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Income Transfers and Assets of the Poor

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Abstract

Compared with nonpoor households, many poor households accumulate little wealth over their lifetimes. This rich-poor wealth gap may be due to different abilities to accumulate assets, possibly because the poor face a lifetime of lower incomes and higher income uncertainty. Alternatively, the wealth gap might be due to different responses to economic incentives to accumulate, such as transfer-program policies. In this paper, I use data from the Panel Study of Income Dynamics and a correlated random-effects estimator to estimate the wealth-disincentive effects of both transfer-program income and policies in a buffer-stock model of asset accumulation. With the estimated parameters, I decompose the rich-poor wealth gap into the fraction attributable to ability-to-accumulate differences and the fraction attributable to differences in responses to asset-accumulation incentives. The results suggest that welfare income and policies discourage accumulation of liquid assets, but do not reduce net wealth. However, the wealth decomposition indicates that at least 75 percent of the rich-poor wealth gap emanates from ability differences. This suggests that the disincentives created by transfer programs have a small impact on the overall asset position of the poor.

Income Transfers and Assets of the Poor

I. INTRODUCTION

Although the motives underlying household saving behavior are varied, it is puzzling that many low-income households accumulate few assets, even in the years leading to retirement. These poor and near-poor households appear to be distinct from their high-income counterparts, which typically adhere to the hump-shaped age-assets profile predicted by the life-cycle model (Carroll 1992, 1997; Deaton 1991; Hubbard, Skinner, and Zeldes 1995). One possibility for the rich-poor wealth gap, put forth by Hubbard, Skinner, and Zeldes (1995), is that the stringent income and liquid-asset tests imposed on current and potential participants in the major transfer programs serve as significant disincentives to accumulate wealth. Indeed, in the current round of welfare reform, many states are adjusting the income and asset limits necessary to qualify for transfer programs in hopes of stimulating saving among the poor.[1] However, it is also the case that the rich and poor differ in ways that affect the ability to accumulate wealth, such as income and income uncertainty. Moreover, the income-ability gap has grown more acute over the past two decades (Karoly 1993; Wolff 1995). Perhaps, then, the wealth gap between the rich and poor emanates not so much from disincentives created by transfer programs, but more from differences in resources available to accumulate wealth. In this paper, I estimate a buffer-stock model of asset accumulation and decompose the fraction of the rich-poor wealth gap attributable to ability-level differences and to differences in the responsiveness to asset-accumulation incentives and disincentives.

In their survey of the saving literature, Browning and Lusardi (1996) offer several explanations that help account for the low asset holdings among the poor. As noted above, the poor may possess little wealth simply as a result of low incomes. This effect is compounded by the fact that the age-earnings

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[1]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.

profiles of the poor tend to be quite flat relative to the nonpoor, reducing the opportunities for "hump-shaped" saving.[2] Moreover, others suggest that aside from having low incomes the poor are "impatient," i.e., they have relatively high subjective discount rates (Lawrance 1991). This implies that saving is inhibited not only from a lack of resources but also from a high marginal propensity to consume out of current and expected future income.

A third hypothesis is that the social safety net provides a consumption floor for the poor and near poor, thereby reducing income uncertainty and the precautionary motive for saving.[3] Deaton (1991) and Carroll (1992, 1997) argue that the orthodox life-cycle model with precautionary saving produces wealth holdings much higher than those actually observed in the data. Instead, they advocate the buffer-stock model of saving whereby income uncertainty induces consumers to hold a target wealth-to-permanent-income ratio, but impatience on the part of the consumer keeps the target low. The uncertainty-reducing effect of the safety net likely diminishes the target even further. If so, this dampened precautionary motive may prove costly for the poor, as Carroll and Samwick (1998) attribute up to 46 percent of wealth holdings to precautionary motives.

A final explanation for low wealth among the poor and near poor is that the primary transfer programs—Temporary Assistance for Needy Families (formerly known, and hereafter referred to, as Aid to Families with Dependent Children [AFDC]), Food Stamps, and Supplemental Security Income (SSI)—have stringent income and liquid-asset tests that levy a 100 percent tax on the benefit for income and assets above the limits.[4] Hubbard, Skinner, and Zeldes (1995) investigate the implications of asset-based means testing in a life-cycle simulation model of saving with earnings uncertainty and out-of-

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[2]If borrowing against future income is constrained, then the poor may prefer flat age-earnings profiles over steep profiles which require an initial investment of low wages in return for higher future wage growth.

[3]Note that low-income households may further spread the risk of income uncertainty by pooling resources through the formation of subfamilies (Gruber 1996; Hutchens, Jakubson, and Schwartz 1989).

[4]Two additional explanations for the low wealth holdings by the poor not explored here are that they may not have an operative bequest motive and that they have relatively high Social Security replacement rates.

pocket medical expenditures. The latter assumptions play the dual roles of generating precautionary saving and of inducing a positive probability that the near poor 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 authors have recently provided empirical support for the Hubbard, Skinner, and Zeldes hypothesis in applications to AFDC (Powers 1998), SSI (Neumark and Powers 1998), and unemployment insurance (UI) (Engen and Gruber 1995).

This paper expands on previous research by estimating simultaneously the wealth-disincentive effects of transfer-program income and policies (AFDC, Food Stamps, SSI, and UI) in a buffer-stock model of asset accumulation with panel data. The main contribution is to provide a wider context in which to judge the relative importance of access to resources that foster asset accumulation as opposed to negative responses to wealth disincentives. The empirical analysis is based on the target wealth-to-permanent-income model of Carroll and Samwick (1997, 1998), where wealth is a function of permanent labor and transfer income, income uncertainty, and measured demographics. Impatience is introduced into the model as a time-invariant correlated random effect. Because of the unobserved heterogeneity and the endogeneity of permanent income and income uncertainty, the asset equations are estimated using a Generalized Method of Moments estimator proposed by Arellano and Bover (1995). The advantage of this estimator is that identification comes internally from the exogeneity between the instrument and both the unobserved heterogeneity and the overall model error, not from exclusion restrictions external to the system. Consequently, the estimator permits the identifying instruments to have a direct effect on wealth, which in this case includes state-specific variation in AFDC-Food Stamp maximum benefits, potential UI benefits, unemployment rates, and personal income.

[5]See the surveys by Danziger, Haveman, and Plotnick (1981) and Moffitt (1992) for evidence on the work-disincentive effects of transfer programs.

To identify differences in the asset accumulation process between the rich and poor, the sample is split into three groups—poor, near poor, and nonpoor—based either on educational attainment or the predicted probability of welfare receipt. Drawing on a wage-decomposition method introduced by Oaxaca and Ransom (1994), the rich-poor wealth gap is decomposed into differences in resources and differences in parameters. Using data from the Panel Study of Income Dynamics, the results suggest that, while transfer income and policies discourage liquid wealth accumulation, at least 75 percent of the rich-poor wealth gap is due to a higher ability by the nonpoor to accumulate wealth.

II. DATA AND DESCRIPTIVE ANALYSIS

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 tax-related information needed to construct disposable income. The sample is drawn from the random Survey Research Center and the nonrandom Survey of Economic Opportunity subsamples, the latter of which oversamples low-income households. Because of 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 (Hoem 1989; Deaton 1997; Fitzgerald, Gottschalk, and Moffitt 1998). Consequently, I weight the descriptive statistics using the family weight constructed by the PSID, but do not weight the regression model.

The sample consists of 1,210 male and female household heads (14,520 person-years) aged 25–52 in 1980, the period in the life cycle during which most preretirement asset accumulation occurs. I restrict attention to those household heads who do not change marital status over the sample period—that is, they are either continuously married or continuously single. 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 and program characteristics because part of the option value of marriage might be welfare participation.[6] Additionally, heads of household who 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.

In 1984 and 1989 the PSID collected comprehensive data on net wealth, including stocks, bonds, checking accounts, and other savings accounts; business equity; vehicle equity; and housing and other real estate equity.[7] Although much of the analysis focuses on net wealth, I also consider liquid wealth, defined as financial assets and vehicle equity. Because AFDC, Food Stamps, and SSI impose liquid-asset tests, we might expect a larger disincentive effect associated with the narrower measure of wealth compared to net wealth.

For the state-specific welfare policy variables, I obtain information from the *Green Book* (U.S. House of Representatives, selected years), and from *Characteristics of State Plans for Aid to Families with Dependent Children* (U.S. Department of Health and Human Services, selected years). The AFDC program, about 95 percent of which is directed at female-headed households, has federally set guidelines; however, states are given latitude to set asset and gross-income limits, as well as the maximum benefit guarantee. Prior to 1981, there was substantial state-specific heterogeneity in asset limits, but by 1984 only five states had vehicle equity limits below the allowable federal maximum of $1,500, and nine states had nonhousing, nonburial personal property limits below the federal maximum of $1,000.[8] Because of so little state variation in asset limits during my sample period, I focus attention on the wealth effects of state-specific variation in gross-income limits—i.e., gross income may not exceed 150 (185) percent of a state's need standard in 1983 (1988)—and in maximum benefit guarantees.

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[6]However, Hoynes (1997) presents evidence that marital status is not affected by AFDC policy among women with children.

[7]See Curtin, Juster, and Morgan (1989) for evidence on the representativeness of PSID wealth data relative to other wealth surveys such as the Survey of Consumer Finances.

[8]With the devolution of welfare beginning in 1993, many states are again raising their income and asset limits, which will "mechanically" lead to larger caseloads (Ziliak et al. 1997).

Unlike AFDC, only about 50 percent of households in the Food Stamp Program are single women with children, while the rest are diversely split between married households and individuals. The program is administered by the U.S. Department of Agriculture, which does not offer states latitude in setting program variables. For example, the liquid-asset limit is fixed at $1,500 (exclusive of housing and vehicle equity). However, state variation in Food Stamp benefits is achieved if viewed in conjunction with AFDC. For example, an individual or couple with no labor market income qualifies for the maximum benefit of AFDC and is also categorically eligible for Food Stamps. Because AFDC income in some states exceeds the gross-income limit for Food Stamps, the household does not receive the maximum Food Stamp benefit, but instead has 30 percent of it withheld on each AFDC dollar above the limit. To abstract from family-size effects, I use the annual AFDC gross-income limit and the combined annual maximum AFDC/Food Stamp benefit for a family of three

Although the maximum benefit and gross-income limit are related, identifying separate effects is possible because states differ in the deductions used to differentiate the need standard from the maximum benefit. Moreover, other states simply set the maximum benefit arbitrarily below the need standard.[9] An increase in the maximum benefit typically generates a higher income limit (unless the benefit reduction rate is reduced), while the income limit can be changed without a simultaneous change in the benefit. Mechanically, then, a higher income limit or benefit may lead to higher wealth among participants because wealthier individuals become eligible for the program after the change in policy. However, an increase in either policy may behaviorally lead to lower wealth if welfare recipients or near recipients

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[9]In previous versions I also considered the effect of SSI program parameters. As with 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.

reduce wealth either because of either the consumption-floor aspect that reduces uncertainty or the liquid-asset test.

A. Descriptive Analysis

To examine whether the sample selected exhibits the patterns of wealth holdings alluded to in the introduction, I first present estimates of the persistence of real net wealth levels from 1984 to 1989 in Table 1. Most prominent in the table is the high degree of persistence in both the lowest and highest wealth categories. The table reveals that 65 percent of the sample with net wealth less than $5,000 in 1984 were still at that level in 1989. Likewise, 89 percent of the sample with 1984 wealth over $100,000 maintained their position in 1989. Interestingly, though, there does appear to be substantial upward movement in wealth position in several categories, especially among those in the $5,000–$10,000 range; however, a quarter of this group also experienced a decline in wealth position. Consequently, persistence appears to be most closely tied to the extremes of wealth holdings.

One of the arguments given for the persistence of low wealth among poor households is that the social safety net provides an uncertainty-reducing consumption floor, thereby weakening the precautionary motive to save. Moreover, risk pooling among subfamilies may reduce income uncertainty even further. Carroll and Samwick (1998) suggest the log variance of log (detrended) income as a measure of income uncertainty. I construct a similar measure of 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 log residual to obtain an individual-specific average uncertainty measure. I compute this for gross labor income of the head and wife and then examine the percentage reduction in uncertainty by first including the contributions from other household members, followed by changes induced by the tax and transfer system. Appendix Table 1 describes the income measures in detail.

TABLE 1
Persistence of Wealth between 1984 and 1989

	Wealth89					
Wealth84	< 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
>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

Notes: Wealth is reported in $1000s. The number refers to the percentage of the sample in an initial 1984 category that fall in the corresponding category in 1989.

To delineate differences in uncertainty among the poor and nonpoor, a method of splitting the sample is required. Following Hubbard, Skinner, and Zeldes (1995), one method of sample splitting is via educational attainment. Specifically, the poor, near poor, and rich are defined by 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). An alternative measure of lifetime poverty risk is to predict the probability of being on welfare and computing the individual-specific time average over the sample period.[10] To that end, I predict the probability of receiving asset-tested welfare (i.e., welfare = 1 if receiving either AFDC, Food Stamps, or SSI) from a reduced-form probit regression on measured demographics.[11] I then split the sample based on the predicted probabilities into recipients, near recipients, and nonrecipients to reflect the poor, near poor, and nonpoor, respectively. For completeness I report results from both sample-splitting methods, and 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 2 contains the point estimates from the probit model.

The estimates of gross earnings uncertainty in Table 2 reveal that income uncertainty is decreasing in educational attainment and increasing in the probability of welfare receipt. However, including subfamilies reduces income uncertainty by 12 percent on average for the whole sample, but the impact is nonneutral with respect to poverty status. Specifically, the poor experience upwards of a 32 percent reduction in income uncertainty when defined by the probability of welfare receipt. Netting out the effect of income taxes reduces income uncertainty an additional 4 percentage points, the effect of

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

[11]This method of predicting the probability of welfare ignores the interdependencies that exist between AFDC, Food Stamps, and SSI. It is possible to qualify simultaneously for AFDC and Food Stamps, or for SSI and Food Stamps, but not for all three programs. Though the relationships might be better captured with a multinomial probit, the advantage of the binomial probit is that it provides a single probability with which to split the sample.

TABLE 2

Estimates of Average Gross Earnings Uncertainty and Percentage Reduction in Uncertainty Due to Subfamiles, Taxes, and Transfers

	Full Sample	< High School	High School	>High School	Recipient	Near Recipient	Nonrecipient
Labor income HW	-1.93	-1.26	-2.08	-2.10	-0.93	-2.06	-2.27
Labor income HW/O	0.12	0.19	0.10	0.12	0.32	0.10	0.09
Net labor income HW/O	0.16	0.24	0.13	0.15	0.36	0.14	0.12
Net labor/transfer income HW/O	0.37	0.53	0.34	0.33	0.65	0.35	0.27
Number of households	1210	230	461	519	230	461	519

Notes: Uncertainty is measured as log variance of log real income, where income is net of observable demographics (education, race, health, occupation, and industry) and a trend. HW refers to the income of the head and wife, while HW/O refers to the income of the head, wife, and possible subfamilies. The first row depicts average gross income uncertainty for the head and wife, while the next three rows depict the percentage reduction in uncertainty from the base level.

which is fairly homogeneous across poverty status. Though some argue that the progressive U.S. income tax system diminishes the need for precautionary saving (Kimball and Mankiw 1989), it appears that this impact is likely to be small because the relative reduction in uncertainty from taxes is small. Most striking, though, is the impact of transfer income on uncertainty—uncertainty falls by an additional 50 percent with the inclusion of transfers. As with the tax system, the relative impact of transfers on uncertainty appears to be similar across the sample splits. Remarkably, the cumulative impacts of subfamilies, taxes, and transfers diminish substantially the differences in uncertainty between the rich and poor, suggesting that the precautionary motive to save may be greatly affected by the presence of subfamilies and transfer income.

I conclude the exploratory analysis by reporting descriptive statistics in Table 3 for the whole sample and for sample splits. To isolate the wealth effects of asset-tested transfer income from non-asset-tested transfers, I subdivide transfer income into two variables, one subject to limits (i.e., AFDC, Food Stamps, SSI) and one not subject to limits (i.e., unemployment compensation, workers' compensation, veterans' benefits, Social Security, child support, help from other relatives). Higher levels of asset-tested transfers are expected to be associated with lower levels of wealth because of the joint effects of asset tests and the consumption floor. Alternatively, the disincentive effects of non-asset-tested transfers should arise solely from the consumption-floor effect. With 12 years of data on labor and transfer income, I compute permanent income as the individual-specific time-mean of income (Carroll and Samwick 1997). The relatively long time series should improve the estimates of permanent income, but at a cost of smaller sample sizes because of the restriction of continuous marital status. All income and wealth data are deflated by the personal consumption expenditure deflator with 1987 as the base year.

Table 3 reveals that the method of splitting the sample results in substantively different compositions for the poor. Households categorized as < High School, as opposed to Recipients, have significantly more permanent labor income and wealth, and less permanent transfer income. In addition,

TABLE 3
Selected Summary Statistics by Educational Level and Predicted Probability of Welfare Receipt

	Full Sample	< High School	High School	>High School	Recipient	Near Recipient	Nonrecipient
Permanent net labor income HW/O	36.15	24.81	29.82	44.34	16.75	30.51	44.41
	(37.08)	(20.47)	(17.70)	(44.46)	(16.15)	(31.67)	(36.85)
	{28.01}	{11.69}	{25.17}	{32.54}	{5.35}	{24.69}	{34.22}
Permanent asset-tested transfer income HW/O	0.12	0.46	0.08	0.03	0.84	0.04	0.01
	(0.71)	(1.73)	(0.46)	(0.27)	(2.37)	(0.20)	(0.18)
	{0.00}	{0.00}	{0.00}	{0.00}	{0.04}	{0.00}	{0.00}
Permanent non-asset-tested transfer income HW/O	0.93	1.16	1.00	0.81	1.57	1.01	0.73
	(2.19)	(2.23)	(2.49)	(1.93)	(3.99)	(2.10)	(1.81)
	{0.15}	{0.18}	{0.18}	{0.11}	{0.18}	{0.20}	{0.11}
Nonhousing, nonbusiness wealth	82.54	21.15	45.47	128.97	8.81	43.64	129.37
	(509.89)	(46.73)	(167.73)	(664.05)	(28.84)	(220.08)	(636.52)
	{11.69}	{1.69}	{9.41}	{23.23}	{0.41}	{8.27}	{28.55}
Net wealth	196.80	58.58	113.83	300.98	24.31	115.49	298.85
	(883.64)	(108.29)	(325.28)	(1136.40)	(61.79)	(606.48)	(1023.47)
	{44.17}	{9.89}	{34.04}	{82.04}	{1.49}	{29.61}	{99.72}
Target wealth to permanent income	3.68	1.93	3.06	5.01	1.37	2.71	5.57
	(10.26)	(3.95)	(5.99)	(14.25)	(4.26)	(5.12)	(14.40)
	{1.71}	{0.95}	{1.53}	{2.29}	{0.25}	{1.47}	{2.83}
Welfare participation	0.04	0.13	0.03	0.01	0.25	0.02	0.003
	(0.16)	(0.35)	(0.14)	(0.08)	(0.47)	(0.08)	(0.03)
AFDC gross income limit	10.06	9.12	10.15	10.30	9.54	10.12	10.14
	(3.71)	(4.43)	(3.71)	(3.41)	(4.79)	(3.84)	(3.30)

(table continues)

TABLE 3, continued

	Full Sample	< High School	High School	>High School	Recipient	Near Recipient	Nonrecipient
AFDC/Food Stamp benefit	6.79	6.34	6.79	6.92	6.41	6.81	6.85
	(1.76)	(1.96)	(1.80)	(1.62)	(2.29)	(1.74)	(1.60)
Female	0.17	0.26	0.17	0.14	0.57	0.20	0.06
	(0.49)	(0.60)	(0.50)	(0.45)	(0.78)	(0.53)	(0.29)
Married	0.78	0.70	0.78	0.80	0.43	0.72	0.90
	(0.54)	(0.62)	(0.55)	(0.51)	(0.77)	(0.59)	(0.37)
White	0.86	0.73	0.85	0.91	0.49	0.86	0.95
	(0.46)	(0.68)	(0.49)	(0.37)	(0.87)	(0.46)	(0.29)
Age	43.66	45.89	43.37	43.16	42.52	42.82	44.57
	(10.56)	(10.85)	(11.11)	(9.98)	(13.24)	(9.61)	(10.21)
Number of households	1210	230	461	519	230	461	519

Notes: The table reports means and (standard deviations) for all variables, as well as {medians}. All income and wealth variables are in $1000s and are deflated by the personal consumption expenditure deflator with 1987 base year.

they are much less likely to be female-headed, unmarried, nonwhite, and actual welfare participants. Table 3 also shows the striking disparity between the poor and nonpoor in terms of permanent labor income and wealth, as well as target net-wealth-to-permanent-income ratios. The income deficiency suggests that the poor and near poor are at a disadvantage relative to the nonpoor in terms of the ability to accumulate, while the low targets may be due to a combination of low incomes, impatience, and transfer programs.

III. ESTIMATION ISSUES

The descriptive analysis indicates that to isolate the effect of transfer programs on asset holdings, it is necessary to control for other factors that affect the ability to accumulate wealth, such as permanent labor income, income uncertainty, impatience, and demographics. In addition, since the poor reside in states with lower welfare benefits on average, it is also important to control for state fixed effects. The econometric model I employ to capture these influences is based on the work of Carroll and Samwick (1997, 1998). They 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 observed demographics. Specifically, for each group j (j = poor, near poor, nonpoor), the empirical specification is

$$W_{jit} = \beta_{j1} + \beta_{j2} PTA_{ji} + \beta_{j3} PT_{ji} + \beta_{j4} PL_{ji} + \beta_{j5} \hat{\eta}_{ji} + \beta_{j6}{}' Z_{ji} + \beta_{j7}{}' X_{jit} + \delta_{jk} + \alpha_{ji} + \nu_{jit}, \qquad \textbf{(1)}$$

where W_{jit} is log wealth for person i (i = 1,...,N) in time t (t = 1,...,T), PTA_{ji} is the log of permanent asset-tested transfer income, PT_{ji} is the log of permanent non-asset-tested transfer income, PL_{ji} is the log of permanent labor income, $\hat{\eta}_{ji}$ is the measure of income uncertainty, Z_{ji} is a vector of time-invariant demographics, X_{jit} is a vector of time-varying demographics (along with the state-specific welfare policy variables), δ_{jk} is a set of time-invariant state fixed effects, and ν_{jit} is a random error term permitted to be conditionally heteroskedastic.[12] A theoretical measure of impatience does not exist in this version of the buffer-stock model. However, under the assumption that impatience is time-invariant and person-specific, I parameterize it with the unobserved heterogeneity term α_{ji}.[13]

The model in equation 1 contains two sources of latent heterogeneity, state effects (δ_{jk}) and person effects (α_{ji}). 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_{ji} and the measured covariates, then with first-differences or deviations from time-means one can no longer identify the time-invariant regressors such as permanent income. An alternative is to assume that some of the regressors are correlated with the individual effect and some are not, which yields the correlated random-effects model of Hausman and Taylor (1981). 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:

$$W_i = D_i\Gamma + \varepsilon_i, \qquad \textbf{(2)}$$

where W_i is the T × 1 vector of log wealth for person i, $D_i = [\iota_T F_i', X_i]$, ι_T is a T × 1 vector of ones, $F_i = [1, PTA_i, PT_i, PL_i, \hat{\eta}_i, Z_i]$ is a P × 1 vector of time-invariant regressors, $\Gamma = [\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7]$ is a (G+P) × 1 vector of unknown parameters to estimate, and $\varepsilon_i = \iota_T\alpha_i + \nu_i$.

[12]Carroll and Samwick (1998) pool labor and transfer income under the assumption that a dollar of transfer income has the same effect on wealth as a dollar of earned income.

[13]Because of the presence of an overall constant term, β_{j1}, one must impose the restriction that $\sum\alpha_{ji} = 0$. Hence, the constant term captures "average impatience" while the α_{ji}'s capture deviations from the mean.

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

$$C = \begin{bmatrix} H \\ \iota_T'/T \end{bmatrix} \qquad \textbf{(3)}$$

where *H* is a (T−1) × 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 (1995) suggest a block-diagonal instrument matrix of the form

$$M_i = \begin{bmatrix} d_i' & & & 0 \\ & d_i' & & \\ & & d_i' & \\ 0 & & & m_i' \end{bmatrix} \qquad \textbf{(4)}$$

where $d_i = (x_i, F_i)$ 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

$$\hat{\Gamma} = [D'\bar{C}'M(M'\bar{C}\hat{\Omega}\bar{C}'M)^{-1}M'\bar{C}D]^{-1}D'\bar{C}'M(M'\bar{C}\hat{\Omega}\bar{C}'M)^{-1}M'\bar{C}W, \qquad \textbf{(5)}$$

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

A. <u>Identification</u>

The key to identification for endogenous 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, ν_i). This implies that the instruments are also permitted to have a direct effect on wealth. In the current model, identification is complicated further because several of the time-invariant regressors are also correlated with ν_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 mismeasured and thus should be treated as endogenous.

Cornwell, Schmidt, and Wyhowski (1992) propose a classification scheme in which X_i is decomposed as $[X_{1i}, X_{2i}, X_{3i}]$ and 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; ν_i, X_{2i} and F_{2i} are called *singly exogenous* because they are assumed to be correlated with α_i but not ν_i; and X_{3i} and F_{3i} are called *doubly exogenous* because they are assumed to be uncorrelated with both α_i and ν_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).[14] A robustness section below tests several of these restrictions. Identification thus 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}). This suggests that one possibility for m_i is the Hausman and Taylor (1981) instrument set with $m_i = [\bar{x}_{3i}, F_{3i}]$, where $\bar{x}_{3i}$ is the individual time-mean of the doubly exogenous X's.

[14]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, Hansen, and Singleton 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.

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 impatience (α_i) and the overall equation error (ν_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 UI; consequently, I use the average potential UI benefit to instrument this variable. Candidates for state-level instruments for permanent labor income are less obvious, but one such candidate is the log of state personal income. Finally, 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 one of my sample-splitting variables is education, I cannot 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 impatience, 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. Meanwhile, variables included in F_{3i} are a constant, marital status, and geographic region.[15] As a check on instrument quality for each of the endogenous regressors, I report the first-stage partial R^2 of instrument correlation. The

[15]In the PSID, the head of household in two-parent households is male by default, although there are exceptions. It is possible to identify both gender and marital effects in the full-sample models, but not the split-sample models. This is especially problematic for the poor since marital rates are low and female-headship is high, resulting in collinearity problems. Hence, I only include marital status among the time-invariant regressors.

partial R^2 (or the canonical correlation) is the appropriate statistic for instrument relevance in models with multiple endogenous variables (Shea 1997). Appendix Table 1 contains a complete categorization of the explanatory variables and instrument sets.

IV. RESULTS

I present results from the GMM wealth regressions for the full sample and for the samples split by education and the predicted probability of welfare receipt.[16] Two specifications are presented in each table, one based on liquid wealth and the other based on net wealth. The measures of permanent labor and transfer income are defined broadly by including the after-tax contributions of the head, wife, and others in the household. While each regression controls for the demographics described above, for brevity I only report results for the income variables and state policies. 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 examine the broader issue of whether the rich-poor wealth gap is due to ability differences or differences in responses to incentives.

A. Full Sample

Table 4 presents evidence that asset-tested and non-asset-tested permanent income have a deterrent effect on both liquid and net wealth accumulation, with the effect being at least twice as large and statistically significant in the case of liquid wealth. The elasticity of liquid wealth with respect to permanent asset-tested transfer income is about −0.4, indicating that a 10 percent increase in benefit receipt results in a 4 percent decrease in liquid wealth. Because state welfare programs only "tax" liquid

[16] All wealth and income variables are in logs, with nonpositive values of wealth set equal to 0. Censoring may be a problem for the group defined as poor, e.g., 10 percent of those with less than high school have zero net wealth (4 percent have negative assets), while 15 percent of those labeled as "Recipients" have zero net wealth. I discuss this potential censoring problem in the robustness section below.

TABLE 4
GMM Estimates of Liquid and Net Wealth for Full Sample

	(1)	(2)
Permanent asset-tested transfer income	-0.386	-0.149
	(0.161)	(0.133)
	[0.102]	[0.102]
Permanent non-asset-tested transfer income	-0.239	-0.106
	(0.095)	(0.085)
	[0.088]	[0.088]
Permanent labor income	1.324	1.935
	(0.480)	(0.369)
	[0.162]	[0.162]
Uncertainty in income	0.171	0.532
	(0.250)	(0.240)
	[0.093]	[0.093]
AFDC/Food Stamp maximum benefit	-1.492	-0.441
	(0.801)	(0.626)
AFDC gross income limit	-0.162	0.024
	(0.351)	(0.271)
UI benefit	-0.133	-0.743
	(0.609)	(0.457)
J-statistic	53.415	60.766
(df, p-value)	(54, 0.497)	(54, 0.245)
Number of observations	2420	2420

Notes: Specification (1) uses liquid wealth; specification (2) uses net wealth. 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. All wealth and income variables are in natural logs, with nonpositive values of wealth set equal to 0. Labor income is based on Net Labor Income HW/O, and uncertainty is defined as Net Labor/Transfer Income HW/O. See the text and Appendix Table 1 for further details.

assets when determining eligibility, it is not surprising to find little effect on net wealth. Likewise, with respect to non-asset-tested transfers, we might expect the larger effect on liquid wealth since receipt of UI is often temporary and not likely to result in changes in large wealth holdings such as homes. Based on the income uncertainty coefficients, there is evidence of an operative precautionary saving motive, particularly for net wealth. Carroll and Samwick (1998) find a similar result and argue that the stronger precautionary motive for net wealth may reflect the fact that households attempt to insure against large, negative shocks that impact their overall wealth position.

Table 4 also reveals that increasing the consumption floor via the AFDC/Food Stamp maximum benefit serves as a disincentive to accumulate liquid wealth, consistent with the Hubbard, Skinner, and Zeldes (1995) hypothesis. A 10 percent increase in the consumption floor leads to a 15 percent reduction in liquid wealth, but only a 4 percent reduction in net wealth. 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, whereas the potential UI benefit has a statistically weak negative effect on net wealth. The larger disincentive effect of potential UI benefits on net wealth compared to liquid wealth is surprising, but given the lack of significance, and the results to follow in Tables 5 and 6, it is likely anomalous.

B. Split Samples

Table 5 presents the results of liquid and net wealth regressions broken down by education level, while Table 6 contains estimates broken down by the predicted probability of welfare receipt. As is evident from the tables, there is substantial heterogeneity in the asset-accumulation process across the poor, near-poor, and nonpoor samples. In addition, as foreshadowed in the descriptive statistics, the method of sample splitting yields different sample compositions and thus different patterns in several of the coefficients. For the education sample, only the nonpoor (i.e. > High School) significantly reduce wealth out of permanent asset-tested transfer income. However, the result is just the opposite for the split

TABLE 5
GMM Estimates of Liquid and Net Wealth by Educational Level

	< High School		High School		> High School	
	(1)	(2)	(1)	(2)	(1)	(2)
Permanent asset-tested transfer income	-0.191	0.109	-0.149	-0.170	-0.461	-0.497
	(0.191)	(0.167)	(0.223)	(0.172)	(0.231)	(0.188)
	[0.221]	[0.221]	[0.116]	[0.116]	[0.127]	[0.127]
Permanent non-asset-tested transfer income	0.449	0.218	-0.452	-0.304	-0.162	-0.099
	(0.159)	(0.143)	(0.146)	(0.098)	(0.093)	(0.072)
	[0.185]	[0.185]	[0.122]	[0.122]	[0.109]	[0.109]
Permanent labor income	1.739	2.078	2.149	1.793	0.028	1.363
	(0.470)	(0.449)	(0.749)	(0.538)	(0.817)	(0.570)
	[0.294]	[0.294]	[0.170]	[0.170]	[0.244]	[0.244]
Uncertainty in income	-0.255	0.202	0.249	0.240	0.374	0.234
	(0.351)	(0.323)	(0.341)	(0.275)	(0.288)	(0.235)
	[0.152]	[0.152]	[0.082]	[0.082]	[0.120]	[0.120]
AFDC/Food Stamp maximum benefit	-1.822	-1.167	-2.236	-0.574	1.593	1.377
	(1.753)	(1.564)	(1.213)	(0.899)	(1.147)	(0.760)
AFDC gross income limit	0.219	0.137	0.768	0.746	-1.128	-0.561
	(0.846)	(0.578)	(0.531)	(0.391)	(0.492)	(0.351)
UI benefit	-2.673	-2.002	-0.409	-0.641	1.015	0.270
	(1.633)	(1.341)	(1.006)	(0.726)	(0.803)	(0.525)
J-statistic	62.849	50.886	48.628	60.875	42.956	48.711
(df, p-value)	(54, 0.192)	(54, 0.595)	(54, 0.681)	(54, 0.242)	(54, 0.859)	(54, 0.678)

(table continues)

TABLE 5, continued

	< High School		High School		> High School	
	(1)	(2)	(1)	(2)	(1)	(2)
Wald (< HS vs HS)	80.645	64.354				
(df, p-value)	(39, 0.000)	(39, 0.007)				
Wald (< HS vs > HS)	92.126	67.084				
(df, p-value)	(39, 0.000)	(41, 0.003)				
Wald (HS vs > HS)	53.438	41.514				
(df, p-value)	(39, 0.051)	(41, 0.362)				
Number of observations	460	460	922	922	1038	1038

Notes: Specification (1) uses liquid wealth; specification (2) uses net wealth. 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. Wald refers to a test of structural differences in the estimated parameters. All wealth and income variables are in natural logs, with nonpositive values of wealth set equal to 0. Labor income is based on Net Labor Income HW/O, and uncertainty is defined as Net Labor/Transfer Income HW/O. See the text and Appendix Table 1 for further details.

TABLE 6
GMM Estimates of Liquid and Net Wealth by Predicted Probability of Welfare Receipt

	Recipient		Near Recipient		Nonrecipient	
	(1)	(2)	(1)	(2)	(1)	(2)
Permanent asset-tested transfer income	-0.287	-0.166	-0.226	-0.056	0.129	0.395
	(0.147)	(0.144)	(0.289)	(0.202)	(0.560)	(0.364)
	[0.216]	[0.216]	[0.072]	[0.072]	[0.053]	[0.053]
Permanent non-asset-tested transfer income	0.568	0.444	-0.459	-0.227	-0.218	-0.126
	(0.176)	(0.173)	(0.129)	(0.096)	(0.102)	(0.067)
	[0.144]	[0.144]	[0.143]	[0.143]	[0.104]	[0.104]
Permanent labor income	1.953	2.092	0.887	1.697	2.037	1.382
	(0.507)	(0.429)	(0.996)	(0.727)	(0.627)	(0.387)
	[0.273]	[0.273]	[0.200]	[0.200]	[0.245]	[0.245]
Uncertainty in income	-0.347	-0.046	0.123	0.178	0.545	0.673
	(0.484)	(0.426)	(0.213)	(0.251)	(0.254)	(0.189)
	[0.167]	[0.167]	[0.123]	[0.123]	[0.117]	[0.117]
AFDC/Food Stamp maximum benefit	0.067	-0.157	-1.171	0.333	-1.102	-0.042
	(1.867)	(1.964)	(1.202)	(0.876)	(1.057)	(0.622)
AFDC gross income limit	-0.749	-1.506	-0.471	-0.025	0.705	0.344
	(0.986)	(0.987)	(0.589)	(0.414)	(0.462)	(0.331)
UI benefit	-2.524	-1.468	0.773	-0.069	0.425	0.104
	(1.845)	(1.849)	(1.154)	(0.840)	(0.708)	(0.416)
J-statistic	54.107	48.959	48.666	64.295	49.143	42.448
(df, p-value)	(54, 0.470)	(54, 0.669)	(54, 0.679)	(54, 0.159)	(54, 0.662)	(54, 0.872)

(table continues)

TABLE 6, continued

	Recipient		Near Recipient		Nonrecipient	
	(1)	(2)	(1)	(2)	(1)	(2)
Wald (Recip -vs- Near)	96.513	54.797				
(df, p-value)	(39, 0.000)	(39, 0.048)				
Wald (Recip -vs- Non)	83.980	75.156				
(df, p-value)	(39, 0.000)	(39, 0.000)				
Wald (Near -vs- Non)	44.957	61.651				
(df, p-value)	(39, 0.237)	(39, 0.012)				
Number of observations	460	460	922	922	1038	1038

Notes: Specification (1) uses liquid wealth; specification (2) uses net wealth. 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. Wald refers to a test of structural differences in the estimated parameters. All wealth and income variables are in natural logs, with nonpositive values of wealth set equal to 0. Labor income is based on Net Labor Income HW/O, and uncertainty is defined as Net Labor/Transfer Income HW/O. See the text and Appendix Table 1 for further details.

based on the predicted probability of welfare receipt—the poor significantly decrease liquid wealth with increases in asset-tested transfers. This result is not entirely surprising when considering that Recipients are on average twice as likely to be actual welfare participants relative to the <High School sample, while the >High School sample is on average three times as likely to be actual welfare participants compared to Nonrecipients. In general, though, permanent asset-tested transfers are a small deterrent to asset accumulation.

An interesting pattern of responses to non-asset-tested transfers and income uncertainty arises across the three groups. 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 UI or workers' compensation have a relatively strong labor force attachment and are at the high end of the wealth distribution within that subgroup. Meanwhile, the group of non-asset-tested welfare recipients among the near poor and nonpoor likely have a comparatively weaker labor force attachment and are at the low end of the wealth distribution for their subgroups. Across both methods of sample splitting, the poor and near poor appear to have weak precautionary motives to save. Indeed, the poor weakly *reduce* liquid wealth when income uncertainty increases, which is not surprising given that they are the most vulnerable members of the population and also have access to the social safety net. The nonpoor, on the other hand, have a strong precautionary motive to save, especially when defined as Nonrecipients.

For the state welfare policy variables, recall that signs on the AFDC/Food Stamp maximum guarantee and the AFDC income limits are indeterminate a priori. An increase in either policy leads to a "mechanical" increase in wealth since wealthier individuals become eligible for the program; however, there could be a "behavioral" reaction to the higher limits by wealthier households reducing wealth in order to qualify for the program. Because no asset test is associated with potential UI benefits, we expect higher potential UI benefits to lead to lower wealth. Focusing on the education split in Table 5, we see that those with high school or less view high AFDC/Food Stamp benefits as a disincentive to accumulate liquid wealth, especially for the high school sample. This latter finding supports the simulation results of Hubbard, Skinner, and Zeldes (1995), who find that those with a significant chance of becoming poor react strongly to AFDC policy. Those with more than high school respond to higher AFDC/Food Stamp benefits with higher wealth, which is consistent with the "mechanical" effect outweighing the "behavioral" effect. However, this group of households reduces wealth in response to higher income limits, reflecting a strong behavioral effect. With the exception of potential UI benefits, the latter results are tempered somewhat because there is no consistent disincentive effect of transfer policy on wealth when the sample is broken down by welfare receipt in Table 6. Since the samples only reflect compositional differences and not size differences, this calls into question the robustness of the disincentive effects of AFDC policy.

Taken as a whole, the poor and near poor, as well as the poor and nonpoor, do respond differently to economic incentives and disincentives to accumulate wealth, as evidenced by the Wald tests in Tables 5 and 6. It does appear that the poor do try to save, as the coefficients on the labor income terms are at least as large for the poor as for the nonpoor. However, the broader issue is whether the rich-poor wealth gap emanates more from these differences in parameters or from differences in the resources to accumulate.

C. Wealth Decomposition: Is It Ability or Responses to Incentives?

To address the differences in asset accumulation among the poor, near poor, and nonpoor in more detail I decompose wealth using a method suggested by Oaxaca and Ransom (1994) for the measurement of wage discrimination. Specifically, I decompose the rich-poor wealth gap into the fraction due to ability differences, i.e., the D_i's from equation 2 such as permanent income, uncertainty, marital status, and occupation, and the fraction attributable to differences in the responses to the ability variables, i.e., the $\hat{\Gamma}$ from equation 2. 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.[17]

In their application to gender wage discrimination, Oaxaca and Ransom (1994) argue that in the absence of discrimination the wage structure is well approximated by a model that pools men and women together. Using a similar line of reasoning, in the absence of differences in the asset-accumulation process between the rich and poor, the wealth structure would resemble a structure generated from a pooled model of poor and nonpoor. Specifically, the difference in mean log wealth between low-income group j and high-income group k is:

$$\bar{W}_j - \bar{W}_k \;=\; \bar{D}_j(\hat{\Gamma}_j - \hat{\Gamma}_{j,k}) \;+\; \bar{D}_k(\hat{\Gamma}_{j,k} - \hat{\Gamma}_k) \;+\; (\bar{D}_j - \bar{D}_k)\hat{\Gamma}_{j,k}, \qquad \textbf{(6)}$$

where the first term on the right-hand side holds group j's ability constant and examines differences in the low-income group's parameters relative to the pooled parameters ($\hat{\Gamma}_{j,k}$), the second term reflects differences in the high-income group parameters relative to the pooled parameters (holding group k's ability constant), and the third term reflects differences in the average ability to accumulate wealth (holding the parameters fixed at the pooled response).[18]

Table 7 presents the decomposition for liquid and net wealth based on the parameter estimates in Tables 5 and 6. The first two columns refer to differences in low-income and high-income group parameters, respectively, while the third column refers to ability differences. For example, in comparing the poor and near poor, the near poor are considered the high-income group. Examining the results based on the education split, about 75 percent of the wealth gap between the poor and nonpoor comes from

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[17]Because of a scaling problem that arises when deciding which dummy variable category to omit, another shortcoming of this decomposition is that it is not possible to separately isolate the contribution of individual $\hat{\Gamma}$'s to the total gap, e.g., the parameters on the policy variables versus the uncertainty variable (Jones 1983).

[18]It is important to note that between-group impatience is captured in the decomposition via the group-specific constant term. Specifically, as noted previously, the constant term captures average impatience within each group while the α_{ji}'s are deviations from the group mean and average out to zero within groups.

TABLE 7
Decomposition of Liquid and Net Wealth into Differences in Responsiveness versus Ability to Accumulate

	% Due to Low-Income Responsiveness	% Due to High-Income Responsiveness	% Due to Ability
Liquid Wealth			
< HS vs HS	8.62	2.15	89.24
< HS vs > HS	14.52	13.62	71.86
HS vs > HS	17.87	21.38	60.75
Recipient vs Near	-15.42	5.97	109.46
Recipient vs Non	-10.76	1.66	109.10
Near Recip vs Non	-15.14	0.88	114.26
Net Wealth			
< HS vs HS	12.96	13.08	73.96
< HS vs > HS	15.68	9.78	74.54
HS vs > HS	11.87	18.59	69.54
Recipient vs Near	-12.66	15.44	97.22
Recipient vs Non	-12.71	2.80	109.92
Near Recip vs Non	-8.86	3.74	105.11

Notes: A negative percentage in the first column occurs if the low-income group is less responsive to positive incentives to accumulate or more responsive to negative incentives to accumulate. The percentages are constrained to sum to 100 percent.

differences in the ability to accumulate wealth. The ability differences are a bit larger for the poor and near-poor comparison, while they are slightly less for the near-poor and nonpoor comparison. Meanwhile, for the predicted probability of welfare receipt sample, the ability gap frequently exceeds 100 percent between the rich and poor. In this case the low-income group is less responsive to positive incentives to accumulate, such as permanent labor income, and/or more responsive to negative incentives to accumulate, such as transfer-program income and policies. As a consequence of the requirement that percentages must sum to 100, the negative percentage in the first column leads to an ability gap over 100 percent. Regardless of sample split, however, the driving force behind the rich-poor wealth gap is differences in the ability to accumulate.

D. Robustness

A number of assumptions underlying the empirical model in equations 1–5 require further analysis, such as assuming that occupation and industry are doubly exogenous. Consequently, in this section I test whether the main conclusion, that an ability gap is the primary factor underlying the rich-poor wealth gap, holds under alternative model specifications. For ease of exposition, and because the results have identical patterns, I present only the sensitivity analysis for net wealth in Table 8.

In the first sensitivity test I remove the state fixed effects from the regression model. Controlling for state fixed effects is likely to be important for identifying the true effect of state-specific welfare policy variables. Indeed, in results not tabulated, the policy variables are frequently less significant, both economically and statistically, without state effects. The first section of Table 8, however, confirms the main conclusion that the wealth gap is caused by a resource gap. In fact, the estimated ability gap between the poor and nonpoor actually increases for the education split, but it decreases for the probability of welfare receipt sample. This suggests that while the qualitative story is unchanged by the omission of state fixed effects, their inclusion is important for identifying the quantitative magnitude.

TABLE 8
Net Wealth Decomposition under Alternative Model Specifications

	% Due to Low-Income Responsiveness	% Due to High-Income Responsiveness	% Due to Ability
No State Fixed Effects			
< HS vs HS	16.13	9.69	74.19
< HS vs > HS	9.67	5.05	85.28
HS vs > HS	1.12	0.36	98.52
Recipient vs Near	16.37	10.92	72.71
Recipient vs Non	8.23	2.49	89.28
Near Recipient vs Non	3.95	7.38	88.67
Only Include Income of Head and Wife (Net Labor/Transfer Income HW)			
< HS vs HS	27.10	10.08	62.82
< HS vs > HS	19.93	13.03	67.04
HS vs > HS	23.63	20.83	55.55
Recipient vs Near	-13.94	18.32	95.62
Recipient vs Non	-5.61	6.10	99.52
Near Recipient vs Non	6.91	16.10	77.00
Occupation and Industry as Singly Exogenous (X_2)			
< HS vs HS	23.01	4.51	72.48
< HS vs > HS	15.94	6.91	77.16
HS vs > HS	18.85	18.31	62.85
Recipient vs Near	0.05	18.30	81.65
Recipient vs Non	-5.39	-1.59	106.98
Near Recipient vs Non	-24.83	-10.27	135.10
Redefine Categories of Recipient, Near Recipient, and Nonrecipient			
Recipient vs Near	-11.25	-8.64	119.89
Recipient vs Non	-10.58	4.55	106.03
Near Recipient vs Non	21.07	6.59	72.34
Compute Permanent Income and Uncertainty over 6-year intervals			
< HS vs HS	-11.97	12.74	99.23
< HS vs > HS	14.25	8.39	77.35
HS vs > HS	20.00	27.31	52.69
Recipient vs Near	6.45	16.35	77.20
Recipient vs Non	2.31	6.60	91.09
Near Recipient vs Non	-1.06	20.97	80.09

(table continues)

TABLE 8, continued

	% Due to Low-Income Responsiveness	% Due to High-Income Responsiveness	% Due to Ability
Alternative Transformation of Wealth			
< HS vs HS	23.55	17.11	59.35
< HS vs > HS	21.73	10.54	67.73
HS vs > HS	-2.27	22.26	80.01
Recipient vs Near	-15.74	20.85	94.89
Recipient vs Non	-12.77	5.02	107.74
Near Recipient vs Non	-15.09	15.25	99.84
Two-Step Tobit Estimator			
< HS vs HS	36.85	15.75	47.40
< HS vs > HS	22.02	7.77	70.21
HS vs > HS	14.31	12.26	73.43
Recipient vs Near	17.61	6.19	76.20
Recipient vs Non	5.30	10.14	84.57
Near Recipient vs Non	19.21	18.40	62.39

Notes: A negative percentage in the first (second) column occurs if the low-income (high-income) group is less (more) responsive to positive incentives to accumulate or more (less) responsive to negative incentives to accumulate. The percentages are constrained to sum to 100 percent.

Next, I narrow the definition of household income by excluding the income of members other than the head or wife. This removes the income generated by any working-age children in the household as well as by any subfamilies. Although the qualitative results hold, the size of the ability gap actually narrows for the education split, contrary to expectations. One might expect that income pooling should reduce, not increase, the ability gap since the income of other household members is a larger fraction of total income for the poor than for the nonpoor. However, in results not tabulated, the poor (both <High School and Recipients) actually experience an increase in average income uncertainty with income pooling, possibly because the contributions from children and subfamilies are unstable. Consequently, the greater certainty of income from the head and wife may lead to a lower rich-poor ability gap.

A maintained assumption up to now is that occupation and industry are doubly exogenous—that is, they are exogenous to both the person-specific effect, α_i, and the overall error term, ν_{it}. It is plausible that one manifestation of impatience is that workers sort into occupations and industries that offer immediate payoffs and do not require an initial investment in low wages. If so, then occupation and industry would be correlated with α_i and thus should be treated as singly exogenous (i.e., an element of X_2 not X_3). The third row of Table 8 reports the results of the wealth decomposition when occupation and industry are singly exogenous. Again, the key finding holds that about three-quarters of the rich-poor wealth gap emanates from ability differences. Moreover, the pseudo likelihood-ratio test of Eichenbaum, Hansen, and Singleton (1988) described in footnote 14 yields p-values ranging from 0.10 to 0.30, indicating that the double exogeneity assumption cannot be rejected.

A motivation for the cutoff points from the predicted probability of welfare receipt was to maintain homogeneity in sample sizes with the sample split based on educational attainment. As a sensitivity check on this issue, I redefine the cutoff points to more closely mimic what might be considered poor, near poor, and nonpoor based on the income distribution. Specifically, the poor now constitute 15 percent of the sample to more closely approximate the poverty rates during the sample period, the near poor constitute the next 25 percent (i.e., the lower middle class that is vulnerable to becoming poor), and the nonpoor constitute the upper 60 percent. As evidenced from the fourth row of Table 8, the results are largely unchanged, with the possible exception of the near-recipient versus nonrecipient comparison where differences in responsiveness play a more important role, but the ability gap is still a dominant 72 percent.

Permanent labor and transfer income, along with income uncertainty, are computed as the individual-specific time-mean over the 12-year sample period. However, Carroll (1997) reminds us that Friedman (1957) did not believe “permanent” was synonymous with “lifetime” in the original formulation of the permanent-income hypothesis. Instead, Friedman argued that while beliefs over what constituted permanent were person-specific, a near-term planning horizon such as 5 years was perfectly consistent with his notion of the hypothesis. To examine whether the results are sensitive to the planning horizon, I compute the permanent income and income uncertainty variables over two 6-year periods, 1980–1985 and 1986–1991. I still employ the correlated random effects estimator because of time-invariant regressors such as the constant term and marital status. However, permanent income and income uncertainty are now treated as time-varying endogenous variables (X_1). Even with this modification, the result that over three-quarters of the rich-poor wealth gap is attributable to ability is still robust.

Finally, I address the issue of possible censoring in the dependent variable. Nearly 15 percent of the poor sample have negative or zero wealth (3–5 percent of the near poor and nonpoor have negative wealth), and thus their data was censored at the origin because of the logarithmic transformation. I consider two alternatives to the model considered, one with wealth transformed by the hyperbolic sine transformation and the other a simultaneous-equations tobit model.[19] While the development of a

[19]The hyperbolic sine transformation permits negative and zero values of wealth and is defined as $\ln(W_i + (W_i^2 + 1)^{0.5})$. This transformation was suggested by Annamaria Lusardi in her discussion of an unrelated paper.

correlated random-effects estimator for a censored dependent variable is beyond the scope of the current project, I estimate a simultaneous-equations tobit model under the assumption of no unobserved heterogeneity. I employ a two-step estimator whereby in the first step I predict the three permanent-income terms and income uncertainty, and in the second step I use the fitted values in a standard tobit regression. With the possible single exception of the poor to near-poor comparison for the education group, the evidence weighs heavily that the main difference in wealth levels between the poor and nonpoor is in the ability to accumulate wealth.

V. CONCLUSION

The persistently low wealth holdings among the poor continue to puzzle economists and policymakers. This weak wealth position could be due to low incomes, weak precautionary motives, impatience, or disincentives created by income and liquid-asset tests imposed on participants in transfer programs. In this paper, I employ panel data and a buffer-stock saving model to estimate the impact of income transfers on the asset accumulation of the poor, near poor, and nonpoor, holding constant permanent labor income, income uncertainty, impatience, and other measured demographics. With the estimated parameters, I address the broader issue of whether the wealth holdings between the rich and poor diverge because the groups respond differently to economic incentives or because they face different opportunities (abilities) to accumulate wealth.

The evidence suggests that the receipt of asset-tested transfer income has a small deterrent effect on liquid-wealth accumulation. In addition, higher maximum AFDC/Food Stamp benefits serve as a significant disincentive to accumulate liquid wealth for the sample as a whole. However, transfer income and policies do not affect net wealth. Moreover, the wealth effects of maximum AFDC/Food Stamp benefits are mixed for the subsamples of poor, near poor, and nonpoor. When the sample is split by educational attainment, higher benefits lead to lower assets for the poor and near poor. Alternatively, when the sample is split based on the predicted probability of welfare receipt, there are no identifiable disincentive effects associated with the maximum benefit guarantee. Regardless of sample split, potential UI benefits are a significant disincentive for the poor to acquire liquid assets and, to a lesser extent, net wealth.

What is the source of the rich-poor wealth gap—ability differences or differences in responses to economic incentives? The evidence here is persuasive. The driving force underlying the rich-poor wealth gap is a gap in the ability to accumulate assets. Under a variety of model specifications, I show that the fraction of the wealth gap attributable to ability differences is at least 75 percent. This suggests that the disincentives created by transfer programs have a small impact on the overall asset position of the poor. In addition, the results suggest that to enhance opportunities for the poor to accumulate wealth, policymakers might focus less on finding the right mix of income and assets limits and more on policies that reduce labor-income inequality.

APPENDIX TABLE 1
Variable Descriptions

Income Measures:

Labor Income HW:	Gross wage and salary income of the household head and wife
Labor Income HW/O:	Gross wage and salary income of the household head and wife and subfamily
Net Labor Income HW/O:	After-tax wage and salary income of the household head and wife and subfamily
Net Labor/Transfer Income HW/O:	After-tax wage, salary, and transfer income of the household head and wife and 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 three
Gssfs:	State-specific maximum SSI/Food Stamp benefit that varies by marital status
Uiben:	State-specific average Unemployment Insurance benefit
Lspi:	Natural log of state personal income
Sur:	Natural log of state-specific unemployment rates

APPENDIX TABLE 2
Probit Estimates of the Probability of Welfare Receipt

Variable		Variable	
Constant	-0.527	White	-0.459
	(0.452)		(0.057)
Age of Head	-0.013	Lths	0.351
	(0.004)	(=1 if <HS)	(0.055)
Age of Wife	0.007	Mths	-0.300
	(0.005)	(=1 if >HS)	(0.069)
Fem	0.545	Flths	0.196
	(0.123)	(=1 if father <HS)	(0.078)
Kids	0.312	Fmths	-0.105
	(0.019)	(=1 if father >HS)	(0.127)
Marry	-0.532	Mlths	0.106
	(0.196)	(=1 if mother <HS)	(0.063)
Home	-0.397	Mmths	0.042
(=1 if own home)	(0.050)	(=1 if mother >HS)	(0.117)
Usth	-0.237	Self	-0.696
	(0.063)	(=1 if self employed)	(0.120)
Dish	0.234	Hocp	0.221
	(0.074)	(=1 if professional)	(0.096)
Disw	0.582	Hocm	-0.321
	(0.083)	(=1 if manager)	(0.134)
Gfarm	-0.059	Hocmse	0.363
(=1 if from farm)	(0.053)	(=1 if self-employed manager)	(0.196)
Ppoor	0.118	Hoccr	-0.242
(=1 if parent poor)	(0.050)	(=1 if clerical/sales)	(0.104)
Vet	0.129	Hocop	0.124
(=1 if a veteran)	(0.064)	(=1 if operator)	(0.093)

(table continues)

APPENDIX TABLE 2, continued

Variable		Variable	
Hocf (=1 if farmer)	0.312 (0.249)	Pers (=1 if personal)	-0.683 (0.129)
Hocs (=1 if service)	0.307 (0.099)	Ers (=1 if entertainment)	-0.968 (0.530)
Aff (=1 if agriculture)	-0.194 (0.222)	Prrs (=1 if professional)	-0.986 (0.092)
Mine (=1 if mining)	-1.295 (0.381)	Pubad (=1 if public admin.)	-1.242 (0.173)
Manuf (=1 if manufacturing)	-0.925 (0.077)	Neast (=1 if North East)	0.285 (0.100)
Tcu (=1 if transportation)	-0.663 (0.099)	Ncent (=1 if North Central)	0.291 (0.097)
Whrt (=1 if wholesale)	-0.719 (0.089)	South (=1 if South)	0.027 (0.098)
Fire (=1 if finance)	-1.004 (0.189)	Lspi	-0.039 (0.031)
Burs (=1 if business/repair)	-0.498 (0.147)	Lsur (level of state unemployment rate)	0.734 (1.297)

Notes: Log-likelihood = −1890.8. Number of observations = 14,520.

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