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. 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 gaps in wealth-to-permanent-income ratio 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 those attributable to differences in the estimated coefficients on the respective characteristics. The results suggest that wealth-to-permanent-income ratios are increasing in permanent labor income and income uncertainty, but that 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 gap between the rich and poor in the ratio of liquid wealth to permanent income is asset-tested transfer income, whereas the leading factor driving the gap in the ratio of net worth to permanent income is labor-market earnings.

I. Introduction

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. In reality, however, wealth-to-permanent-income ratios for low-lifetime-resource households are regularly significantly less than comparable ratios for high-lifetime-resource households. One implication of this rich-poor gap in the wealth-to-permanent-income ratio 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, Skinner, & Zeldes, 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, Skinner, & Zeldes, 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). Although much research has been conducted on each topic, often in isolation from the others, empirical work on decomposing the wealth-to-permanent-income gap between the rich and poor to determine the relative importance of each 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 latent preferences such as impatience. In order to identify differences in the asset accumulation 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 & Ransom, 1994).

Estimation of the model for the wealth-to-permanent-income ratio is complicated by the presence of asset-tested 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 & 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 & 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,

TABLE 1.—PERSISTENCE OF NET WORTH BETWEEN 1984 AND 1989

		Net Worth 1989:					
		<5	>5, <10	>10, <30	>30, <50	>50, <100	>100
Net Worth 1984:	<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
	>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

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.

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 gap in the ratio of wealth to permanent income 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 gap in the ratio of liquid wealth to permanent income between the rich and poor is asset-tested transfer income, while the key factor driving the gap in the ratio of net worth to permanent income is labor market earnings.

II. Background and Empirical Model

The wealth position of American families tends to be persistent (Browning & Lusardi, 1996; Carney & Gale, 1999; Hubbard, Skinner, & Zeldes, 1994; Hurst, Luoh, & Stafford, 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% of households with net worth under $5,000 in 1984 still had net worth under $5,000 in real terms in 1989. Likewise, 89% 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. In view of the net-worth-to-permanent-income ratios presented in figure 1, however, this is clearly not the case. Not only are the ratios higher for the rich than for the poor and near-poor, but the differences are increasing as one moves up distribution of the wealth-to-permanent-income ratio from the 25th to the 75th percentile.[2]

Several explanations have been proffered in the literature for the observed divergence in wealth-to-permanent-income ratio between the rich and poor (Browning & Lusardi, 1996; Venti & 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 gap in the wealth-to-permanent-income ratio 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 income uncertainty. In order for income uncertainty to explain the observed gap in wealth-to-income ratio between the rich and poor, it must be that either the rich face a higher 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. Although 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 income uncertainty if capital income makes up a sizable portion of their total income and it is highly volatile. Moreover, 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 gap in wealth-to-income ratio 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 & Hagstrom, 1999; Engen & Gruber, 2001; Hubbard et al., 1995). While all social insurance programs (such as 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]

[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 that 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 predate 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

FIGURE 1.—NET-WORTH-TO-PERMANENT-INCOME RATIOS BY PERCENTILE AND WELFARE RECIPIENT CLASS
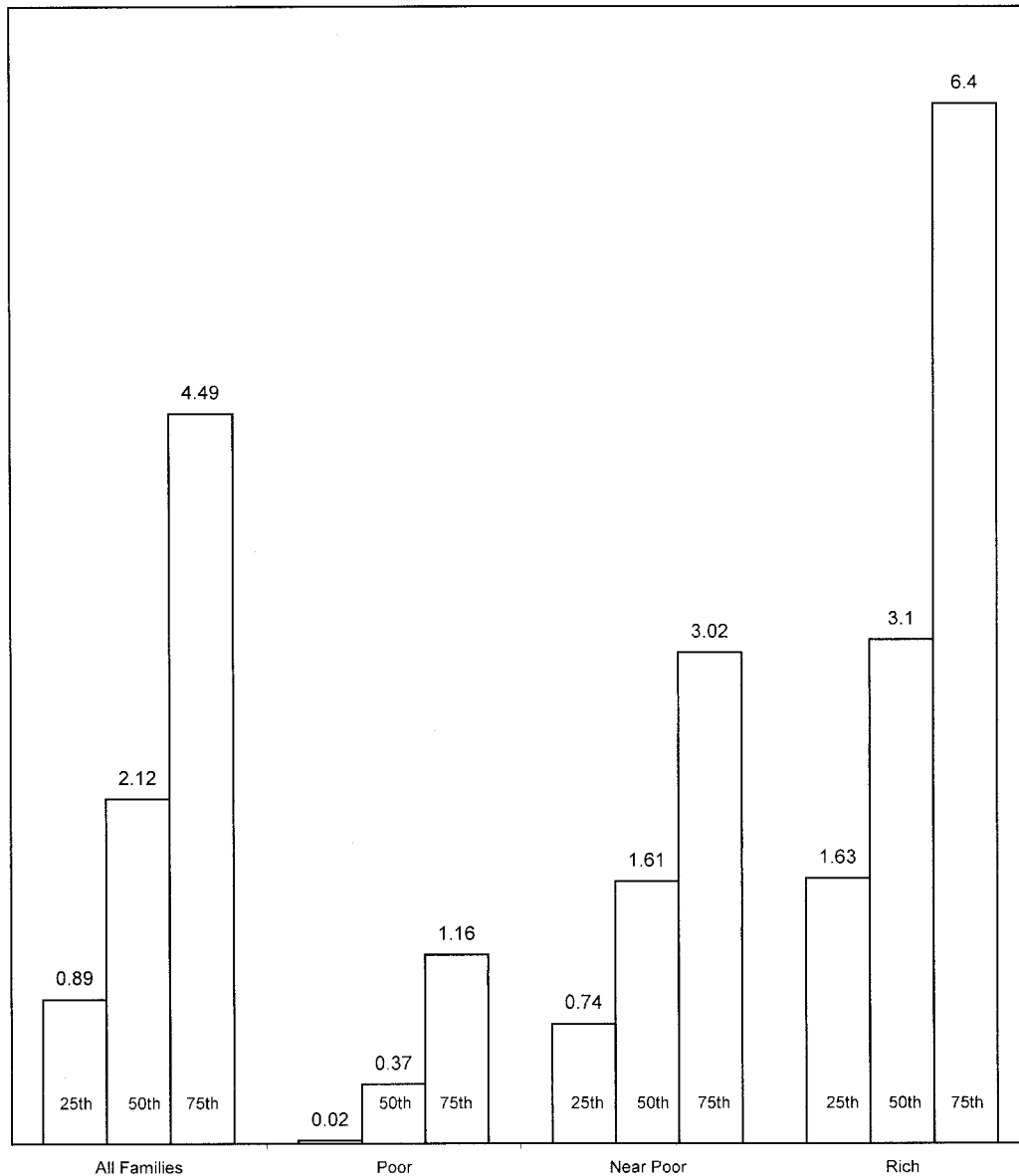
Hubbard et al. (1995) investigated the implications of asset-based means testing in a life cycle simulation model of saving with earnings uncertainty and out-of-pocket medical expenditures. The latter assumptions play the dual roles of generating precautionary saving and of inducing a positive probability 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% 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 & Yelowitz, 1999; Hurst & Ziliak, 2001; Neumark & Powers, 1998; Powers, 1998). If

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 (for example, 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 may 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 policymakers is to minimize the extent to which the higher limits lead to *behavioral* reductions in saving.

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 gap in wealth-to-permanent-income ratio.

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); if so, 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 and thus as an end in itself. Each of the latter behavioral explanations reflects characteristics that are often viewed as unobserved by 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 & Graham, 1990; Charles & Hurst, 2000; Chitegi & Stafford, 1999). For example, the presence of a black-white gap in the wealth-to-income ratio could exacerbate the rich-poor wealth gap if blacks are over-represented among the poor.

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 ($i = 1, \ldots, N$) at time t ($t = 1, \ldots, T$), 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 (for example, 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 (that is, 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 subscript j and the state effects for notational simplicity, consider the following reformulation of equation (1):

$$\tilde{W}_i = D_i \Gamma + \varepsilon_i, \quad (2)$$

where $\tilde{W}_i$ is the $T \times 1$ vector of log wealth-to-permanent-income ratio 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; $\Gamma = [\beta_1, \ldots, \beta_7]$ 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 instru-

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[6] Other possible sources, which are not explored here, are bequest motives (Dynan et al., 2000) and differences in social security replacement rates (Huggett & Ventura, 2000). In addition, this 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, 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 and (say) impatience.

[8] Because of the presence of the overall constant term β_1^j, one must impose the restriction that $\Sigma_i \alpha_i^j = 0$. 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 the mean.

ments 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 (that is, 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 (that is, 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 $M_i = I_T \otimes [d'_i, d'_i, \ldots, d'_i, m'_i]$, 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

$$\hat{\Gamma} = [D'\bar{C}'M(M'\bar{C}\hat{\Omega}\bar{C}'M)^{-1} M'\bar{C}D]^{-1} \\ \times D'\bar{C}'M(M'\bar{C}\hat{\Omega}\bar{C}'M)^{-1} M'\bar{C}\tilde{W}, \tag{4}$$

where $\bar{C} = I_N \otimes C$, 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 constitute 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 determined jointly. 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, Schmidt, and Wyhowski (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* because 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, Hansen, and Singleton (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 with 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, so 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, because 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

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[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 nonparticipants, and all wealth and income variables are in logs, with nonpositive values set equal to zero. As noted by Heckman and Robb (1985), the method of instrumental variables, as employed here, is an attractive one for 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; for example, around 15% 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.

instruments. Because the choice of industry and occupation may be correlated with unobserved heterogeneity in general (that is, 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). Table A1 in the appendix 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). Although later waves of data are available, 1991 is the last year the PSID staff generated the 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 oversamples low-income households. Because of the oversampling, 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, Gottschalk, & Moffitt, 1998; Hoem, 1989). Consequently, I only weight the descriptive statistics, using the family weight constructed by the PSID.

The sample consists of a balanced panel of 1,210 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, that is, 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 preaccumulation years (students), in their 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 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 (including the Earned Income Tax Credit). I include not only the income 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 pretax and pretransfer 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 the state unemployment rate—come from various sources. The transfer policy variables are obtained from selected volumes of the U.S. House of Representatives Committee on Ways and Means *Green Book* and the U.S. 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-

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[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 were 2285 household heads that met 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, Juster, and Morgan (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 probably important, because low-income families may spread the risk of income uncertainty by pooling resources through the formation of subfamilies (Gruber, 2000; Hutchens, Jakubson, & Schwartz, 1989).

income limit, that is, 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 & Cullen, 2000). State-level data on income come from the Bureau of Economic Analysis 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 delineating 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 according to 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) divide their sample into the poor, near-poor, and rich as those household heads with less than high school, high school, 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

TABLE 2.—SELECTED SUMMARY STATISTICS

Statistic	Mean (S.D.) {Median}			
	All Families	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 stamp 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)
No. of households	1210	230	461	519

The table reports means, standard deviations in parentheses, and medians in braces. 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 to households at moderate risk of entering welfare, and rich to households at low risk of entering welfare.

education split. Table A2 in the appendix contains the point estimates from the probit model.

I conclude the data section by reporting selected descriptive statistics in table 2 for all families 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. 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 nonpoor in 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 nonpoor (possibly because the poor tend to

[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 & 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 identify their influence separately. 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 & 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 my sample restriction to households without permanently disabled 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 base year 1987.

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

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 model for the wealth-to-permanent-income ratio in equation (1), first for all families, 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 decompositions of the wealth-to-permanent-income ratio.

A. All Families

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 ratio with respect to permanent asset-tested transfer income is about −0.04, indicating that a 10% increase in benefit receipts results in a 0.4% decrease in liquid-wealth-to-income ratio. The comparable elasticity is about one-half the magnitude in the net-worth regression. Because state welfare programs tax only 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, because 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 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 ratio is increasing in permanent labor market income, particularly net-worth accumulation. A 10% increase in permanent labor market income leads to a 1.2% increase in the net-worth-to-permanent-income ratio. Moreover, from the income uncertainty coefficients there is evidence of an operative precautionary saving motive, with respect to both liquid assets and net

TABLE 3.—GMM ESTIMATES OF LOG WEALTH-TO-PERMANENT-INCOME RATIOS FOR ALL FAMILIES

Variable	Coefficient (Standard Error) [Partial R^2]	
	Liquid Assets	Net Worth
Permanent asset-tested transfer income	−0.0452 (0.0152) [0.1016]	−0.0238 (0.0132) [0.1016]
Permanent non-asset-tested transfer income	−0.0191 (0.0094) [0.0876]	−0.0069 (0.0084) [0.0876]
Permanent net labor income	0.0876 (0.0436) [0.1620]	0.1216 (0.0357) [0.1620]
Uncertainty in net labor and transfer income	0.0426 (0.0278) [0.0928]	0.0403 (0.0241) [0.0928]
AFDC/food stamps benefit	−0.1812 (0.0801)	−0.0511 (0.0631)
AFDC gross income limit	−0.0157 (0.0346)	0.0061 (0.0275)
UI benefit	−0.0429 (0.0605)	−0.0957 (0.0467)
J-statistic	50.07 {54, 0.63}	59.68 {54, 0.28}

Heteroskedasticity-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 nonpositive values of wealth set equal to zero. There are 2,420 person-years.

worth. Because the coefficient is hypothesized to be positive, according to one-tailed test the uncertainty terms are statistically significant at the 7% and 5% levels for liquid assets and net worth, respectively.

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 Hubbard et al.'s (1995) hypothesis. A 10% increase in the consumption floor leads to a 1.8% reduction in the liquid-wealth-to-permanent-income ratio, but to only a 0.5% 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 the net-worth-to-permanent-income ratio, but surprisingly no effect on liquid assets.

B. Poor, Near-Poor, and Rich Families

In Table 4 I present the results of regressions log wealth-to-permanent income 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

TABLE 4.—GMM ESTIMATES OF LOG-WEALTH-TO-PERMANENT-INCOME RATIOS FOR THE POOR, NEAR-POOR, AND RICH

| | Coefficient (Standard Error) [Partial R^2] | | | | | |
| | Liquid Assets | | | Net Worth | | |
Variable	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]
Uncertainty of net labor and transfer income	−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}

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 1,038 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-versus-near-poor, poor-versus-rich, and near-poor-versus-rich in liquid-asset models, and the 0.00, 0.00, and 0.00 levels in net-worth models.

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 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 subgroup, whereas the near-poor who are likely to receive non-asset-tested transfer income tend to have a 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-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 display precautionary saving motives in their 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 does not appear to differ significantly across the distribution.

C. Decomposing Gaps in the Wealth-to-Permanent-Income Ratio

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 the 0.00 level). This is in contrast to the standard, homothetic life cycle model of consumption and

[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 ratio is increasing in permanent labor market income for the poor and near-poor, but not the rich, also obtains when I split the sample according to educational attainment. In addition,

even though the regressors are instrumented, I also tested whether this result was due in part to possible collinearity between uncertainty and permanent income, by scaling uncertainty with respect to mean income. The pattern of results was unchanged.

saving, which predicts that the coefficients will be jointly equal to zero. 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 gap in the wealth-to-permanent-income ratio 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 gaps in wealth-to-permanent-income ratio 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 $\bar{W}_i$ is the log wealth-to-permanent-income ratio for household i, D_i is the matrix of characteristics, and $\hat{\Gamma}$ is 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 reference set of coefficients consists of those estimated from the pooled sample of all families.[24]

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

$$\bar{W}_j - \bar{W}_k = \bar{D}_j(\hat{\Gamma}_j - \hat{\Gamma}) + \bar{D}_k(\hat{\Gamma} - \hat{\Gamma}_k) + (\bar{D}_j - \bar{D}_k)\hat{\Gamma}, \tag{5}$$

where $\bar{W}_l$ is the average log wealth-to-income ratio for group $l = j, k$, $\bar{D}_l$ 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 (poor or near-poor) and k represents the high-lifetime income group (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 all-families coefficients.[25] The third term in the expression can be decomposed into the individual contributions of the separate characteristics to the total gap. Thus I apportion the contributions to differences in labor earnings,

asset-tested transfers, non-asset-tested transfers, income uncertainty, observed demographics (such as 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 decompositions for ratios of liquid assets and net worth to permanent income. 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 ratios 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% of the gap is explained by characteristics, which could occur, for example, if the poor are more responsive to disincentives to save than the pooled sample, or less responsive to incentives to save.

A striking result emerges when examining the subcategories of characteristics—42% of the rich-poor gap in the wealth-to-income ratio is attributed to differences in asset-tested transfer income. Alternatively, 25% of the gap is due to labor-income differences, 26% is due to differences in observed demographics, and income uncertainty actually lowers the gap 3%, because the 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 gap in liquid-wealth-to-income ratio. This is true for the near-poor–poor gap as well. However, on comparing the near poor with 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 poor with near-poor, poor with rich, or near-poor with rich. Almost as important as labor income are differences in observed demographics. The poor are less likely to be white, are less likely to be married, are 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-

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[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 according to 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, and 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). Thus no attempt will be made at attributing the constant term to 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.

TABLE 5.—DECOMPOSITION OF LOG WEALTH-TO-PERMANENT-INCOME RATIOS

Component	Contribution		
	Poor versus Near-Poor	Poor versus Rich	Near-Poor versus Rich
Liquid Assets			
Adjusted total gap	−0.2725	−0.3904	−0.1179
Percentage 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
Percentage Attributable to Differences in Coefficients:	−0.0555	−0.0101	0.0950
Poor versus all families	−0.0576	−0.0402	
Near-poor versus all families	0.0021		−0.0049
Rich versus all families		0.0302	0.0999
Net Worth			
Adjusted total gap	−0.3466	−0.4476	−0.1010
Percentage 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
Percentage attributable to differences in coefficients:	0.2911	0.2178	−0.0337
Poor versus All Families	0.2292	0.1775	
Near poor versus all families	0.0619		−0.2123
Rich versus all families		0.0403	0.1786

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.

asset gap, though, there is a larger role for differences in responsiveness to incentives and disincentives to accumulate net worth, such that 22% of the rich-poor gap is attributable to differences in coefficients. The overwhelming factor, however, is differences in average characteristics.

D. Robustness

In this subsection I test the robustness of the decompositions reported in table 5 to a key assumption—the method

of sample separation into the poor, near-poor, and rich.[27] Hubbard et al. (1995) use educational attainment as the method of determining lifetime income groups, the poor being those with less than high school, the near-poor those with high school but no college, and the rich those with more than high school. I reestimate 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 gaps in the wealth-to-income ratios are substantially smaller on separating the sample according to education, but the qualitative results of the decompositions remain unchanged. Nearly all of the gaps in the wealth-to-income ratios are due to differences in average characteristics, and around 40% to 50% of near-poor–poor and rich-poor gaps in the ratio of liquid wealth to permanent income 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 it is attributed to non-asset-tested transfers and to regional/state labor market conditions. In the case of the net-worth-to-permanent-income ratio 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 policymakers. This weak asset position could be due to differences in saving rates, differences in income uncertainty and the attendant precautionary motive to save, differences in patience or other time preferences, or disincentives created by transfer programs, which not only reduce 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 effects 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 gaps in wealth-to-income ratios 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 the accumulation of assets, particularly liquid

[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. Though some quantitative values changed, the qualitative conclusions of the study remain the same.

TABLE 6.—DECOMPOSITION OF LOG WEALTH-TO-PERMANENT-INCOME RATIOS WITH ECONOMIC STATUS DETERMINED BY EDUCATION ATTAINMENT

Component	Contribution		
	Less than HS versus HS	Less than HS versus More than HS	HS versus More than HS
Liquid Assets			
Adjusted total gap	−0.1582	−0.2451	−0.0869
Percentage 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
Percentage attributable to differences in coefficients:	0.1564	0.0758	−0.0712
Less than HS versus all families	0.0656	0.0424	
HS versus all families	0.0908		−0.1654
More than HS versus all families		0.0334	0.0942
Net Worth			
Adjusted total gap	−0.1292	−0.2041	−0.0750
Percentage 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
Percentage attributable to differences in coefficients:	0.1660	0.0793	−0.0700
Less than HS versus all families	0.0658	0.0416	
HS versus all families	0.1002		−0.1727
More than HS versus all families		0.0377	0.1027

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.

assets. The results indicated important differences in the estimated wealth-to-permanent-income processes across the poor, near-poor, and rich. Although 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, the wealth-to-permanent-income ratio is increasing in permanent labor income within the group of poor and near-poor, 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. Although differences in labor market earnings and observed demographics are important, the leading factor driving the gap in liquid-wealth-to-permanent-income ratio between the near-poor and poor, and between the rich and poor, is asset-tested transfer income. However, in comparing the near-poor with the rich, or examining differences in net-worth-to-permanent-income ratios across all groups, the driving force underlying the gaps is 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 gap in liquid-wealth-to-permanent-income ratio between the poor and nonpoor. Consumption floors in general reduce incentives to accumulate assets, but the asset tests seem to exacerbate those disincentives among the poor. 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 the gap between their overall asset-to-income ratios and those of the rich, they must first narrow the gap in lifetime labor market earnings.

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APPENDIX

TABLE A1.—DESCRIPTION OF VARIABLES

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. The 12-year time mean of AFDC, food stamp, and SSI income.

PT: Permanent non-asset-tested transfer income. The 12-year time mean of unemployment insurance, social security, child support, alimony, veterans benefits, workers compensation, and family assistance.

PL: Permanent labor income. The 12-year time mean of labor earnings from all jobs.

$\hat{\eta}$: Income uncertainty. The average squared residual of detrended log net income.

Time-invariant doubly exogenous regressors (F_3):

A constant term, a dummy variable = 1 if white, a dummy variable = 1 if married, a dummy variable = 1 if in North East region, a dummy variable = 1 if in North Central region, a dummy variable = 1 if in West region.

Time-varying doubly exogenous regressors (X_3):

The age of the household head, the square of age, the number of individuals in the household, the number of children of the household head living at home, a dummy variable = 1 if a union member, a dummy variable = 1 if the household head has a disability limiting market work, a dummy variable = 1 if the wife has a disability limiting market work, state-specific maximum AFDC/food stamp benefit for a family of three, state-specific AFDC gross-income limit for a family of three, state-specific average unemployment insurance benefit, natural log of state personal income, natural log of state-specific unemployment rates.

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)

Log-likelihood = −2,039.4; number of observations = 14,520.