panel A shows a decomposition of the population rank-rank slope of capitalized assets into the direct and labor income channels. The capitalization method is described in Section 5.5 and Appendix A.8. The direct and labor income channels are derived from simultaneous equations (s1) and (s2), and 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 "savings/investment" channel — the interaction effect between child earnings and parent housing assets.

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

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



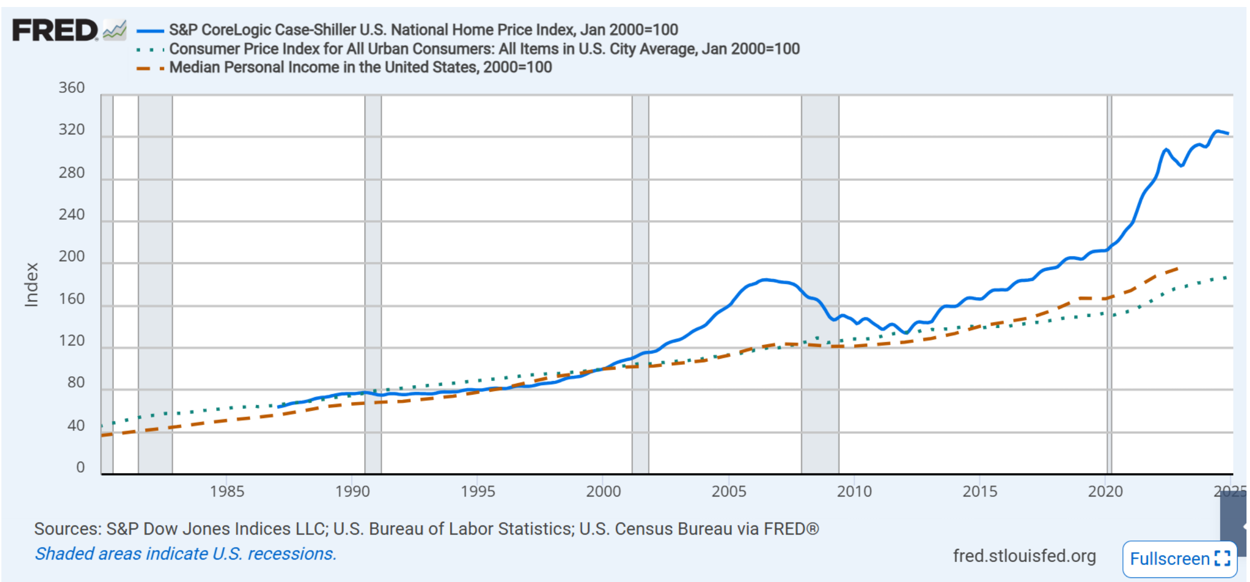
(b) Parent housing v. non-housing wealth



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



F.2. Appendix Tables

Table F.3: Summary statistics by parent housing rank

Parent Housing Rank (%tile)	Average Housing Assets	Income mean	Income median	Income std dev	Labor earnings mean	Labor earnings median	Investment income mean	Investment income median
11	0	52,894	41,862	77,223	40,714	31,063	442	0
24	33,804	47,572	40,636	41,660	36,773	30,846	308	0
27	77,892	54,275	48,115	41,505	42,638	37,564	396	0
30	106,377	59,535	54,446	40,249	47,557	43,274	459	0
33	130,017	64,097	59,333	42,855	51,405	47,867	533	9
37	153,656	68,798	64,376	41,304	55,765	52,847	560	19
41	177,296	74,384	70,055	54,632	60,466	58,263	665	33
46	200,935	79,892	75,547	56,401	65,260	63,057	791	50
51	224,574	86,160	81,878	51,187	70,520	68,922	976	74
58	265,943	95,299	89,589	81,583	77,533	75,485	1,215	112
67	325,042	105,959	98,775	77,239	85,866	83,166	1,570	158
74	384,140	116,696	106,952	96,851	92,894	89,015	2,352	221
80	443,239	129,310	116,696	161,677	101,847	96,634	2,518	310
85	531,887	145,835	128,193	164,935	113,360	104,842	3,597	459
90	650,084	167,573	140,947	180,141	126,021	111,560	4,725	651
94	827,379	206,363	162,297	271,995	149,807	123,678	7,618	1,060
98	1,637,265	398,916	229,326	989,766	251,514	147,495	27,836	2,884

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. 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.

Table F.4: Rank-rank parameters of housing and income mobility

	Housing Capital	Total Income	Labor Income
Full Sample			
β	0.427***	0.347***	0.286***
	(0.0007)	(0.0005)	(0.0005)
α	36.5	33.26	34.61
δ	1.74	.	.
White			
β	0.425***	0.314***	0.248***
	(0.0008)	(0.0006)	(0.0006)
α	36.74	36.91	38.77
δ	4.95	.	.
Black			
β	0.260***	0.245***	0.244***
	(0.0027)	(0.0015)	(0.0015)
α	31.86	24.91	24.43
δ	-2.61	.	.

Notes: This table shows estimate parameters from our rank-rank specification of intergenerational mobility (Equation (1)). The first column shows the main estimates for housing capital: 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 next two columns show estimates 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). Total Income is measured as average adjusted gross income (AGI) over three years. Labor Income is the average total wage and salary earnings. 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.

Table F.5: 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 F.6: 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 F.7: 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 F.8: 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 F.9: 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.8); 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 F.10: 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,	0.254***	0.233***	0.306***	0.00078***	0.241***	0.207***
parent housing	(0.00063)	(0.00135)	(0.00061)	(0.00001)	(0.00067)	(0.00076)
Labor income channel,	0.173***	0.165***	0.070***	0.00250***	0.124***	0.081***
parent housing	(0.00060)	(0.00054)	(0.00001)	(0.00000)	(0.00031)	(0.00013)
savings/investment		0.00038***				
(interaction term)		(0.00002)				
Direct channel,					0.0286***	
parent labor inc					(0.00053)	
Labor income channel,					0.093***	
parent labor inc					(0.00017)	
Direct channel,						0.070***
parent income						(0.00063)
Labor income channel,						0.120***
parent income						(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 "savings/investment" 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 F.11: 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,	0.810***	-2.554***	8.400***	-0.0932***	0.737***	0.583***
parent housing	(0.0723)	(0.136)	(0.0952)	(0.0014)	(0.0722)	(0.0750)
Labor income channel,	0.936***	0.950***	1.761***	0.0158***	0.694***	0.595***
parent housing	(0.0201)	(0.0207)	(0.0640)	(0.0001)	(0.0119)	(0.0095)
savings/investment		0.0818***				
(interaction term)		(0.00281)				
Direct channel,					-0.0634***	
parent labor inc					(0.00106)	
Labor income channel,					-0.149***	
parent labor inc					(0.0004)	
Direct channel,						-0.081***
parent income						(0.00111)
Labor income channel,						-0.158***
parent income						(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 "savings/investment" 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 F.12: 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*** (0.0023)	0.058*** (0.0044)	0.243*** (0.0033)	-0.00049*** (0.00005)	0.093*** (0.0025)	0.081*** (0.0027)
Labor income channel, parent housing	0.144*** (0.00042)	0.125*** (0.00032)	0.078*** (0.00013)	0.00255*** (0.00000)	0.082*** (0.00014)	0.064*** (0.00025)
savings/investment (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 "savings/investment" 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 F.13: 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*** (0.0007)	0.270*** (0.0016)	0.309*** (0.0007)	0.00089*** (0.00001)	0.259*** (0.0007)	0.223*** (0.0008)
Labor income channel, parent housing	0.154*** (0.00048)	0.154*** (0.00048)	0.064*** (0.00001)	0.00214*** (0.00000)	0.113*** (0.00026)	0.073*** (0.00011)
savings/investment (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 "savings/investment" 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 F.14: Components of Capitalized Wealth Across the Distribution

Decile	Wealth	Private Bus	Corp. Equities	Fixed Inc	Housing	Pensions
Mean						
p0-10	1,112	41	43	62	49	765
p10-20	22,130	31	92	300	38	19,900
p20-30	61,070	326	815	1,494	5,932	46,270
p30-40	152,000	1,643	3,208	4,367	68,210	63,360
p40-50	267,200	2,725	4,361	5,220	177,300	67,940
p50-60	366,100	3,805	5,733	6,688	256,600	82,390
p60-70	479,400	6,524	9,495	9,860	336,000	103,700
p70-80	638,100	13,420	17,680	16,250	434,000	137,200
p80-90	931,700	40,510	43,380	33,620	578,000	204,800
p90-100	4,019,000	1,023,000	890,500	475,900	1,034,000	508,200
Median						
p0-10	0	0	0	0	0	0
p10-20	21,430	0	0	0	0	19,450
p20-30	54,190	0	0	0	0	44,210
p30-40	153,700	0	0	0	50,000	55,490
p40-50	269,200	0	0	0	196,000	57,350
p50-60	366,900	0	0	0	273,000	73,110
p60-70	479,700	0	0	477	355,000	91,320
p70-80	636,200	0	0	1,792	455,000	117,000
p80-90	913,700	0	1,544	5,227	596,100	166,100
p90-100	1,909,000	0	58,080	27,050	878,000	329,500
75^{th} percentile						
p0-10	1,971	0	0	0	0	1,376
p10-20	27,420	0	0	0	0	25,960
p20-30	70,340	0	0	0	0	59,150
p30-40	188,400	0	0	1,593	135,000	88,550
p40-50	293,900	0	0	1,791	231,000	83,170
p50-60	394,000	0	13	3,067	312,000	100,700
p60-70	515,600	0	879	5,413	406,000	127,300
p70-80	693,600	0	6,376	10,540	531,000	172,200
p80-90	1,045,000	0	33,890	25,940	730,000	266,900
p90-100	3,076,000	553,100	311,100	149,000	1,285,000	575,500
90^{th} percentile						
p0-10	6,015	0	0	35	0	5,592
p10-20	34,060	0	0	35	0	31,630
p20-30	102,800	0	96	3,375	0	74,140
p30-40	226,400	0	4,344	10,130	171,400	123,900
p40-50	329,500	0	4,628	10,170	262,000	123,000
p50-60	435,000	0	8,159	14,030	348,600	139,100
p60-70	567,700	0	19,800	22,870	452,000	179,100
p70-80	767,700	0	48,500	40,530	599,000	250,000
p80-90	1,173,000	89,770	136,000	88,700	860,000	400,000
p90-100	6,107,000	2,149,000	996,600	580,900	1,875,000	946,800

Notes: This tables shows the components of our total wealth measure across deciles of the child wealth distribution. The first column shows the total wealth measure and the next columns show the main components.

Table F.15: 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
$(\alpha,\beta,\delta)\cdot\mathbf{F}'_{\mathbf{d(c)}}\cdot\mathbf{F_b}$	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 large county dummy $S(c)$.

Table F.16: 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	-.036	-.040	.019	.023	-.038	-.028	-.045	-.036
	(.013)	(.014)	(.016)	(.016)	(.045)	(.044)	(.018)	(.020)	(.020)	(.019)
... in α (Absolute)	.039	.028	.039	.037	-.004	-.015	.043	.034	.033	.026
	(.009)	(.010)	(.011)	(.012)	(.023)	(.021)	(.013)	(.015)	(.012)	(.012)
... in δ (Renter)	-.029	-.020	-.029	-.030	.012	.019	-.024	-.032	-.003	-.006
	(.010)	(.012)	(.014)	(.016)	(.021)	(.019)	(.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 F.15. "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.