The Importance of Sample Attrition in Life Cycle Labor Supply Estimation

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ABSTRACT

We examine the importance of possible nonrandom attrition to an econometric model of life cycle labor supply using both a Wald test comparing attriters to nonattriters and variable addition tests based on formal models of attrition. Estimates using the Panel Study of Income Dynamics show that nonrandom attrition is of little concern when estimating prime-age male labor supply because the effect of attrition is absorbed into fixed effects in labor supply. The wage measure and instrument set have much larger effects on the estimated labor supply function of prime-age men than how one adjusts for panel attrition.

I. Introduction

Discontinued participation in a panel survey, known as attrition, can happen for several reasons. Some people move and cannot be traced, others become institutionalized or die, and others are rotated out by a sampling design. Because attrition is cumulative, it becomes a potentially more serious econometric concern as a panel continues. As a point of reference, 40 percent of the original 1968 Panel Study of Income Dynamics (PSID) sample had left the panel by 1981 (Becketti et al. 1988). Our research examines the importance of panel attrition when estimating the life cycle labor supply of prime-age men with data from the PSID.

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The key issue is whether attrition is random. If attrition is random, say due to survey design, then parameters estimated from a panel of nonattriters are consistent, although there may be efficiency gains by including the incomplete information from the attriters (Hsiao 1986). If attrition is not random but systematically related to the model's endogenous variables then econometric estimates based only on nonattriters are inconsistent. Given the central role that labor supply plays in discussions of tax reforms, an assessment of the possible complicating effects of attrition on labor supply estimates is valuable.

In their widely cited study Hausman and Wise (1979) examined the effects of nonrandom attrition on earnings equations estimated from the Gary Income Maintenance Experiment. Because high-wage experimentals received no treatment-related income Hausman and Wise argued that the decision by high-wage experimentals to leave the experiment could be related to latent heterogeneity that made them high-wage earners. They emphasized that ignoring the relation between the decision to attrite and latent heterogeneity could lead to inconsistent estimates of the earnings equation in general and of the treatment effect in particular. Their focal econometric result, the estimated NIT treatment effect, did not change after careful modeling of attrition.

There is a similarly compelling reason for studying the importance of attrition to life cycle labor supply estimates in the presence of income taxation. Our specification of the worker's labor supply schedule includes the net (after-tax) wage plus net wealth at the beginning and end of the year as regressors, all of which are endogenous to labor supply. If the decision to attrite comes from unobserved preferences to work (earn income) then labor supply parameters and subsequent deadweight loss calculations are inconsistently estimated if attrition is not included in the structure of the econometric model.

To date little empirical research has examined the impact of attrition on structural labor supply estimates. When estimating a static employment status model with the Seattle and Denver negative income tax experiments' data, controlling for possible endogenous sample composition made no significant difference to the estimated treatment effect (Robins and West 1986). Our research has little in common with Robins and West because we estimate a life cycle consistent labor supply model with nonlinear income taxes and latent worker heterogeneity. In the research most similar to ours Zabel (1994) found significant selection correction terms in the labor force participation of white men, but structural labor supply parameters that did not change significantly after correcting for attrition. What distinguishes our research from Zabel's is that we include joint nonlinear taxation of wage and nonwage income, examine various specifications of the attrition (panel continuation) probability equation in the context of a two-step GMM estimator, and offer a wider context for judging the econometric importance of how one adds sample attrition to an econometric labor supply model.

Specifically, we use a sequential econometric procedure to examine the effects of nonrandom attrition in a model of the labor supply of prime-age men. First, we estimate our labor supply model separately for attriters and nonattriters without formally modeling the attrition process. The separate regressions permit a Wald test of the statistical differences in the underlying labor supply parameters for attriters versus nonattriters (Lo and Newey 1985). Although the Wald test indicates whether it is advisable to pool attriters and nonattriters the Wald test has low power to detect nonrandom attrition and it is useful to explore a more formal specification of the attrition process. Next we model attrition as a discrete hazard process because attrition in the PSID is an absorbing state in that departure from the sample is permanent once a person misses a wave. We then use the estimates of the discrete hazard model of attrition to construct the inverse Mill's ratio to append to the labor supply equation, which is a standard correction in two-step sample selection models (Heckman 1979). Evidence of nonrandom attrition includes both statistical significance of the selection correction term and economically different labor supply parameters.

Our main finding is that the estimated net wage and wealth effects on labor supply are generally unaffected by whether we add attrition to the econometric model because attrition is adequately modeled in a fixed effect in labor supply. As a point of reference we further demonstrate that labor supply estimates for prime-age men are more sensitive to other decisions researchers make that are frequently taken for granted, such as choosing the wage rate measure or instrument set.

II. Econometric Background

We begin by describing the economic model underlying our structural econometric model of labor supply while for the moment maintaining maximum econometric generality when describing panel attrition. Because both capital and wage incomes are taxed nonlinearly in the United States we account for the associated intertemporally nonseparable lifetime budget constraint by conditioning labor supply on the worker's asset positions at the beginning and end of each year (Blomquist 1985). The econometric model we use to study attrition's consequences is a linear labor supply function that conditions on current and lagged assets, which is a life cycle consistent model under two-stage budgeting.[1]

A. *Life Cycle Consistent Labor Supply*

We estimate the familiar linear labor supply function allowing nonstochastic latent worker heterogeneity

$$(1) \quad h_{it} = \alpha\omega_{it} + \delta A_{it-1} + \phi A_{it} + \gamma' X_{it} + \eta_i + \xi_{it},$$

where i indexes workers, t indexes time period, h is annual hours worked, ω is the net after-tax hourly wage, A is net wealth, X is a vector of time-varying demographics affecting intratemporal preferences for work, $\Lambda = [\alpha, \delta, \Phi, \gamma']$ are the parameters of intratemporal preferences, and the error term ξ_{it} is iid with mean zero and constant variance. The net wage and assets are endogenous because the marginal tax rate depends on contemporaneous hours worked through earnings. Finally, the time-invariant worker-specific effect, η_i, is generally not independent of the regressors

1. Our estimating equation identifies intratemporal, but not intertemporal, preferences. For a two-step estimator that also recovers intertemporal preference parameters see Ziliak and Kniesner (1996).

because life cycle wealth has person-specific components unknown to the econometrician.[2]

B. Incorporating Nonlinear Income Taxes

The most influential econometric research on the static labor supply effects of income taxes has applied the maximum likelihood approach to represent the piecewise linear budget constraint (Hausman 1981). Because of the econometric complexity of maximum likelihood in a panel context and because reported taxable income is relatively free of measurement error in the PSID we approximate the marginal tax rate with a differentiable polynomial in taxable income (MaCurdy, Green, and Paarsch 1990; Rodgers, Brown, and Duncan 1993).

A differentiable marginal rate also can be integrated to infer total taxes, which facilitates constructing net wealth. Adopting the differentiable marginal tax rate approach of MaCurdy, Green, and Paarsch to construct net wages and assets also simplifies parameterizing the tax base for social security taxes. During our sample period most states also had progressive income tax schedules where about 75 percent of the states used federal Adjusted Gross Income or federal taxable income as their bases. We judge the possible labor supply effects of state income taxes too important to ignore but too complicated to include completely. In our labor supply estimates we augment the worker's federal marginal tax and social security tax rates with an average state tax rate that is the ratio of individual state income tax collections to AGI in the state.[3]

C. Incorporating Sample Attrition

Hours worked by person i at time t in (1) can be written compactly as

$$(2)\quad h_{it} = \Lambda Z_{it} + \nu_{it},$$

where $Z_{it} = [\omega_{it}, A_{it-1}, A_{it}, X_{it}]'$, $\Lambda = [\alpha, \delta, \Phi, \gamma']$, and, $\nu_{it} = \eta_i + \xi_{it}$, collects latent heterogeneity (η_i) and the overall random shock (ξ_{it}). When panel nonresponse is possible (2) is observed when an indicator function, $r_{it} = 1$. That is, we now admit the possibility of attrition ($r_{it} = 0$) such that only nonattriters are observed for all t in the PSID.

The indicator function for sample survival obeys the relationship with a latent variable r^*_{it} such that for

$$(3)\quad r^*_{it} = \beta Z^*_{it} + \nu^*_{it}$$

$$(4)\quad r_{it} = 1 \text{ if } r^*_{it} > 0; \text{ and } r_{it} = 0 \text{ otherwise.}$$

The elements of Z^*_{it} are regressors that explain the outcome of continuing in the

2. We limit latent worker-specific labor supply heterogeneity to the intercept. Allowing worker heterogeneity in the coefficients of endogenous wages or wealth given the complexity of nonlinear income taxation and possible endogenous attrition is best left for the future. See Kniesner and Li (1996) for a general econometric model of labor supply with heterogeneous response parameters.

3. For more discussion see Ziliak and Kniesner (1996).

panel, some of which also may influence labor supply, and v_{it}^* is the error term. We discuss the details of the panel continuation equation shortly.

1. Two-Step Estimation

A common econometric approach for handling endogenous worker heterogeneity is as nonstochastic (fixed) effects. One way to estimate a fixed-effects model is to use the within estimator, and another way is to estimate the model in first-differences. The within estimator for (1) is inconsistent if predetermined or lagged endogenous variables such as the net wage and assets are instrumental variables because the within transformed labor supply error is a function of predetermined information and is not orthogonal to the instruments. The first-differences estimator we use for labor supply (1) is consistent when appropriately lagged predetermined (endogenous) variables are instruments (Keane and Runkle 1992).[4]

Estimating a structural model in the presence of nonrandomly changing sample composition without controls for a possibly endogenous panel continuation process yields inconsistent parameter estimates (Heckman 1979). Heckman suggests a consistent two-step estimator where the first step produces estimates of the probability of sample participation, and the estimated sample participation parameters are then used to construct the inverse Mill's ratio to include in the second step regression recovering the structural parameters of interest from a sample of complete observations. Heckman's two-step method is readily extended to panel data with possible nonrandom attrition.[5]

Attrition from the PSID is an absorbing state; once someone leaves the panel they are gone for good. The implication of attrition in the PSID is that panel continuation cannot be viewed simply as a continuous binary outcome. We must instead treat attrition as a discrete hazard process. During each period every observation comprises the risk set, where risk is the probability of continued participation in the panel. As soon as attrition takes place a worker is no longer part of the risk set. The dependent variable in our discrete hazard function equals one for each period someone is in the sample and equals zero the first (and only) time a worker departs the PSID.

In the first step we assume that panel continuation follows a normal distribution and estimate a discrete hazard probit. We then use the probit estimates to construct the sample selection variable, $\hat{\lambda} = \phi(\hat{\beta}Z^*)/\Phi(\hat{\beta}Z^*)$, where $\phi(\cdot)$ is the pdf of the normal distribution, and $\Phi(\cdot)$ is the cdf of the normal distribution.[6] The second-step structural supply equation we estimate that corrects for the likelihood of continued panel participation under the normal probability process is

$$(5)\quad \Delta h_{it} = \alpha\Delta\omega_{it} + \delta\Delta A_{it-1} + \phi\Delta A_{it} + \gamma'\Delta X_{it} + \sigma\hat{\lambda}_{it} + \Delta\varepsilon_{it}.$$

4. Another problem with the within estimator is the difficulty of finding good instruments whereas in the first differences estimator endogenous variables lagged two or more periods can be used as instruments. On the downside first-differencing may exacerbate any measurement error (Altonji 1986). If our instruments are uncorrelated with the measurement error the parameter estimates are still consistent.

5. One does not always need a parametric form for the attrition process and can consider nonparametric alternatives (Manski 1989, 1993).

6. Sample selection corrections based on discrete logit hazards made no difference to our conclusions and are not reported in the interest of space.

2. The GMM Estimator

To account for the endogeneity of net wages and wealth in (5) we apply a generalized-method-of-moments estimator (GMM). Define the function $g(Z, D; \Lambda)$ as

$$(6) \quad g(Z, D; \Lambda) = D'(\Delta h - \Delta Z\Lambda) \equiv D'\Delta\xi,$$

where ΔZ is the $(N(T-2) \times L)$ matrix of differenced regressors in the labor supply function (5), D is an $(N(T-2) \times K)$ matrix of instruments with $K \geq L$, Δh is the $(N(T-2) \times 1)$ vector of hours worked, and Λ is the vector of $(L \times 1)$ preferences parameters that are the coefficients in the linear labor supply function, $(\alpha, \delta, \phi, \gamma')$.

The criterion function we minimize in our GMM differences model is

$$(7) \quad J_T = g(Z, D; \Lambda)'S_{gg}^{-1}g(Z, D; \Lambda),$$

where S_{gg} is an optimal weighting matrix, $D'E(\Delta\xi\Delta\xi')$D. Initial consistent estimates for the error vector Δ come from a consistent but suboptimal weighting matrix, the identity matrix. Solving the criterion function for the feasible GMM estimator gives

$$(8) \quad \hat{\Lambda} = [\Delta Z'D\hat{S}_{gg}^{-1}D'\Delta Z]^{-1}\,\Delta Z'D\hat{S}_{gg}^{-1}D'\Delta h,$$

which has the estimated covariance matrix for large N and finite T

$$(9) \quad \mathrm{Var}(\hat{\Lambda}) = [\Delta Z'D\hat{S}_{gg}^{-1}D'\Delta Z]^{-1}.$$

Estimating the first-differenced labor supply (5) as a way of coping with latent heterogeneity and possible life-cycle rational expectations creates an MA(1) process in the transformed random disturbance, $\xi_t - \xi_{t-1}$, which influences the functional form of the weighting matrix, S_{gg} (Maeshiro and Vali 1988). The weighting matrix in our GMM first-differences model $\hat{S}_{gg}$ is the sum of a conditionally heteroskedastic matrix $(\hat{\Omega}_0)$ and an autocorrelation matrix $(\hat{\Omega}_1)$ such that

$$(10) \quad \hat{S}_{gg} = \hat{\Omega}_0 + [\hat{\Omega}_1 + \hat{\Omega}_1'],$$

where

$$(11) \quad \hat{\Omega}_0 = (1/N(T-2)) \sum_i \sum_t (D_{it}'\Delta\hat{\xi}_{it}\Delta\hat{\xi}_{it}'D_{it})$$

$$(12) \quad \hat{\Omega}_1 = (1/N(T-2)) \sum_i \sum_t (D_{it}'\Delta\hat{\xi}_{it}\Delta\hat{\xi}_{it-1}'\mathrm{D}_{it-1}),$$

$i = 1, \ldots, N$, and $t = 1, \ldots,$ T.[7] Predetermined variables dated $t-1$ and earlier and endogenous variables dated $t-2$ and earlier can be instruments in light of the MA(1) errors in the first-differenced life cycle consistent labor supply (Griliches and Hausman 1986). The first differencing, lagged regressors and instruments, and correction for the MA(1) term in the weight matrix together mean we can only use in estimation observations present in four waves so that there are $N(T-3)$ observations in the estimation of the labor supply parameters and the covariance matrix elements.

We choose as identifying instruments for the three endogenous regressors,

7. When the weighting matrix is not positive definite we use a method of modified Bartlett weights (Newey and West 1987b).

Δw_{it}, ΔA_{it-1}, and ΔA_{it}, the net wage at $t-2$, virtual wealth at $t-2$, and assets at $t-2$.[8] Because we have available many more instrumental variables than endogenous regressors, a basic specification test in our GMM estimator is a test of validity of the overidentifying restrictions. The overidentification test statistic is the value of the criterion function, J_T, at the final GMM parameter estimates and is distributed as $\chi^2(p)$, where p is the number of instruments less regressors. In general, restrictions can be tested with the objective function test (a pseudo likelihood ratio test) of the form

$$(13)\quad J = T[J_T(\hat{\Lambda}_r) - J_T(\hat{\Lambda})] \sim \chi^2(p),$$

where the subscript r indicates the restricted model, and the p degrees of freedom in the computed chi-squared statistic is the number of restrictions imposed (Eichenbaum, Hansen, and Singleton, 1988).

3. Ignorable Attrition

It is worth emphasizing that a sufficient condition for ignorable attrition in the fixed-effects labor supply model estimated in first-differences is $E[\xi_{it}^d | r_{it}, r_{it-1}] = 0$, where the superscript d indicates first-differences (Verbeek and Nijman 1992).[9] Even though attrition may have an individual effect common to labor supply, η_i, ignoring attrition will not introduce selectivity bias in the fixed-effects estimator when attrition is independent of ξ_{it}^d. An attrition effect in labor supply that is time invariant is captured in the fixed effect and swept out by first-differencing.

D. A Wald Test of the Significance of Attrition

Because a joint model of labor supply and sample attrition is computationally complex, simple tests of whether attrition from the panel is a problem are useful to determine the necessity of modeling the attrition process itself (Verbeek and Nijman 1992, 1996). A Wald test for nonrandom attrition is a useful starting point for models where attrition bias is of concern.

The Wald procedure for a linear simultaneous equations system tests whether the underlying labor supply process is the same for workers who attrite as for workers who continue in the panel survey (Lo and Newey 1985). If $V(A)$ is the estimated covariance matrix for attriters and $V(NA)$ is the estimated covariance matrix for non-attriters then the Wald test statistic to use is

$$(14)\quad W = (\hat{\Lambda}(A) - \hat{\Lambda}(NA))'[V(A) + V(NA)]^{-1}(\hat{\Lambda}(A) - \hat{\Lambda}(NA)) \sim \chi^2(k),$$

where k is the number of regressors in the first-differenced labor supply equation.

8. Because workers do not face their marginal tax rates for all taxable income we create virtual wealth by adding a capitalized lump-sum transfer to lagged wealth (A_{t-1}) equal to $[(\tau(I_t) - T(I_t)/I_t) * I_t]/r_t$ where r_t is the annual average of the nominal three-month T-bill rate, τ is the marginal tax rate, and T is taxes paid, which depend on income, I_t. We adjust wealth because lagged wealth, A_{t-1}, enters the current period's tax function.

9. Verbeek and Nijman (1996) discuss the many degrees of ignorability. They show that mean independence is sufficient for attrition to be ignorable if one is only interested in the first moment of the parameter vector. However, attrition is still informative in the sense that efficiency gains are possible.

III. Data

We use data from Waves I-XXII (interview years 1968–89) of the Panel Study of Income Dynamics to estimate labor supply parameters and examine the econometric consequences of panel attrition. The PSID began in 1968 with about 4,800 households and more than 18,000 persons; by the 1989 wave the PSID had more than 7,000 families and 37,000 persons. About 61 percent of the initial PSID households were a random sample of the U.S. population selected by the Survey Research Center (SRC), and the remaining 39 percent of the initial PSID households were a sample of the low-income families drawn from the Survey of Economic Opportunity (SEO). Because the SEO oversampled the poor, researchers pooling the SRC and SEO samples should weight the first and second moments of population statistics. There is much disagreement on the merits of weighting a regression model, and in a sample of both attriters and nonattriters it is even unclear which weight to use for the population statistics (Hoem 1989). On the one hand it seems reasonable to use the weight from the most recent wave that a person contributes data (Hill 1992, p. 61). On the other hand it seems appropriate to use the original 1968 weights, which were designed to adjust for stratified sampling (Lillard 1989, p. 508). We follow Lillard's suggestion and use the 1968 weights for the population statistics reported in Table 2 and do not weight the data for the econometric models of labor supply.[10]

A. Samples

We construct two samples from the overall PSID: a balanced panel and an unbalanced panel. In the balanced panel there are data on all regression variables in every year that the person is a panel participant. In the unbalanced panel only a person year is absent when a missing value occurs. The two designs differ only in how they treat item nonresponse. The balanced panel eliminates the entire time-series for a person with item nonresponse in any year and the unbalanced panel eliminates only the year of the item nonresponse. The balanced design has substantially fewer observations than the unbalanced design; the benefit of the balanced design is that it does not mingle wave nonresponse with item nonresponse.

Our selection rules for the balanced panels are similar to other research: men ages 25–43 in 1968 who were continuously employed wage and salary workers. Because the oldest worker is 64 we can safely ignore possible endogenous retirement decisions. We permit marital status to vary over the sample period and allow marital status change to be predetermined with labor supply (Johnson and Skinner 1986). In addition, we do not include nonsample members, persons who marry into the sample, or persons who attrite due to death because the data-generating process may distort our tests of attrition's consequences (Lillard 1989). The selection criteria we used created (1) a balanced panel with 200 attriters contributing 711 person years and 89 nonattriters contributing 1958 person years and (2) an unbalanced panel with

10. For discussion of the PSID sample design, composition, attrition rates, and weighting see Becketti et al. (1988), Lillard (1989), and Hill (1992).

303 attriters contributing 1867 person years and 315 nonattriters contributing 7,100 person years.[11]

B. Key Variables

The variables in our econometric models are defined in Table 1. To compute real wages, income, interest rates, and assets we used the annual averages for the year before the interview relative to the GDP deflator for personal consumption expenditures. We now discuss the key labor supply regression variables that a researcher must construct when using the PSID, which are the wage rate, wealth, and taxes.

1. Wage Rate

We use multiple measures of the gross and net (post-tax) hourly wage rate: (1) average hourly earnings computed as the ratio of annual wage earnings to annual hours worked on all jobs (termed the imputed wage), (2) average hourly earnings computed as the ratio of annual wage earnings to annual weeks worked times usual hours worked per week on the main job (termed the weeks-worked wage), and (3) the hourly pay the respondent reports on his main job (termed the reported wage). It is well documented that average hourly earnings computed with the dependent variable of the labor supply regression (wage measures (1) and (2)) induces a so-called negative division bias into the labor supply wage parameter (Conway and Kniesner 1994, Ziliak and Kniesner 1996). By using three different wage measures we highlight the relative importance of choosing an accurate wage measure compared to whether one considers attrition in labor supply model estimation.

2. Wealth

Because the PSID does not have detailed information on either consumption or saving constructing the components of wealth is time consuming. We define wealth as the sum of liquid and illiquid assets. Liquid assets include nominal rent, interest, and dividend incomes capitalized by a nominal interest rate (Runkle 1991). We divide the first $200 of rental income by an annual average passbook savings rate and capitalize interest income exceeding $200 by the annual average three-month T-Bill rate. Because the value of liquid assets understates the total wealth of a household, we add an illiquid component of assets defined as the value of home equity. We measure home equity as the difference between house value and outstanding loan principal

11. We also relaxed the selection criterion that a man work in every year. After applying all other data screens allowing annual hours worked of zero increased the sample size by only three percent. Because the small gain in sample size by permitting employment status changes seems outweighed by the additional computational burden we limit our regressions to continuously working men. Zabel (1994) shows that no selection bias arises by ignoring the male labor force participation decision in the PSID.

Table 1
Definitions of Variables Used in Estimation[a]

Anhh	Annual hours of work on main job
*Riwag*1	Real gross hourly wage defined as (annual earnings on main and extra jobs)/(annual hours on main and extra jobs), known as the imputed wage
*Riwag*2	Real gross hourly wage defined as (annual earnings on main and extra jobs)/(weeks worked * usual hours per week on the main job), known as the weeks-worked wage
Rrwag	Real gross hourly wage defined as the reported hourly or salary wage rate, known as the reported wage
*Riatwg*1	Real after-tax wage rate defined as *riwag*1 * (1-mtr)
*Riatwg*2	Real after-tax wage rate defined as *riwag*2 * (1-mtr)
Rratwg	Real after-tax wage rate defined as *rrwag* * (1-mtr)
Mtr	marginal tax rate defined as a cubic polynomial in taxable income
Lasset	Real liquid assets defined as the ratio of rent, interest, dividend income over nominal interest rate
Equity	Real home equity defined as house value less principal remaining
Assets	Combined values of Lasset and Equity
Age	Age of the male head of household
Kids	The number of children residing in the household
Educ	The number of years of schooling for the head
Aged	Interaction of age * educ
Race	A dummy variable equal to 1 if the head is white
Home	A dummy variable equal to 1 if the head owns his home
Married	A dummy variable equal to 1 if the head is married
Seo	A dummy variable equal to 1 if the head is part of the SEO subsample
Head	A dummy variable equal to 1 if the head was the respondant for the interview
Phone	A dummy variable equal to 1 if the interview was conducted by telephone
Intlg	The length of the interview
Mover	A dummy variable equal to 1 if the head moved since last interview
Wmove	A dummy variable equal to 1 if the head is thinking of a move soon
Calls	The natural log of the number of phone calls required to reach the respondant
Neast	A dummy variable equal to 1 if the head resides in the Northeast
Ncent	A dummy variable equal to 1 if the head resides in the NorthCentral
South	A dummy variable equal to 1 if the head resides in the South
West	A dummy variable equal to 1 if the head resides in the West, Alaska, or Hawaii
Waves	A linear trend indicating the number of waves in the sample prior to current survey
Year	Calendar year in sample inclusive of current wave
IMR	The inverse of Mill's Ratio

a. All wage and wealth variables are deflated by the 1987 Personal Consumption Expenditure Deflator.

remaining.[12] The PSID collected comprehensive wealth data in 1984 and 1989, including data on home equity, net value of other real estate, net value of vehicles, net value of a farm or other business, and net value of other assets. The more direct measure of total wealth from the PSID has been used by others (Hubbard, Skinner, and Zeldes 1995). Variation in our measure of liquid wealth explains about half the variation in total wealth and including home equity makes our measure explain about 80 percent of the variation in directly measured wealth (Ziliak 1994). The ability of our wealth measure to track total wealth when measured independently is our justification for including both liquid and illiquid wealth components in our definition of wealth.[13] Our wealth summary statistics are comparable to wealth measures from the Survey of Income Program Participation (Engen, Gale, and Scholz 1994).

3. *Taxes*

In constructing annual taxable income we assumed that each person filed either a joint tax return if married or a head-of-household return if not married. Adjusted gross income (AGI) is the sum of the labor earnings for the man along with his interest income. Taxable income in each year is defined as adjusted gross income less deductions and exemptions.

The PSID records the number of exemptions (dependents) taken for tax purposes. For years before 1983 we followed the convention established in the PSID for computing deductions. Using information from the Internal Revenue Service's *Statistics of Income,* we generated the typical value of itemized deductions based on adjusted gross income. Using 1968 as an example of what we did in 1968–83, if AGI was less than $5,000 in 1968 then the percent itemized from AGI was set to 23 percent; if AGI was greater than $5,000 but less than $10,000 then the percent itemized from AGI was set to 19 percent. We followed the process of imputing deductions based on national averages until AGI was greater than $20,000 when the average percent itemized from AGI is 15 percent. We imputed deductions similarly for the other years.

In the years 1968–77 we constructed taxable income as follows. Using 1968 as an example, we first compared the standard deduction, which was 10 percent of AGI in 1968, to the so-called minimum standard deduction, which was $200 plus $100 times the number of exemptions in 1968. We then took the larger of standardized deductions and the minimum standard deduction and compared it to average percent itemized from AGI. If either the standard deduction or the minimum standard deduc-

12. Because principal remaining is missing for all persons in 1968, 1973–1975, and 1982 we follow the convention of the PSID staff and take 90 percent of the previous year's principal. Because data on home equity are still not available in the first year, 1968, we first set home equity in 1968 to its 1969 value then set home equity in 1968 to zero. Imputing 1968 illiquid wealth is less important than it may seem. The value of home equity in 1968 comes into the model only as an instrument in the MA(1) part of the error term. Because results were similar for the two 1968 asset imputations we tabulated only the results where home equity was set to zero in 1968.

13. For completeness we ran parallel regressions with assets defined as liquid assets alone which produced no qualitative differences in our results.

tion were largest, we then computed taxable income as AGI less exemptions and the greater of the standard deduction and minimum standard deduction. If the average percent itemized were largest then we computed taxable income as AGI less exemptions and percent itemized.

The values for the standard deduction, minimum standard deduction, and average percent itemized varied over the years. Beginning in tax year 1978 until tax year 1987 the minimum standard deduction does not exist because the standard deduction is built into the tax tables. For 1978–87 we took the difference between itemized deductions and the standard deduction, known as excess itemized deductions. If positive we subtracted excess itemized deductions from adjusted gross income to compute taxable income; if excess itemized deductions were nonpositive then taxable income is AGI minus exemptions. Since the Tax Reform Act of 1986 (TRA86) the standard deduction is no longer built into the tax tables. For years when TRA86 rules are in effect when excess itemized deductions were nonpositive we then computed taxable income as AGI less exemptions and the standard deduction.

C. Summary Statistics

Table 2 presents weighted selected summary statistics for attriters and nonattriters in the balanced and unbalanced samples. Table 2 illustrates that, on average, the attriters are younger, work fewer hours, earn a lower hourly wage, have a lower marginal tax rate, have lower liquid and illiquid assets, have less education, are more likely to be black, are less likely to own a home, and are less likely to be married. Because attriters and nonattriters are in the sample for different years, as noted by the fact that the typical attriter is gone by 1973, comparing means is problematic. We offer some alternative calculations that may be more informative. First, we compute the mean differences in wages and hours between attriters and nonattriters for each year and then average the differences over all years that attriters contribute data. We find that on average nonattriters earn about 23 percent more and work about 20 percent more hours per year than attriters. Wages grew about 0.5 percentage points faster annually and hours rose about 1.2 percentage points faster annually for nonattriters than attriters.

IV. Results

As described earlier we use a Wald test and a variable addition procedure to examine the econometric importance of possible nonrandom panel attrition in labor supply estimation. Although their coefficients are not tabulated in the interest of space, each labor supply specification includes as control variables the head's age, number of children in the home, health status, and marital status. The instrument set includes a constant, age, age^2, age $*$ education, union status, health status, home ownership, marital status, and number of children at home, all dated $t-1$ and $t-2$, plus gross and net wage, net wealth, net virtual wealth, and the net three-month T-Bill yield, all dated $t-2$. Based on results from Ziliak and Kniesner (1996) we also include time dummies in the instrument set, which makes a maximum of

Table 2
Weighted Summary Statistics for the Balanced and Unbalanced Samples for 1968–89[a]

	Balanced SRC/SEO Sample[b]		Unbalanced SRC/SEO Sample[b]	
Variable	Nonattriters	Attriters	Nonattriters	Attriters
Anhh	2326.58	1882.83	2290.22	1914.01
	(460.49)	(616.55)	(529.54)	(647.81)
*Riwag*1	17.21	11.64	16.34	11.58
	(10.92)	(8.21)	(9.55)	(10.25)
*Riatwg*1	12.15	8.90	11.64	8.65
	(6.13)	(5.35)	(5.68)	(6.01)
Mtr	0.28	0.18	0.27	0.19
	(0.09)	(0.09)	(0.09)	(0.10)
Lasset ($1000's)	14.21	1.26	15.17	3.42
	(55.62)	(8.21)	(55.87)	(25.85)
Equity ($1000's)	53.56	18.60	53.20	25.84
	(59.05)	(68.57)	(67.99)	(59.52)
Age	45.65	33.01	45.00	34.77
	(9.30)	(9.14)	(9.25)	(8.77)
Kids	1.67	1.56	1.61	1.58
	(1.59)	(1.89)	(1.67)	(2.03)
Educ	12.36	10.05	12.10	9.61
	(4.65)	(4.25)	(4.52)	(4.84)
Race	0.92	0.72	0.92	0.67
	(0.24)	(0.49)	(0.38)	(0.57)
Home	0.87	0.53	0.86	0.60
	(0.40)	(0.58)	(0.41)	(0.57)
Married	0.98	0.75	0.96	0.78
	(0.23)	(0.39)	(0.29)	(0.38)
Waves	11.04	3.57	10.77	5.03
	(6.92)	(5.22)	(7.06)	(6.00)
Year	1978.50	1972.04	1978.42	1973.50
	(6.92)	(5.22)	(7.06)	(6.00)
Observations	1,958	711	7,100	1,867

a. Sample means are reported in the first row and standard deviations are in parentheses. The balanced sample deletes the entire time-series of persons if any missing values are encountered while in the sample; the unbalanced sample deletes only the person-year when missing values are encountered.
b. SRC = Survey Research Center; SEO = Survey of Economic Opportunity.

40 instruments.[14] For every labor supply function we present estimates using both the balanced and unbalanced panels from the unweighted joint SRC/SEO data in the PSID.

A. *Wald Test Results*

Table 3 contains estimates of the life cycle consistent labor supply equation parameters separately for attriters and nonattriters. For brevity we report only the wage and wealth coefficients and the associated wage elasticities computed at the means of the sample used in estimation. Because wealth is endogenous the compensated wage elasticity is a first-order approximation to the true compensated wage elasticity (MaCurdy 1983).

The columns labeled (1) in Table 3 use the imputed wage (*Riatwg1*) as both the wage regressor and an instrument and the columns labeled (2) use the imputed wage as the regressor but the weeks-worked wage (*Riatwg2*) as an instrument. We expect division bias to be more pronounced in the results in Column (2) because the weeks-worked wage is defined with the same hours measure as the dependent variable.

1. Balanced Panel

In general, the *J*-statistic does not reject the null hypothesis that the overidentifying restrictions hold for the labor supply models estimated with the balanced panels. Visually comparing the estimated wage coefficients in Table 3 suggests differing labor supply responses across attriters and nonattriters. Wald test results indicate no significant difference between attriters and nonattriters, however. Recall that there are only 89 nonattriters in the balanced panel. As noted earlier we need at least four years of data to estimate the model so that only 145 attriters remain when estimating with the balanced panel, each attriter contributing about 2.5 years of data for computing the point estimates. The substantial, yet statistically insignificant, differences between the estimated labor supply functions of attriters and nonattriters stem from the small sample sizes in the balanced panels.

The first four columns of Table 3 also illustrate that the labor supply parameters and their standard errors are sensitive to the wage measure in the instrument set. Replacing average hourly earnings with average earnings per usual hours worked in the instrument set in the columns labeled (2) leads to a substantial relative efficiency loss in estimation for both attriters and nonattriters and exacerbates the negative division bias problem in the estimated wage effect as expected. Using Bartlett weights does not solve the problem of a negative definite variance-covariance matrix for the attriters in columns (2) of Table 3, which makes the Wald test statistic undefined. We emphasize that the results in the first four columns of Table 3 are based on small samples, which is a fact of life when constructing a balanced panel of prime-aged men from the PSID. There is evidence from other contexts of a small-sample downward bias in GMM relative to 2SLS (Altonji and Segal 1996, Ziliak

14. There are 37 instruments in the balanced attriter sample because the last year a worker may be present is 1986; there are 39 instruments in the unbalanced attriter sample because the last year a worker may be present is 1988.

Table 3
Wald Tests Comparing Attriters and Non-Attriters Life-Cycle Consistent Labor Supply for the Years 1968–89[a]

	Balanced SRC/SEO Sample[b]				Unbalanced SRC/SEO Sample[b]			
Variable	Nonattriters (1)	Attriters (1)	Nonattriters (2)	Attriters (2)	Nonattriters (1)	Attriters (1)	Nonattriters (2)	Attriters (2)
*Riatwg*1 (α)	20.542	−100.034***	14.587	−159.577	22.634**	−48.384**	18.214*	−42.433*
	(21.969)	(35.197)	(13.1E1)	(—)	(9.632)	(23.081)	(9.656)	(23.194)
Lagged assets (δ)	0.416	−3.825	−0.782	−10.328	0.653**	−1.062	0.423	−1.439*
	(0.442)	(2.698)	(7.270)	(18.567)	(0.274)	(0.792)	(0.275)	(0.782)
Current assets (ϕ)	0.167	3.113	−0.556	10.304	1.483	−8.832***	0.872	−8.021***
	(1.737)	(4.932)	(10.584)	(28.610)	(0.896)	(2.997)	(0.935)	(2.941)
Uncompensated wage	0.103	−0.492***	0.073	−0.785	0.109**	−0.215**	0.088*	−0.189*
	(0.110)	(0.173)	(0.655)	(—)	(0.047)	(0.102)	(0.047)	(0.103)
Compensated wage	0.101	−0.524***	0.079	−0.890	0.094**	−0.131	0.079	−0.112
	(0.112)	(0.180)	(0.665)	(—)	(0.048)	(0.106)	(0.048)	(0.107)
J-statistic	21.470	11.676	0.951	0.462	62.129	15.734	60.799	25.754
[dof, p]	[33, .939]	[30, .998]	[33, .999]	[30, .999]	[33, .002]	[32, .993]	[33, .002]	[32, .774]
Wald test		9.799		—		25.990		21.541
[dof, p]		[7, 0.200]				[7, .001]		[7, .003]
Observations	1,691	369	1,691	369	6,086	1,186	6,086	1,186

a. Standard errors are given in parentheses. The balanced sample deletes the entire time-series of persons if any missing values are encountered while in the sample; the unbalanced sample deletes only the person-year when missing values are encountered.
b. Results in columns labelled (1) are based on the imputed wage, *Riatwg*1, both as regressor and as instrument, while results in Column (2) are based on *Riatwg*1 as a regressor and the weeks-worked wage, *Riatwg*2, as an instrument.
Statistical Significance: * = 10 percent level; ** = 5 percent level; *** = 1 percent level.

forthcoming) and we experience some of the downward bias in our wage parameter estimates of Table 3. It is likely that a linear dependency in the sample moments occurs in Column (2) of attriters, which causes the negative definite covariance matrix. However, the 2SLS parameter estimates for attriters were equally volatile depending on the wage measure and instrument choice and are a no more promising avenue to test for differences between attriters and nonattriters. The results from the balanced panel of attriters highlights some of the perils of IV estimation in small samples. Although the balanced panel allows us to focus on wave nonresponse as separate from item nonresponse in the PSID the small sample sizes result in unrobust parameter estimates and low-power test statistics for comparing the labor supply functions of attriters versus nonattriters.

2. *Unbalanced Panel*

Comparing the balanced and unbalanced sample results in Table 3 illustrates the relative efficiency gain from moving to the unbalanced panel. The three to four times larger samples in the unbalanced panel produce more similar parameter estimates across columns and more powerful test statistics than in the balanced panel. Nonattriters satisfy Slutsky integrability conditions but the attriters do not. The Wald statistics indicate a significant difference in the labor supply equations of attriters and nonattriters that is robust to the different wage instruments. The compensated wage estimates are theoretically correct for nonattriters but inconsistent with labor supply theory for attriters, which contrasts with the result that the overidentifying restrictions are rejected for nonattriters but not rejected for attriters in the unbalanced panel.

3. *Summary*

Although the unbalanced panel may muddy discussion of wave nonresponse and item nonresponse relative to the balanced panel the larger sample sizes in the unbalanced panel are necessary to have confidence in the estimated wage and asset parameters and overall J and Wald test statistics. We conclude that the data generating process for labor supply may be different for workers who left the PSID compared to workers who continued. To examine the differences between attriters and nonattriters more closely and their econometric consequences for estimating male labor supply we now move to two-step selection corrected labor supply models.

B. The Panel Continuation Process and Selectivity Corrected Results

Table 4 presents estimates of the discrete hazard functions for continued participation in the PSID. For completeness we estimate discrete hazard probit models with and without the number of waves completed prior to the current sample as a regressor for both the balanced and unbalanced samples.

To estimate the discrete hazard functions we assemble the data in person years such that in each year we construct the risk set for the probability of continuing in the panel. A worker is assigned an outcome value of one if he remains in the PSID in a given year and assigned a zero in the year he attrites. A worker could then contribute at most 22 years of data and had to contribute at least one year of data.

Table 4
Discrete Hazard Probit Models for Probability of Panel Continuation[a]

Variable	Balanced Panel Models		Unbalanced Panel Models	
Constant	−1.662	−0.044	−0.517	−0.212
	(1.247)	(1.176)	(0.726)	(0.725)
Age	0.098*	0.001	0.062**	0.046
	(0.056)	(0.052)	(0.031)	(0.031)
*Age*²	−0.002**	0.000	−0.001*	−0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Educ	0.010	0.017	0.034	0.033
	(0.051)	(0.055)	(0.028)	(0.030)
Aged	−0.000	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Race	0.274**	0.323**	0.100	0.119
	(0.133)	(0.130)	(0.073)	(0.073)
Seo	0.126	0.153	0.002	0.042
	(0.129)	(0.126)	(0.073)	(0.073)
Kids	0.017	0.011	0.028	0.012
	(0.027)	(0.026)	(0.018)	(0.018)
Phone	0.105	0.862***	0.210**	0.532***
	(0.153)	(0.112)	(0.089)	(0.078)
Head	0.468***	0.414***	0.369***	0.329***
	(0.136)	(0.132)	(0.078)	(0.077)
Married	0.266*	0.174	0.257***	0.223**
	(0.151)	(0.146)	(0.090)	(0.089)
Mover	0.377**	0.468***	0.117	0.144*
	(0.155)	(0.154)	(0.086)	(0.085)
Wmove	−0.229**	−0.234**	−0.117*	−0.113*
	(0.099)	(0.097)	(0.064)	(0.063)
Intlg	−0.001	−0.001	0.001	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Home	0.256**	0.288***	0.257***	0.285***
	(0.109)	(0.107)	(0.070)	(0.068)
Calls	−0.423***	−0.362***	−0.319***	−0.276***
	(0.068)	(0.065)	(0.041)	(0.040)
Neast	0.066	0.117	−0.024	−0.014
	(0.141)	(0.137)	(0.093)	(0.092)
Ncent	−0.116	−0.153	−0.003	0.004
	(0.139)	(0.134)	(0.087)	(0.086)
South	0.017	0.116	0.011	0.059
	(0.133)	(0.128)	(0.082)	(0.081)
Waves	0.131***		0.068***	
	(0.019)		(0.009)	
LL	−525.7	−552.6	−1,220.4	−1,253.9
Observations	2,580	2,580	8,659	8,659

a. Standard errors are given in parentheses. LL is the value of the log-likelihood function at the maximum. Statistical Significance: * = 10 percent level; ** = 5 percent level; *** = 1 percent level.

(See Allison (1984) for a succinct discussion of discrete hazard models.) The panel continuation hazard functions we estimate control for nonlinearity in age and education, length and other interview characteristics, race, poverty status, martial and family status, home ownership, location history, and time in the PSID.[15] Although time in the PSID may reflect duration dependence, because we do not formally control for latent heterogeneity the coefficient of time in the PSID does not have a single interpretation. Other research has found little evidence of latent heterogeneity in continuing in the PSID so that time in the panel should largely reflect duration dependence (Lillard and Panis 1994).

The likelihood of continuing in the PSID significantly increases at a decreasing rate as the participant ages in three of the four specifications in Table 4. The likelihood of panel continuation increases with education, although insignificantly so in both samples. Being white, married, and a homeowner significantly increase the probability of panel continuation; most other location and socioeconomic status variables have no significant estimated impact on whether a prime-age man continues participating in the PSID. In general, the most important factors in terms of significant coefficients that are robust across models are interview characteristics, who was interviewed, and how long the respondent was already in the panel. If we draw on the results of Lillard and Panis (1994) who conclude that attrition from the PSID is adequately explained by measured covariates with no significant room remaining for latent individual heterogeneity, we can interpret the coefficient of Waves in Table 4 as indicating substantial duration dependence in continuing to participate in the PSID.

C. Two-Step Labor Supply Results

Table 5 displays two-step labor supply equation estimates corrected for the expected likelihood of continuing in the PSID. Because the presence of waves as a regressor in the continuation hazards may introduce endogeneity into the inverse Mills' ratio term in the labor supply equation we estimate the second step both with and without the waves regressor. Alternatively, we estimated the models in Table 5 with average hourly earnings as both the regressor and instrument set member (Column 1) and with the weeks-worked wage as an instrument (Column 2). We emphasize that the key to understanding the econometric consequences of possible nonrandom attrition from the PSID is not only whether the coefficient of the additional regressor capturing the probability of continuing to participate in the PSID is significant but also whether the economic coefficients of interest, particularly the estimated wage elasticities, change.

None of the selectivity terms is significantly different from zero in Table 5. The

15. To have time varying covariates in the hazard functions requires lagging regressors one year because information is not available in the year of attrition. Time varying covariates are troublesome because we lose the first year of data, and the bulk of persons who attrite contribute only one person year. To learn the consequences of using time-varying regressors for labor supply research we also estimated panel continuation hazards with only time invariant regressors, one for 1968–1989 and the other for 1969–1989. A Wald test indicates that the results for the two time periods are the same, which gives us confidence that our study of the consequences of panel attrition based on the panel continuation hazards with time varying regressors in Table 4 are not biased against finding nonrandom attrition.

Table 5
Two-Step Attrition Tests in a Life-Cycle Consistent Labor Supply Model for the Years 1968–89[a]

	Balanced SRC/SEO Sample[b]				Unbalanced SRC/SEO Sample[b]			
Variable	Probit w/ Waves (1)	Probit w/o Waves (1)	Probit w/ Waves (2)	Probit w/o Waves (2)	Probit w/ Waves (1)	Probit w/o Waves (1)	Probit w/ Waves (2)	Probit w/o Waves (2)
*Riatwg*1 (α)	14.778	20.391	13.256	30.293	22.786**	23.733**	18.383*	18.783*
	(33.391)	(30.123)	(13.7E2)	(79.446)	(9.605)	(9.784)	(9.553)	(9.735)
Lagged assets (δ)	0.222	0.209	0.195	−0.909	0.650**	0.630**	0.411	0.418
	(0.756)	(0.698)	(40.332)	(4.537)	(0.272)	(0.276)	(0.276)	(0.276)
Current assets (φ)	0.028	−0.029	1.237	1.546	1.443	1.427	0.838	0.882
	(2.619)	(2.401)	(11.7E2)	(11.471)	(0.899)	(0.899)	(0.936)	(0.929)
Uncompensated wage	0.074	0.102	0.066	0.152	0.111**	0.115**	0.089*	0.091*
	(0.167)	(0.151)	(6.856)	(0.398)	(0.047)	(0.047)	(0.046)	(0.047)
Compensated wage	0.074	0.103	0.053	0.135	0.095**	0.100**	0.080*	0.082*
	(0.169)	(0.153)	(6.973)	(0.418)	(0.048)	(0.048)	(0.047)	(0.048)
IMR	−129.272	−160.796	−157.365	−242.621	−118.648	13.531	−121.575	7.751
	(217.608)	(219.769)	(57.6E2)	(24.8E1)	(10.1E1)	(21.416)	(12.2E1)	(21.484)
J-statistic	8.270	10.379	0.008	0.124	60.799	61.809	59.566	61.474
[dof, p]	[32, .999]	[32, .999]	[32, 1.00]	[32, 1.00]	[32, .002]	[32, .001]	[32, .002]	[32, .001]
Observations	1,691	1,691	1,691	1,691	6,086	6,086	6,086	6,086

a. Standard errors are given in parentheses. The balanced sample deletes the entire time-series of persons if any missing values are encountered while in the sample; the unbalanced sample deletes only the person-year when missing values are encountered.
b. Results in columns labelled (1) are based on the imputed wage, *Riatwg*1, both as regressor and as instrument, while results in Column (2) are based on *Riatwg*1 as a regressor and the weeks-worked wage, *Riatwg*2, as an instrument.
Statistical Significance: * = 10 percent level; ** = 5 percent level; *** = 1 percent level.

estimated wage and asset coefficients from the balanced sample are sensitive to the choice of selectivity correction and wage instrument, but tests of the differences across models are again of low power because of the relatively small size of the balanced panel. Unlike the balanced panel results the larger unbalanced panel results are notably similar across selectivity terms and wage measures with division bias more pronounced in columns (2). We note that the overidentifying restrictions are rejected in all the two-step labor supply models estimated with the unbalanced panel in Table 5. There is no evidence of attrition being endogenously determined with labor supply.

Table 6 displays results that further examine the relative importance of possible nonrandom attrition by using the subsample of 1976–89 when the preferred reported hourly wage rate measure is available in the PSID. The first four columns of Table 6 have no selectivity correction terms and the last four columns include selectivity correction terms based on the discrete probit hazards with duration dependence presented in Table 4. Note that the columns of Table 6 differ by wage measure in the regression and instrument set. Finally, we examine the importance of latent heterogeneity to labor supply estimates by estimating labor supply under the null hypothesis of worker homogeneity (common intercepts) in hours levels in the fourth and last columns of Table 6.

Comparing the columns labeled (2) and (3) to the columns labeled (1) in Table 6 illustrates the downward division bias inherent in labor supply functions estimated with the wage measured as average hourly earnings. Using average hourly earnings instead of the more accurate reported hourly wage reduces the estimated wage elasticities by 60–70 percent. The overidentifying restrictions are not rejected only in labor supply functions permitting heterogeneity and using the reported hourly wage. The most important result in Table 6 is that the only case where the selectivity correction is statistically significant is in specifications that improperly ignore latent labor supply heterogeneity. The result that ignoring latent person-specific labor supply heterogeneity produces the misleading conclusion of significant attrition bias is more pronounced in untabulated cases: models using a probit-based hazard without waves to construct the selection correction and models using the imputed wage as both the regressor and an instrument. We conclude from our results using popular parametric specifications of the panel continuation process that any econometric bias that might result from ignoring attrition will be avoided by estimating a fixed-effects labor supply specification. The likelihood of attriting, while possibly endogenous, is largely person-specific and time-invariant so that fixed-effects labor supply models for prime-age men obviate the need for two-step estimation with a first-step equation for the likelihood of continuing in the PSID.

V. Conclusion

We have examined the consequences of possible nonrandom panel attrition in a life cycle consistent model of labor supply permitting intertemporally progressive taxation of wage and interest incomes and latent worker specific heterogeneity. We examined Wald tests of whether the labor supply behavior of attriters is the same as nonattriters and variable addition tests involving two-step labor supply

Table 6
Two-Step Attrition Tests in a Life-Cycle Consistent Labor Supply Model for the Unbalanced Sample Over the Years 1976–89[a]

Variable[b]	(1)	(2)	(3)	(4)	Probit w/ Waves (1)	Probit w/ Waves (2)	Probit w/ Waves (3)	Probit w/ Waves (4)
Net wage (α)	51.978***	21.477**	15.915*	62.114***	50.720***	19.693**	14.719	60.84***
	(16.344)	(9.132)	(9.059)	(3.866)	(16.720)	(9.084)	(8.969)	(4.198)
Lagged assets (δ)	0.313	0.452	0.196	1.678***	0.300	0.405	0.156	1.38***
	(0.285)	(0.301)	(0.305)	(0.533)	(0.287)	(0.301)	(0.305)	(0.585)
Current assets (ϕ)	0.715	0.973	0.265	−4.062***	0.652	0.797	0.084	−3.69***
	(1.036)	(1.061)	(1.073)	(0.711)	(1.051)	(1.073)	(1.081)	(0.754)
Uncompensated wage	0.238***	0.106**	0.079*	0.307***	0.232***	0.090**	0.067	0.28***
	(0.075)	(0.045)	(0.045)	(0.019)	(0.076)	(0.042)	(0.041)	(0.019)
Compensated wage	0.231***	0.096	0.072	0.350***	0.225***	0.082*	0.066	0.32***
	(0.076)	(0.047)	(0.048)	(0.021)	(0.077)	(0.043)	(0.042)	(0.021)
IMR					−85.696	−226.482	−238.774	−897.999*
					(23.9E1)	(22.1E1)	(21.4E1)	(49.5E1)
J-statistic	37.059	50.326	49.626	364.128	36.986	50.115	49.333	278.117
[dof, p]	[25, .057]	[25, .002]	[25, .002]	[26, .000]	[24, .043]	[24, .001]	[24, .002]	[25, .000]
Observations	3,489	3,489	3,489	3,827	3,489	3,489	3,489	3,827

a. Standard errors are given in parentheses. The balanced sample deletes the entire time-series of persons if any missing values are encountered while in the sample; the unbalanced sample deletes only the person-year when missing values are encountered.

b. Results in columns labelled (1) are based on the reported wage, *Rratwg;* results in Column (2) are based on the imputed wage, *Riatwg*1, both as regressor and as instrument; results in Column (3) are based on Riatwg1 as a regressor and the weeks-worked wage, *Riatwg*2, as an instrument; results in Column (4) are based on the reported wage, *Rratwg,* for the model estimated in levels under the null hypothesis of no latent heterogeneity in hours levels.

Statistical Significance: * = 10 percent level; ** = 5 percent level; *** = 1 percent level.

models that declare ex ante a discrete hazard function for panel continuation and then examine whether the labor supply coefficients of interest are affected significantly by adding the likelihood of continuing in the panel. Our preferred estimates are found in the first column of Table 6, which use the reported hourly wage, and show mean uncompensated and compensated wage elasticities of about 0.2. Our main conclusion is that alternative econometric specification decisions such as instrument set choice and wage regressor definition matter more than how one allows for the possible nonrandom attrition when estimating labor supply of prime-age men with the PSID. Using a fixed-effects labor supply equation conditions out any bias from possible nonrandom attrition.

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