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August 14, 2024

WP 2024-21

https://doi.org/10.21033/wp-2024-21

FEDERAL RESERVE BANK of CHICAGO

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Abstract

We estimate intergenerational elasticities (IGE) of housing consumption and income in the US. Using surnames to link 1940 and 2015, we estimate a one-generation housing-consumption IGE of 0.73, higher than that of income at 0.52. Housing consumption IGE is higher for White compared to Black Americans and higher in the Northeast, patterns that contrast with income IGE. Inverting Engel curves suggests a total-consumption IGE of 0.72. Complementary to income IGE, consumption mobility is a closer measure of welfare mobility, and comparisons with income IGE inform intergenerational consumption insurance.

JEL classification: J62, N32
Keywords: Intergenerational elasticity, Consumption mobility

*We thank Orazio Attanasio, Marianne Bertrand, Stéphane Bonhomme, Mariacristina De Nardi, Erik Hurst, Paymon Korrhami, Geng Li, Magne Mogstad, Raghuram Rajan, Raaj Sah, Amir Sufi, Luigi Zingales, as well as seminar participants at the University of Chicago and Federal Reserve Bank of Chicago, for their insightful comments. We thank Stephanie Grove for excellent research assistance. These views are those of the authors and do not reflect those of the Federal Reserve Bank of Chicago or the Federal Reserve System. All errors are our own.

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The increase in inequality of earnings, consumption and wealth over the last decades is large and widely documented.[1] This dramatic increase has led to concerns that society is getting more and more stratified with few opportunities for mobility of individuals at the bottom of the distribution. Partly in response, a large literature on intergenerational mobility of income has emerged and found estimates of the intergenerational elasticity of earnings in the US ranging between 0.3 and 0.6 which suggests a reasonable level of mobility.[2]

In this paper, we show that focusing on housing consumption leads to lower estimates of intergenerational mobility than the estimates in the previous literature that are based on average yearly income.[3] We estimate a one-generation housing-consumption IGE of 0.73, higher than an income IGE of 0.52 in the same time period and with the same methodology. Because the consumption Engel curve for housing consumption is close to linear and has a high R^2, housing consumption is a good potential proxy for total consumption. Inverting group-specific Engel curves translates the housing-consumption IGE into a total-consumption IGE of 0.72.

We also find that consumption IGE has large differences between racial groups: Black Americans have relatively lower within-race persistence in consumption than White Americans. This is in contrast to the pattern for earnings. Recent studies on race-specific intergenerational dynamics of earnings generally converge on the findings that Black and White Americans experience relatively similar within-race mobility but Black Americans have much lower absolute mobility.[4] A potential explanation for the larger racial gap in persistence of consumption relative to earnings is that limited access to credit and instruments of asset accumulation hinders the ability of blacks to insure future generations.

Finally, the patterns of regional heterogeneity in consumption mobility that we uncover also contrast with the patterns found for earnings mobility in the previous literature. In particular, while we find–consistent with previous literature (Chetty et al. (2014))–a higher persistence of earnings in the South than in the Northeast, persistence in consumption is larger in the Northeast than in the South.

[1]See for instance Autor (2014), Murphy and Topel (2016) for labor income; Saez and Zucman (2016) for wealth; Piketty, Saez, and Zucman (2017) for labor and capital income. See Attanasio, Hurst, and Pistaferri (2014) for consumption.

[2]For studies on mobility in earnings, see Chetty, Hendren, Kline, and Saez (2014) as well as related work by the same team of researchers and collaborators, Solon (1999) for a survey, and Mazumder (2015). Regarding mobility of wealth, see for instance Charles and Hurst (2003). More recently, researchers have also studied race-specific intergenerational dynamics of earnings and their relation to the racial gap (Bhattacharya and Mazumder (2011), Mazumder (2014), Davis and Mazumder (2018), Chetty, Hendren, Jones, and Porter (2020)).

[3]Mazumder (2015) shows that averaging over more years of income (up to 15 years) lead to larger estimates of IGE. Focusing on consumption, we find slightly higher persistence.

[4]See Bhattacharya and Mazumder (2011), Mazumder (2014), Davis and Mazumder (2018), and Chetty et al. (2020). In particular, Black Americans have lower rates of upward mobility and higher rates of downward mobility than White Americans. Chetty et al. (2020) show that these dynamics - when extrapolated to a steady-state economy - account for the persistence of the current racial gap.

Most studies on intergenerational mobility have focused on earnings and–to a lesser extent–wealth, with relatively little attention to consumption.[5] Addressing Marx and Piketty's fears of a stratified society however requires measuring persistence through the transmission of both traits affecting earnings and physical capital. In Marx's view, *La bourgeoisie* has no labor income but is nevertheless pulling apart from the rest of society. In other words, intergenerational persistence in permanent income is affected not only by the transmission of human capital but also by the ability to pass physical capital onto the next generation as well as the correlation between wealth and returns to wealth. These channels have received a lot of attention in the debate on taxation of bequests. Another mechanism of insurance typically missed by income measures are government assistance programs: both cash - typically under-reported in survey income measures - and in-kind.[6] For example, Meyer and Sullivan (2017) find lower poverty rates and inequality using consumption based measures. Finally, families may also share risk through pecuniary and non-pecuniary *intervivos* transfers. Consumption and its intergenerational dependence captures all these channels of transmission of economic well-being and maps more directly into welfare. Comparing these estimates to the much studied persistence in earnings is informative on the ability of families to smooth consumption across generations and insure against shocks. A simple version of the neoclassical model would predict an intergenerational correlation of consumption of 1. The previous literature has typically found numbers well below this benchmark.[7] Studying the intergenerational elasticity of consumption and its heterogeneity across ethnicities and place therefore has the potential to complement studies on the persistence of earnings and bring insights into the transmission of welfare and long-run savings behavior of "dynasties."

Another - but closely related - reason for focusing on consumption has to do with the permanent income hypothesis (Friedman (1957)). Individuals' consumption decision–and eventually welfare–depends on their permanent income. Directly measuring permanent income would require extensive knowledge of the lifetime income process of the individual–decomposed in transitory and permanent income shocks–along with a measure of credit constraints. Simply averaging household income over years does not quite measure permanent income. The value of average yearly income for the individual is a function of the credit constraints, the variance of income and its pro-cyclicality among other things. Focusing on consumption solves this issue by *letting the household do the averaging*. These considerations may be important in the context of measuring intergenerational mobility because

[5]There are notable exceptions. Studies on intergenerational mobility of consumption include Mulligan (1997), Aughinbaugh (2000), Waldkirch, Ng, and Cox (2004) and Charles, Danziger, Li, and Schoeni (2014).

[6]See Meyer, Mok, and Sullivan (2015) for evidence on the underreporting of government assistance in surveys.

[7]**?** preferred estimates are between 0.7 and 0.8. Charles et al. (2014) find a much lower correlation around 0.3.

the variance, pro-cyclicality of income and credit constraints are likely to systematically differ across the income distribution–and race–leading to biased estimates of mobility in permanent income.

The lack of datasets with information on consumption have hindered research on the intergenerational elasticity of consumption. To our knowledge, all previous evidence was derived using the Panel Study of Income Dynamics (PSID). Mulligan (1997) uses a weighted sum of housing, spending on utilities and automobiles as a proxy for consumption and find an intergenerational elasticity of around $0.7-0.8$. More recently, Charles et al. (2014) use the more comprehensive measures of expenditures collected in the PSID since 2005 and find a correlation of 0.28. We complement the previous literature by presenting long-run estimates for the period 1940-2015, by computing the first estimates of heterogeneity by race and geography and our evidence is the first that is not based on the PSID. Though the PSID is a natural starting point for studies of intergenerational persistence of consumption, these studies need to be complemented with evidence from other data sources. The PSID has a relatively small sample size which - among other things - restricts possibilities to study heterogeneity across demographic groups. Blundell, Pistaferri, and Saporta-Eksten (2016) compare PSID aggregates of nondurables and services expenditures to National Income and Product Accounts (NIPA). The PSID to NIPA ratio varies between 0.64 and 0.73 across years 1998 to 2008 which raises questions about the quality of its consumption data. Finally, the PSID starts in 1968 and only enriches its collection of consumption data in 1999 and then again in 2005. As a result, consumption measures for the previous generation must necessarily be imputed from categories such as housing, automobiles and spending on utilities.

We propose an alternative methodology to track consumption across generations. We measure housing consumption in the 1940 full-population Census and in current data on 94% of all homes. We use last names to define cohorts and link the two datasets. Our method allows us to go back further in time and estimate persistence over 1940-2015. The dataset in each period is rich and includes virtually the entire population.[8] This allows us to explore heterogeneity across races and geography. On the other hand, our data contains only housing–not total–consumption. In section 4, we assess the quality of housing consumption as a proxy for overall consumption and discuss assumptions under which persistence in housing is equal to persistence in overall consumption. An advantage of our method is the following. Most studies use a noisy measure of consumption (either simply because of imperfect reporting in surveys or because only partial measures of consumption are observed). This typically leads to concerns that the estimates of intergenerational persistence are attenuated by the presence of classical measurement error. Under the assumption that last names are uncorrelated with the measure-

[8] The 1940 Census is a full population Census while the CoreLogic sample used for current data includes 94% of homes.

ment error in consumption (which in our case mostly means that surnames need to be uncorrelated with a preference for housing), the surname-level correlations are immune to the attenuation bias.

On the other hand, using surname-level correlations brings its own set of issues. Even absent measurement issues, last-name level correlations do not necessarily need to equal their individual-level counterparts. This is an occurrence of what is known in statistics and related fields as the *ecological inference problem*.[9] In section 3, we derive assumptions under which surname- and individual-level estimates coincide. We come up with a heterogeneity-adjusted estimator that explicitly takes into account mobility heterogeneity across racial groups and geographies.

Our paper makes three broad contributions. First, we document that consumption IGE–or at least housing consumption IGE–is large and in particular larger than income IGE. Second, we find consumption IGE is higher for White Americans compared to Black Americans, and higher in the Northeast compared to other geographies, patterns which contrast against income IGE. Third, we formalize the assumptions underlying surname-based mobility estimators and devise an adjusted estimator that explicitly takes into account heterogeneity in mobility parameters.

1 Data and Variables

Our estimates of intergenerational mobility in housing consumption and income combine multiple data sets: the 1940 Census, CoreLogic, Infogroup and Experian. We use the Consumer Expenditure Survey (CEX) for years 1960, 1972, 1983-2016 to impute overall consumption based on housing consumption in 1940 and 2015. Finally, we also use the 2010 Census list of frequently occurring surnames. This list contains all last names for which there are more than 100 members in the US that year, for a total of 149,436 surnames. Online Appendix Figure OA.1 illustrates in a schematic how we link these data sets together.

1.1 Census 1940

Dataset Description: The 1940 Census surveyed 100% of the US population in that year. It is the first Census to include questions about an individual's income and education. In addition, the original manuscripts–containing first and last names of individuals–were released in 2012 as they are no longer protected under the 72 year privacy period. We obtained a digitized version of the 1940 Census collected by Ancestry.com and made available to researchers affiliated with the NBER.

[9] On the ecological inference problem, see King (1997), King, Tanner, and Rosen (2004) and Spenkuch (2018) among others.

Sample Definition: We keep all male heads of households who did not live in group quarters in 1940. The rationale for keeping only the heads of household is that housing is a public good within the household. We drop women from the sample because surnames are traditionally inherited from male ancestors. In addition, we get rid of observations with missing housing consumption, race or Census region. When regressing on the logarithm of wages, we drop all farm (head of) households due to concerns about mis-measurement of farming income. When regressing on the logarithm of housing consumption in 1940 (defined below), we drop renters with reported rent above $81 and homeowners with reported home value below $100. Panel (A) and (B) in figure OA.2 illustrate the rationale behind this additional sample restriction. Panel (A) shows that, prior to the additional sample restriction, various socio-economic characteristics predictive of earnings positively correlate with log housing consumption. However, there is a non-monotonic pattern in the tails, suggesting that housing consumption is mis-measured at the extremes of its distribution. Panel (B) shows that the relationship between predicted wage and log housing consumption is essentially monotonic after imposing these sample restrictions.

Variable Definitions: Housing consumption is defined as the monthly rent for renters. For owner occupied housing, we divide self-reported house value by 100. This is justified by (1) the original Census questionnaire which indicates that 1 percent of the total house value is a fair monthly rental if there is no other basis for estimating the rental value of the home, and (2) it corresponds to existing estimates of the price-to-rent ratio in the US in 1940. We use the logarithm of housing consumption in our regressions. We define three race categories: White, Black and Other. In terms of geography, we focus on the 4 Census regions: Northeast, South, Midwest and West.[10] Regarding surnames, we harmonize them in the following way: we drop all special characters and numbers, leading and trailing spaces as well as consecutive blank spaces. We then convert all letters to upper case.

1.2 CoreLogic

Sample Definition: CoreLogic is the basis for our 2014-2015 sample (henceforth refereed to as the 2015 sample). It provides public records on housing characteristics (including the values) collected from county assessor offices. CoreLogic includes a cross-section, in 2014-2015, of house values for about 94% of all residential real estate in the US. The coverage is slightly biased towards urban areas.

[10] Northeast: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York and Pennsylvania. South: Delaware, DC, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma and Texas. Midwest: Illinois, Indiana, Michigan, Ohio and Wisconsin. West: Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming, Alaska, California, Hawaii, Oregon and Washington.

For each house in the dataset, whenever the mailing address of the owner matches the address of the house, we consider that it is the individual's primary residence.

Variable Definitions: We harmonize surnames in exactly the same way as in the 1940 Census. For each last name (records contain the full names of the owners), we average the log of the value of primary residences.

In the 2014-2015 assessor data that we use, there are a few duplicate observations by property. The absolute max-min deviation among these duplicate observations' values for primary residences is 0.23% of the value on average. Sample includes the following property types: single family residence and townhouse, residential condominium, duplex, triplex, quadplex and apartment.

1.3 Infogroup

From Infogroup, we obtain information on who lives where. For rental residential properties identified in CoreLogic, we match their addresses to Infogroup, and attribute the property value to the residents identified in Infogroup. It is important that we be able to attribute a housing consumption value to renters this way. The same way as with homeowners, we assign the value of the property in which the renter lives as the housing consumption for that renter. The address-based match is noisy, with a slightly above 50% match rate.

1.4 Experian

To measure income that corresponds to the CoreLogic measures of housing consumption, we obtain income information for 2014 from Forebears.[11] Forebears provided us with surname averages of income, based on Experian's imputed income measures. As a consumer credit reporting agency, Experian does *not* have actual income data; instead Experian estimates individuals' income using their credit history. The estimation introduces a source of error in observing the true income, but also smooths out transitory movements that would be observed in actual income by using endogenous behavioral information. Because this income measure is only used as the left-hand side variable, the prediction error in Experian's income imputation should not bias our estimated IGE.

[11] http://forebears.io/

1.5 Consumer Expenditure Survey (CEX)

Dataset Description: The CEX is collected by the Bureau of Labor Statistics and used mainly for revising the CPI. We use the interview portion of the CEX. It is a rotating panel with about 5,000 families interviewed each quarter until 1998 and about 7,500 thereafter.[12] Each family is interviewed up to 5 times and provide information about quarterly expenditures, annual income and demographics.

Sample Definition: We pool all years from 1959-1961, 1972-1973 and 1984-2016.[13] We keep only respondents that have been interviewed four times. The head of household is defined as the person or one of the persons who owns or rents the unit. Each household can potentially be interviewed in two different calendar years depending on the start date. We link each observation to the year for which there is at least a 6 months overlap with the interview period. The final sample contains 144,486 households.

Variable Definitions: Demographics such as age, gender, race and education of the head of household, urban/rural status, SMSA status, region, state and home ownership are measured in the third interview (corresponding more or less to the midpoint of the interview period). All expenditure variables are obtained by summing quarterly expenditures reported in each of the four interviews. We closely follow Meyer and Sullivan (2017) for the definition of total expenditures, total consumption and housing consumption. Expenditures are total expenditures reported in the interview minus miscellaneous expenditures and cash contributions, which have not been collected in all interviews. Consumption is defined as expenditures minus educational expenses (which are better described as investment), out of pocket medical expenses (which may reflect needs rather than consumption value) and payments to retirement accounts, pension plans and social security. Again, following Meyer and Sullivan (2017), housing and vehicle expenses are converted to service flows. Appendix A describes how those service flows are calculated (and which exact expenditures are converted). All variables are converted into 2016 real dollars using the CPI. For housing consumption, we use a comprehensive measure that includes utilities and other housing services in addition to the rent paid by renters (or rental equivalent for homeowners), as it is as close as possible to an ideal measure of housing consumption.

[12] 13,728 families are interviewed in 1960-1961 and 19,975 families in 1972-1973.

[13] Data for years 1982-1983 had no rural sample and are therefore not nationally representative.

2 Correlation across Last Names

2.1 Surname-level Correlation

We motivate surname-level estimators from the family-level IGE. For family i across two generations $o = 1940$ (older) and $y = 2015$ (younger),

$$x_i^y = \alpha + \beta x_i^o + \varepsilon_i \tag{1}$$

where x is either income or housing consumption in logs. β here is the IGE (of consumption or income). It is a best linear predictor (BLP), and cannot be interpreted as the causal effect of parent income or consumption on child income or consumption.

We estimate the surname-level correlation using the following estimation equation:

$$\bar{x}_\ell^y = a + b\bar{x}_\ell^o + \tilde{\varepsilon}_\ell \tag{2}$$

for surname ℓ, and $\bar{x}_\ell^v \equiv \frac{1}{n_\ell}\sum_{i\in\ell} x_i^v$ is the surname-level average of log housing consumption or income, for generation (or vintage) $v \in \{o, y\}$, and n_ℓ is the number of households with surname ℓ in 1940. Observations are weighted by n_ℓ. The full expression for the estimator is shown in the proof of Proposition 1 in Section 3. We formalize the conditions under which b recovers β in Section 3.

Figure I shows the raw data: the correlation - across last names - between average log housing consumption in 2015 and the same measure in 1940. The OLS coefficient is 0.50 between 1940 and 2015. In other words, if the O'Sullivans have, on average, a 1% higher housing consumption in 1940 relative to the Washingtons, they tend to have a 0.50% higher housing consumption in 2015. Assuming that there are roughly three generations separating these two samples, this number translates into an estimated IGE of housing consumption between two successive generations of 0.79.[14] The corresponding OLS coefficient for income on housing consumption is lower, at 0.25 between 1940 and 2015.

The surname-level correlation b is similar if we measure x_i as rank within each sample rather than log, at 0.52 for housing consumption in each period and at 0.26 for income against housing consumption in each period (Figure II). Importantly, persistence is still higher in housing consumption than in income. This suggests that the higher estimated persistence is not simply a byproduct of the skewness of distribution of housing consumption (which may have increased between 1940 and 2015). The higher persistence is driven by a higher correlation between percentiles in each cross-section (i.e. is driven by the copula).

[14] This assumes that the average age difference between parents and children is 25. Wang, Al-Saffar, Rogers, and Hahn (2023) find 26.9 years.

The actual estimates are presented in the first column of Table I. It also presents the surname-level income-on-income coefficient of 0.303. Again using three generations between 1940 and 2015, this implies a one-generation IGE of income of 0.67. This estimate is in line with the range of family-level estimates on the income IGE in the literature, on the higher end (Deutscher and Mazumder (2023)). That our estimate is on the higher end is as expected: using a surname-level average income averages out the transitory component of family-level income, which lowers IGE estimates in family-level regressions.

Table I shows that the IGE of housing consumption is larger than the IGE of income. Using surname linkages across multiple generations has its econometric issues, which we discuss in more detail in subsequent sections, but those issues affect both housing consumption and income IGEs that we estimate. Even holding the 1940 regressor fixed as housing consumption, the slope of 2015 housing consumption is larger than that of income, both in log (0.502 vs. 0.252) and in ranks (0.520 vs. 0.259). We further instrument for the 1940 housing consumption with 1940 income in two-stage least squares (2SLS) in Online Appendix Figure OA.3: Both housing consumption on housing consumption and housing consumption on income slopes of 0.48 and 0.26, respectively, are very similar to the estimates obtained using ordinary least squares in logs and in ranks.

Beyond the IGE as a single parameter to summarize intergenerational mobility, we also examine the non-linear relationship in housing consumption and income between 1940 and 2015. We motivate the non-linear estimator using the family-level estimator in equation 3, in which the regressors are the percentile indicators by 1940 x_i^o. Since we have the family-level x_i^o for 1940 but only surname-level $\bar{x}_\ell^y$ in 2015, we average the nonlinear specification at the surname level in equation 4, instead regressing on the fraction of families in each surname that belong to each percentile by x_i^o in 1940:

$$x_i^y = \sum_{k=1}^{100} \gamma^k 1\left(\in k\text{th percentile by } x_i^o\right) + \epsilon_i \tag{3}$$

$$\bar{x}_\ell^y = \sum_{k=1}^{100} c^k \overline{P}_\ell^{o,k} + \tilde{\epsilon}_\ell \tag{4}$$

where the percentile share $\overline{P}_\ell^{o,k} \equiv \frac{1}{n_\ell}\sum_{i\in\ell} 1\left(\in k\text{th percentile by } x_i^o\right)$ for each $k \in \{1,2,...,100\}$. The results are plotted in hollow circles in Figures I (in logs) and II (in ranks).

Figures I, II and OA.3 also show that there is quite a bit of variance in log housing consumption in 1940 across surnames. This large between-surname variance in housing consumption is necessary to estimate any meaningful IGE.[15] Between-surname correlations however need not equal their individual-

[15] We verify that between-surname variation is sufficient to recover the true IGE in simulation exercises in Online Appendix Section D.

level counterpart – that is the correlation that would be measured if we were able to link ancestors directly to their descendants. Deviations between the two arise due to both the ecological inference problem as well as immigration and differential family dynamics.[16] We address these deviations in Section 3.

Other studies have used surnames to study intergenerational mobility.[17] Clark (2015) compiles evidence from multiple countries and time periods. He finds consistent measures of between surname intergenerational correlations across settings, with implied elasticity on the order of $0.7 - 0.8$. Clark (2015) argues that any single measure - for instance income, education or wealth - usually considered in the literature is merely a noisy signal of some underlying social status. By looking at surnames, Clark (2015) argues, one encompasses other dimensions of class and social status which explains why long-run surname regressions tend to show less intergenerational regression to the mean. Chetty et al. (2014)–in their appendix D–compare their individual estimates to surname based estimates in their tax data. They compute both measures for samples of more and less common last names. The surname-based estimates tend to be only slightly larger than individual-level estimates (i.e. 0.42 compared to 0.33) when including all surnames or when restricting to rare surnames. The surname-level estimates tend to blow up only when restricting the sample to the 7 most common last names in which case they attain a magnitude roughly comparable to the between race correlation between the two periods considered. Chetty et al. (2014) conclude that last names are informative about ethnicity and that surname based estimates, especially those including only the most common last names, place more weight on the between race component of the covariance. We make a similar point and adjust our estimates for race in Section 3. Olivetti and Paserman (2015) by contrast uses the informativeness of received first names regarding one's parents social status to estimate social mobility in the late 19th and early 20th century. It is, as pointed by the authors themselves a “Two Sample Two Stage Least Square" estimator and is similar in that regard to our methodology. Our methodology differs from theirs in that we use surnames–instead of first names–as instruments in the estimation. We also allow for heterogeneity in mobility across demographics. Güell et al. (2015) use a calibrated model of the joint evolution of the distribution of surnames and economic advantage. Using cross-sectional data and the calibrated structural model, they recover IGE measures. Santavirta and Stuhler (2024) formalizes and compares across different methodologies that use names to estimate intergenerational mobility.

[16]On the ecological inference problem, see King (1997) and King et al. (2004) among others.

[17]See among others Collado, Ortuño-Ortín, and Romeu (2012),Clark and Cummins (2015), Clark (2015), Olivetti and Paserman (2015) and Güell, Rodríguez Mora, and Telmer (2015).

2.2 Heterogeneity by Race and Geography

We now turn to estimating IGEs that depend on race and geography. As with the nonlinear estimator in equation 4, we have the microdata in 1940 in which we see the race and geography at the family level along with housing consumption and income.[18] We motivate our estimator with the family-level estimator in equation 5, in which the regressors are dummies for each group g (race, Census region, or race × Census region) and an interaction between each dummy and x_i^o: The estimated $\{\alpha^g, \beta^g\}$ are coefficients from within-g regressions run on each subsample. We average equation 5 to the surname level to obtain equation 6:

$$x_i^y = \sum_g \left[\alpha^g D_i^g + \beta^g \left(D_i^g x_i^o\right)\right] + \eta_i \tag{5}$$

$$\bar{x}_\ell^y = \sum_g \left[a^g \overline{S}_\ell^{o,g} + b^g \overline{X}_\ell^{o,g}\right] + \tilde{\eta}_\ell \tag{6}$$

where $\overline{S}_\ell^{o,g} \equiv \frac{1}{n_\ell}\sum_{i\in\ell} D_i^g$ and $\overline{X}_\ell^{o,g} \equiv \frac{1}{n_\ell}\sum_{i\in\ell} D_i^g x_i^o$, and D_i^g is a dummy variable for whether family i belongs to group g.

The estimated b^g are displayed in Tables II and III, with $\bar{x}_\ell^v$ in average log and average rank, respectively. While the estimated within-group mobility b^g in labor earnings is similar between White and Black families (consistent with the previous literature), we find much lower within-group persistence in housing consumption for Black relative to White families. The estimated 1940-2015 correlation in log earnings is 0.113 for Black families and 0.102 for White families, while the correlation in housing consumption is 0.172 and 0.432, respectively. Using roughly three generations between 1940 and 2015, these imply one-generation IGE of housing consumption of 0.56 and 0.76 for Black and White families, respectively. One potential explanation for the larger racial gap in persistence of consumption relative to earnings is that limited access to credit and instruments of asset accumulation hinders the ability of blacks to insure future generations. Note that the persistence in housing consumption and earnings is essentially the same for Black families. This would be predicted by our model in Section 5.1 if Black families were all credit-constrained.

Figure III further highlights the Black-White difference in IGEs, by plotting the nonlinear, race-specific coefficients from:

$$\bar{x}_\ell^y = \sum_g \sum_{k=1}^{100} c^{k,g} \overline{P}_\ell^{o,k,g} + \tilde{v}_\ell \tag{7}$$

where the percentile share $\overline{P}_\ell^{o,k,g} \equiv \frac{1}{n_\ell}\sum_{i\in\ell} 1\left(\in k\text{th percentile by } x_i^o \cap \text{ in group } g\right)$ for each $k \in \{1,2,\ldots,100\}$

[18] We observe individual-level housing consumption and income in 2015, but not race.

sorted by housing consumption in 1940, and g is for Black, White and other. Coefficients in which $\bar{x}_{\ell}^{y}$ is the average log housing consumption is plotted in hollow circles, and those for the average log income is plotted in crosses. The coefficients on Black families are in blue and those for White families are in red.

We also find meaningful heterogeneity in the housing-consumption IGE between geographies. Among the four Census regions, housing-consumption IGE is the highest in the Northeast, with one-generation elasticity at 0.78 in logs and 0.77 in ranks (Tables II and III). By contrast, the one-generation IGE is 0.66-0.68 in the Midwest, 0.71-0.73 in the South and 0.56-0.60 in the West.

These patterns contrast with the findings of the previous literature on earnings persistence. For the period 1980-2015, Chetty et al. (2014) find more persistence in the South than other regions. We find a similar geographical pattern in earnings IGE (Table II), with one-generation earnings IGE of 0.56 in the South, relative to 0.48 in the Northeast, 0.50 in the Midwest and 0.47 in the West. This reversal between the Northeast and South–when looking at housing consumption instead of earnings–may also be driven by the financial sector being more developed in the Northeast.

3 Family-level Housing Consumption IGE

We discuss two broad issues with inferring family-level IGE from surname-level correlations, along with adjustments to address them. First, suppose we have family-level linked data as with equation 1, then we average to the surname level and run estimation at the surname level according to equation 2. The respective coefficients β and b could still be different due to the issue of ecological inference (Robinson (1950)). We discuss and address this issue in the first sub-section.

Second, the older and younger generations in our two samples do not correspond to each other one-to-one. For one, there would be immigrants among the younger generation, who do not have corresponding ancestors in the older sample. Similarly, there would be those in the older generation who do not have descendents in the younger sample. More broadly, differential numbers of children and grandchildren would break the one-to-one correspondence between the two samples. We discuss and address this issue in the second sub-section.

3.1 Inferring Individual Correlations from Group Correlations

We have previously noted that last-name level correlations need not be equal to their individual level counterparts (Robinson (1950)). In this section, we develop an econometric framework to clarify under what assumptions they coincide and how to evaluate the plausibility of the underlying assumptions. We are interested in estimating - at the individual level - the population Best Linear Predictor (BLP) of 2015 (log) consumption using the (log) consumption of one's ancestor in 1940.

For the discussion in this subsection, we work under the assumption that the 1940 ancestors and 2015 descendants are matched one-to-one, only as a benchmark. We discuss deviations from that assumption (which we show is false) in the next subsection.

Proposition 1 (Inferring from unadjusted correlation)**.** *For the surname-level coefficient b from equation 2 and the family-level IGE β from equation 1,*

$$b \xrightarrow{p} \beta \tag{8}$$

if

$$Cov_{n_\ell}\left(E\left[\varepsilon_i | z_i^\ell\right], E\left[x_i^o | z_i^\ell\right]\right) = 0 \tag{9}$$

where covariance is over ℓ *and weighted by* n_ℓ*, with* $z_i^\ell = 1$ *if family i has surname* ℓ *and 0 otherwise, and each family i has one observation in o and y.*

All proofs are in the Appendix. The condition on the covariance means that the deviations in child outcome above and beyond what is predicted by the parent outcome cannot be predicted on average at the surname level by the surname level average outcome of the parents. For example, suppose those with surname A had high income in 1940, but the 2015 descendants with surname A have even higher income than is predicted by a homogeneous β. This condition is satisfied only if there are other surnames who had high income in 1940 on average, whose descendants in 2015 have lower income on average than is predicted by the homogeneous β.

This condition is violated if the intergenerational parameters α and β are heterogeneous in a way that is correlated with the surnames and the level of x_i^o in 1940. For example, surnames are partially informative about Black and White racial identities of families, and Black families had lower income in 1940 (see Section 2.2). Further, White families had a higher α of income than Black families in recent decades (Chetty et al. (2020)). Under these conditions, the assumption of Proposition 1 is violated.

Not only the α of income between Black and White families, but we found the IGE β of housing consumption was different between Black and White families and between Census regions in Section 2.2. We therefore derive an estimator that accounts for such heterogeneity in the mobility parameters.

Definition 2 (Group-adjusted estimator)**.** *We define the group-adjusted estimator* $\hat{b}$ *as*

$$\hat{b} \equiv \frac{Var\left(\bar{x}_g^o\right)}{Var\left(x_i^o\right)}\bar{b} + \sum_g \frac{\frac{N_g}{N} Var_g\left(x_i^o\right)}{Var\left(x_i^o\right)} b^g \tag{10}$$

where

$$\bar{b} = \frac{Cov\left(\bar{x}^o_g, b^g \bar{x}^o_g + a^g\right)}{Var\left(\bar{x}^o_g\right)} \tag{11}$$

and a^g and b^g are within-group intercepts and slopes from equation 6 respectively.

Intuitively, since deviation between family-level and surname-level BLP arise from heterogeneous mobility parameters that co-vary with surnames and with the 1940 level of the variable of interest, this group-adjusted estimator estimates the heterogeneous mobility parameters directly and uses them to reassemble the overall IGE.

Proposition 3 (Inferring from group-adjusted correlation)**.** *For the group-adjusted surname-level coefficient $\hat{b}$ from equation 10 and the family-level IGE β from equation 1,*

$$\hat{b} \xrightarrow{p} \beta \tag{12}$$

if

$$Cov_{n\ell}\left(E\left[\eta_i | z^\ell_i, D^g_i\right], E\left[x^o_i | z^\ell_i, D^g_i\right]\right) = 0 \tag{13}$$

$$Cov_{n\ell}\left(E\left[\eta_i | z^\ell_i\right], E\left[D^g_i | z^\ell_i\right]\right) = 0 \tag{14}$$

where covariances are over ℓ and weighted by n_ℓ, and ancestors and descendants are matched 1-to-1.

Heterogeneity-adjusted IGE estimates are in columns (2)-(4) of Table I. Column (2) defines g as a partition into three race categories: White, Black and other races. Column (3) defines g as the four Census regions. Finally, column (4) defines g as the intersection of race and Census regions. The estimates vary between 0.39 (the specification that adjust for both geography and race) and 0.5 (the unadjusted specification). This translates into an intergenerational elasticity of consumption between 0.73 and 0.79 and a similar magnitude for the rank-rank correlation.

As for the intergenerational persistence in earnings, our one-generation estimates range from 0.53 (adjusted for both race and geography) to 0.67 (unadjusted). Again, these values are consistent with the previous literature which has generally found elasticities ranging from 0.3 to 0.6. We find relatively similar magnitudes for the rank-rank correlations.

These adjusted estimators reiterate the main finding that the IGE of housing consumption is higher than the IGE of earnings. While inference from surname-based linkages has econometric issues, several reasons support the robustness of this main finding. First, as shown on the second line of Table I (and on Figure I), the measured persistence in housing consumption is larger than the measured persistence in earnings even when holding the measure on the x-axis, and the estimation method, constant. Second, the estimated magnitudes of intergenerational persistence in labor earnings are consistent with the existing literature which suggests that the ecological inference problem may only lead to a small bias in our sample (which would also be consistent with the placebo results on proxies for human capital shown in Appendix Table OA.4 as well as the aforementioned online appendix D in Chetty et al. (2014)). Third, as evidenced on Figure I, the estimates of average persistence are largely robust to allowing for a non-linear relationship between 1940 log housing consumption and 2015 log housing consumption (and similarly for log income). Fourth, though adjusting for race and geography does slightly decrease the estimates, this is true for both housing consumption and labor earnings. As a result, persistence in housing consumption is higher than the persistence in earnings across all specifications.

3.2 Noisy Linkage: Immigration and Differential Family Dynamics

Another empirical issue with surname-level correlation is the deviation from family-level correlations that match one ancestor to one descendant. Several forces can cause this deviation. One significant factor is immigration; for example, if many Rossi families migrated to the US after 1940, some Rossis in 2015 might be unrelated to any Rossis in 1940. Another factor is the number of children families have and how many of those retain the same surname, either due to the gender of the child or by choice. In extreme cases, some families might not have surviving descendants with the same surname by 2015.[19]

Such noisy linkages likely introduce classical measurement errors that bias the estimated IGE downwards. We examine the extent of this downward bias in the context of immigration. We leverage surname data categorized by country of origin, utilizing Infogroup's ethnic identification scheme based on Infogroup's proprietary ethnic research and linguistic rules.[20]

We derive country-specific IGEs by grouping surnames according to their respective countries of origin. Subsequently, we plot IGEs of consumption and income against a proxy indicating the fraction of immigrants arriving from each country before and after 1940, obtained from Gibson and Jung (2006).[21] We compute the share of the US population born in each origin country per decade,

[19]Even in milder cases when fertility rates differ between families, this can lead to a deviation from the one-to-one matching assumption. Imagine two ancestors in 1940, one of whom has one descendant in 2015 and the other has two. In a family-level correlation, the second ancestor would have double the observation count as the first one (or the descendants of the second ancestor would have half weights). By contrast, in surname-level averages, the ancestors have equal weights, whereas the descendants of the second ancestor have double weights in 2015.

[20]The identification scheme mainly relies on full names and geography.

[21]Can be accessed at `https://www.census.gov/content/dam/Census/library/working-papers/2006/demo/POP-twps0081.pdf`. Specifically, we use Table 4 on "World Region and Country or Area of Birth of the Foreign-Born Population, With Geographic Detail Shown in Decennial Census Publications of 1930 or Earlier: 1850 to 1930 and 1960 to 2000."

then average the shares across decades pre- and post-1940. Sorting countries based on the ratio of post-1940 immigration share to the sum of the two, we analyze the relationship between immigration intensity and surname-level IGEs.

Figure IV plots country-specific IGEs against the proxy for post-1940 immigration intensity. Circle size denotes surname prevalence in 2015, indicating the prevalence of descendants from each origin country in the US, with the corresponding ISO 3166-1 alpha-2 country codes in green labels. Detailed counts and estimated IGEs of housing consumption and income can be found in the Appendix Table OA.2.

Higher immigration rates post-1940 lead to increased measurement error in inferring family-level IGEs from surname-level data, as evidenced by the disparity in surname-level estimates. Notably, IGEs for Irish and German surnames (IE and DE) are higher, reflecting predominant immigration pre-1940, whereas estimates are lower for countries like Italy (IT) with significant post-1940 immigration.

This empirical analysis highlights the impact of immigration on surname-level IGE estimates, indicating underestimation of underlying family-level IGEs. Adjusting for the effects of immigration and other noisy linkages proves challenging, thus we interpret our findings as evidence of underestimation.

4 From Housing Consumption to Total Consumption

Though intergenerational correlations in housing consumption are interesting in their own right, we also use these numbers to inform IGEs of overall consumption. We use the CEX, a nationally representative sample, to estimate the following log-linear housing demand equations:

$$h_i^v = \theta_0^v + \theta_1^v c_i^v + \nu_i^v \tag{15}$$

for generation (or vintage) $v \in \{o, y\}$, where h is log housing consumption and c is log total consumption.[22]

Figure V shows strong support for the assumption of log linearity. It plots the mean log housing consumption, using our most comprehensive measure of housing, for each percentile of total consumption. The relationship is remarkably linear - including in the tails - and has a slope of 0.92 (Appendix Table OA.3). The R-squared is 0.83. As the slope is very close to 1, we conclude that preferences for housing seem very close to homothetic. In Figure V, we also break down the Engel curves by Census region, race and decade. We find relatively little heterogeneity across these subsamples which is reassuring

[22] In practice, we estimate the Engel curves in the closest years in our CEX sample to either 1940 and 2015. This means 1959-1961 and 2000-2016.

for the use of housing consumption as a proxy for overall consumption. Appendix Table OA.3 shows the Engel curve estimation by decade. Again, we uncover relatively little changes in θ_1^v over time.

We impute overall consumption in the 1940 and 2015 samples based on these Engel curve estimations. We estimate Engel curves in the CEX and allow θ_0^v and θ_1^v to vary across observable demographics and year. A proxy for overall consumption can then be formed in each sample equal to:

$$c_i^{*v} = -\frac{\theta_0^v\left(M_i^v\right)}{\theta_1^v\left(M_i^v\right)} + \frac{1}{\theta_1^v\left(M_i^v\right)} h_i^v \tag{16}$$

where M_i^v are demographics that are observable in both the CEX and housing consumption sample for generation v. We run the surname level regressions on this proxy instead of housing consumption.

The estimated IGE of imputed total consumption c_i^{*v} is shown in Table IV. Based on the heterogeneity-adjusted estimator of equation 10 at the bottom right corner, the imputed consumption IGE is 0.72 per generation, similar to the housing consumption IGE of 0.73. As expected from the linear Engel curve for housing, explicitly imputing total consumption by inverting the Engel curve does not change the estimated consumption IGE much.

We discuss under what conditions using housing consumption as a proxy for total consumption leads to consistent estimates of the intergenerational elasticity of total consumption. There are two important considerations: (1) The relative intergenerational persistence of consumption and preference for housing, and (2) The informativeness of surnames on preferences for housing.

First, if we had run OLS - which is infeasible in our dataset - using housing consumption as a proxy for total consumption, the OLS coefficient would be biased downward due to the fact that the proxy is a (classical) error-ridden measure of the true regressor.[23] The use of last names solves the measurement error problem if last names are uncorrelated with housing preferences.

Second, consistency requires last names to be a "valid" instrument that is uncorrelated with housing preferences. In case last names are correlated with housing preferences, the estimate is a weighted average between the true elasticity of housing consumption and the intergenerational persistence of housing preferences. This leads to a downward bias if preferences are less persistent across generations than consumption (and vice-versa). As the formula makes clear in appendix B, a larger R-squared of the Engle curve regressions lead to a smaller bias (in the sense that more weight is then placed on the true parameter of interest β). Intuitively, if the R-squared is close to 1, measuring housing consumption is "almost as good" as observing total consumption. In that regard, it is encouraging–but far from

[23]We show the complete formula in appendix B. The attenuation bias may be canceled by another source of (upward) bias coming from potential intergenerational persistence in housing preferences.

perfect–that the Engel curve regressions have a reasonably large R-squared of 0.83 (Table OA.3).

There are precedents in the literature for imputing total consumption based on narrower categories. One such early example is Skinner (1987) who estimates a linear prediction of total consumption in the CEX based on housing consumption, utilities, number of automobiles and food at home and away from home. The coefficients from this regression are then used to impute total consumption in the PSID based on the same items. More recently, Blundell, Pistaferri, and Preston (2008) estimate a demand function for food expenditure in the CEX. They invert the estimated Engel curve to impute nondurable consumption in the PSID. They study inequality in consumption and derive conditions under which their proxy accurately measure trends in cross-sectional inequality. Our focus is on the covariance of consumption across generations.

5 Interpretation and Discussion

5.1 Interpreting Consumption IGE

We interpret the estimated consumption IGE through the lens of a canonical Euler equation.[24] Let i denote a dynasty, and t denote one generation (note that this is not an overlapping-generations framework). A parent generation maximizes the NPV of its own and future generations' flow utility $u(C)=\frac{C^{1-\eta}}{1-\eta}$, discounting future flows with discount factor δ_{it}, which varies between dynasties and generations. Given the generational frequency, δ_{it} is a combination of subjective discount factor ("patience") and altruism toward children. The parent maximizes the NPV of utility subject to:

$$W_{i,t+1}=(W_{it}+Y_{it}-C_{it})R_{it} \tag{17}$$

$$C_{it}\leq W_{it}+Y_{it} \tag{18}$$

where W_{it} is inheritance (both gift and estate), Y_{it} is income and R_{it} is total return, again varying between dynasties and generations. The inequality is a borrowing constraint (or a no-negative-inheritance constraint), with ξ_{it} as the Lagrange multiplier on the borrowing constraint.

Proposition 4. *IGE of consumption has the following first-order approximation:*

$$\frac{Cov\left(\log C_{i,t+1},\log C_{it}\right)}{Var\left(\log C_{it}\right)}\approx 1+\frac{\frac{1}{\eta}Cov\left(\log\delta_{it},\log C_{it}\right)}{Var\left(\log C_{it}\right)}+\frac{\frac{1}{\eta}Cov\left(\log R_{it},\log C_{it}\right)}{Var\left(\log C_{it}\right)}-\frac{\frac{1}{\eta}Cov\left(\log\left(1-\frac{\xi_{it}}{C_{it}^{-\eta}}\right),\log C_{it}\right)}{Var\left(\log C_{it}\right)} \tag{19}$$

[24] For example, Blundell and Preston (1998) use the Euler equation to study the relationship among income, consumption and welfare inequality.

The last term (including the negative sign) is likely to be negative, since $\log\left(1-\frac{\xi_t}{C_t^{-\eta}}\right)=0$ is the highest value, for unconstrained parents who are more likely to have higher levels of consumption also.

Corollary 5. *If $\delta_{it}=\bar{\delta}$ and $R_{it}=\bar{R}$ for all i,t and no borrowing constraint, the IGE of consumption ≈ 1.*

The corollary clarifies the random-walk intuition behind the consumption IGE in the frictionless benchmark: Because consumption is chosen by forward-looking agents who care about children and their children, parents would ensure their consumption advantage is passed down to their descendants.

Proposition 4 suggests deviations from this benchmark. The R_{it} term relates to positive correlation between income level and asset return (Fagereng, Guiso, Malacrino, and Pistaferri (2020)). Parents who have better technology to grow assets for their children leave more behind. With housing as one vehicle of wealth accumulation for middle class Americans, if higher-consumption parents also have access to levered housing portfolios, that would also increase the consumption IGE (Aaronson, Hartley, and Mazumder (2021)). As this simple model is a generational model, the δ_{it} term relates to both patience and altruism. For example, Mulligan (1997) micro-found a model of endogenous altruism that delivers a negative correlation between income and altruism, which would lower the consumption IGE. Borrowing constraints also lowers the consumption IGE as discussed above.

5.2 Conclusion

In this paper, we have estimated the intergenerational correlation of housing consumption across surnames in the United States between 1940 and 2015. We map these estimates into an estimated intergenerational elasticity of total consumption at the individual-level. We write down the assumptions under which surname-level correlations correspond to their individual counterpart. From this analysis, we conclude that it is potentially important to adjust for race when calculating the individual level elasticity using between last name variation. We also estimate heterogeneous elasticities by races and regions. Both the raw surname level estimates and our "adjusted estimates" show similar patterns across races and regions. Black Americans have much lower elasticities than White Americans. Though predicted 2015 consumption at the very bottom of the distribution - for a given level of 1940 consumption - is similar for Black and White Americans, the lower elasticity imply that richer Black families have much lower expected 2015 consumption than White families with similar level of 1940 consumption. The Northeast has much larger persistence - controling for race - than the other three regions including the South. This is a sharp reversal compared to the regional patterns found in the previous literature on intergenerational persistence of earnings. An open question is what drives this racial gap.

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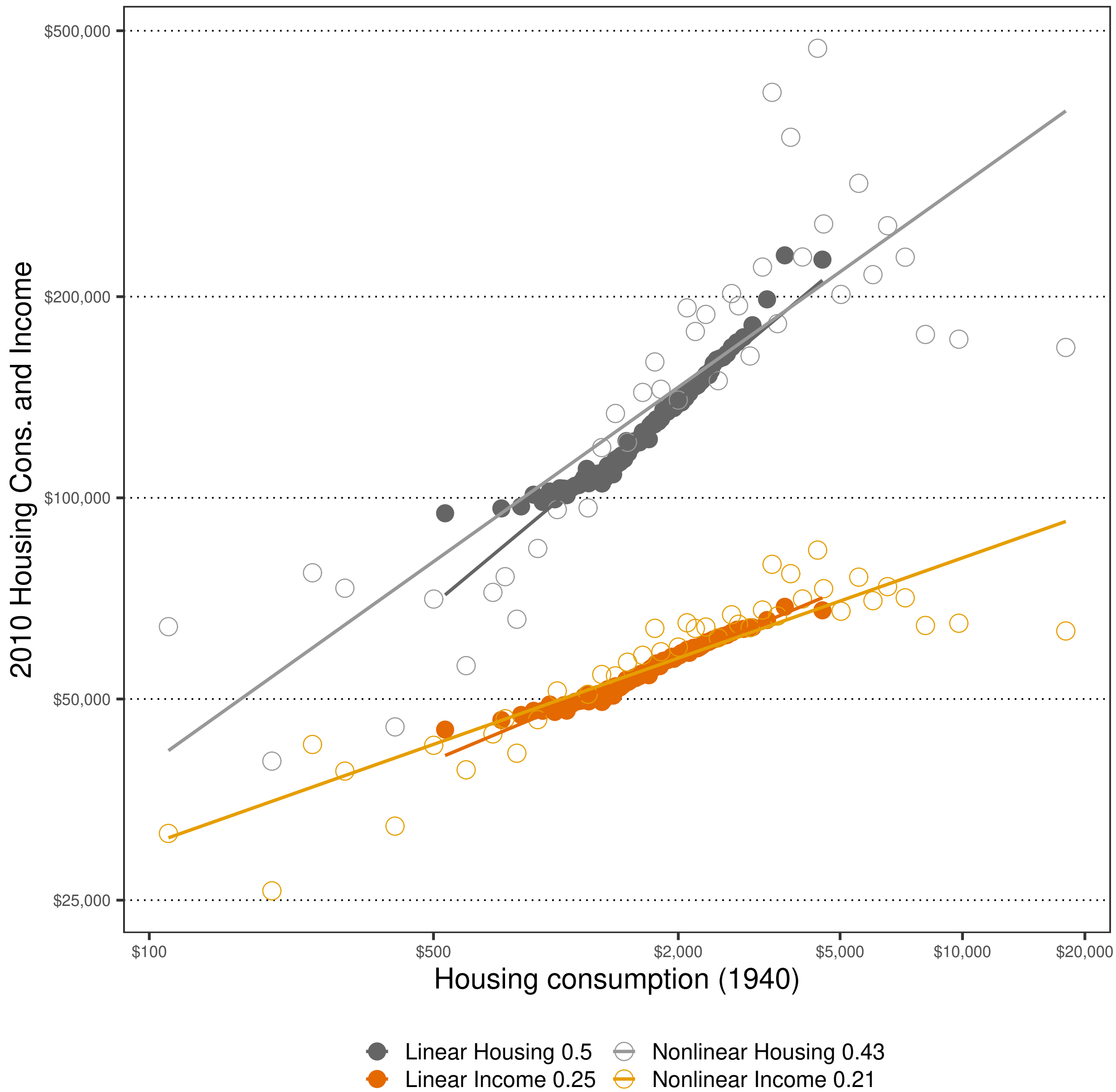
FIGURE I

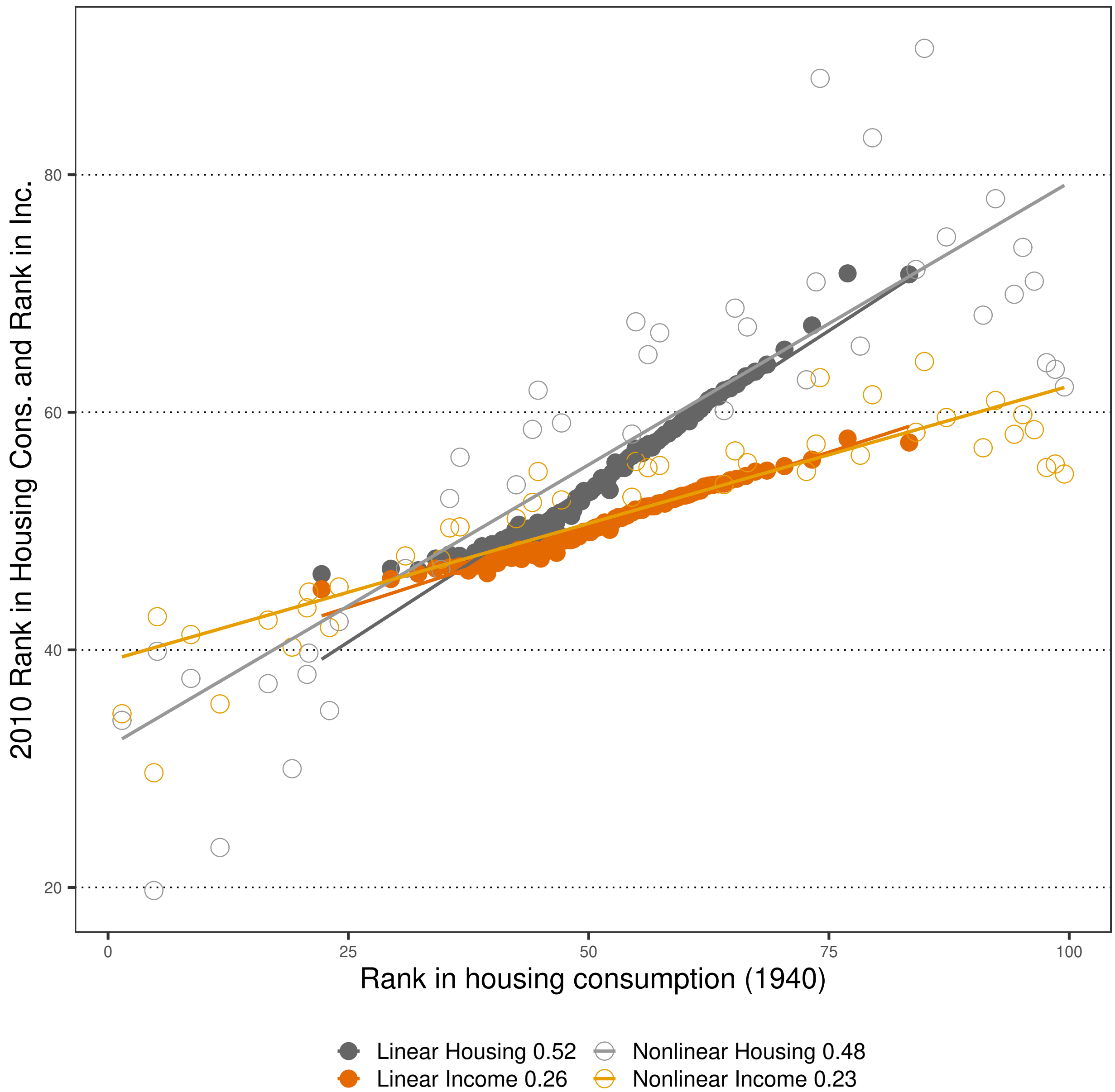
SURNAME-LEVEL LOG-LOG CORRELATIONS BETWEEN 1940 AND 2015



Notes. The figure displays binscatters corresponding to two specifications (linear and non-linear) for each of two outcomes: 2015 labor income and 2015 housing value. The linear specification simply regresses the outcome (in logs) on the (surname-) average log housing value in 1940. The non-linear specification regresses the outcome (in logs) on shares of male heads of households, in each surname, belonging to 100 percentiles of the 1940 distribution of housing value. The hollowed dots show the predicted 2015 outcome against the average 1940 log housing value for each percentile. The reported coefficient is the slope of a OLS regression through these 100 dots. All four reported coefficients are slopes of log-log specifications but units displayed on the x- and y-axes are converted to dollar values for ease of interpretation.

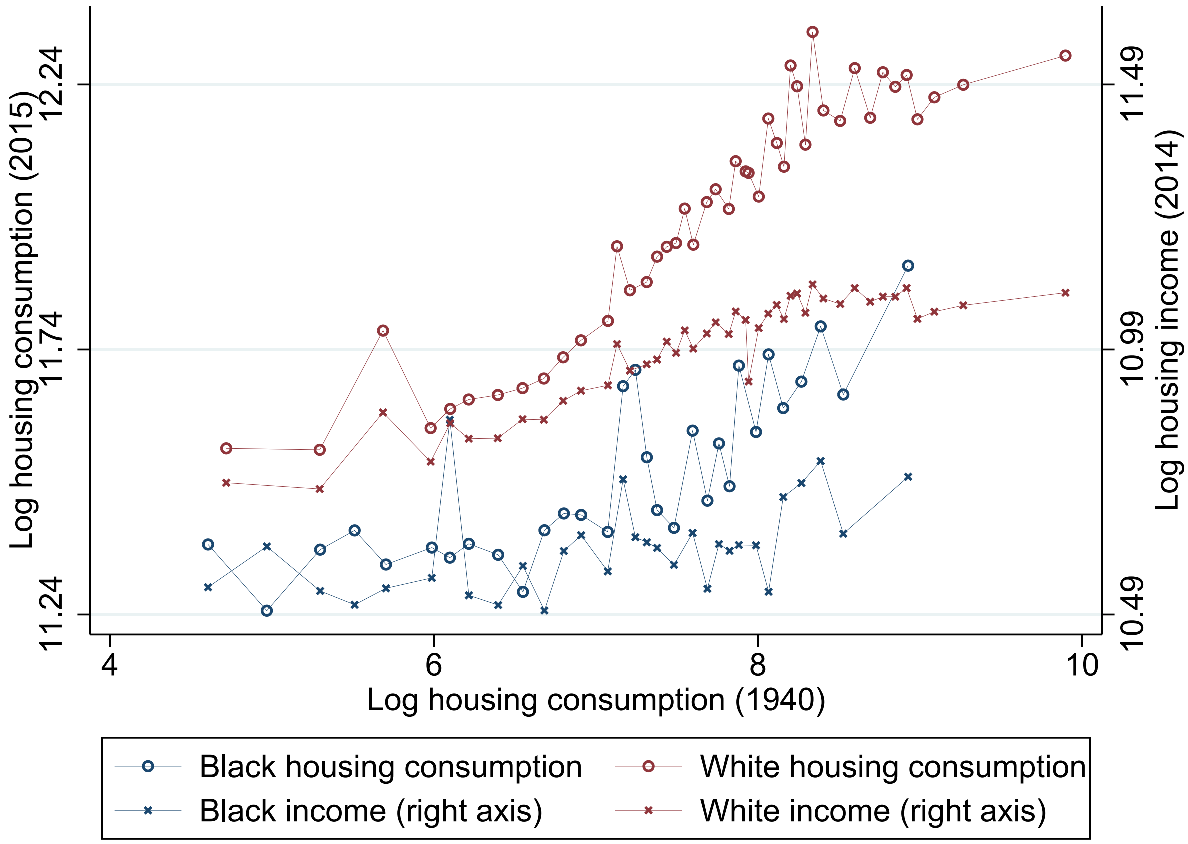
Figure II

Surname-level Rank-on-rank Correlations between 1940 and 2015



Notes. The figure displays binscatters corresponding to two specifications (linear and non-linear) for each of two outcomes: ranks in 2015 distribution of labor income and in 2015 distribution of housing value. The linear specification simply regresses the outcome on the (surname-) average rank in the 1940 distribution of housing value. The non-linear specification regresses the outcome on shares of male heads of households, in each surname, belonging to 100 percentiles of the 1940 distribution of housing value. The hollowed dots show the predicted 2015 outcome (rank) against the percentile in the 1940 distribution of housing value. The reported coefficient is the slope of a OLS regression through these 100 dots.

Figure III
Nonlinear IGE by Race

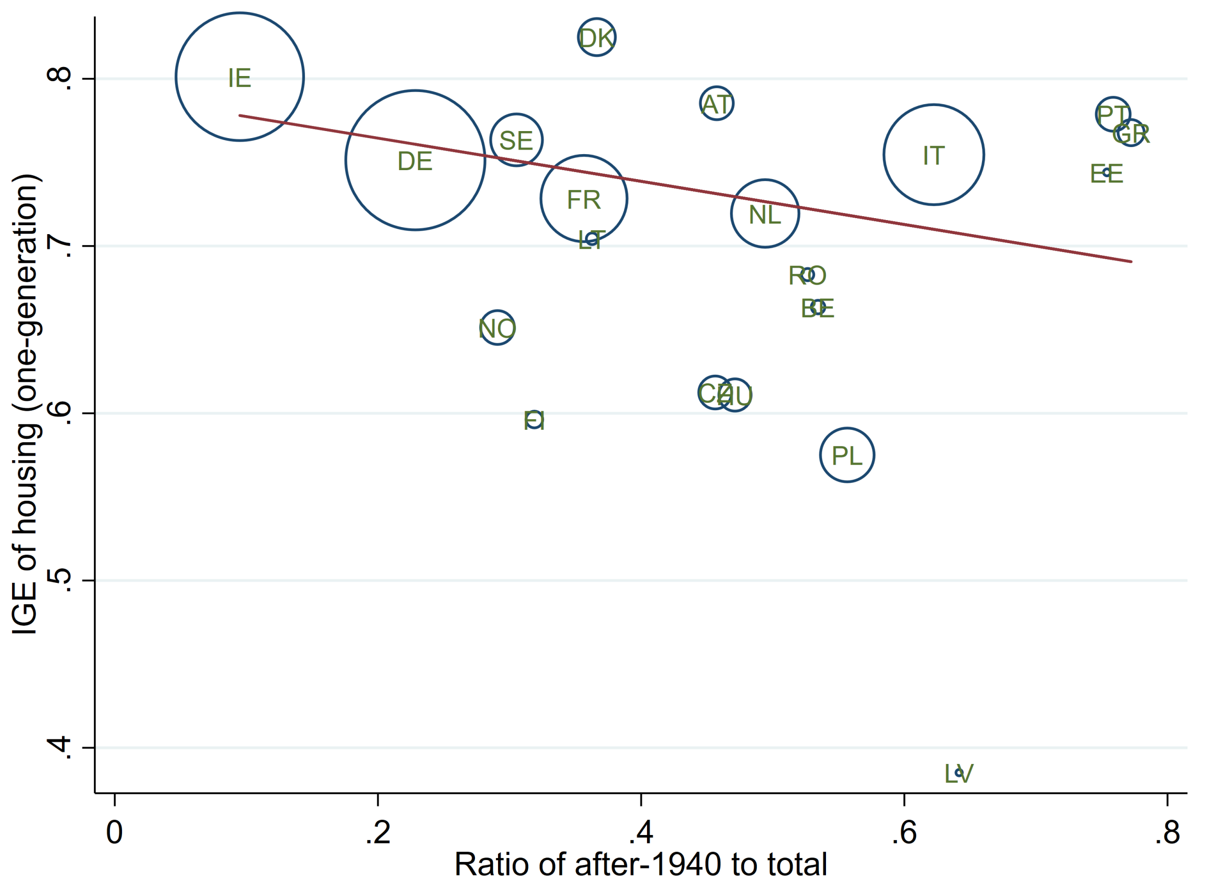


Notes. The figure plots coefficients from equation 7:

$$\tilde{x}^{y}_{\ell} = \sum_{g} \sum_{k=1}^{100} c^{k,g} \overline{P}^{o,k,g}_{\ell} + \tilde{v}_{\ell}$$

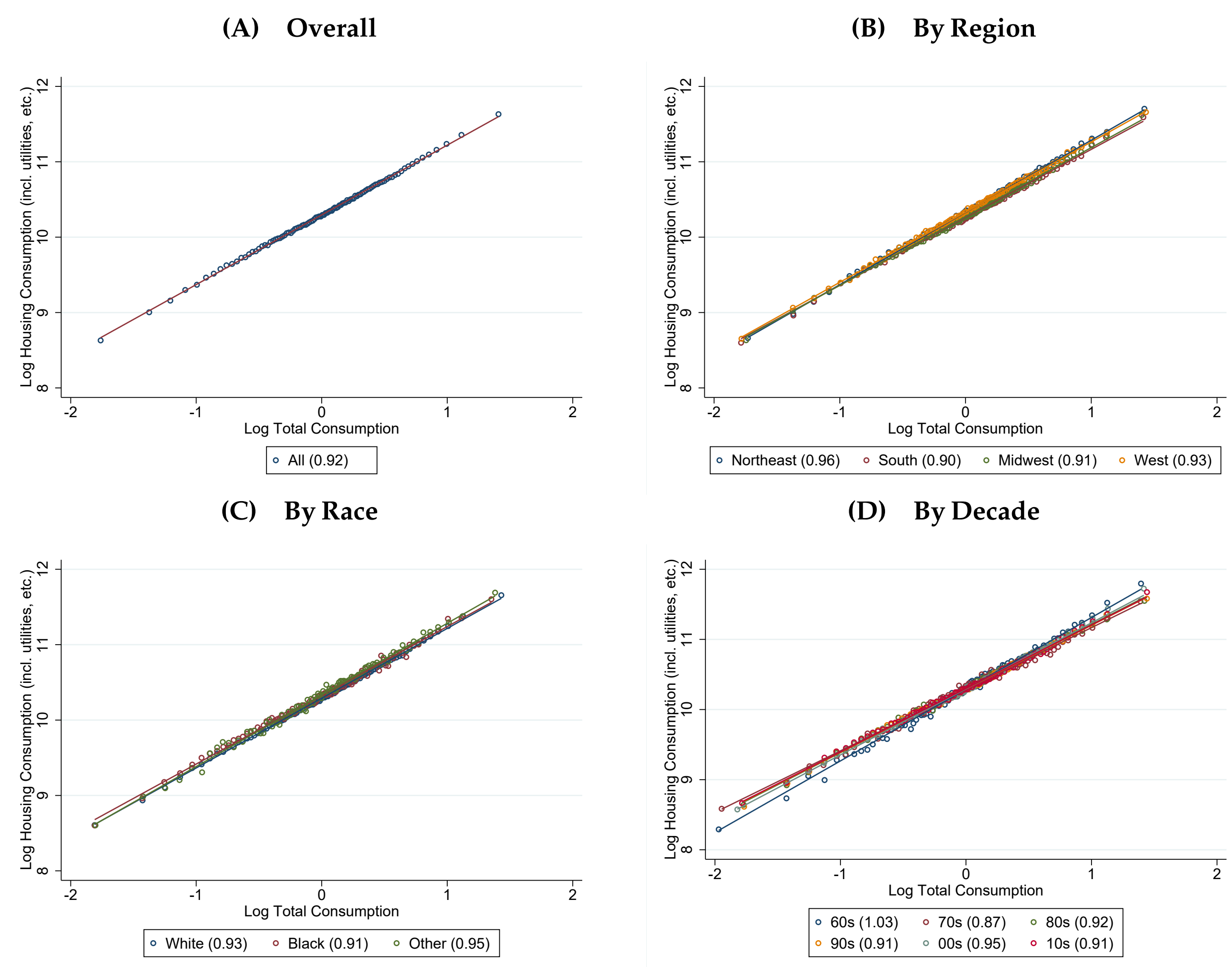
where the percentile share $\overline{P}^{o,k,g}_{\ell} \equiv \frac{1}{n_\ell} \sum_{i \in \ell} 1\left(\in k\text{th percentile by } x^{o}_{i} \cap \text{ in group } g\right)$ for each percentile $k \in \{1,2,...,100\}$, and the groups g are racial groups: Black, White and Other. That is, the regressors are shares of each surname belonging to a racial group and a percentile group by log housing consumption in 1940. The outcome variable is the surname-level average log housing consumption (in hollow circles and on the left axis) or average log income (in crosses and on the right axis). Coefficients for the 100 percentiles for Black and White groups are plotted in blue and red, respectively.

Figure IV
IGE of Housing Consumption by Surname Origin



Notes. The figure plots the surname-level correlation in average log housing consumption for subsets of surnames belonging to a single country of surname origin (equation 2), converted to a single-generation IGE, on the y-axis, against a rough measure of the amount of immigration into the US that happened after 1940. The size of the hollow circle is proportional to the number of individuals in 2015. Each country's ISO 3166 alpha-2 code is labeled in green. A population-weighted line of best fit is shown in red, with a slope of -0.129 (0.003). For more details on the estimates, refer to Appendix Table OA.2.

Figure V
Engel Curves for Housing Consumption



Notes. Each figure displays binscatter(s) and slope(s) of OLS regression(s) illustrating the relationship between housing consumption and total consumption (aka "Engel curves" of housing consumption). Figures (b)-(c) show this relationship in different subsamples and illustrate (the lack of) heterogeneity across them. Data are from the Consumer Expenditure Survey (1960, 1970, 1984-2016). The measure of housing consumption includes rent (or rent equivalent) as well as spending on utilities, housing services, etc. Each figure pools years 1959-1961, 1972-1973 and 1984-2016, includes year fixed effects, and includes controls for age, race, urban/rural and region. Slopes are displayed in parentheses.

Table I
Estimated IGE

	Slope Coefficient: b			
	(1)	(2)	(3)	(4)
Outcomes				
Housing on Housing	0.502	0.464	0.419	0.389
	(0.004)	(0.004)	(0.004)	(0.002)
Income on Housing	0.252	0.210	0.210	0.182
	(0.002)	(0.002)	(0.002)	(0.001)
Income on Income	0.303	0.211	0.278	0.145
	(0.005)	(0.002)	(0.003)	(0.002)
Rank Hous. on Rank Hous.	0.520	0.478	0.425	0.395
	(0.004)	(0.004)	(0.004)	(0.002)
Rank Inc. on Rank Hous.	0.259	0.221	0.213	0.190
	(0.002)	(0.002)	(0.002)	(0.001)
Covariates Adjustment				
Race		x		
Census Region			x	
Race by Census Region				x

Notes. Estimates of overall intergenerational mobility in the US (1940-2015) according to various specifications and outcomes. Each row corresponds to a different dependent and/or independent variable. Regressions are at the surname-level. Each column corresponds to a different set of covariates used to adjust the slope coefficient b. Observations are weighted by number of male heads of households. Standard errors are block-boostrapped at the surname-level.

TABLE II
ADJUSTED IGE: HETEROGENEITY - LOG-LOG RELATIONSHIPS

b^g Log Housing	Region				
	Northeast	*Midwest*	*South*	*West*	*All*
Race					
White	0.478 (0.006)	0.312 (0.003)	0.338 (0.004)	0.200 (0.004)	0.432 (0.003)
Black	0.273 (0.035)	0.167 (0.037)	0.176 (0.015)	0.154 (0.070)	0.172 (0.015)
Other	0.204 (0.023)	0.344 (0.020)	0.376 (0.015)	0.501 (0.014)	0.529 (0.011)
All	0.479 (0.006)	0.319 (0.004)	0.362 (0.005)	0.218 (0.004)	0.389 (0.002)

b^g Log Income	Region				
	Northeast	*Midwest*	*South*	*West*	*All*
Race					
White	0.098 (0.001)	0.103 (0.001)	0.115 (0.001)	0.093 (0.001)	0.102 (0.001)
Black	0.112 (0.005)	0.110 (0.005)	0.126 (0.003)	0.134 (0.011)	0.113 (0.003)
Other	0.105 (0.005)	0.107 (0.004)	0.125 (0.004)	0.121 (0.003)	0.154 (0.003)
All	0.113 (0.002)	0.123 (0.002)	0.179 (0.003)	0.104 (0.002)	0.145 (0.002)

Notes. Estimates of mobility in the US by race and Census region (1940-2015) for two outcomes: current log housing consumption (on 1940 log housing consumption) and current log labor income (on 1940 log labor income). Estimates are based on surname-level regressions adjusted for race by Census region. Observations are weighted by number of male heads of households. Standard errors are block-boostrapped at the surname-level.

Table III
Adjusted IGE: Heterogeneity - Rank-rank relationships

b^g Rank Housing	Region				
	Northeast	*Midwest*	*South*	*West*	*All*
Race					
White	0.459 (0.005)	0.281 (0.003)	0.356 (0.004)	0.144 (0.004)	0.416 (0.003)
Black	0.260 (0.042)	0.150 (0.042)	0.222 (0.023)	0.148 (0.084)	0.202 (0.021)
Other	0.117 (0.028)	0.379 (0.024)	0.516 (0.019)	0.636 (0.017)	0.656 (0.013)
All	0.459 (0.005)	0.292 (0.003)	0.395 (0.006)	0.179 (0.005)	0.395 (0.002)

b^g Rank Income	Region				
	Northeast	*Midwest*	*South*	*West*	*All*
Race					
White	0.193 (0.002)	0.136 (0.001)	0.154 (0.002)	0.129 (0.003)	0.190 (0.001)
Black	0.120 (0.020)	0.039 (0.024)	0.109 (0.013)	0.157 (0.049)	0.088 (0.012)
Other	0.055 (0.015)	0.223 (0.014)	0.228 (0.011)	0.286 (0.009)	0.275 (0.006)
All	0.198 (0.002)	0.141 (0.002)	0.192 (0.003)	0.144 (0.003)	0.190 (0.001)

Notes. Estimates of mobility in the US by race and Census region (1940-2015) for two outcomes: rank in distribution of current housing consumption and rank in distribution of current labor income. In both cases, the independent variable is the rank in the 1940 distribution of housing consumption. Estimates are based on surname-level regressions adjusted for race by Census region. Observations are weighted by number of male heads of households. Standard errors are block-boostrapped at the surname-level.

Table IV
Adjusted IGE of Consumption

b^g **Log Consumption**	*Northeast*	*Midwest*	*South*	*West*	*All*
White	0.416	0.328	0.364	0.305	0.401
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Black	0.294	0.264	0.318	0.291	0.315
	(0.015)	(0.017)	(0.008)	(0.032)	(0.009)
Other	0.317	0.329	0.368	0.427	0.412
	(0.011)	(0.011)	(0.010)	(0.010)	(0.008)
All	0.412	0.324	0.397	0.311	0.367
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)

Notes. Estimates of mobility in the US by race and Census region (1940-2015) for total consumption imputed from housing consumption. Estimates are based on surname-level regressions adjusted for race by Census region. Observations are weighted by number of male heads of households. Standard errors are block-boostrapped at the surname-level.

Appendix

A Proofs

A.1 Proposition 1

We work in matrix notations for ease of exposition. Let $X \equiv \begin{bmatrix} 1 & x_i^o \end{bmatrix}$ be the $N \times 2$ matrix of regressors in equation 1, $Y \equiv \begin{bmatrix} x_i^y \end{bmatrix}$ be the $N \times 1$ matrix, $Z \equiv \begin{bmatrix} z_i^1 ... z_i^L \end{bmatrix}$ be the $N \times L$ matrix of surname dummies, and W be the $L \times L$ diagonal weighting matrix where the ℓth diagonal element is $\frac{n_\ell}{N}$, where L is the number of surnames, n_ℓ is the number of families with surname ℓ and $N \equiv \sum_\ell n_\ell$ is the total number of families.

The estimators in equations 1 and 2 respectively are given by:

$$\begin{bmatrix} \alpha \\ \beta \end{bmatrix} = \left(X^T X \right)^{-1} X^T Y \tag{A.20}$$

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(X^T Z W Z^T X \right)^{-1} X^T Z W Z^T Y \tag{A.21}$$

Rearrange the sufficient condition in equation 9 in matrix notation (the first line of the matrix condition is true by construction):

$$X^T Z W Z^T \left(Y - X \left(X^T X \right)^{-1} X^T Y \right) \xrightarrow{p} 0 \tag{A.22}$$

Then using this condition:

$$\left(X^T Z W Z^T X \right)^{-1} X^T Z W Z^T Y \xrightarrow{p} \left(X^T Z W Z^T X \right)^{-1} X^T Z W Z^T X \left(X^T X \right)^{-1} X^T Y \tag{A.23}$$

$$= \left(X^T X \right)^{-1} X^T Y \tag{A.24}$$

A.2 Proposition 3

The family-level IGE β decomposes into the between- and within-group components as:

$$\beta = \frac{Var\left(\bar{x}_g^o \right)}{Var\left(x_i^o \right)} \bar{\beta} + \sum_g \frac{\frac{N_g}{N} Var_g\left(x_i^o \right)}{Var\left(x_i^o \right)} \beta^g \tag{A.25}$$

$$\bar{\beta} = \frac{Cov\left(\bar{x}_g^o, \beta^g \bar{x}_g^o + \alpha^g \right)}{Var\left(\bar{x}_g^o \right)} \tag{A.26}$$

mirroring equations 10 and 11 of the group-adjusted estimator in Definition 2, and α^g and β^g are defined in equation 5.

If $\begin{bmatrix} a^g \\ b^g \end{bmatrix} \xrightarrow{p} \begin{bmatrix} \alpha^g \\ \beta^g \end{bmatrix} \forall g$, then $\hat{b} \xrightarrow{p} \beta$ by the continuous mapping theorem.

The consistency of within-group estimators $\{\alpha^g, \beta^g\}$ follows similarly from the proof of Proposition 1. Matrices Y, Z and W are the same as above. Let $\hat{X} \equiv \begin{bmatrix} D_i^1 ... D_i^G & D_i^1 x_i^o ... D_i^G x_i^o \end{bmatrix}$ be the $N \times 2G$ matrix of regressors in equation 5, where G is the number of groups or partitions along which the mobility parameters are heterogeneous.

The $2G \times 1$ matrix of coefficients in equations in equations 5 and 6 respectively are given by:

$$\begin{bmatrix} \alpha^g \\ \beta^g \end{bmatrix} = \left(\hat{X}^T \hat{X}\right)^{-1} \hat{X}^T Y \tag{A.27}$$

$$\begin{bmatrix} a^g \\ b^g \end{bmatrix} = \left(\hat{X}^T ZWZ^T \hat{X}\right)^{-1} \hat{X}^T ZWZ^T Y \tag{A.28}$$

Following the exact same proof as above in equations A.23 and A.24 in Subsection A.1, the necessary and sufficient condition for the consistency of $\{\alpha^g, \beta^g\}$ is:

$$\hat{X}^T ZWZ^T \left(Y - \hat{X}\left(\hat{X}^T \hat{X}\right)^{-1} \hat{X}^T Y\right) \xrightarrow{p} 0 \tag{A.29}$$

Rewriting this condition in scalar form:

$$Cov_{n_\ell}\left(E\left[\eta_i | z_i^\ell\right], E\left[D_i^g x_i^o | z_i^\ell\right]\right) = 0 \quad \forall g \tag{A.30}$$

$$Cov_{n_\ell}\left(E\left[\eta_i | z_i^\ell\right], E\left[D_i^g | z_i^\ell\right]\right) = 0 \quad \forall g \tag{A.31}$$

The second condition is given by equation 14 of Proposition 3. Take the first condition:

$$Cov_{n_\ell}\left(E\left[\eta_i | z_i^\ell\right], E\left[D_i^g x_i^o | z_i^\ell\right]\right) = Cov\left(\eta_i, D_i^g x_i^o\right) - E_{n_\ell}\left[Cov\left(\eta_i, D_i^g x_i^o | z_i^\ell\right)\right] \tag{A.32}$$

$$= \sum_h Pr\left(D_i^h\right) E_{n_\ell}\left[Cov\left(\eta_i, D_i^g x_i^o | z_i^\ell, D_i^h\right)\right] \tag{A.33}$$

$$= Pr\left(D_i^g\right) E_{n_\ell}\left[Cov\left(\eta_i, D_i^g x_i^o | z_i^\ell, D_i^g\right)\right] \tag{A.34}$$

$$= Pr\left(D_i^g\right)\left[Cov\left(\eta_i, x_i^o | D_i^g\right) - Cov_{n_\ell}\left(E\left[\eta_i | z_i^\ell, D_i^g\right], E\left[x_i^o | z_i^\ell, D_i^g\right]\right)\right] \tag{A.35}$$

$$= Pr\left(D_i^g\right) Cov\left(\eta_i, x_i^o | D_i^g\right) \tag{A.36}$$

$$= Pr\left(D_i^g\right) E\left(\eta_i x_i^o | D_i^g\right) = 0 \tag{A.37}$$

where A.32 follows from law of total covariance, A.33 from orthogonality of η_i under BLP and law of total expectation, A.34 from definition of D_i^g, A.35 from law of total covariance, A.36 from the condition 13 of Proposition 3, first equality in A.37 from covariance formula, and the final equality in A.37 from BLP orthogonality:

$$Cov\left(\eta_i, D_i^g x_i^o\right) = E\left(\eta_i, D_i^g x_i^o\right) \tag{A.38}$$

$$= \sum_h Pr\left(D_i^h\right) E\left(\eta_i D_i^g x_i^o | D_i^h\right) \tag{A.39}$$

$$= Pr\left(D_i^g\right) E\left(\eta_i x_i^o | D_i^g\right) = 0 \tag{A.40}$$

with $Pr\left(D_i^g\right) \neq 0$ implying $E\left(\eta_i x_i^o | D_i^g\right) = 0$

A.3 Proposition 4

The household problem gives us the following Euler equation (suppressing the i subscript):

$$C_t^{-\eta} = \delta_t R_t E_t\left[C_{t+1}^{-\eta}\right] + \xi_t = \left(\delta_t R_t E_t\left[C_{t+1}^{-\eta}\right]\right)\left(\frac{1}{1 - \frac{\xi_t}{C_t^{-\eta}}}\right) \tag{A.41}$$

Take logs of both sides:

$$-\eta \log C_t = \log \delta_t + \log R_t + \log E_t C_{t+1}^{-\eta} - \log\left(1 - \frac{\xi_t}{C_t^{-\eta}}\right) \tag{A.42}$$

Take first-order approximation (to deal with log and expectation), then express expectation as:

$$\log C_{t+1} \approx \log C_t + \frac{1}{\eta}\log\delta_t + \frac{1}{\eta}\log R_t - \frac{1}{\eta}\log\left(1 - \frac{\xi_t}{C_t^{-\eta}}\right) + \nu_{t+1} \tag{A.43}$$

Taking covariance with $\log C_t$ and dividing by variance of it, across i:

$$\frac{Cov\left(\log C_{i,t+1}, \log C_{it}\right)}{Var\left(\log C_{it}\right)} \approx 1 + \frac{\frac{1}{\eta}Cov\left(\log\delta_{it}, \log C_{it}\right)}{Var\left(\log C_{it}\right)} + \frac{\frac{1}{\eta}Cov\left(\log R_{it}, \log C_{it}\right)}{Var\left(\log C_{it}\right)} - \frac{\frac{1}{\eta}Cov\left(\log\left(1 - \frac{\xi_{it}}{C_{it}^{-\eta}}\right), \log C_{it}\right)}{Var\left(\log C_{it}\right)} \tag{A.44}$$