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NEIGHBORHOOD WEALTH DISTRIBUTIONS [1]

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Abstract

This paper uses data from the neighborhood clusters sample of the 1989 American Housing Survey and the Panel Study of Income Dynamics and its 1989 wealth supplement to study the distribution of wealth within US residential neighborhoods. It uses the Bourguignon decomposable inequality index and finds that wealth is more unequally distributed than income, and income more than housing wealth, at all levels of aggregation, that is, neighborhoods, metropolitan areas, regions and the entire US.

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1 Introduction

Research in economics and sociology has drawn attention neighborhood sorting of individuals according to income and other characteristics. Following Tiebout (1956), individuals are seen to sort themselves into communities according to their preferences for local public services. While the literature in the Tiebout tradition has been able to explain income stratification across communities, it has also in a sense predicted too much stratification. This has been remedied by recent contributions, especially by the work of Epple and Platt (1998), Epple, Romer and Sieg (1999) and Epple and Sieg (1999). Epple and Platt show that if individuals differ with respect to income and an additional characteristic, then the resulting sorting at equilibrium is partial but incomplete. Individuals with identical incomes may be found in different communities at equilibrium, which accords with the facts. Since the additional characteristic could be a preference parameter, or a socioeconomic characteristic other than income, such an outcome would be consistent with a variety of motives. The determinants of residential sorting are important to policy makers as well. For example, local communities, state governments and even the U.S. government have staked out positions on the desirability of income (and ethnic) mixing in residential patterns and adopted policies to promote them.

This paper aims at a better understanding of the distribution of income and wealth within urban neighborhoods and contrasts them with the national income and wealth distribution. It uses the American Housing Survey neighborhood clusters data for metropolitan areas in the United States. Hardman and Ioannides (1998) and Ioannides (2001) also use the same data for studying neighborhood income distributions. Using US government definitions of income categories, Hardman and Ioannides describe the extent of income mixing in US residential neighborhoods, defined as comprised of a randomly selected household and ten nearest neighbors of the basic random sample. They find that low income households are widely represented in small neighborhoods: very low and extremely low income households are present, for example, in almost nine- tenths of all US neighborhoods. In three out of five neighborhoods sampled, the poorest two or three households (out of ten) come from the poorest 30 % of the population. High income households (the richest 30 %) are widely distributed. They are present in almost three fourths of all neighborhoods, and are represented by at least two or three households out of ten in about two in about two fifths of all neighborhoods. Most previous work on neighborhood sorting has used contextual information associated with the census tract where a unit of observation belongs. The importance of analysis at the micro neighborhood level is emphasized by the work of Thomas Schelling [Schelling (1971))].

If individuals differ with respect to many characteristics, observed imperfect sorting would be consistent with different behavioral patterns. Sorting according to income is particularly interesting. But, economic theory provides little or no guidance regarding sorting in terms of other characteristics on their own. Here we examine neighborhood sorting in terms of wealth. Differences among individuals in terms of income may not necessarily imply differences in terms of wealth. That is, neighborhoods may be mixed in terms of people of different ages, whose incomes differ because they happen to be on different points in the life cycles and but whose wealths might differ by less. Although it is known that wealth is more unequally distributed than income in the entire economy, it is not known what the level of inequality is at the local level.

The paper aims at mitigating a basic difficulty one encounters in studying neighborhood wealth distributions, which is due to unavailability of direct data. Micro data on housing wealth and debt are the only components of wealth that are available within the AHS. The paper exploits a fortuitous occurrence, that is, availability of data from on wealth, income and other socioeconomic characteristics from the Panel Study of Income Dynamics and its wealth supplement for 1989, which may be used to predict household wealth based on data on neighbors' characteristics in AHS. It then compares the distribution of income and wealth across neighborhoods, metropolitan areas, regions as well as the entire US.

Our comparisons rest on a decomposable inequality index due to Bourguignon [Bourguignon (1979); see also Shorrocks (1999)]. This index allows us to compare the contribution to total inequality of dispersion in income and wealth at different levels of geographic disaggregation.

The remainder of this paper is organized as follows. Section 2 outlines an intuitive model of neighborhood sorting. Section 3 discusses the data, where we explain how we combine data from both the American Housing Survey and the Panel Study of Income Dynamics. Section 4 presents the results and 5 concludes.

2 Neighborhood Sorting

We fix ideas and set notation as follows. Let $\mathcal{I}$ denote a set comprising of all individual members of the economy at each of the time periods when the data are collected, possibly very large, and let I denote the total population of the economy at the corresponding time, $I = |\mathcal{I}|$. Let $F(y)$ denote the distribution function of household income y in the entire economy. Suppose the population is distributed into N different geographical areas, neighborhoods, $\mathcal{I}_\nu,\ \nu = 1, \ldots, N$, each with population $I_\nu = |\mathcal{I}_\nu|$, and neighborhood distribution function F_ν, $\nu = 1, \ldots, N$. The decomposition of the population into neighborhoods is assumed to be exhaustive: $\mathcal{I} = \bigcup_{\nu=1}^{N} \mathcal{I}_\nu$. We will make this assumption for simplicity. In that case, the *the national income distribution,* is given by:

$$F(y) = \sum_{\nu=1}^{N} \frac{I_\nu}{I} F_\nu(y). \tag{1}$$

We shall say that the national income distribution exhibits *perfect mixing*, if all neighborhood income distributions are identical to the national one: $F_\nu(y) \equiv F(y),\ \forall \nu$. It exhibits *perfect sorting*, if the supports of the neighborhood income distributions do not overlap. E.g., in the simplest case where the $F_\nu(y)$'s are degenerate, then: $F_\nu(y) = 1, \text{if } \ y = y_\nu;\ F_\nu(y) = 0, \text{if } y \neq y_\nu, \forall \nu$, and where all the y_ν's are all different. The objective of decomposable inequality indices is to express an inequality measure for $F(\cdot)$ in terms of those for the $F_\nu(\cdot)$'s.

Why should income distributions differ across neighborhoods? To answer this question requires that we consider how individuals sort themselves into neighborhoods. Let individuals differ in terms of income y, and of a preference characteristic. In terms of the above notation, how do individuals allocate themselves) into N neighborhoods so as $F(y)$ decompose into the $F_\nu(y)$'s, as in Equ. (1)?

In the Epple and Sieg (1999) sorting model, individuals sort themselves into neighborhoods according to their evaluation of a neighborhood characteristic and of the price of housing in each neighborhood. If individuals do not differ in terms of their evaluation of the neighborhood characteristic, then the neighborhood income distributions are simply doubly truncated segments of the national distribution. The double truncation occurs because individuals have to choose from a discrete set of alternatives, indexed by housing prices. For any two neighborhoods characterized by different prices, there exists a value of income which makes an individual indifferent between the respective two alternatives. If, on the other hand, individuals' evaluations differ, the neighborhood income distribution extends over the entire support of the national income distribution, even if income and the individual preference characteristic are uncorrelated. That is, for each individual there exists a threshold value of income, which determines location between any two alternatives. Since the threshold depends on the individual's preference characteristic, even if it is uncorrelated with income, preference heterogeneity causes the truncation points to differ across individuals, thus producing a greater income dispersion within each neighborhood. As Hardman and Ioannides (1998) and Ioannides (2001) argue, neighborhood selection may cause bimodal neighborhood income distributions to emerge at equilibrium sorting. This is more likely to happen, the closer the neighborhood mean income is to mean national income.

This basic model of sorting can be extended to the case of individuals' differing with respect to other observable characteristics. Since several observable characteristics are good predictors of household wealth, our strategy is to use predictions of household wealth, obtained from micro data to infer properties of neighborhood wealth distributions.

2.1 Decomposable Measures of Inequality

In order to assess the importance of the neighborhood component of income and wealth distributions, it would be helpful to be able to measure inequality at every level of aggregation. The population-weighted decomposable inequality index proposed by Bourguignon (1979) allows exactly that. It is defined as the logarithm of the arithmetic mean minus the geometric mean of income, that is, the mean of the logarithms of income, within each grouping of the population. Proposition 4 in Bourguignon (1979) proves that this measure is the only differentiable, symmetric and zero-homogeneous in incomes *population-weighted* decomposable measure.[2] That is, the inequality measure for a group of size I_ν with incomes $(y_1, \ldots, y_j, \ldots, y_{I_\nu})$ is:

$$L_\nu(y_1, \ldots, y_j, \ldots, y_{I_\nu}) = \ell n \left(\frac{1}{I_\nu} \sum_{j=1}^{I_\nu} y_j \right) - \frac{1}{I_\nu} \sum_{j=1}^{I_\nu} \ell n y_j. \tag{2}$$

Concavity of the logarithm function ensures that the Bourguignon measure is positively valued; it is equal to zero for the case of equality. The higher its magnitude, the greater the inequality in the underlying distribution. The inequality index for a population consisting of groups of sizes

[2] Proposition 5 in *ibid.* proves that Theil's coefficient, also known as Theil's entropy measure, is the only decomposable *income-weighted* measure.

$\{I_1, \ldots, I_\nu, \ldots, I_N\}$ is given by:

$$L = \sum_{\nu=1}^{N} \frac{I_\nu}{I} L_\nu + L_N(\bar{y}_{I_1}, \ldots, \bar{y}_{I_1}, \ldots, \bar{y}_{I_\nu}, \ldots, \bar{y}_{I_\nu}, \ldots, \bar{y}_{I_N}, \ldots, \bar{y}_{I_N}), \tag{3}$$

where $\bar{y}_{I_\nu}$ denotes mean income in group ν, and $\sum_{\nu=1}^{N} I_\nu = I$. That is, the index for a population which consists of the N neighborhoods of sizes $\{I_1, \ldots, I_\nu, \ldots, I_N\}$ is defined as the average value of the index among all groups, the first term in the RHS of (3) plus the index defined for the entire population, with each individual being assigned the mean income for the group to which she belongs. The second term in the RHS of (3) may be written out as:

$$L_N = \ell n \left(\frac{1}{I} \sum_{\nu=1}^{N} I_\nu \bar{y}_{I_\nu} \right) - \frac{1}{I} \left(\sum_{\nu=1}^{N} I_\nu \ell n \bar{y}_{I_\nu} \right). \tag{4}$$

For small deviations, the measure may be approximated by the average relative deviations around the geometric mean, $\bar{y}^g = \frac{1}{I} \sum_{j=1}^{I} \ell n y_j$. That is: $\frac{1}{I} \sum_{j=1}^{I} y_j = \bar{y}^g \frac{1}{I} \sum_{j=1}^{I} \frac{y_j - \bar{y}^g}{\bar{y}^g}$. By taking logarithms, we have: $L \approx \frac{1}{I} \sum_{j=1}^{I} \frac{y_j - \bar{y}^g}{\bar{y}^g}$.

Here is why the decomposability of the Bourguignon measure is particularly useful in describing the contribution to inequality from hierarchical levels of aggregation.In our data, observations are classified into: Census regions, $r = 1, \ldots, R$; each region r contains $s = 1, \ldots, S_r$; MSAs, each MSA s contains $\nu = 1, \ldots, N_s$ neighborhood clusters; and, each cluster ν contains I_ν observations. That is, we may consider that (3) measures inequality within an SMSA s, in terms of the inequality within each neighborhood cluster $\nu = 1, \ldots, N_s$, where we apply (2), Therefore, inequality within a region r is made up of the sum of the mean inequality across all SMSAs in the region, $s = 1, \ldots, S_r$, plus the index defined for the entire set of SMSAs, with each SMSA being assigned the mean wealth for the group to which it belongs. Equ. (2) is used first, for each neighborhood cluster in the data, and then it is applied at the level of each SMSA according to (3) and (4). Then these computations are aggregated at the level of the region and then again for the entire country. Descriptive statistics for the Bourguignon measure across SMSAs and for aggregate measure for each of four regions are reported in Table 4. Decomposability, even after it has been generalized [Shorrocks (1980; 1999)] comes, unfortunately, at the price of exclusion of zero or of negatively valued variables.

3 Data

The empirical investigation reported here is based on data from the 1989 wave of the American Housing Survey (AHS) and on data from the 1989 wave of the Panel Study of Income Dynamics (PSID). We discuss first the AHS data and then the PSID data.

The AHS is a panel of housing units and involves more than 50,000 dwelling units that are interviewed each two years. This paper explores an additional dimension of the urban subsample of the data, namely data on neighborhood clusters, which are available for years 1985, 1989, and 1993. In those years only, a random sample of originally 680 (and subsequently more)urban units were selected and for each one of them a number of neighbor units, usually ten, were interviewed. Each such cluster includes the randomly chosen member of the national file (which is an urban AHS unit), the so-called *kernel,* and the neighboring units that have been interviewed. The cluster may contain fewer than 10 units if some could not be interviewed. The total number of observations for 1989 was 8433, however, only 7705 were usable for estimation purposes due to missing data. A basic set of descriptive statistics are given in Table 1. Among household heads, 84.1% are white, with an average age of 48.4 years, and 60.9% owner occupants. For additional details on the data, see Hardman and Ioannides, *op. cit.,* and Ioannides, *op. cit.*.

The AHS does not contain information on wealth. While we could pursue an analysis of dispersion of household characteristics within neighborhoods, we think that predicting the dispersion of wealth within and across neighborhoods provides a meaningful way to summarize dispersion in terms of a multitude of characteristics. We proceed by using data from another micro data, the PSID, which provides comparable detail in terms of socioeconomic characteristics. Both data sets' 1989 surveys provide 1988 data.

The PSID, begun in 1967, is a annual longitudinal survey of a representative sample of U.S. individuals and the households in which they live. The main (family) survey includes a variety of economic and demographic data, with emphasis on income sources and amounts, employment, and changes in family composition [Hill (1992)]. In 1989, but also in 1984 and in 1994, the PSID includes a supplement on household wealth. In this paper, we employ the 1989 main PSID data set and wealth supplement as a means of predicting wealth in the 1989 wave of AHS data including the neighborhood cluster survey. The 1989 main survey includes data from 7114 heads of household and their wives (if applicable). Referring again to Table 1, we see that 84.5% of respondents are white, 60.9% of respondents are home-owners, and their average age is 47.2 years. With regard to housing tenure, 54.1% own their home. Average real net wealth is $108,043, with a standard deviation of $8494. Unlike the AHS, the PSID main survey includes very limited contextual (geographical) data. Households are identified by state and county only. Hence, by using these data sets together, we are able to predict household wealth within much smaller geographic areas than we would be able to by using the PSID alone.

The computations of the Bourguignon measure of inequality for income and house value are straightforward, that for wealth generates a practical difficulty. Of 7114 observations nearly 10%, that 687 observations, are negatively valued and additional 675 observations have zero values for wealth. The mean negative value is $ -7,661. For these observations, the Bourguignon measure cannot be computed. In order to compute the Bourguignon measure without having to delete all observations with negative and zero values, we computed the measure by adding, alternatively, the values of $ 5000, $7500, $ 10000, $ 12500 and $15000. We report results with all those samples, which allows us to assess the sensitivity of this obviously arbitrary procedure.

4 Results

Real wealth is defined as assets minus liabilities. Assets include both financial assets and real assets like housing, etc. Letting Ω_i, Y_i, and X_i, denote, respectively, real wealth, income and a vector of socioeconomic characteristics for individual i. The basic regression we use to predict real wealth is:

$$\Omega_i = a_0 + a_1 Y_i + A X_i, \tag{5}$$

where a_0, a_1, are scalar parameters and A a vector of parameters. The vector of individual characteristics was limited to variables available in both data sets, to insure the most accurate predictions of wealth later on. In order to constrain our predictions of wealth to positive values, we carried out weighted OLS regressions in logs, and one Tobit regression, in which the dependent variable was truncated at a value of one and then logged. Regression results are reported in Table 2.

The OLS regressions produced reasonably good fits, with the fit worsening as the adjustment of the wealth measure increased. The Tobit regression, unfortunately, did not perform as well as we had hoped, both in terms of fit (R^2 of 0.13 versus 0.60) and signs of coefficients as expected. Home ownership, as might be expected, had the largest and most statistically significant effect on total net wealth in all regressions. Among other personal characteristics, age, sex, race, highest grade completed, and number of children had more modest, but significant, effects.[3]

Using the predicted values of wealth for individuals within neighborhoods, we calculated Bourguignon statistics aggregated at the SMSA, regional, and national level. The results can be found in Table 3, along with the Bourguignon statistics for income and housing value. As one would expect, the degree of mixing in all categories grew as the level of aggregation increased. Housing value showed the smallest amount of mixing at all levels, followed by income, and then total net wealth. No particular region showed greater mixing across categories than any other region. In our sensitivity analyses, the Bourguignon statistic for wealth decreased as the amount of the adjustment increased, implying that the closer the prediction of wealth gets to the "unbiased" prediction, the greater the dispersion of wealth at both the SMSA and regional levels.

5 Conclusion

Given that ours is the first study using decomposable indices to compare income and wealth mixing at various levels of aggregation, we are hard pressed to comment on the closeness of our results to the true measures of mixing. Hence we set these numbers out as a benchmark for future studies in the area of spatial economics as it relates to inequality. The results, however, do support the findings of Epple and Platt (1998) in that individual sorting by both income and wealth results in partial but incomplete sorting in both characteristics. Given that mixing is greater in wealth than in income, our findings thus do not support the hypothesis that the substantial income mixing [as found in Hardman and Ioannides (1998)] masks sorting on a secondary level, that of wealth. Work with more general measures, as proposed by Shorrocks (1999) and Foster and Shneyerov (2001), appears to be promising.

[3] Ideally, we would have liked to regress nonhousing wealth on housing wealth, income, and our vector of demographic characteristics, predict nonhousing wealth, and add that to the data on housing wealth that already exists in the AHS. Unfortunately, the AHS data on residual mortgages (or housing "debt") proved to be extremely unreliable in terms of the number of missing values/nonresponses.

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Table 1: Descriptive Statistics

PSID Descriptive Statistics, Weighted Values

Number of observations (*) = 7114

Mean	Estimate	Standard Error
assets89	124891.3	8552.468
rwlth89	108042.8	8494.309
rhouse89	47583.55	1146.364
equity89	33055.77	992.7519
nhasst89	77307.76	8191.085
nhwlth89	74987.02	8191.492
hdebt89	14527.77	452.7575
odebt89	2320.747	153.8509
rinc89	30682.47	665.5357
age89	47.16219	0.2874708
sex89	0.6804662	0.0074208
white89	0.8454902	0.0052153
marry89	0.5256161	0.0076463
widow89	0.1247432	0.0055283
divor89	0.1835509	0.006235
own89	0.6086501	0.007408
grade89	12.57423	0.0456688
retd89	0.1979552	0.0065327
child89	0.6687234	0.0144879
moved88	0.2146381	0.0061473
ne	0.2149494	0.0065462
so	0.3294724	0.0069362
west	0.179298	0.0058561

(*) Some variables contain missing values

key to variables:

assets89	gross worth
rwlth89	net worth
rhouse89	gross housing wealth
equity89	net housing wealth
nhasst89	gross nonhousing wealth
nhwlth89	net nonhousing wealth
hdebt89	mortgage debt
odebt89	other debt
rinc89	family money income
linc89	log of family income
own89	homeowner
grade89	highest grade completed
retd89	retired
child89	number of children
moved88	whether moved in past year
ne	northeast region
so	southern region
west	western region

AHS descriptive statistics

Number of observations = 7705

Variable	Mean	Std. Dev.
linc89	10.02168	0.9187738
rinc89	31741.52	25967.76
age89	48.39883	17.16288
sex89	0.6716418	0.4696464
white89	0.8407528	0.3659302
marry89	0.5645685	0.4958456
widow89	0.1117456	0.3150737
divor89	0.1671642	0.3731466
retd89	0.219987	0.4142644
own89	0.6093446	0.487929
grade89	12.71019	3.249648
child89	0.7358858	1.165193
moved88	0.2495782	0.432797
ne	0.2628164	0.4401921
so	0.2725503	0.4453003
west	0.2743673	0.4462239

Descriptive statistics for predicted wealth

Number of observations = 5168

Variable	Mean	Std. Dev.
5K adjustment	66186.00	62746.11
7.5K adjustment	68705.69	60261.22
10K adjustment	71666.92	58986.56
12.5K adjusment	74446.12	57924.33
15K adjustment	77929.20	57848.11

Table 2: Regression Results

	5K adjustment	7.5K adjustment	10K adjustment	12.5K adjustment	15K adjustment
linc89	0.2527	0.2322	0.2165	0.2091	0.2009
	(0.0476)**	(0.0445)**	(0.0421)**	(0.0401)**	(0.0386)**
age89	0.0464	0.0433	0.0432	0.0397	0.0379
	(0.0059)**	(0.0054)**	(0.0051)**	(0.0048)**	(0.0046)**
age2	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(0.001)**	(0.0001)**	(0.0001)**	(0.00004)**	(0.00004)**
sex89	0.1996	0.1707	0.1465	0.1284	0.1058
	(0.0495)**	(0.0467)**	(0.0421)**	(0.0401)**	(0.0368)**
white89	0.2706	0.2255	0.2224	0.1763	0.1604
	(0.0407)**	(0.0389)**	(0.0385)**	(0.0347)**	(0.0329)**
marry89	0.0350	0.0876	0.0753	0.0630	0.0690
	(0.0643)	(0.0607)	(0.0556)	(0.0523)	(0.0511)
widow89	-0.1425	-0.0906	-0.1194	-0.1275	-0.1309
	(0.0727)*	(0.0679)	(0.0639)	(0.0606)*	(0.0573)*
divor89	-0.2428	-0.1749	-0.1713	-0.1841	-0.1737
	(0.0549)**	(0.0515)**	(0.0457)**	(0.0445)**	(0.0411)**
retd89	0.0351	0.0168	0.0090	0.0115	0.0086
	(0.0581)	(0.0525)	(0.0498)	(0.0478)	(0.0460)
own89	1.3266	1.1729	1.0652	0.9953	0.9163
	(0.0447)**	(0.0401)**	(0.0374)**	(0.0360)**	(0.0330)**
grade89	0.1034	0.0981	0.0904	0.0871	0.0784
	(0.0221)**	(0.0202)**	(0.0187)**	(0.0182)**	(0.0169)**
grade2	-0.0003	-0.0004	-0.0004	0.0005	-0.0002
	(0.0010)	(0.0009)	(0.0008)	(0.0008)	(0.0008)
child89	-0.0702	-0.0624	-0.0529	-0.0537	-0.0498
	(0.0148)**	(0.0137)**	(0.0128)**	(0.0126)**	(0.0118)**
moved88	-0.0392	-0.0448	-0.0201	0.0079	-0.0016
	(0.0421)	(0.0380)	(0.0345)	(0.0327)	(0.0309)
ne	0.2418	0.2291	0.2244408	0.2109	0.1955
	(0.0448)**	(0.0413)**	(0.0391)**	(0.0381)**	(0.0363)**
so	0.0036	-0.0078	-0.0128023	-0.0115	-0.0174
	(0.0369)	(0.0346)	(0.0330)	(0.0309)	(0.0291)
west	0.2126	0.1827	0.1762174	0.1591	0.1540
	(0.0442)**	(0.0409)**	(0.0383)	(0.0368)**	(0.0344)**
constant	3.8505	4.4993	4.962486	5.3906	5.7664
	(0.4051)**	(0.3767)**	(0.3586)**	(0.3389)**	(0.3243)**
R^2	0.6020	0.5921	0.5855	0.5691	0.5667
N	6865	6917	6962	6983	6990

* significant at the 5% level
**significant at the 1% level
Dependent variable is log of wealth, with adjustments as indicated

Table 3: Bourguignon Statistics

	Income	Housing Value (rhouse>0)	Total Predicted Wealth 5K adj	Total Predicted Wealth 7.5K adj	Total Predicted Wealth 10K adj	Total Predicted Wealth 12.5K adj	Total Predicted Wealth 15K adj.
Northeast	0.43726	0.4158886	0.7381022	0.6210442	0.5365573	0.4745321	0.4239671
	(1546)	(724)	(1546)	(1546)	(1546)	(1546)	(1546)
South	0.5158966	0.3585368	0.7770654	0.655346	0.5699251	0.5018961	0.4515758
	(1236)	(591)	(1236)	(1236)	(1236)	(1236)	(1236)
West	0.4227946	0.401548	0.9555831	0.8032646	0.6909792	0.6111535	0.5463476
	(1519)	(660)	(1519)	(1519)	(1519)	(1519)	(1519)
Midwest	0.4388515	0.4024127	0.7303269	0.6158032	0.5326092	0.4674194	0.4183921
	(867)	(415)	(867)	(867)	(867)	(867)	(867)
Mean across Regions	0.4537007	0.3945965	0.8002694	0.6738645	0.5825177	0.5137503	0.4600706
Variance across Regions	0.0420884	0.0249204	0.1055422	0.0880311	0.0742197	0.0666146	0.0593196
	(4)	(4)	(4)	(4)	(4)	(4)	(4)
Entire Sample	0.6113116	0.3012571	1.141562	0.9626265	0.8332546	0.7358152	0.6594054
	(5168)	(2390)	(5168)	(5168)	(5168)	(5168)	(5168)
Mean across SMSAs	0.2680944	0.1865654	0.4296821	0.360368	0.3102671	0.2730156	0.2438591
Variance Across SMSAs	0.1508328	0.144781	0.2424982	0.2029802	0.1735408	0.1520774	0.1357082
	(98)	(96)	(98)	(98)	(98)	(98)	(98)

	PSID income	PSID Housing>0	PSID wealth	AHS income	AHS Housing>0	AHS Wealth 5K
Entire Sample	0.4322367	0.4017668	1.261708	0.3436985	0.3009472	0.5259857
(Not accounting for grouping)	(7114)	(3847)	(6942)	(7705)	(2965)	(7705)
				0.3485403		0.5587399
				(5168)		(5168)

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