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Income Transfers and Assets of the Poor

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Abstract

Contrary to the predictions of the standard life-cycle model, many low lifetime-income households accumulate little wealth relative to their incomes compared to households with high lifetime income. In this paper, I use data from the Panel Study of Income Dynamics and a correlated random-effects Generalized Method of Moments estimator to decompose the rich-poor wealth-to-permanent income gaps into the portions attributable to differences in characteristics such as labor-market earnings, income uncertainty, observed demographics, and the utilization of transfer programs which may have stringent income and liquid-asset tests, and to differences in the estimated coefficients on the respective characteristics. The results suggest that while wealth-to-permanent income ratios are increasing in permanent labor income and income uncertainty, transfer income, with or without asset tests, discourages liquid-asset accumulation. The decompositions indicate that most of the rich-poor wealth gap is attributable to differences in average characteristics and not coefficients. The leading factor driving the liquid wealth-to-permanent income gap between the rich and poor is asset-tested transfer income, while the primary factor driving the net worth-to-permanent income gap is labor-market earnings.

Income Transfers and Assets of the Poor

The standard life-cycle model of consumption and saving predicts that the wealth profile of the rich is simply a 'scaled-up' version of the wealth profile of the poor such that the wealth-to-permanent income ratios are similar across the lifetime income distribution. A regularly appearing result, however, is wealth-to-permanent income ratios for low-lifetime resource households that are significantly less than comparable ratios for high-lifetime resource households. One implication of this rich-poor wealth-to-permanent income gap might be inadequate financial preparation for retirement among the poor. Another implication might be an exacerbation of the distributional impacts of the recently enacted tax reform which expanded IRA and 401(k) contribution limits if it is the rich who primarily employ IRAs and 401(k)s as saving vehicles.

Several explanations have been proffered in the literature for the observed divergence in wealth-to-permanent income ratios between the rich and poor, ranging from the observation that saving rates rise with income (Dynan et al. 2000), to the possibility that income uncertainty and the attendant precautionary saving motive differs across the distribution (Carroll 1992, 1997; Deaton 1991; Dynan et al. 2000; Hubbard et al. 1995), to the presence of income-transfer programs for the poor that not only reduce income volatility but also impose benefit-eligibility tests based on the level of liquid assets (Hubbard et al. 1995), to the possibility that the poor are impatient or follow other time inconsistent preferences (Laibson 1997; Lawrence 1991). While much research has been conducted on each topic, often in isolation of the others, empirical work on decomposing the wealth-to-permanent income gap between the rich and poor to determine the relative importance of each potential factor is lacking.

In this paper, I use data from the Panel Study of Income Dynamics to estimate an expanded version of the buffer-stock saving model of Carroll and Samwick (1997, 1998), where the ratio of wealth-to-permanent income is modeled as a function of permanent labor income, permanent transfer income that is subject to liquid-asset tests, permanent transfer income that is not asset tested, income uncertainty, measured demographics such as race and marital status, and unobserved time-invariant heterogeneity. The unobserved heterogeneity is intended to capture such latent preferences as impatience. In order to identify differences in the asset accumulation process between the rich and poor, the sample is split into three groups—poor, near poor, and rich—based on the predicted probability of welfare receipt. Given the estimated parameters I decompose the rich-poor wealth-to-permanent income gaps into the portions attributable to differences in average characteristics and to differences in the estimated coefficients on the respective characteristics (Oaxaca and Ransom 1994).

Estimation of the wealth-to-permanent income model is complicated by the presence of asset-test transfer income, which is endogenous to wealth by virtue of the asset tests, by the presence of possible measurement error in the permanent income and income uncertainty regressors, and by the presence of unobserved heterogeneity. To deal simultaneously with the time-invariant endogenous regressors, measurement error, and latent heterogeneity, I employ a correlated random-effects Generalized Method of Moments estimator (Arellano and Bover 1995). This panel-data estimator achieves identification via the correlated random-effects assumption, whereby some characteristics are correlated with the unobserved heterogeneity and others are uncorrelated (Hausman and Taylor 1981). The identifying instruments are state-level income-transfer policies and labor-market conditions, which are assumed to be uncorrelated with idiosyncratic heterogeneity.

The results suggest that while wealth-to-permanent income ratios are increasing in permanent labor income and income uncertainty, transfer income, with or without asset tests, discourages liquid-asset accumulation. There are important differences in the wealth-to-permanent income processes across the poor, near poor, and rich. While there is evidence of an operative precautionary saving motive among the near poor and rich, there is no such evidence among the poor. In addition, within the group of poor and near poor, the wealth-to-permanent income ratio is increasing in permanent labor income, but not within the group of rich households. The decompositions indicate that most of the rich-poor wealth-to-permanent income gap is attributable to differences in average characteristics and not to differences in the degree of responsiveness to incentives and disincentives to save. Importantly, the leading factor driving the liquid wealth-to-permanent income gap between the rich and poor is asset-tested transfer income, while the key factor driving the net worth-to-permanent income gap is labor-market earnings.

II. Background and Empirical Model

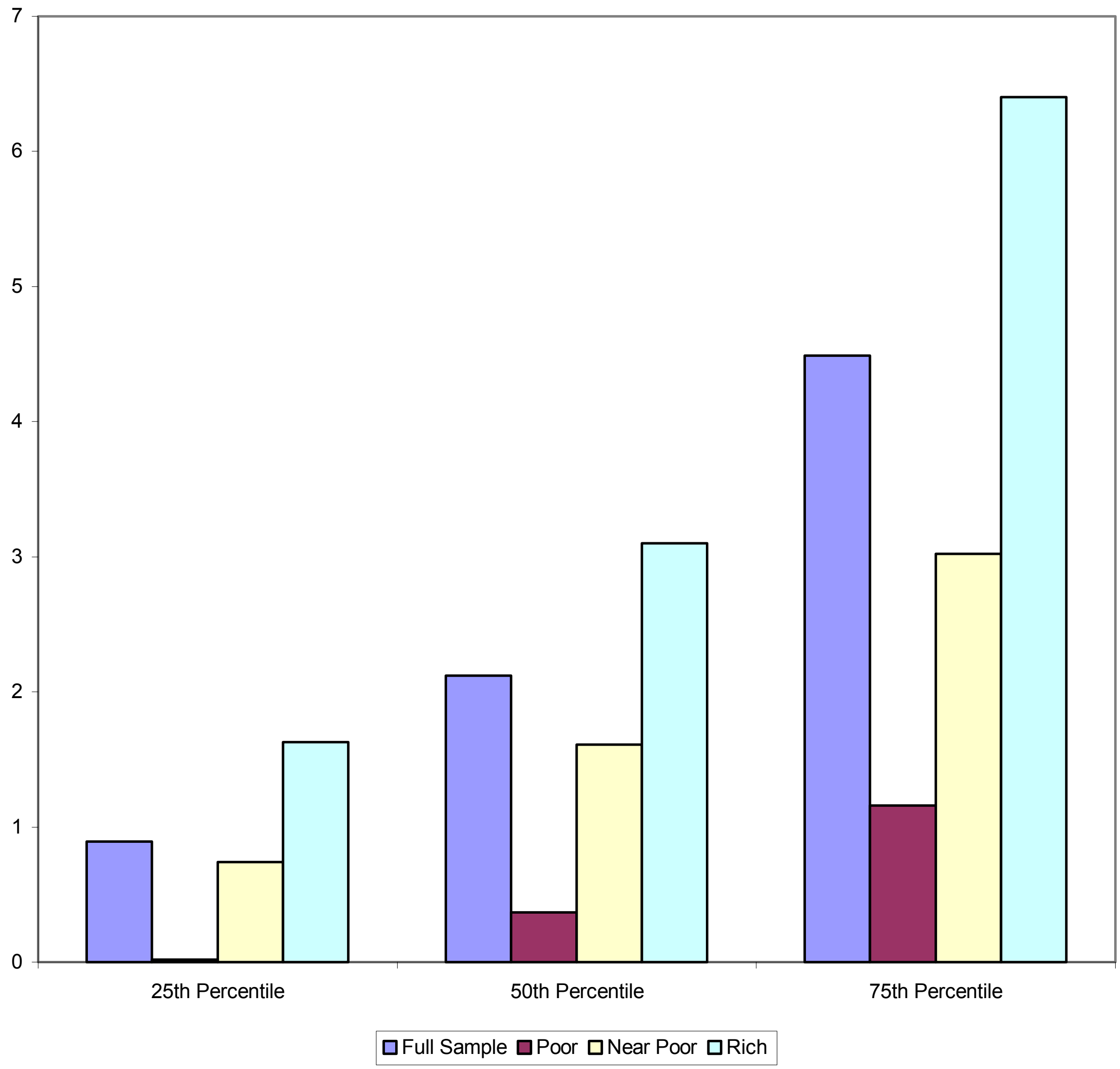
The wealth position of American families tends to be persistent (Browning and Lusardi 1996; Carney and Gale 1999; Hubbard et al. 1994; Hurst et al. 1998). As evidenced from Table 1, this persistence is most heavily concentrated in the tails of the distribution.[1] Over the five-year period from 1984 to 1989, 65 percent of households with net worth under $5,000 in 1984 still had net worth under $5,000 in real terms as of 1989. Likewise, 89 percent of households with initial net worth of over $100,000 maintained that position after five years. In and of itself, this persistence does not pose any problems provided that as a fraction of lifetime income these wealth profiles are roughly similar across the income distribution. Based on the net worth-to-permanent income ratios presented in Figure 1 this is clearly not the case. The ratios are not only

Table 1.—Persistence of Net Worth Between 1984 and 1989

		Net Worth 1989					
		< 5	5>, <10	>10, <30	>30,<50	>50,<100	>100
	<5	0.65	0.06	0.17	0.06	0.06	0.00
	>5,<10	0.25	0.00	0.50	0.25	0.00	0.00
Net Worth 1984	>10,<30	0.13	0.07	0.40	0.20	0.13	0.07
	>30,<50	0.00	0.00	0.14	0.36	0.36	0.14
	>50,<100	0.00	0.00	0.05	0.11	0.37	0.47
	>100	0.00	0.00	0.00	0.04	0.07	0.89

Note: Net worth is reported in $1000's. The number refers to the percentage of the sample in an initial 1984 category that falls in the corresponding category in 1989.

Figure 1.--Distribution of Net Worth-to-Permanent Income Ratios



higher for the rich compared to the poor and near poor, but the differences are increasing as one moves up the wealth-to-permanent income distribution from the 25th to the 75th percentiles.[2]

Several explanations have been proffered in the literature for the observed divergence in wealth-to-permanent income gaps between the rich and poor (Browning and Lusardi 1996; Venti and Wise 1998). One leading candidate is that saving rates tend to rise with lifetime income (Dynan et al. 2000). The permanent income hypothesis predicts higher saving with higher current income, but not lifetime income. If wealth-to-income ratios rise with lifetime income then the rising income inequality over the past twenty years in the United States, if permanent, is likely to lead to greater divergence over time in wealth holdings across the income distribution.

Another contender for the observed wealth-to-permanent income gap is income uncertainty and the attendant precautionary saving motive (Deaton 1991; Carroll 1992, 1997; Dynan et al. 2000; Hubbard et al. 1995). If households have precautionary saving motives, and income is uncertain, say due to concerns over health, mortality, or unanticipated business-cycle shocks, then wealth-to-permanent income ratios will rise with the level of income uncertainty. In order for income uncertainty to explain the observed wealth-to-income gap between the rich and poor it must be that either the rich face a higher level of income uncertainty and/or the rich have stronger precautionary saving motives such that their wealth-to-permanent income ratios are more responsive to a given change in income uncertainty. While the poor tend to face more acute health problems and to be located in more cyclically sensitive industries, it is possible for the rich to have a higher level of income uncertainty if capital income makes up sizable portion of their total income and it is highly volatile. Moreover, income transfer programs targeted to the poor and designed to reduce income volatility may weaken precautionary motives (Hubbard et al. 1995).

This leads to the next possible source of the wealth-to-income gap that has recently received a considerable amount of research attention; namely, the impact of transfer programs on saving when those programs not only reduce income volatility but may also impose stringent income and liquid-asset tests in order to qualify for benefits (Bird and Hagstrom 1999; Engen and Gruber forthcoming; Hubbard et al. 1995). While all social insurance programs (e.g. Unemployment Insurance and Workers Compensation) are designed to reduce income volatility, other programs such as Aid to Families with Dependent Children (AFDC) and food stamps also have explicit income and liquid-asset tests that must be passed for benefit eligibility.[3,4]

Hubbard et al. (1995) investigated the implications of asset-based means testing in a life-cycle simulation model of saving with earnings uncertainty and out-of-pocket medical expenditures. The latter assumptions play the dual roles of generating precautionary saving and of inducing a positive probability that not only the poor but the near poor as well may experience a sufficiently large negative shock that causes them to become poor and to take up welfare. However, with a 100 percent benefit reduction rate above the asset limit, the near poor, like the poor themselves, are compelled to hold few assets.[5] Several studies have recently produced empirical support for the hypothesis that asset tests are a disincentive to save (Gruber and Yelowitz 1999; Hurst and Ziliak 2001; Neumark and Powers 1998; Powers 1998). If the differences in the utilization of transfer programs across the income distribution are large, and the disincentives to accumulate assets out of transfer income acute, then these programs could be a large contributor to the wealth-to-permanent income gap.

Finally, significant differences in wealth-to-income ratios between the rich and poor may emanate from differences in time discount rates and other behavioral factors that affect saving preferences.[6] Some have suggested that the poor are 'impatient' (Lawrence 1991), or have time-inconsistent preferences (Laibson 1997), which if true then in the context of a buffer-stock model of saving these households are likely to maintain low target wealth-to-permanent income ratios (Carroll 1997; Deaton 1991). Carroll (2000) argued recently that perhaps it is not the poor who are so different from the typical household, but rather it is the rich who are different in that they may view wealth as a positional good; that is, it is not just a means to an end, but an end in and of itself. Each of the latter explanations reflects characteristics that are often viewed as 'unobserved' to the econometrician because they are difficult to quantify.[7] At the same time, heterogeneity that is readily quantifiable such as race, marital status, age, and geographic location may also affect saving preferences (Blau and Graham 1990; Charles and Hurst 2000; Chitegi and Stafford 1999). For example, if there is a black-white wealth gap, and black families are over-represented among the poor, then this could exacerbate the rich-poor wealth-to-income gap.

The latter discussion suggests factors that are likely to drive a wedge in the wealth-to-permanent income ratio between the poor, near poor, and rich—permanent labor and transfer income, income uncertainty, observed demographics, impatience, and other unobserved preferences to accumulate wealth. The econometric model I employ to capture these influences is based on the work of Carroll and Samwick (1997, 1998), who show that in a "buffer-stock" model of saving one can write the target log wealth-to-permanent income ratio as a linear function of uncertainty and other characteristics. Specifically, for each group *j* (*j*=poor, near poor, rich), the empirical specification is

$$\frac{W_{it}^{j}}{P_{i}^{j}} = \beta_1^j + \beta_2^j PTA_i^j + \beta_3^j PT_i^j + \beta_4^j PL_i^j + \beta_5^j \hat{\eta}_i^j + \beta_6^{j\prime} Z_i^j + \beta_7^{j\prime} X_{it}^j + \delta_k^j + \alpha_i^j + \upsilon_{it}^j, \quad (1)$$

where W_{it}^{j} is the log of wealth for person *i* (*i*=1,...,*N*) in time *t* (*t*=1,...,*T*), P_i^j is the log of permanent total income, PTA_i^j is the log of permanent transfer income that is subject to asset-tests, PT_i^j is the log of permanent transfer income not subject to asset tests, PL_i^j is the log of permanent labor income, $\hat{\eta}_i^j$ is a proxy measure of income uncertainty, Z_i^j is a vector of time-invariant demographics, X_{it}^{j} is a vector of time-varying demographics, δ_k^j is a vector of time-invariant state fixed effects designed to capture unobserved cross-state differences in saving behavior, α_i^j is a person-specific time-invariant factor that is intended to capture unobserved cross-person differences in saving behavior such as impatience or perhaps bequest motives, and υ_{it}^{j} is a random error term permitted to be conditionally heteroskedastic.[8]

III. Estimation Issues

The model in equation (1) contains two sources of latent heterogeneity, state-specific effects (δ_k^j) and person-specific effects (α_i^j). Controlling for state effects is readily handled with a vector of state dummy variables. Dealing with the person-specific heterogeneity is more complicated in the framework of equation (1) because if one assumes unrestricted correlation between α_i^j and the measured covariates, then with first-differences or the 'within' transformation one can no longer identify the time-invariant regressors (e.g. permanent labor and transfer income, income uncertainty, and the demographics contained in Z_i^j). An alternative is to assume that the unobserved heterogeneity is uncorrelated with the explanatory variables (i.e. a random effect), but this implies, for example, that unobserved time preferences have no correlation with labor-market earnings or transfer income. A compromise, then, is to adopt the 'correlated' random effects approach of Hausman and Taylor (1981) whereby some of the regressors are correlated with the individual effect and some are not correlated.

I adopt the correlated random-effects estimator developed by Arellano and Bover (1995), who recently unified this estimator within the Generalized Method-of-Moments (GMM) framework. Suppressing the *j* subscript and the state effects for notational simplicity, consider the following reformulation of equation (1)

$$\tilde{W}_i = D_i\Gamma + \varepsilon_i, \tag{2}$$

where $\tilde{W}_i$ is the $T \times 1$ vector of log wealth-to-permanent income for person *i*, $D_i = [\iota_T F_i', X_i]$ is the $T \times (G+P)$ matrix of regressors for person *i* in which ι_T is a $T \times 1$ vector of ones and $F_i = [1, PTA_i, PT_i, PL_i, \hat{\eta}_i, Z_i]$ is a $G \times 1$ vector of time-invariant regressors, $\Gamma = [\beta_1, ..., \beta_7]$ is a $(G+P) \times 1$ vector of unknown parameters to estimate, and $\varepsilon_i = \iota_T \alpha_i + \upsilon_i$.

To obtain consistent estimates of Γ, the idea is to find some nonsingular transformation, *C*, and a matrix of instruments, M_i, such that the moment conditions $E(M_i' C\varepsilon_i) = 0$ are satisfied. One possible transformation is

$$\begin{bmatrix} H \\ \iota_T' / T \end{bmatrix}, \tag{3}$$

where *H* is a $(T-1) \times T$ matrix containing the deviation-from-time mean transformation (i.e., ‘within-groups’), and ι_T' / T converts a variable into its time mean. Notice that *H* eliminates α_i from the first (*T*-1) rows, thus allowing the identification of the coefficients on time-varying regressors. The term, ι_T' / T, creates an equation in levels (i.e., ‘between-groups’), and permits identification of the coefficients on time-invariant regressors. For the instruments, Arellano and Bover suggest a block-diagonal instrument matrix of the form $M_i = I_T \otimes \left[d_i', d_i', ..., d_i', m_i'\right]$, where I_T is a $T \times T$ identity matrix, $d_i = (F_i, x_i)$ is a typical row from D_i and m_i is a subset of d_i

that is assumed to be uncorrelated in levels with α_i. Stacking the observations across all *i*, the GMM estimator is given as

$$\hat{\Gamma} = [D'\overline{C}'M(M\overline{C}\hat{\Omega}\overline{C}'M)^{-1}M\overline{C}D]^{-1}D'\overline{C}'M(M\overline{C}\hat{\Omega}\overline{C}'M)^{-1}M\overline{C}\widetilde{W}\,, \qquad (4)$$

where $\overline{C} = I_N \otimes C$, I_N is an $N \times N$ identity matrix, and $\hat{\Omega}$ is a conformable matrix with estimated squared residuals on the principal diagonal from a first-stage 2SLS regression.

A. *Identification*

The key to identification for correlated random effects is the choice of instruments that comprise m_i. It is important to emphasize that, unlike standard instrumental variables, identification does not come from exclusion restrictions outside of the system, but instead from inside the system via assumptions about correlation with α_i and, of course, υ_i. This implies the instruments are also permitted to have a direct effect on the wealth-to-permanent income ratio. In the current model, identification is complicated further by noting that several of the time-invariant regressors are also correlated with υ_i. It is clear that because of the liquid asset tests, wealth and permanent asset-tested transfer income are jointly determined. Moreover, permanent labor income, permanent non asset-tested transfer income, and income uncertainty are likely to be measured with error and thus should be treated as endogenous.[9]

Cornwell et al. (1992) proposed a classification scheme where the time-varying X_i are decomposed as $[X_{1i}, X_{2i}, X_{3i}]$ and the time-invariant F_i as $[F_{1i}, F_{2i}, F_{3i}]$. In this case X_{1i} and F_{1i} are called *endogenous* because they are correlated with both α_i and υ_i, X_{2i} and F_{2i} are called *singly exogenous* because they are assumed to be correlated with α_i but not υ_i, and X_{3i} and F_{3i} are called *doubly exogenous* as they are assumed to be uncorrelated with both α_i and υ_i. In the base case, I assume that there are no X_{1i}, X_{2i}, or F_{2i}. The latter assumptions are readily testable in the GMM framework using both Hansen's (1982) overidentifying restrictions test and the pseudo likelihood-ratio test of Eichenbaum et al. (1988).[10] It is the doubly exogenous X_{3i} that are critical for identification; that is, identification requires the number of time-varying doubly exogenous variables (X_{3i}) to be at least as large as the number of time-invariant endogenous variables (F_{1i}). Hausman and Taylor (1981) suggest one possibility for $m_i = [\bar{x}_{3i}, F_{3i}]$, where $\bar{x}_{3i}$ is the individual time-mean of the doubly exogenous X's.

As identifying instruments for the four regressors in $F_{1i} = [PTA_i, PT_i, PL_i, \hat{\eta}_i]$, I rely on time-varying state-level variables, which should be uncorrelated both with person-specific heterogeneity (α_i) and the overall equation error (υ_i), but correlated with the endogenous variable. Specifically, the maximum annual asset-tested transfer income is capped by the states such that a natural instrument for permanent asset-tested transfer income is the maximum AFDC/Food Stamp benefit. Permanent non asset-tested transfer income contains many components, one of which is Unemployment Insurance; consequently, I use the average potential Unemployment Insurance benefit to instrument this variable. State-level instruments for permanent labor income are less obvious, but one such candidate is the log of state personal income. Lastly, since income uncertainty is likely to be higher in states with higher unemployment rates, I use the natural log of state-specific unemployment rates as an instrument for uncertainty (Lusardi 1997).

Throughout the analysis, exogeneity of the state-level instruments is a maintained assumption; however, it is possible to gain further instruments at the household level. For example, Carroll and Samwick (1997, 1998) use education, occupation, and industry as identifying instruments for permanent income and income uncertainty. Because in the robustness section one of my sample-splitting variables is education, I do not include it in the instrument set due to lack of variation within subgroups. However, I include industry and occupation in X_{3i} as overidentifying instruments. Because the choice of industry and occupation may be correlated with unobserved heterogeneity in general (i.e. they might belong in X_{2i}), and impatience in particular, I test this categorization with the specification tests described above. Additional variables included in X_{3i} are age of the head and its square, family size, the number of children, union status of the head, and disability status of the head and wife. Variables included in F_{3i} are a constant, race, marital status, and geographic region. As a check on instrument quality for each of the endogenous regressors, I report the first-stage partial R^2 of instrument correlation. The partial R^2 (or the canonical correlation) is the appropriate statistic for instrument relevance in models with multiple endogenous variables (Shea 1997). Appendix Table A.1 contains a complete categorization of the explanatory variables and instrument sets.

IV. Data

The data come from the interview years 1980-1991 of the Panel Study of Income Dynamics (PSID). While later waves of data are available, 1991 is the last year the PSID staff generated tax-related information needed to construct disposable income. The sample is drawn from both the random Survey Research Center and the nonrandom Survey of Economic Opportunity subsamples, the latter of which over-samples low-income households. Because of over-sampling, researchers using the combined subsamples should weight the first and second moments of population statistics; however, much disagreement exists on the merits of weighting a regression model (Deaton 1997; Fitzgerald et al. 1998; Hoem 1989). Consequently, I weight the descriptive statistics using the family weight constructed by the PSID, but not the regression model.

The sample consists of a balanced panel of 1210 male and female household heads (14,520 person-years) aged 25-52 in 1980, the period in the life cycle where most pre-retirement asset accumulation occurs. I restrict attention to those household heads that do not change marital status over the sample period, i.e. they are either continuously married or continuously single.[11] Following households with stable heads will abstract from variations in wealth holdings due to major family compositional changes, but may dampen the potential disincentive effects of transfer income because part of the option value of marriage might be welfare participation.[12] Additionally, heads of household who in any given year are either in their pre-accumulation years (students), asset-decumulation years (retired), or significantly hindered in their labor-market activities (permanently disabled or institutionalized) are omitted.[13]

In 1984 and 1989 the PSID collected comprehensive data on net worth, including stocks, bonds, checking accounts, savings accounts, business equity, vehicle equity, and housing and other real estate equity.[14] Because the transfer programs that contain asset tests such as AFDC, food stamps, and Supplemental Security Income (SSI) impose the tests on liquid assets such as cash, checking and savings accounts, and vehicle equity I consider two definitions of wealth, liquid assets and net worth, where the former omits home and business equity.

For the purposes of this project net income is defined as the sum of labor earnings (inclusive of self-employment earnings), transfer income that imposes liquid asset tests (AFDC, food stamps, and SSI), and transfer income that does not impose such tests (unemployment insurance, workers compensation, veterans benefits, child support, gifts from relatives, and social security) less any tax payments (the latter includes the Earned Income Tax Credit). I include the income not only from the head of household, but also income of the spouse and/or other family members and possible subfamilies when present.[15] Because I follow the same household head for 12 years, I define 'permanent' income as the household-specific 12-year average.

In their study Carroll and Samwick (1998) defined income uncertainty as the log variance of log (detrended) income. I use a similar methodology and compute income uncertainty by estimating log earnings on observable demographics (such as age, education, race, health, marital status, occupation, industry, and a trend) and taking the time mean of the squared log residual to obtain an individual-specific average uncertainty measure. I focus on net income uncertainty in the regression model, but for descriptive purposes below I also compute uncertainty in terms of pre-tax and pre-transfer income.

Data on the state-level identifying instruments, that is the maximum AFDC/food stamp benefit for a three-person household, the potential UI benefit, the log of state personal income, and the log of state unemployment rate, come from various sources. The transfer policy variables are obtained from selected volumes of the Committee on Ways and Means' *Green Book*, and the Department of Health and Human Services' *Characteristics of State Plans for Aid to Families with Dependent Children*. In addition to the maximum AFDC/food stamp benefit, I also include the state AFDC gross-income limit, i.e. the cutoff point where the household's income surpasses the maximum allowed, as an instrument for asset-tested transfer income.[16, 17] Potential UI benefits are calculated using a detailed algorithm based on data from the Survey on Program Participation along with state-specific UI replacement rates (Gruber and Cullen 2000). State-level data on income come from the Bureau of Economic Analysis's Web site at http://www.bea.doc.gov/, and data on state unemployment rates come from the Bureau of Labor Statistics Web site at http://www.bls.gov/.

A final data task is devising a mechanism to split the sample into the poor, near poor, and rich. Ideally this mechanism is exogenous to the asset-accumulation process, but at the same time relevant to delineate differences in transfer-program utilization and income uncertainty. The primary approach taken here to measuring lifetime poverty risk is to predict the probability of being on welfare and computing the individual-specific time average over the sample period.[18] To that end, I predict the probability of receiving asset-tested welfare (i.e., welfare =1 if receiving either AFDC or Food Stamps) from a reduced-form probit regression on measured demographics.[19] I then split the sample based on the predicted probabilities into those at high risk of entering welfare (the poor), moderate risk of entering welfare (the near poor), and low risk of entering welfare (the rich).

Hubbard et al. (1995) delineate their sample into the poor, near poor, and rich as those household heads with less than high school, a high school diploma, and more than high school education, respectively. However, education is only one determinant of the risk of being poor, and it might be endogenous to the wealth accumulation process if it is viewed as another form of wealth or if it functions as a proxy for impatience as argued by Attanasio et al. (1999). For robustness I report the decompositions from both sample-splitting methods, and in order to isolate sample-composition effects from sample-size effects, the cutoff points for the predicted probabilities are chosen to yield identical sample sizes as with the education split. Appendix Table A.2 contains the point estimates from the probit model.

I conclude the data section by reporting selected descriptive statistics in Table 2 for the whole sample and separately for the poor, near poor, and rich.[20] The summary statistics reveal a striking disparity in the permanent net labor-market income between the poor, near poor, and rich—a disparity that is even more pronounced at the medians than at the means of the samples.

Table 2.—Selected Summary Statistics

	Pooled Sample	Poor	Near Poor	Rich
Permanent Net Labor Income	33.30 (25.86) {29.73}	15.92 (10.68) {11.91}	26.61 (11.63) {25.63}	42.06 (31.82) {36.80}
Permanent Asset-Tested Transfer Income	0.12 (0.66) {0.00}	0.84 (1.75) {0.05}	0.05 (0.22) {0.00}	0.01 (0.14) {0.00}
Permanent Non-Asset-Tested Transfer Income	0.93 (1.86) {0.28}	1.31 (1.68) {0.62}	1.02 (2.01) {0.32}	0.78 (1.76) {0.19}
Gross Labor Income Uncertainty	-2.21 (1.52)	-1.21 (1.75)	-2.96 (1.33)	-2.96 (1.39)
Net Labor and Transfer Income Uncertainty	-3.06 (1.39)	-2.89 (1.30}	-3.23 (1.33)	-3.17 (1.40)
AFDC Gross Income Limit	10.06 (3.13)	9.76 (3.13)	9.88 (3.15)	10.26 (3.09)
AFDC/Food Stamps Benefit	6.79 (1.41)	6.42 (1.45)	6.77 (1.38)	6.88 (1.42)
Female	0.17 (0.38)	0.59 (0.49)	0.24 (0.43)	0.02 (0.15)
Married	0.78 (0.42)	0.40 (0.49)	0.70 (0.46)	0.91 (0.28)
White	0.86 (0.35)	0.43 (0.50)	0.87 (0.34)	0.95 (0.22)
Age	43.66 (8.40)	41.54 (8.07)	42.50 (7.88)	44.99 (8.63)
# Households	1210	230	461	519

Note: The table reports means, standard deviations in parentheses, and medians in { }. Permanent is defined as the 12-year person-specific time mean. Income includes the income of head, spouse if present, and possible subfamilies if present. Poor refers to households at high risk of entering welfare, near poor are households at moderate risk of entering welfare, and rich are households at low risk of entering welfare.

Likewise there are substantial differences across groups in the permanent asset-tested transfer income, but those differences are much less acute for non asset-tested transfers. Also striking are the differences between the poor and non-poor in terms of gross labor-earnings uncertainty, and how those differences are largely mitigated (at least at the mean) with the inclusion of taxes and transfers.[21] This is suggestive that the consumption floor provided by transfers, coupled with reduced after-tax income volatility provided by the tax code, results in average levels of income uncertainty that are quite similar across the income distribution. Lastly, the table reveals that the poor tend to reside in states with significantly lower welfare benefits and gross-income limits than the non-poor, possibly because the poor tend to be concentrated in relatively low-income states overall, and that the poor are much less likely to be white or married.

V. Results

I present estimates of the GMM wealth-to-permanent income model in equation (1) first for the pooled sample, and then for the samples split by the predicted probability of welfare receipt. Two specifications are presented in each table, one based on liquid wealth and the other based on net worth. For brevity I only report results for the income variables and state transfer-program policies, but in addition each regression controls for a constant, a quadratic in age of the head, family size, number of children, state unemployment rate and income, dummy indicators for race, marital status, region, union status, health status, industry, and occupation, and state fixed effects. Both the partial R^2 for first-stage instrument relevance and Hansen's J-Statistic of overidentifying restrictions are presented for model fit. After describing the results from the asset-accumulation models, I then present wealth-to-permanent income decompositions.

A. *Pooled Sample*

In Table 3 there is evidence that asset-tested and non asset-tested permanent transfer income have a deterrent effect on liquid wealth-to-permanent income ratios, with the former also significantly negatively affecting net worth-to-income ratios. The elasticity of liquid wealth-to-permanent income with respect to permanent asset-tested transfer income is about –0.04, indicating that a 10 percent increase in benefit receipt results in a 0.4 percent decrease in liquid wealth-to-income. The comparable elasticity is about one-half the magnitude in the net worth regression. Because state welfare programs only tax liquid assets when determining eligibility, it is not surprising to find a more pronounced effect on liquid assets. Likewise, with respect to non asset-tested transfers we might expect the larger effect on liquid assets since receipt of UI is often temporary and not likely to result in changes in large wealth holdings such as the home. Given the larger elasticity (in absolute value) associated with asset-tested transfers, these results indicate that not only does the presence of the consumption floor reduce incentives to accumulate wealth relative to income, but that the presence of asset tests reinforces those disincentives.

Consistent with the findings of Dynan et al. (2000) who examined saving rates, the estimates in Table 3 indicate that wealth-to-permanent income is increasing in permanent labor-market income, particularly net worth accumulation. A 10 percent increase in permanent labor-market income leads to a 1.2 percent increase in the net worth-to-permanent income ratio. Moreover, from the income uncertainty coefficients there is evidence of an operative precautionary saving motive, both with respect to liquid assets and to net worth. Because the coefficient is hypothesized to be positive, based on a one-tailed test the uncertainty terms are statistically significant at the 7 and 5 percent levels for liquid assets and net worth, respectively.

Table 3.—GMM Estimates of Log Wealth to Permanent Income Ratios for the Pooled Sample

	Liquid Assets	Net Worth
Permanent Asset-Tested Transfer Income	–0.0452	–0.0238
	(0.0152)	(0.0132)
	[0.1016]	[0.1016]
Permanent Non Asset-Tested Transfer Income	–0.0191	–0.0069
	(0.0094)	(0.0084)
	[0.0876]	[0.0876]
Permanent Net Labor Income	0.0876	0.1216
	(0.0436)	(0.0357)
	[0.1620]	[0.1620]
Net Labor and Transfer Income Uncertainty	0.0426	0.0403
	(0.0278)	(0.0241)
	[0.0928]	[0.0928]
AFDC/Food Stamps Benefit	–0.1812	–0.0511
	(0.0801)	(0.0631)
AFDC Gross Income Limit	–0.0157	0.0061
	(0.0346)	(0.0275)
UI Benefit	–0.0429	–0.0957
	(0.0605)	(0.0467)
J-Statistic	50.07	59.68
	{54, 0.63}	{54, 0.28}

Notes: Heterskedasticity robust standard errors are reported in parentheses, and partial R^2's for the first-step of instrument correlation are reported in square brackets. The J-Statistic is Hansen's test of the overidentifying restrictions. The regression controlled for a constant, a quadratic in age of the head, family size, number of children, state unemployment rate and income, dummy indicators for race, marital status, region, union status, health status, industry, and occupation, and state fixed effects. All wealth and income variables are in natural logs, with non-positive values of wealth set equal to zero. There are 2420 person years.

Table 3 also reveals that increasing the consumption floor via the AFDC/Food Stamp maximum benefit guarantee serves as a disincentive to accumulate liquid wealth relative to permanent income, which is consistent with the Hubbard et al. (1995) hypothesis. A 10 percent increase in the consumption floor leads to a 1.8 percent reduction in the liquid wealth-to-permanent income ratio, but to only a 0.5 percent reduction in net worth. Because of the stronger effect on liquid wealth, this suggests that the maximum benefit is also capturing some aspects of the liquid-asset test. Regardless of wealth measure, AFDC gross income limits have no effect on asset accumulation, while the potential UI benefit has a statistically significant negative effect on net worth-to-permanent income, but surprisingly no effect on liquid assets.

B. *Split Samples*

In Table 4 I present the results of liquid- and net worth-to-permanent income regressions for the poor, near poor, and rich. As evidenced from the table there is substantial heterogeneity in the wealth-to-income processes across the lifetime income distribution. The disincentive effect of accumulating liquid wealth relative to income out of asset-tested transfers is acute among the poor, but there is no statistical evidence of such an effect among the near poor and the rich. In addition, there are diverse responses to non asset-tested transfers across the samples. The poor respond to higher non asset-tested transfers by increasing their wealth, while the near poor respond with a strong negative effect. One plausible explanation for this outcome is that the poor who tend to receive transfers such as Unemployment Insurance or Workers Compensation have a relatively strong labor-force attachment and are at the high end of the wealth distribution within that sub-group. Meanwhile, the near poor who are likely to receive non asset-tested transfer income likely have a comparatively weaker labor-force attachment and are at the low end of the wealth distribution for the near poor as a whole. These results suggest that the near

Table 4.—GMM Estimates of Log Wealth to Permanent Income Ratios for the Poor, Near Poor, and Rich

	Liquid Assets			Net Worth		
	Poor	Near Poor	Rich	Poor	Near Poor	Rich
Permanent Asset-Tested Transfer Income	–0.0331	–0.0228	–0.0376	–0.0136	–0.0031	–0.0386
	(0.0141)	(0.0251)	(0.0467)	(0.0143)	(0.0181)	(0.0308)
	[0.2517]	[0.0792]	[0.0613]	[0.2517]	[0.0792]	[0.0613]
Permanent Non Asset-Tested Transfer Income	0.0240	–0.0404	–0.0155	0.0343	–0.0139	–0.0061
	(0.0160)	(0.0125)	(0.0103)	(0.0161)	(0.0090)	(0.0057)
	[0.1934]	[0.1429]	[0.0899]	[0.1934]	[0.1429]	[0.0899]
Permanent Net Labor Income	0.1512	0.1735	–0.0002	0.1816	0.1274	–0.0110
	(0.0434)	(0.0939)	(0.0549)	(0.0423)	(0.0588)	(0.0315)
	[0.3112]	[0.1991]	[0.2512]	[0.3112]	[0.1991]	[0.2512]
Net Labor and Transfer Income Uncertainty	–0.0214	0.0499	0.0357	–0.0247	0.0324	0.0418
	(0.0370)	(0.0333)	(0.0245)	(0.0354)	(0.0251)	(0.0139)
	[0.1899]	[0.1048]	[0.1142]	[0.1899]	[0.1048]	[0.1142]
AFDC/Food Stamps Benefit	–0.1480	–0.1209	–0.0829	0.0077	–0.0245	0.0305
	(0.1993)	(0.1259)	(0.0907)	(0.2112)	(0.0944)	(0.0503)
AFDC Gross Income Limit	–0.0261	0.0253	–0.0130	–0.1606	0.0315	–0.0366
	(0.1084)	(0.0550)	(0.0377)	(0.0949)	(0.0411)	(0.0230)
UI Benefit	–0.3190	–0.0681	0.0558	–0.1463	–0.0920	0.0395
	(0.1841)	(0.0978)	(0.0697)	(0.1922)	(0.0759)	(0.0362)
J-Statistic	51.39	45.00	55.09	58.68	70.41	49.67
	{54, 0.58}	{54, 0.80}	{54, 0.43}	{54, 0.31}	{54, 0.07}	(54, 0.64}

Notes: Heterskedasticity robust standard errors are reported in parentheses, and partial R^2's for the first-step of instrument correlation are reported in square brackets. The J-Statistic is Hansen's test of the overidentifying restrictions. The regression controlled for a constant, a quadratic in age of the head, family size, number of children, state unemployment rate and income, dummy indicators for race, marital status, region, union status, health status, industry, and occupation, and state fixed effects. There are 460, 922, and 1038 person years in the poor, near poor, and rich samples respectively. Wald tests reject the null hypothesis that the coefficients are pairwise the same across the groups at the 0.00, 0.00, and 0.10 levels for the poor-vs-near poor, poor-vs-rich, and near poor-vs-rich in liquid asset models, and 0.00, 0.00, and 0.00 levels in net worth models.

poor reduce their wealth-to-income ratios in response to consumption floors in general, but contrary to the prediction of Hubbard et al. (1995) there is no evidence that they reduce the ratio in response to asset-tested transfers.[22]

Importantly, while wealth-to-permanent income ratios among the poor and near poor tend to rise with permanent labor-market income, there is no evidence of this among the rich. Hence, while overall wealth-to-income ratios do tend to rise with lifetime income, among the population with the lowest risk of becoming poor and taking up welfare these ratios do not respond to further gains in lifetime income. This suggests that relative to their permanent incomes the poor and near poor are actively accumulating assets out of net additions to labor-market earnings.[23]

Also striking is that whereas the near poor and rich demonstrate precautionary saving motives out liquid and illiquid forms of wealth holdings, wealth-to-permanent income ratios among the poor do not respond to uncertainty. As noted in Table 2, gross labor income uncertainty among the poor is substantially higher than among the near poor and rich, but once one factors in transfer income and nets out tax liability the level of uncertainty across the distribution is roughly comparable. It is plausible that the social safety net proxies for precaution among the poor, thereby mitigating the need to accumulate wealth relative to income for unforeseen contingencies. That said, with the exception of potential UI benefits in the liquid-wealth model of the poor, and AFDC gross-income limits in the net worth model of the poor, the impact of transfer program policies on wealth-to-permanent income ratios do not appear to differ significantly across the distribution.

C. *Decomposing Wealth-to-Permanent Income Gaps*

Taken as a whole, the poor, near poor, and rich respond differently to economic incentives and disincentives to accumulate wealth relative to permanent income. Indeed, Wald tests soundly reject the null hypothesis that the coefficients are pairwise the same across the three groups (in most cases at 0.00 level). This is in contrast to the standard, homothetic life-cycle model of consumption and saving which would predict that the coefficients would be jointly equal to zero and equal to each other. In this section the objective is to understand the relative contributions of the various factors driving a wedge between the rich and the poor; that is, to decompose the rich-poor wealth-to-permanent income gap into differences in average characteristics such as labor-market earnings, income uncertainty, observed demographics, and the utilization of transfer programs, and to differences in estimated coefficients from Tables 3 and 4.

The method employed to decompose the wealth-to-permanent income gaps is based on the work of Oaxaca and Ransom (1994), who used the approach to study wage discrimination. Specifically, recall the notation from equation (2) where $\tilde{W}_i$ represents the log wealth-to-permanent income for household *i*, D_i is the matrix of characteristics, and $\hat{\Gamma}$ the vector of estimated coefficients. In the absence of differences between the poor, near poor, and rich the estimated wealth-to-permanent income process would be well approximated by the estimated coefficients in Table 3. This suggests that in examining the gaps between the poor and near poor, the poor and rich, and the near poor and rich the appropriate set of reference coefficients are those estimated from the pooled sample.[24]

The difference in average log wealth-to-permanent income ratios between any two groups can thus be decomposed as

$$\overline{\tilde{W}}_j - \overline{\tilde{W}}_k = \overline{D}_j(\hat{\Gamma}_j - \hat{\Gamma}) + \overline{D}_k(\hat{\Gamma} - \hat{\Gamma}_k) + (\overline{D}_j - \overline{D}_k)\hat{\Gamma}, \qquad (5)$$

where $\overline{\tilde{W}}_l$ is the average log wealth-to-income ratio for group l=j,k, $\overline{D}_l$ is the matrix of average characteristics for group l, and $\hat{\Gamma}_l$ is the vector of estimated coefficients for group l. In this case group j represents the low-lifetime income group (i.e. poor or near poor) and k represents the high-lifetime income group (i.e. the near poor or rich). Thus the decomposition consists of three components, the difference between low-income and pooled coefficients weighted by low-income group characteristics, the difference between high-income and pooled coefficients weighted by high-income group characteristics, and the difference between low- and high-income-group characteristics weighted by the pooled coefficients.[25] The third term in the expression can be decomposed into the individual contributions of the separate characteristics to the total gap. As such I apportion the contributions to differences in labor earnings, asset-tested transfers, non-asset-tested transfers, income uncertainty, observed demographics (e.g. age, race, marital status, occupation), regional and state labor market conditions (state personal income, state unemployment rate, regional dummy variables, and state fixed effects), and state social insurance policies (AFDC/food stamp benefit, AFDC gross income limit, potential UI benefits).[26]

In Table 5 I present the decomposition for liquid- and net worth-to-permanent income ratios. The 'adjusted total gap' reported in the table refers to the fitted values of the left-hand side of equation (5). This implies that the difference in liquid wealth-to-permanent income ratios between the poor and rich is 0.39 log points and the comparable gap for net worth-to-permanent income is 0.45 log points. Beginning with the rich-poor liquid asset gap the decomposition reveals that virtually all the gap is attributable to differences in average characteristics and not differences in coefficients. Indeed, more than 100 percent of the gap is explained by

Table 5.—Decomposition of Log Wealth to Permanent Income Ratios

	Liquid Assets		
	Poor-vs-Near Poor	Poor-vs-Rich	Near Poor-vs-Rich
Adjusted Total Gap	–0.2725	–0.3904	–0.1179
Percent Attributable to Differences in Average Characteristics:	1.0555	1.0101	0.9050
Labor Income	0.2444	0.2501	0.2632
Asset-Tested Transfer Income	0.5156	0.4235	0.2104
Non Asset-Tested Transfer Income	0.0481	0.0771	0.1441
Income Uncertainty	–0.0538	–0.0308	0.0222
Observed Demographics	0.2440	0.2604	0.2985
Regional/State Labor Market	0.1022	0.0865	0.0503
State Social Insurance Policies	–0.0450	–0.0567	–0.0837
Percent Attributable to Differences in Coefficients:	–0.0555	–0.0101	0.0950
Poor –vs- Pooled Sample	–0.0576	–0.0402	
Near Poor –vs- Pooled Sample	0.0021		–0.0049
Rich –vs- Pooled Sample		0.0302	0.0999

	Net Worth		
	Poor-vs-Near Poor	Poor-vs-Rich	Near Poor-vs-Rich
Adjusted Total Gap	–0.3466	–0.4476	–0.1010
Percent Attributable to Differences in Average Characteristics:	0.7089	0.7822	1.0337
Labor Income	0.2670	0.3030	0.4265
Asset-Tested Transfer Income	0.2140	0.1950	0.1296
Non Asset-Tested Transfer Income	0.0137	0.0244	0.0611
Income Uncertainty	–0.0400	–0.0255	0.0245
Observed Demographics	0.2298	0.2746	0.4280
Regional/State Labor Market	0.0361	0.0285	0.0024
State Social Insurance Policies	–0.0117	–0.0177	–0.0384
Percent Attributable to Differences in Coefficients:	0.2911	0.2178	–0.0337
Poor –vs- Pooled Sample	0.2292	0.1775	
Near Poor –vs- Pooled Sample	0.0619		–0.2123
Rich –vs- Pooled Sample		0.0403	0.1786

Notes: A negative contribution is possible as the percentages are required to sum to one. The subcategories of the characteristics are constrained to sum to the total percentage attributable to the differences in characteristics.

characteristics, which could occur, for example, if the poor are more responsive to disincentives to save relative to the pooled sample or less responsive to incentives to save.

A striking result emerges when examining the sub-categories of characteristics—42 percent of the rich-poor wealth-to-income gap is attributed to differences in asset-tested transfer income. Alternatively, 25 percent of the gap is due to labor-income differences, 26 percent due to differences in observed demographics, and income uncertainty actually lowers the gap 3 percent since average uncertainty is higher among the poor. This implies that transfers that not only reduce income volatility but also impose stringent asset tests are the leading factor underlying the rich-poor liquid wealth-to-income gap. This is true for the near poor-poor gap as well. However, when comparing the near poor to the rich this result no longer obtains as the predominant factors underlying the gap between these groups are differences in observed demographics and differences in labor-market income.

The story for the rich-poor gap changes though when we examine net worth-to-permanent income ratios. In this case it is differences in labor-market earnings that underlie the between-group gaps, whether comparing the poor to near poor, poor to rich, or near poor to rich. Almost as important as labor income are differences in observed demographics. The poor are less likely to be white, less likely to be married, less likely to be self-employed, and are younger, yet the estimated wealth-to-income ratio is increasing in each of the latter factors. Unlike the liquid-asset gap though, there is a larger role for differences in responsiveness to incentives and disincentives to accumulate net worth such that 22 percent of the rich-poor gap is attributable to differences in coefficients. The overwhelming factor, however, is differences in average characteristics.

D. *Robustness*

In this section I test the robustness of the decompositions reported in Table 5 to a key assumption—the method of splitting the sample into the poor, near poor, and rich.[27] Hubbard et al. (1995) use educational attainment as the method of determining lifetime income groups, with the poor being those with less than high school, the near poor as those with high school but no college, and the rich as those with more than high school. I re-estimate the model in equation (1) using this method of sample separation and record the results of the decompositions in Table 6.

In Table 6 it is clear that the levels of the wealth-to-income gaps are substantially smaller when separating the sample based on education, but the qualitative results of the decompositions remain unchanged. Nearly all of the wealth-to-income gaps are due to differences in average characteristics, and around 40 to 50 percent of near poor-poor and rich-poor liquid wealth-to-permanent income gaps are attributed to differences in average levels of permanent asset-tested transfer income. Unlike the splits based on the risk of entering welfare, less of the gap based on education splits is attributed to observed demographics, and more of the gap is attributed to non asset-tested transfers, and to regional/state labor-market conditions. In the case of the net worth-to-permanent income gap the primacy of labor-market earnings in accounting for the gap is even more in evidence.

VI. Conclusion

The persistently low wealth-to-permanent income ratios among the lifetime poor compared to lifetime-rich households continue to puzzle economists and policy makers. This weak asset position could be due to differences in saving rates, differences in income uncertainty and the attendant precautionary motive to save, impatience or other time inconsistent preferences, or from disincentives created by transfer programs, which may not only reduce

Table 6.—Decomposition of Log Wealth to Permanent Income Ratios with Economic Status Determined by Education Attainment

	Liquid Assets		
	Less than HS-vs-HS	Less than HS-vs-More than HS	HS -vs-More than HS
Adjusted Total Gap	–0.1582	–0.2451	–0.0869
Percent Attributable to Differences in Average Characteristics:	0.8436	0.9242	1.0712
Labor Income	0.2673	0.3048	0.3731
Asset-Tested Transfer Income	0.4822	0.4314	0.3390
Non Asset-Tested Transfer Income	0.0349	0.0930	0.1988
Income Uncertainty	–0.0998	–0.0794	–0.0422
Observed Demographics	0.1258	0.1529	0.2023
Regional/State Labor Market	0.1215	0.1135	0.0989
State Social Insurance Policies	–0.0883	–0.0920	–0.0986
Percent Attributable to Differences in Coefficients:	0.1564	0.0758	–0.0712
Less than HS –vs- Pooled Sample	0.0656	0.0424	
HS –vs- Pooled Sample	0.0908		–0.1654
More than HS –vs- Pooled Sample		0.0334	0.0942
	Net Worth		
	Less than HS-vs-HS	Less than HS-vs-More than HS	HS-vs-More than HS
Adjusted Total Gap	–0.1292	–0.2041	–0.0750
Percent Attributable to Differences in Average Characteristics:	0.8340	0.9207	1.0700
Labor Income	0.4548	0.5082	0.6003
Asset-Tested Transfer Income	0.3118	0.2734	0.2073
Non Asset-Tested Transfer Income	0.0155	0.0405	0.0836
Income Uncertainty	–0.1157	–0.0902	–0.0462
Observed Demographics	0.1597	0.1757	0.2034
Regional/State Labor Market	0.0476	0.0540	0.0651
State Social Insurance Policies	–0.0397	–0.0411	–0.0435
Percent Attributable to Differences in Coefficients:	0.1660	0.0793	–0.0700
Less than HS –vs- Pooled Sample	0.0658	0.0416	
HS –vs- Pooled Sample	0.1002		–0.1727
More than HS –vs- Pooled Sample		0.0377	0.1027

Notes: A negative contribution is possible as the percentages are required to sum to one. The subcategories of the characteristics are constrained to sum to the total percentage attributable to the differences in characteristics.

income volatility but also impose benefit-eligibility tests based on the level of liquid assets. In this paper, I employed panel data and an expanded buffer-stock saving model to estimate the impacts of permanent labor-market earnings, permanent transfer income with and without asset tests, income uncertainty, and observed demographics, while controlling for unobserved heterogeneity, on wealth-to-permanent income ratios of the poor, near poor, and rich. I then decomposed the between-group wealth-to-income gaps into differences in average characteristics and differences in the estimated coefficients.

The estimates suggest that wealth-to-permanent income ratios are increasing in permanent labor income and income uncertainty, but transfer income, with or without asset tests, discourages asset accumulation, particularly liquid-assets. The results indicated important differences in the estimated wealth-to-permanent income processes across the poor, near poor, and rich. While there is evidence of an operative precautionary saving motive among the near poor and rich, wealth-to-income ratios of the poor do not respond to changes in income uncertainty. A plausible explanation for this is that the social safety net proxies for precaution among the poor, thereby mitigating the need to accumulate wealth relative to income for unforeseen contingencies. In addition, within the group of poor and near poor, the wealth-to-permanent income ratio is increasing in permanent labor income, but not within the group of rich households. Moreover, the results suggest that the near poor reduce their wealth-to-income ratios in response to consumption floors in general, but contrary to the prediction of Hubbard et al. (1995) there is no evidence that they reduce the ratio in response to asset-tested transfers.

The decompositions indicate that across all groups most of the wealth-to-permanent income gaps are attributable to differences in average characteristics and not to differences in the degree of responsiveness to incentives and disincentives to save. While differences in labor-market earnings and observed demographics are important, the leading factor driving the liquid wealth-to-permanent income gap between the near poor and poor, and between the rich and poor, is asset-tested transfer income. However, in comparing the near poor to the rich, or examining differences in net worth-to-permanent income ratios across all groups, the driving force underlying the gaps are differences in lifetime labor-market earnings.

The evidence presented here suggests that recent state efforts to raise liquid-asset limits for benefit eligibility as part of the 1996 welfare reform are likely to reduce the disincentives to save and may aid in reducing the liquid wealth-to-permanent income gap between the poor and non poor. Consumption floors in general reduce incentives to accumulate assets, but the asset tests seem to exacerbate those disincentives. This does not imply consumption floors should be abolished in order to improve the asset position of the poor as the floors serve as an important consumption-smoothing device (Gruber 2000; Kniesner and Ziliak 2001); however, loosening asset limits may reduce barriers for the poor to save. At the same time, if the poor or the near poor are to significantly narrow their overall asset-to-income positions relative to the rich, they must first narrow the gap in lifetime labor-market earnings.

Appendix Table A.1.—Variable Descriptions

Income Measures:

Gross Labor Income :	Gross wage and salary income of the household head and wife, and possible subfamily.
Net Labor and Transfer Income:	After-tax wage, salary, and transfer income of the household head and wife, and possible subfamily.

Time-Invariant Endogenous Regressors (F_1):

PTA:	Permanent asset-tested transfer income
PT:	Permanent non-asset-tested transfer income
PL:	Permanent labor income
$\hat{\eta}$:	Income uncertainty

Time-Invariant Doubly Exogenous Regressors (F_3):

Con:	A constant
White:	A dummy variable = 1 if white
Marry:	A dummy variable = 1 if married
Neast:	A dummy variable = 1 if North East region
Ncent:	A dummy variable = 1 if North Central region
Nwest:	A dummy variable = 1 if West region

Time-Varying Singly Exogenous Regressors (X_2):

Occ:	A vector of seven 2-digit occupational dummies
Ind:	A vector of eleven 2-digit industry dummies

Time-Varying Doubly Exogenous Regressors (X_3):

Age:	The age of the household head
Age^2:	The square of age
Famsz:	The number of individuals in the household
Kids:	The number of children of the household head living at home
Usth:	A dummy variable = 1 if a union member
Dish:	A dummy variable = 1 if the household head has a disability limiting market work
Disw:	A dummy variable = 1 if the wife has a disability limiting market work
Gaffs:	State-specific maximum AFDC/Food Stamp benefit for a family of 3
Gafdi:	State-specific AFDC gross-income limit for a family of 3
Uiben:	State-specific average Unemployment Insurance benefit
Lspi:	Natural log of state personal income
Sur:	Natural log of state-specific unemployment rates

Appendix Table A2.—Probit Estimates of the Probability of Welfare Receipt

Constant	-0.679
	(0.426)
Age of Head	-0.018
	(0.004)
Age of Wife	0.005
	(0.005)
Female (=1 if female head)	0.729
	(0.119)
Kids	0.309
	(0.018)
Marry (=1 if married)	-0.411
	(0.188)
Home (=1 if own home)	-0.540
	(0.048)
Dish (=1 if head is disabled)	0.367
	(0.068)
Disw (=1 if wife is disabled)	0.436
	(0.083)
Gfarm (=1 if from farm)	0.064
	(0.049)
Ppoor (=1 if parent poor)	0.142
	(0.048)
Vet (=1 if a veteran)	0.197
	(0.060)
White (=1 if head is white)	-0.477
	(0.054)
Lths (=1 if Less than High School)	0.533
	(0.051)
Mths (=1 if More than High School)	-0.333
	(0.065)
Neast (=1 if North East)	0.193
	(0.094)
Ncent (=1 if North Central)	0.205
	(0.091)
South (=1 if South)	–0.093
	(0.093)
Lspi (log of state personal income)	-0.071
	(0.029)
Sur (level of state unemployment rate)	0.530
	(1.240)

Notes: Log-likelihood = -2039.4; Number of Observations = 14,520.

Endnotes

[1] Based on author's calculations from the Panel Study of Income Dynamics.

[2] The categories of poor, near poor, and rich are determined by reduced-form predicted probabilities of the risk the household is likely to take up welfare. This methodology is explained in detail below.

[3] As part of the 1996 welfare reform, AFDC is now known as Temporary Assistance to Needy Families. Because the data in this study pre-date this change I refer to the program as AFDC.

[4] The primary asset-tested transfer programs are AFDC, food stamps, and Supplemental Security Income (SSI). To qualify for AFDC the household must contain children under age 18, and meet income and asset tests. The program primarily serves single female-headed households. Certain program rules are set at the federal level, while others are at state discretion (e.g. income limits, maximum benefit guarantees). The Food Stamp Program is a federal program designed to stabilize food consumption among low income and low asset households. About one-half of food stamp recipients also receive AFDC. SSI is a program targeted primarily to the blind, disabled, or aged. The asset tests for SSI are the same as those covering food stamps. It is not possible for an individual to receive SSI and AFDC simultaneously, but a household could receive both.

[5] As first suggested by Ashenfelter (1983), we would expect higher income and asset limits to lead to higher saving for purely "mechanical" reasons. This arises because the higher limits make households that were previously ineligible now categorically eligible. The challenge confronting policy makers is to minimize the extent to which the higher limits lead to "behavioral" reductions in saving.

[6] Other possible sources, which are not explored here, are bequest motives (Dynan et al. 2000), and differences in social security replacement rates (Huggett and Ventura 2000). In addition, the paper is silent on the alternative tax treatment of savings (Bernheim 1999).

[7] Indeed, to the extent that the bequest motive is treated as unobserved heterogeneity then the empirical model below will capture both within group and (average) between-group differences in the bequest motive. However, it is not possible in this model to separately identify bequest motives from say impatience.

[8] Because of the presence of the overall constant term, β_1^j, one must impose the restriction that $\sum_i \alpha_i^j = 0$. This implies that if α_i^j reflects impatience alone, then the constant term captures average impatience for group *j* and α_i^j is the individual deviation from mean.

[9] Another form of endogeneity might arise from 'selection on observables' or 'selection on unobservables' into the transfer programs. In the empirical model I include welfare participants as well as non-participants, and all wealth and income variables are in logs, with non-positive values set equal to zero. As noted by Heckman and Robb (1985) instrumental variables such as employed here is an attractive method of correcting for both forms of selection as it invokes minimal assumptions and is computationally convenient. There is also the issue of censoring in the dependent variable, e.g. around 15 percent of the poor have zero or negative net worth. In an earlier version I estimated a two-step tobit instrumental variables model with little change in the conclusions of the paper.

[10] Hansen's test is the minimized value of the GMM criterion function, and is distributed asymptotically as χ^2 with degrees of freedom equal to the number of instruments less regressors. The test of Eichenbaum et al. is the difference between restricted and unrestricted GMM

criterion functions, and is distributed asymptotically as χ^2 with degrees of freedom equal to the difference in the number of instruments used across models.

[11] In the PSID, the head of household in two-parent households is male by default, although there are exceptions. It is not possible to identify both gender and marital effects in some of the subsamples, especially in the sample of poor households where marital rates are low and female-headship is prevalent. Hence only marital status is included among the time-invariant regressors.

[12] However, Hoynes (1997) presents evidence that marital status is not affected by AFDC policy.

[13] In 1980 there are 2285 household heads that meet the basic selection criteria. Following these same heads until 1991 reduces the available set to 1452, and then eliminating those households with missing data results in the sample size of 1210, or 14,520 person-years.

[14] See Curtin et al. (1989) for positive evidence on the representativeness of PSID wealth relative to other wealth surveys such as the Survey of Consumer Finances.

[15] Including the contributions of other family members is likely important because low-income families may spread the risk of income uncertainty by pooling resources through the formation of subfamilies (Gruber 2000; Hutchens et al. 1989).

[16] Prior to 1981, there was substantial state-specific heterogeneity in asset limits, but federal legislation in the early 1980s eliminated most of the state variation, which prevents me from including state-level asset limits as part of the welfare policies. As part of the recent round of welfare reform, much of the previous heterogeneity has been restored (Hurst and Ziliak 2001).

[17] In previous versions I also considered the effect of SSI program parameters. Like AFDC there is not much state variation in SSI asset limits. Moreover, because the SSI maximum benefit and gross-income limit are linear functions it is not possible to separately identify their influence. About 25 states offer different maximum benefits, but the time-variation between 1983 and 1988

was not very substantial, resulting in ill-determined coefficients. The results of this study, both qualitative and quantitative, are not significantly altered by their omission.

[18] Neumark and Powers (1998) use a similar method of sample splitting in their cross-sectional analysis.

[19] As noted previously I include SSI in the calculation of asset-tested transfer income but not in the probability of welfare model mainly because of my sample restriction of no permanently disabled household heads implies that there are few heads on SSI. The results are little changed when I include SSI in the probability of welfare model.

[20] All income and wealth data are deflated by the personal consumption expenditure deflator with 1987 base year.

[21] In results not tabulated income uncertainty is also declining with increases in educational attainment. Carroll and Samwick (1997) found a similar pattern.

[22] This finding is consistent with Hurst and Ziliak (2001) who found that in light of the recent welfare reforms the saving of the poor increased in response to higher asset limits but the saving of the near poor did not change.

[23] The result that wealth-to-income is increasing in permanent labor-market income for the poor and near poor, but not the rich, also obtains when I split the sample based on educational attainment. In addition, even though the regressors are instrumented, I also tested whether this result was due in part from possible collinearity between uncertainty and permanent income by scaling uncertainty with respect to mean income. The pattern of results were unchanged.

[24] In decompositions of this nature, an index number problem arises because a reference set of parameters must be chosen, and the results of the decomposition may differ based on the reference group. However, if between-group differences in response surfaces were to disappear

the likely set of coefficients to emerge would be from the pooled sample and not the individual coefficient vector from the poor, near poor, or rich.

[25] It is important to note that between-group unobserved heterogeneity such as impatience is captured in the decomposition via the group-specific constant term. Specifically, as noted previously, the constant term captures average latent heterogeneity within each group while the α_i are deviations from the group mean and average out to zero within groups.

[26] Because of a scaling problem that arises when deciding which dummy-variable category to omit, it is not possible to uniquely isolate the contribution of individual $\hat{\Gamma}$'s to the total gap (Jones 1983). This implies that no attempt will be made at attributing the constant term as 'impatience' since its value depends on the omitted dummy variable category. This scaling problem does not affect the total differences in coefficients, the total differences in characteristics, or the individual differences in characteristics.

[27] In results not tabulated, I conducted an extensive set of robustness checks, including testing the omission of state fixed effects, redefining income to exclude contributions of subfamilies, permitting time-variation in permanent income, replacing the log transformation with the hyperbolic sine transformation, testing the assumption that industry and occupation are singly exogenous, and permitting censoring in the dependent variable. While some quantitative values changes, the qualitative conclusions of the study remain the same.

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