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DOES LABOR SUPPLY EXPLAIN FLUCTUATIONS IN AVERAGE HOURS WORKED?

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ABSTRACT

Economists have long debated over what labor supply has to do with fluctuations in hours worked. This paper uses a time series of cross-sections from the 1964-88 Current Population Surveys to study whether microeconomic intertemporal substitution models can explain time series fluctuations in annual averages. Conditional on a parametric trend, labor supply equations fit the 1975-87 data remarkably well. But estimates for 1963-74 are not robust, and estimated labor supply elasticities are much lower in the earlier period.

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I. Introduction

Twenty years ago, Lucas and Rapping (1970) proposed that unemployment be interpreted as a labor supply response to temporarily low wage rates. Since then economists have continued to argue over what labor supply has to do with fluctuations in employment and hours worked, most recently in the debate over Real Business Cycle theory (Plosser 1989, Mankiw 1989). At a minimum, intertemporal substitution theories such as that of Lucas and Rapping require that wages and hours worked be positively correlated. Recent evidence that wages are procyclical include the work of Bils (1985) and Solon and Barsky (1988). On the other hand, Chirinko (1980), Geary and Kennan (1982), and others have argued that wages are noncyclical. Even if wages are procyclical, the fact that hours rise when wages rise does not mean that hours rise <u>because</u> wages rise.

In addition to wage cyclicality, the contemporary discussion of intertemporal substitution appears to revolve around two issues. Some authors have focused on the fraction of variance in hours worked that can be explained by changes in wage rates. For example, in his recent survey of the labor supply literature, Pencavel (1986) concludes that the behavioral response to changing wage rates is a "second order effect". Others have been concerned with whether labor supply models pass a variety of specification tests. The ability of labor supply models to pass such tests can be taken as a litmus test for whether labor supply explains <u>any</u> of the variance in hours worked.[1]

In this paper, a time series of cross-sections from the Current Population Survey (CPS) is used to study whether microeconomic intertemporal substitution models can explain time series fluctuations in average hours worked. Labor supply equations are fit to annual averages tabulated from each CPS from 1963 through 1987. Paralleling the two branches of argument over intertemporal substitution theories of the business cycle, the empirical work has two components. First, real wages are shown to be strongly procyclical between 1975 and 1987, but only weakly procyclical or noncyclical between 1963 and 1974. Second, goodness-of-fit tests are used to evaluate the labor supply interpretation of the correlation between average hours worked and wages.

Section II outlines an econometric framework for the application of microeconomic models to annual averages. The main point in this section is that when individual observations are grouped into a fixed number of annual averages, period effects must be excluded from the underlying microeconomic equation. Thus, if period effects are found to be necessary in individual labor supply equations, such equations cannot be used to explain movements in annual averages. If period effects need not be included, however, they may be used as instrumental variables. Use of period effects as instrumental variables for a microeconomic model is the same as Generalized Least Squares (GLS) on annual averages. Furthermore, the overidentification test associated with instrumental variables can be interpreted as a test of goodness-of-fit of the microeconomic model to annual averages.

Other issues raised in Section II include the possibility of simultaneous equations bias in models fit to annual averages, the implications of uncertainty in the micro model and random effects in the aggregate model, and the implications of including only working men in the estimating sample. Given the assumptions commonly invoked in life-cycle models, there is no simultaneous equations bias in estimates based on grouped data. Allowing for uncertainty or random effects does not change this conclusion, although standard errors and test statistics are affected. As is well known, restricting the sample to working men does bias labor supply estimates, but in some circumstances consistent estimates can be recovered simply by including aggregate macroeconomic variables as regressors in equations for annual averages.

Section III presents graphical and statistical evidence on the labor supply interpretation of movements in wages and hours. Conditional on a quadratic trend, labor supply equations fit the 1975-87 data rather well. But estimates for 1963-74 are not robust, and estimated labor supply elasticities are generally much lower in the earlier period.

Estimation using data for 1963-74 is complicated by the lack of information on hours and weeks worked, and annual hours worked must be imputed for these years. Section IV presents evidence that aggregation of the micro model eliminates most of the bias induced by the use of imputed data in 1963-75, so that reduced procyclicality of wages in the earlier period is not a consequence of measurement error in hours data. Section V discusses labor supply equations with measures of aggregate demand included as regressors, and Section VI offers a summary and conclusions.

II. Econometric Framework

Estimating Life-Cycle Labor Supply Models

In standard life-cycle theory, consumers are assumed to face a known stream of wages and prices, and to maximize a lifetime utility function that is intertemporally additive and additively separable in consumption and leisure. Given these assumptions, current period labor supply or labor earnings depends solely on contemporaneous wage rates and the time-invariant marginal utility of lifetime wealth. In fact, for the purposes of estimation, any time-invariant individual characteristics may be viewed as being absorbed into a fixed effect. Life-cycle theory therefore provides a parsimonious specification for empirical research.[2]

One commonly estimated life-cycle model is a log-linear equation for hours, derived from the utility function discussed by Heckman and MaCurdy (1980) and MaCurdy (1981). When the rate of time preference and the interest rate are constant, the Heckman and MaCurdy hours equation for individual i at time t is ($i = 1, \ldots, N$; $t = 1, \ldots, T$)

$$h_{it} = \alpha_1 + \beta_1(\rho - r)t + \theta_1 w_{it} + \lambda_i + u_{1it}, \tag{1}$$

where λ_i is proportional to the log of i's time-invariant marginal utility of wealth, r is the interest rate and ρ is the rate of time preference. h_{it} and w_{it} are the log of hours and wages, and θ_1 denotes the intertemporal substitution elasticity.

As originally pointed out by MaCurdy (1981), equation (1) generates a relationship between log hours and log earnings that may also be used to estimate the labor supply elasticity. Adding θh_{it} to both sides of equation (1) and dividing by $(1+\theta)$ gives

$$h_{it} = \alpha_2 + \beta_2(\rho - r)t + [\theta_2/(1+\theta_2)]y_{it} + \lambda_i + u_{2it}, \tag{2}$$

where y_{it} is log earnings. Elasticities based on this equation have been relabelled θ_2, and λ_i includes $1/[1+\theta_2]$. Defining $\mu = \theta_2/[1+\theta_2]$, we have $\theta_2 = \mu/[1-\mu]$. Note that because the log of earnings equals log wages plus log hours, equation (2) must be estimated by instrumental variables.

Most of the empirical work based on equations (1) and (2) uses panel data to control for λ_i, which is necessarily correlated with wage rates.[3] Bias from the unobserved λ_i is usually eliminated by transformations such as differencing or deviations from means, and bias from measurement error is treated with instrumental variables.

In a survey of applied labor supply research, Ashenfelter (1984) points out that the life-cycle framework may also be used to investigate the ability of intertemporal substitution models to explain <u>macroeconomic</u> fluctuations. Ashenfelter notes that because the only source of omitted variables bias in (1) and (2) is the time-invariant λ_i, consistent estimates of θ_1 or $\theta_2/(1+\theta_2)$ may be tabulated by fitting (1) or (2) to annual averages. For example, equation (1) is fit to annual averages by estimating

$$\bar{h}_t = [\beta_0 + \bar{\lambda}] + \beta_1(\rho - r)t + \theta_1\bar{w}_t + \bar{u}_{1t}. \tag{3}$$

Ashenfelter's point about annual averages (an observation also made by MaCurdy [1985]) is primarily a statistical one. Although θ does capture the response to a perfectly foreseen business cycle, life-cycle models are not really formulated to explain responses to transitory wage changes. Rather, θ is meant to capture intertemporal substitution in response to evolutionary wage changes over the life-cycle, say as a consequence of human capital accumulation. Nevertheless, microeconometric evidence from life-cycle models has been widely used to evaluate intertemporal substitution theories of aggregate fluctuations (e.g., Card 1987, Mankiw 1989). The justification for this is that in models where wages are uncertain, the impact of unforseen movements in wages on λ_i is small relative to the impact on contemporaneous wage rates (e.g., Altonji 1986). The life-cycle model under uncertainty is therefore conceptually more attractive for relating cyclical fluctuations to intertemporal substitution. But for empirical strategies, the practical consequences of uncertainty are rather minor. Therefore, most of the discussion that follows uses the simpler framework of life-cycle labor supply under certainty.

Angrist (1991) offers an instrumental variables interpretation of grouped equations like (3). It is well known that the minimum variance estimator for grouped data is a form of Generalized Least Squares (Prais and Aitchison 1954). In the standard case where the micro residual is homoscedastic, the GLS estimator is simply weighted least squares with weights proportional to the group size. In Angrist (1991), the Prais and Aitchison Generalized Least squares (GLS) estimates of an equation such as (3) are shown to be Two-Stage Least Squares (TSLS) estimates, where the instruments consist of dummy variables that indicate each period. Thus, the key identifying assumption required for estimation using grouped data is that there be no group effects in the ungrouped equation.[4] If this assumption is satisfied, grouping provides a means of controlling for time invariant unobserved heterogeneity, and for eliminating bias from measurement error in regressors.[5]

The TSLS interpretation of grouping also provides a simple framework for evaluating whether equations such as (1) and (2) can explain cyclical fluctuations. If the underlying micro model contains a period specific intercept, then period effects will not be legitimate instrumental variables. On the other hand, if period effects are legitimately excluded from (1) and (2), possibly after conditioning on other macroeconomic variables, then Ordinary Least Squares (OLS) or Generalized Least Squares (GLS) estimates of the grouped equations will be consistent. The exclusion of period effects may be formally tested using standard TSLS over-identification tests, which give a measure of the correlation between instruments and residuals in the underlying microeconomic model. The test may also be interpreted as measuring the goodness of fit of the micro model to sample means.[6]

Simultaneous Equations Bias

In an equilibrium labor market, how can it be that least squares estimates of equation (3) are consistent ? The reason simultaneous equations bias may be ignored in this model is that the aggregate supply curve is assumed to be fixed over time. The only temporal variation in average wages and hours comes from demand shocks that "trace out" the aggregate supply curve. To see this more formally, assume that the following equation characterizes firm f's demand for labor

$$\sum_{i \epsilon f} h_{it} = \gamma_0 + \gamma_1 \left[\sum_{i \epsilon f} w_{it} \right] + \delta_t + \epsilon_{ft}. \tag{4}$$

Thus, the firms' demand for hours is function of the total wage bill. In this model average hours work demanded are

$$\bar{h}_t = [\gamma_0 + \delta_t]\kappa_t + \gamma_1\bar{w}_t + \bar{\varepsilon}_t, \tag{5}$$

where κ_t is the reciprocal of the average number of workers hired per firm in period t.

κ_t is likely to be determined as part of equilibrium in a larger system, but the level of average wages and hours is assumed to be determined by equality of supply and demand. Therefore, the reduced form for average wages is given by

$$\bar{w}_t = \pi_0 + \pi_1 t + \pi_t + [\bar{u}_{1t} - \bar{\varepsilon}_t]/\pi_2,$$

where π_0, π_1 and π_2 denote reduced form parameters and π_t is the reduced form period effect.

Although the error term $\bar{u}_{1t}$ appears in both the grouped supply curve and the reduced form for grouped wages, it is asymptotically negligible when group size gets large. Intuitively, period effects in the reduced form for wages can be thought of as the sole source of random error in the model grouped into annual averages; there is no time series random error in the grouped supply curve. Because the supply curve is fixed over time, shifts in π_t identify intertemporal substitution elasticities.

It should be noted that the question of simultaneity bias turns on the assumption that group sizes are large enough for a valid asymptotic approximation. If group size is held fixed while the number of groups get large, then it is clear from the reduced form for wages that regressor-error correlation will not be asymptotically negligible. Furthermore, when asymptotics are done on the number of groups, group sample means no longer converge to population means. The sample means must then be treated as mismeasured observations of the population means. Deaton (1985) develops this approach to grouped estimation, and offers formulas to correct estimates and standard errors for attenuation bias from measurement error.

A Note on Random Effects and Uncertainty

The estimation of equations grouped into annual averages is justified by the assumption that there are no period effects in the underlying micro labor supply model, and therefore no period effects in the grouped equation. An alternative specification adds an aggregate random effect that is uncorrelated with average wages to the grouped equation. This modification is attractive because the basic life-cycle model generates no "macro residual". That is, population means should fit the grouped life-cycle model perfectly.

In an equilibrium labor market model, the random period effect must be "tacked on" to the equation for annual averages. Otherwise, if the period effect is assumed to appear in the underlying microeconomic model, the same period effect will appear in the reduced form for wages as appears in the labor supply error term. Thus, the random effects model is an ad hoc generalization of the model discussed above; average wages are determined in equilibrium by equations (5) and (1), but the aggregate hours equation has the form

$$\bar{h}_t = [\beta_0 + \bar{\lambda}] + \beta_1(\rho - r)t + \theta_1\bar{w}_t + [\xi_t + \bar{u}_{1t}]. \tag{3'}$$

where ξ_t is asymptotically uncorrelated with the regressors in (3').

The assumption that ξ_t is asymptotically uncorrelated with wages implies that GLS estimates of parameters in (3') will be consistent as both T and N get large. But standard errors and test statistics must be revised to take account of the fact that the variance of ξ_t is not negligible even for very large N.

To keep the notation simple, assume that ξ_t and u_{1it} are uncorrelated, with variances τ^2 and σ^2, and that the groups are of equal size, n. Assuming that the ξ_t are not serially correlated, the correct GLS weighting matrix is diagonal with elements equal to $\tau^2 + (\sigma^2/n)$.[7] But estimates constructed using time dummies as instruments are equivalent to GLS estimates using a weighting matrix with $(\tau^2 + \sigma^2)/n$ on the diagonal. Therefore, the over-identification test statistic for the random effects model (equal to the quadratic form minimized by GLS) is the over-identification test statistic for the model without random effects multiplied by

$$\omega^2 = [\tau^2 + \sigma^2]/[n\tau^2 + \sigma^2]$$

Similarly, standard errors for parameters in the random effects model are computed by multiplying the standard errors from the model without random effects by ω^{-1}. An estimator for the numerator of ω^2 is the residual variance reported by most TSLS software. The denominator may be estimated by substituting the TSLS parameter estimates into equation (3') to compute an average residual with variance equal to $\tau^2 + (\sigma^2/n)$.

An alternative random effects-type model for grouped data can be motivated by the life-cycle model with uncertainty. In MaCurdy's (1985) version of the life-cycle model where consumers maximize expected utility, λ obeys the following stochastic process:

$$\lambda_{it} = \lambda_{it-1} + b + \epsilon_{it} = \lambda_{i0} + bt + \sum_{j=0}^{t} \epsilon_{ij},$$

where ϵ_{it} is a one-period forecast error. The parameter b is fixed when interest rates and discount rates are assumed constant. The annual average of λ_{it} is therefore

$$\bar{\lambda}_t = \bar{\lambda}_0 + bt + \sum_{j=0}^{t} \bar{\epsilon}_j,$$

where $\bar{\epsilon}_j$ is the average forecast error in period j. The term $\bar{\lambda}_0$ may be absorbed into the constant, and bt is the same trend as in the model with certainty. But the sum of average forecast errors is a random effect that becomes part of the grouped regression error.

In contrast to the case where an arbitrary random period effect is tacked on, the sum of average forecast errors is clearly heteroscedastic. The question of whether $\bar{\lambda}_t$ has a variance that is asymptotically negligible turns on whether there is a common component in the individual forecast errors. For example, when the errors are independent over i and the group size is n_t, then the variance of $\sum_{j=0}^{t} \bar{\epsilon}_j$ is just $t\tau^2/n_t$ where τ^2 is the variance of ϵ_{it}. Even here, the residual variance may not be asymptotically negligible if the asymptotics are done on both n_t and T.

A simple procedure for estimating the uncertainty model with uncorrelated forecast errors is weighted least squares, where the weights are equal to the inverse variances of the grouped residuals. That is, the weights are given by σ_t^2/n_t, where σ_t^2 is the variance of residuals in period t. This may be contrasted with the homoscedastic Prais and Aitchison

(1954) case, where the same σ^2 is used each period. As when the micro residuals are homoscedastic, the more general weighted least squares procedure is also a TSLS estimator. In this case, the TSLS equivalent of grouping is White's (1982) optimally weighted TSLS estimator for independent, not identically distributed samples.[8]

Sample Selection

An important feature of labor supply behavior is the participation decision. Because individuals who work are not a random sample of the population, allowance should be made for the possibility of sample selection bias. Heckman (1979) shows that a general solution to the selection bias problem can be obtained by including the conditional mean of the error term in an equation estimated using the selected sample. In the micro labor supply model, the problem of sample selection is treated by fitting

$$h_{it} = \alpha_1 + \beta_1(\rho - r)t + \theta_1 w_{it} + \lambda_i + E(u_{1it}|SSR) + \eta_{it} \tag{6}$$

to individuals with positive hours and earnings, where $E(u_{1it}|SSR)$ denotes the mean of the error term conditional on the Sample Selection Rule (SSR).

A consequence of equation (6) is that the sample selection can be analyzed as a problem of missing regressors. Of particular interest here is the question of whether sample selection induces a period effect in the labor supply model. Suppose that the sample is selected according to whether the expected wage exceeds the reservation wage, where the expected wage is linear combination of variables, X_1, and the reservation wage is a linear combination of variables, X_2. Then participation by individual i at time t is determined by the condition

$$X_{1it}\psi_1 - \nu_{1it} > X_{2it}\psi_2 - \nu_{2it} \tag{7}$$

where ψ_1 and ψ_2 are parameters, and ν_{1it} and ν_{2it} are random variables. It is convenient to rewrite this as

$$Z_{it}\psi > \nu_{it}, \tag{8}$$

where $Z_{it} = X_{1it}-X_{2it}$, and $\nu_{it} = \nu_{1it}-\nu_{2it}$.

Following Olsen (1980), I assume that $E(u_{1it}|\nu_{it})$ is a linear function of ν_{it}, and that ν_{it} is uniformly distributed. Then $E(u_{1it}|SSR)$ is a linear function of $Z_{it}\psi$, so that sample selection bias may be eliminated simply by including additional regressors, Z_{it}. If Z_{it} has no time-varying components, then sample selection does not induce a period effect in the grouped model. On the other hand, if expected or reservation wages are a function of aggregate labor market conditions, then the period mean of Z_{it} will not be fixed. In this case, the parameters of labor supply equations cannot usually be identified solely by time series variation in hours and wages or hours and earnings.[9]

The need to control for sample selection may justify the inclusion of demand side variables in the labor supply equation. Ham (1986), Card (1987), and others have argued that one important implication of equilibrium models is that suppliers obtain all the information they need about the demand side of the market from equilibrium wage rates. According to this view, nonzero coefficients on measures of aggregate labor market conditions in individual labor supply equations should be taken as evidence against the equilibrium hypothesis. But in the sample selection model, demand side aggregates should be included in equilibrium labor supply equations whenever these aggregates determine offered or reservation wages. For example, if reservation wages are determined partly by unemployment rates, these rates may appear as a regressors even though unemployment is not a result of constraints on supply.[10]

III. Intertemporal Substitution: 1963-87

Data

Data on earnings and hours worked from 1975-87 are drawn from March CPS Public Use Tapes for 1976-88. Earnings data for 1963-74 are drawn from the Mare-Winship Uniform Extracts of March CPS data for 1964-1975. The sample is divided into two periods because the quality of information on hours worked changes in 1976. From 1976 on, the March CPS records the number of weeks worked and the usual hours worked per week in the year preceding the survey year. For 1975-87, annual hours worked last year is then estimated as the product of these two variables. Preceding the 1976 CPS, however, information on usual hours per week is not recorded, and weeks worked are only recorded as a categorical variable with seven categories.[11]

For the purposes of estimation in the earlier period, annual hours worked were imputed using two approximations. First, men were assigned the midpoint of the category interval for weeks worked last year. For example, men in category 1 worked 1-13 weeks and were assigned a value of 7. Second, usual hours per week <u>last year</u> was replaced by actual hours worked <u>last week</u>. The first of these approximations is unsatisfactory because the use of interval midpoints for categorical dependent variables leads to inconsistent estimates (Stewart 1983). The second approximation is poor because the R^2 from a regression of hours last week on usual hours last year is only 0.15 .[12]

Imputation of hours worked is also complicated by the fact that there are people with positive hours worked last year but no hours worked last week. This is approximately 10% of men in 1976-88 CPS's. Again a simple approach to this problem was taken - men with hours last year who did not work last week were discarded from the 1963-74 estimating sample.

To evaluate the consequences of imputation, data from 1976-88 were used to compute both imputed and actual hours worked. The R^2 from a regression of log imputed hours on log actual hours is only 0.54 in a regression with period effects. Average hourly earnings (wages) were also computed from imputed hours worked. For log wages, the R^2 is considerably higher than for log hours, equal to 0.83. Imputed wages remain a noisy signal, however, and OLS estimates of coefficients on wages and earnings reflect substantial measurement-error bias when tabulated using imputed data. Nevertheless, the grouped estimates appear remarkably insensitive to the use of imputed data. This fact is documented in Section IV, below.

Individuals sampled for the CPS are interviewed a total of 8 times over a period of 16 months: one interview a month for four months, eight months without an interview, and again one interview a month for four months. Thus, the CPS sample is designed so that consecutive March Surveys have a 50% overlap, with respondents who were in the sample 1-4 times as of their first March Survey appearing the following year for sample months 5-8. The reappearance of sampled individuals generates year to year correlation in individual earnings and hours, inducing a nondiagonal covariance matrix in data grouped into annual averages. The theoretical structure of this covariance matrix is easily derived, but estimation of the parameters in the covariance structure requires information from other sources.[13] To avoid the problems generated by a nondiagonal covariance matrix, individuals in sample months 5-8 were simply discarded, so that the remaining data points are independently distributed over both i and t.

The extracts used in estimation contain all 25-50 year old men in sample months 1-4 with positive hours worked and positive wage and salary earnings. Attention is focused on men aged 25-50 because results reported below suggest that data for this group are most likely to fit the labor supply model. Figure 1 plots the time series of real wages, hours worked and labor force participation (defined here as having positive earnings). An important feature of the labor force participation series is the five percentage point increase in the fraction of the sample with positive earnings between 1964-67. This apparent increase is an artifact of the improvements in data collection procedures during the early years of the CPS, and not a reflection of labor force behavior.[14]

As predicted by the intertemporal substitution hypothesis, Figure 1 shows that wages and hours move together in most of the later years. After 1967, labor force participation is also procyclical. In the earlier years, however, wages appear only weakly procyclical or noncyclical.

Microeconomics with Grouped Data

Figure 2 depicts the 1975-87 profiles of average hourly earnings and hours worked for 5-year cohorts aged 18-55 in 1976. For example, the solid line at the left of the figure shows the 1975-87 earnings of men aged 18-23 in 1976. Lines for different cohorts exhibit different trends, but common period shocks are apparent in patterns of deviation from trend. Of course, different period shocks hit different cohorts at different ages.

A labor supply interpretation of the data in Figure 2 is presented in Figure 3. Points plotted in Figure 3 were tabulated by removing a cohort specific intercept and a cohort specific linear trend term from the average wages and hours data plotted in Figure 2. A separate trend was removed from averages for each five year age group. Thus, the slope of the line drawn through the points corresponds to an estimate of θ_1 in

$$\bar{h}_{ct} = \beta_{0c} + \beta_{1c}(\rho - r)t + \theta_1 \bar{w}_{ct} + \bar{u}_{1ct}, \tag{9}$$

where the subscript c indexes cohorts. This is the grouped equivalent of model (1) with a cohort specific trend, where instruments used to group the micro model consist of year and cohort main effects and interactions.

Note that β_{0c} in (9) captures the time-invariant cohort specific mean of λ_i. Equation (9) is therefore a form of Analysis of Covariance based on the removal of cohort fixed effects. This approach is an application of Deaton's (1985) suggestion that panel data be formed from a time series of cross-sections by following cohorts over time.

Figure 3 depicts an upward sloping relationship that seems to fit well for data on the wages and hours of men aged 25-50. Different symbols are used to distinguish the earnings of this middle group from the earnings of younger and older men. Data points for the younger and older cohorts are less likely to fall around the regression line (which has slope 0.46).

Labor supply estimates to accompany Figure 3 are reported in Table 1a. This table reports estimates of equation (9) using data on the 1975-87 earnings of men aged 25-50 in 1976, while Table 1b reports the corresponding estimates for 1963-74. Both OLS and TSLS estimates are reported -- as noted above, the instrument list for TSLS includes a full set of year and cohort main effects and interactions. Therefore, even if the underlying micro equation includes a period effect, labor supply parameters in equation (9) are still identified, and so estimates with and without period effects are shown.

Estimates of θ_1 are reported in column (1) of Table 1a. OLS estimates of θ_1 are quite small, though significantly different from zero because of the large sample size. For example, the OLS estimate of θ_1 in a model with period effects is 0.035 . TSLS estimates are substantially larger, suggesting the presence of measurement error in the OLS estimates. The overidentification test statistic for TSLS estimates of θ_1 in a model without period effects is 160.7, and compared to a chi-square distribution with 54 degrees of freedom this indicates a poor fit.[15] Inclusion of period effects improves the fit to the point where the model is accepted at conventional levels of significance. Interestingly, the overidentification test strongly suggests that period effects belong in the equation, but estimates of θ_1 do not appear particularly sensitive to the presence of period effects.

Estimates of θ_2 are reported in Column (2) of Table 1a. As usual, these estimates are larger than the estimates of θ_1. Again, the estimates are not sensitive to the inclusion of period effects, although period effects must be included to pass the overidentification test. Reasonably precise elasticities in the range 0.3 - 0.8 are generated by models with and without period effects.

Table 1b reports estimates of equation (9) for 1963-74. As suggested by the lack of procyclical wage movements in Figure 1, here the labor supply model performs poorly. TSLS estimates of θ_1 are zero in a model without period effects and negative in a model with period effects. Estimates of θ_2 are positive, though not statistically different from zero in the model with period effects. This is consistent with Solon and Barsky's (1988) finding of reduced cyclicality in earlier years. On the other hand, a labor supply optimist might prefer the TSLS estimate of θ_2 from a model without period effects - this number is 0.357 with a standard error of 0.075.

Macroeconomics

Estimation of equation (9) using data grouped by cohort and year is a natural analog of fixed effects techniques for panel data. Of primary interest here, however, is the question of whether labor supply models can be used to explain year to year fluctuations in hours worked, without controlling for cohort specific trends.

Table 2a reports estimates of equations (1) and (2) fit to annual averages from 1975-87. The TSLS equivalent of this procedure is to use a full set of period dummies as instrumental variables. Three sets of estimates are reported. The first shows results from equations with no trend, theoretically justified when the interest rate equals the rate of time preference. The second and third sets of estimates are for equations that include a linear and quadratic trend. Estimates are tabulated using two separate samples. The first sample includes all men aged 25-50 in 1976, and is the same as the sample used to construct the estimates in Table 1a.[16] In time series macroeconomics, however, it is not customary to follow true cohorts, and results for a second sample including all men 25-50 <u>each</u> year are also reported. Assuming there is no sample selection bias and that labor supply parameters do not vary with age, these samples should lead to the same (within sampling variance) parameter estimates.

Estimates of models without a trend, reported in column (1) of Table 2a, show that the simple correlation between hours and wages or earnings for 1975-87 is positive. Overidentification test statistics lead to a strong rejection of models without a trend, however, and the addition of a one or two parameter trend substantially improves the fit. The trend is more important for goodness of fit in models estimated with the sample of men aged 25-50 each year. Remarkably, given the large sample size, equation (2) estimated with a quadratic trend is close to passing the overidentification test at conventional levels of significance ($\chi^2(9)$ 1% critical value = 21.7) .

In models with a trend, estimates of θ_2 are all bigger than unity, while estimates of θ_1 are range from 0.6 to 1.1 . The elasticities are generally largest in models with a quadratic trend. Parameter estimates based on men aged 25-50 each year do not differ importantly from estimates based on men aged 25-50 in 1976.

Table 2b shows results for annual averages for 1963-74. In contrast to the later period, the raw correlation of hours and earnings or wages in this period, reported in column (1), is zero or negative. Estimates of θ_1 using a linear trend are on the order of 0.3, and estimates of θ_2 using a linear or quadratic trend are 0.37 to 0.79 . But estimates of θ_1 using a quadratic trend are negative, and the quadratic term (not reported) has a t-statistic around 3. On the other hand, the quadratic trend specification may be rejected on relative goodness-of-fit grounds.[17] As in Table 2, the estimates do not appear sensitive to whether the sample is selected on the basis of age in 1964 or age each year.

The estimates from specifications with a linear trend in Tables 2a and 2b are all larger than the TSLS linear trend estimates reported in Tables 1a and 1b for models grouped by cohort and year, and estimated without period effects. This suggests that grouping data by cohort and year so as to remove period effects has a cost: the reduction in group size that is a consequence of finer grouping may lead to increased measurement error bias. In fact, additional results (not reported) from experimentation with alternative group sizes and classification schemes support this hypothesis. Larger group size is usually associated with larger estimates of θ_1 and θ_2.

<u>The Impact of Random Effects and Uncertainty on the Macro Estimates</u>

In the discussion of Table 1, it was noted that allowance for period effects in a model grouped by cohort and year improves goodness-of-fit without substantially affecting inferences regarding the magnitude of intertemporal substitution. This suggests that random period effects may provide a useful strategy for the analysis of grouped labor supply data. Random period effects do not affect the consistency of estimates when the number of periods gets large, but standard errors and test statistics must be adjusted. The adjustment factor is the residual variance for the micro model estimated using time dummies as instruments, divided by the group size times the residual variance from the same model fit to annual averages.

As an example, consider the model used to estimate θ_1 in column (3) of Table 2a. The residual variance estimate for TSLS estimates using year dummies as instruments is 0.641 . Using the TSLS coefficients to compute a residual from the 13 annual averages gives a residual variance of 0.0001748. The average group size is roughly 9,600. Therefore, the over-identification test statistic reported in Table 2a should be multiplied by

$$.641/(9600 * .0001748) = .382.$$

The standard error in Table 2a should be multiplied by $1/\sqrt{.382} = 1.62$. This calculation is meant to be illustrative; 13 annual observations is not enough to estimate the denominator of ω^2 very precisely. But the calculation suggests that the test statistics reported for models with a quadratic trend indicate a substantially better fit than would appear at first blush. Similarly, standard errors are probably somewhat higher than reported.

A similar conclusion regarding standard errors emerges when the microeconomic life-cycle model allows for uncertainty. As noted in Section II, the appropriate grouped data estimation strategy for models with uncertain wages is weighted least squares on the group means. In this case, the weights reflect the fact that the residual variance, as well as the group size, differs across groups.

Using the TSLS estimate of θ_1 from Table 2a (for the sample of men aged 25-50 in 1976, in a model with quadratic trend) to estimate residuals, weighted least squares estimates of θ_1 are 0.967 with a standard error of 0.249 . This differs little from the TSLS estimate of 0.941, although the standard error is nearly 80% larger. Given that the t-statistics are on the order of 6 or 7, however, such a change has little impact on inferences. The test statistic in this example falls only 10 percent, from 32.7 to 29.3 . A complete set of weighted least squares estimates for the uncertainty model, corresponding to Tables 2a and 2b, is reported in Appendix Tables A1 and A2.

Additional Results: Interest Rates and Education

Table 3 reports estimates for models that include real interest rates as an additional regressor. When interest rates are not assumed constant in the Heckman-MaCurdy version of the life-cycle model, the parametric trend should be augmented by the sum of all past rates. As an approximation to this more general specification, contemporaneous interest rates were included as regressors in the basic labor supply models.[18] The rate used here is the annualized real expected 3-month treasury bill rate calculated by Barro and Sala-I-Martin (1990). The interest rate is treated as endogenous, so that TSLS using time dummies is the same as fitting annual averages.

The results in Table 3 are for the samples of men aged 25-50 in 1976 and men aged 25-50 in 1964. Models with interest rates lead inferences similar to those arising in models without interest rates. For example, the estimate of θ_1 in models with a linear trend and the interest rate included as regressors is 0.530, whereas the same parameter is estimated to be 0.581 when the interest rate is excluded. The goodness-of-fit statistic is actually larger when the interest rate is included. Coefficients on the interest rate vary from -0.544 to 0.632, although they are often not statistically significant. It may be noted that macroeconomic Real Business Cycle models suggest the interest rate should be positively related to hours worked because when interest rates are high, current labor supply has a bigger payoff than future labor supply. But the results in Table 3 seem to support Mankiw's (1989) contention that interest rates and labor supply are not systematically related.

Considerable information is lost in aggregate models such as those discussed here. For example, it could be that spurious inferences are generated when one group's hours are rising at fixed wage rates while another's wages are rising with no change in hours. To check on this, the analysis was repeated separately for men with different levels of education. Tables 4a and 4b show estimates for models equivalent to those in Table 2a and 2b, tabulated separately for men who did not finish high school, high school graduates, and men with some college. The general pattern found in Table 2 is replicated for each subgroup in Table 4. There are substantial positive elasticities estimated in the more recent period, while there appears to be little labor supply response in the earlier period. Interestingly, the least educated sub-sample appears to have the most elastic labor supply.

IV. Missing Data Problems for 1963-74

Data underlying the annual hours worked variable are of poorer quality in 1963-74 than in 1975-87. Imputation of hours worked for 1963-74 undoubtedly adds measurement error to the dependent variable, log hours. Measurement error is also added to the regressor in model (1), log wages, because wages are defined here to be the ratio of annual earnings to annual hours worked.

To gauge the extent of bias in estimates for 1963-74, data from 1985-87 were used to calculate a variety of imputed wage and hours measures. Estimates using imputed variables are then compared with estimates based on the best available annual hours variable. The two imputations used in the earlier period are the assignment of interval midpoints to categorical weeks worked, and the substitution of actual hours worked last week for usual hours per week last year. Combining the imputations with the best available data, a total of five variables were constructed:

(1) weeks worked last year * usual hours/week last year

(2) <u>grouped weeks worked last year</u> * usuál hours/week last year

For the sample with positive hours last week only:

(3) weeks worked last year * usual hours/week last year

(4) weeks worked last year * <u>hours worked last week</u>

(5) <u>grouped weeks worked last year</u> * <u>hours worked last week</u>.

The hours measures range in quality from having no imputed input in variable (1), used in Table 2, to the imputed hours variable, (5), used in Table 2b. Variable (3) differs from variable (1) only in that the sample is restricted to men with positive hours last week. It should be noted that many researchers have also been concerned with the possibility of measurement error in variable (1).[19] The maintained assumption here is that grouping (instrumental variables) eliminates measurement error bias in parameter estimates based on (1). We can then ask whether grouping also eliminates bias in estimates based on variables (2)-(5).

OLS and TSLS estimates of θ_1 are reported in the first two rows of Table 5a. All estimates are reported for the sample of men aged 25-50 in 1976 in a specification with a quadratic trend. OLS estimates appear highly sensitive to the use of imputed hours, declining from 0.037 in column (1) to -0.112 in column (4). Differences in the OLS estimates are highly significant. TSLS estimates decline from 0.94 in column (1) to 0.67 in column (5). Although larger in magnitude than the decline in OLS estimates, the attenuation of TSLS estimates represents less than 30% of the estimate in column (1). Furthermore, comparison of columns (1) and (3) suggest that the decline in TSLS is entirely attributable to the elimination of men with zero hours of work last week. Thus, the imputation appears to induce selection bias; measurement error bias is eliminated by the grouping procedure.

The lower half of Table 5a reports estimates of θ_2. OLS estimates do not appear very sensitive to the use of imputed hours, moving from 0.44 to 0.28 as the imputation becomes increasingly crude, a decline of 35%. This is not surprising given that model (2) puts all the measurement error on the left hand side; there is no bias from classical measurement error in dependent variables (Durbin 1954). TSLS estimates of θ_2 appear even less sensitive to the use of imputed data, ranging from 1.3 to 0.95, a decline of 25%, with most of the decline again attributable to sample selection.

Thus, imputation does not appear to explain the fact that estimates of θ_2 in the earlier period are roughly half as large as estimates for 1975-87.

As a final check on the estimates for 1963-74, Table 5b reports estimates for both 1963-74 and 1975-87 from equations fit to weeks worked. Estimates of θ_1 in Table 5b were tabulated by regressing the log of weeks worked on the log of average weekly earnings. Estimates of θ_2 were tabulated by regressing the log of weeks worked on annual earnings. For the 1975-87 subsample, weeks worked were coded as the interval midpoints for a categorical variable identical to that available in the earlier period. Thus, estimates for the two period are based on identical measures of labor supply. Elasticities in Table 5b for 1964-75 are all positive in models with a trend. But estimates for the earlier period tend to be around half as large as those for the later period.

It is interesting to contrast the elasticities in Table 5b with those in Table 2a. For 1975-87, elasticities estimated using weeks worked are roughly half of those estimated using hours worked. This suggests that a substantial fraction of the labor supply response to changing wage rates is in changing hours per week.[20]

V. Labor Supply with Demand-Side Variables

Bias induced by conditioning on labor force participation may be reduced by adding regressors from the sample selection rule to labor supply models. This fact justifies the inclusion of "demand side" variables in the labor supply equation and leads to an estimating equation for micro data of the form

$$h_{it} = \alpha_1 + \beta_1(\rho - r)t + \theta_1 w_{it} + Z_{it}\phi + \lambda_i + \eta_{it}, \tag{10}$$

where Z_{it} are regressors from the sample selection rule (8). The grouped version of this equation is

$$\bar{h}_t = [\alpha_1 + \bar{\lambda}_i] + \beta_1(\rho - r)t + \theta_1\bar{w}_t + \bar{z}_t\phi + \bar{\eta}_t \tag{11}$$

As a preliminary exploration of the empirical implications of equation (11), we set $Z_{it} = \bar{z}_t$ = the unemployment rate for all workers.

In addition to correcting for sample selection, the inclusion of unemployment rates in labor supply models has been interpreted as a test of labor market equilibrium.[21] But as Pencavel (1986) and Card (1987) have pointed out, even in equilibrium labor markets it is likely that the error term in an hours equation will be correlated with other dimensions of the same time-allocation problem. Furthermore, hours worked and hours unemployed are linked by an identify that necessarily induces negative correlation. One response to these criticisms is to look for instrumental variables for unemployment, although there are no obviously attractive candidates.

In the current context, the focus is not on whether ϕ is zero, but on what happens to θ_1 and θ_2 when unemployment is included in the estimating equations. Inclusion of unemployment rates or other measures of aggregate demand in labor supply regressions may be a simple strategy for reducing the impact of sample selection on parameter estimates. As in the previous analysis, time dummies as used as instrumental variables for all regressors in the model, including the unemployment rate.

Table 6a reports estimates of equation (11) for versions with linear and quadratic trends and the unemployment rate, and estimates for regressions on annual earnings instead of wages. The sample is men aged 25-50 in each year, corresponding more closely to the type of data studied by macroeconomists than the cohort samples.

As a bench mark, columns (1) and (2) show the estimates from models with a linear trend that were previously reported in Table 2. Columns (3) and (4) report the results of adding the unemployment rate to these equations, and columns (5) and (6) show the results of adding the unemployment rate and a quadratic trend term.[22] For models with and without the quadratic trend, addition of the unemployment rate causes estimates of both θ_1 and θ_2 in 1975-87 to drop by over half. For 1963-74, estimates of θ_1 in models with the unemployment rate are not statistically different from zero, although the estimate of θ_2 is not substantially reduced in the model with a quadratic trend.

The fact that estimated labor supply elasticities drop when unemployment rates are included as regressors suggests that adding unemployment to the labor supply model is not an effective control for sample selection bias. This is because the theoretical consequence of omitting $E(u_{1it}|Z_{it} > \nu_{it})$ is negative bias in θ_1 and θ_2, so that estimated labor supply elasticities should rise when Z_{it} is included. To see why sample selection is likely to induce negative bias, note that if hours are high when labor force participation is high, then u_{1it} and ν_{it} will be negatively correlated. If wages are also high when labor force participation is high, then w_{it} and the omitted variable, $E(u_{1it}|Z_{it} > \nu_{it})$ will be negatively correlated as well.[23]

The unemployment rate is scaled so that the coefficient ϕ is an elasticity. Estimates of ϕ appear to fluctuate around unity, suggesting that the relationship between hours of labor supply and unemployment rates largely reflects the identity linking different types of hours. Not surprisingly, inclusion of the unemployment rate improves the goodness-of-fit of the grouped equations. Equations for 1975-87 that include the unemployment rate easily pass the overidentification test at conventional levels. Goodness-of-fit is also improved in the earlier period. In both periods, inclusion of the unemployment rate causes the two trend terms to become insignificant.

The unemployment rate may be a poor choice of exogenous variation for the control of sample selection bias. Results using alternative controls are reported in Table 6b, which shows estimates from versions of equation (11) that include the growth rate of M1 and defense spending as additional regressors. Columns (3) and (4) in Table 6b show estimates from a specification with linear trend. The additional regressors do not lead to any substantial change in either estimates of θ_1 or θ_2. For example, the estimate of θ_1 in the model with a linear trend estimated using the sample of men aged 25-50 in 1975-87 is 0.833 . Column (1) of Table 6b shows that this estimate increases trivially to 0.866 when the growth rate of M1 is included as a regressor. Inclusion of the percent change in M1, however, does lead to a substantial improvement in fit. On the other hand including the growth rate of defense spending does not affect parameter estimates very much or lead to an improvement in fit.

Results from a model that includes the growth rate of M1 along with a quadratic trend are reported in columns (5) and (6) of Table 6b. In this specification, elasticities are larger, although the contrast with specifications that exclude the growth rate of M1 is not statistically significant. The models in columns (5) and (6) fit the data for 1975-87 quite well and lead to some of the largest elasticity estimates in the paper. In fact, these are on the order of the representative estimate of 1.4 preferred by Lucas and Rapping (1970) in their work with aggregate data. But it should be noted that the estimate of θ_1 for the earlier period, which corresponds more closely to the period studied by Lucas and Rapping, is zero.

VI. Summary and Conclusions

Does labor supply explain fluctuations in average hours worked ? I began this project with the hope that labor supply models would either fit the data well for the whole sample period, or that the labor supply interpretation of fluctuations in annual hours would be decisively rejected. Perhaps not surprisingly, the results support neither of these conclusions unambiguously.

On the positive side, the estimates in Table 1a, based on cohort and year groups, suggest that intertemporal substitution elasticities are positive for 1975-87, and that labor supply models pass goodness-of-fit tests when year dummies are included. Table 2a suggests that an important component of aggregate movements in hours worked from 1975-87 is the labor supply response to changing wages. The elasticities reported in Table 2a are larger than many previously reported. For example, MaCurdy (1981) and Altonji both report estimates on the order of 0.3 using a sample of men from the PSID. On the other hand, estimates constructed using annual averages from the PSID are closer to those found here, ranging from 0.6 to 0.8 (Angrist 1991).

The results for 1975-87 are robust to the specification of trend, and models with a quadratic trend come close to passing the overidentification test at conventional levels of significance. The quadratic trend models pass these tests easily when allowance is made for uncorrelated, random period effects or uncertainty.[24] None of the estimates were found to be sensitive to whether the sample analyzed was a true cohort or repeated observations on the same age group. This is encouraging because macroeconomists commonly apply representative agent models to samples of the latter type.

In contrast to the generally favorable picture for 1975-87, the estimates in Table 2b suggest that labor supply behavior is less important in 1963-75, or that the models are misspecified for this period. TSLS estimates of the coefficient on hourly wages are negative in models that include a quadratic trend. Although the quadratic specifications may be rejected on goodness-of-fit grounds, other labor supply elasticities estimated for this period are also substantially less than those estimated for 1975-87.

Detailed analysis in the rest of the paper supports these basic findings. Many of the results are summarized in Table 7, which shows partial R^2's from unweighted time series regressions of average log wages on average log hours and earnings. The sample contains all men aged 25-50 each year. Movements in average wages account for a surprisingly large fraction -- roughly 2/3 -- of the variance in average hours worked between

1975 and 1987. The fraction of variance accounted for between 1963 and 1975 is considerably lower, and the importance of wages and earnings for hours fluctuations from 1963-74 is disturbingly sensitive to the details of model specification. Accounting for differences between estimates for the two sample periods appears to be a natural candidate for future research.

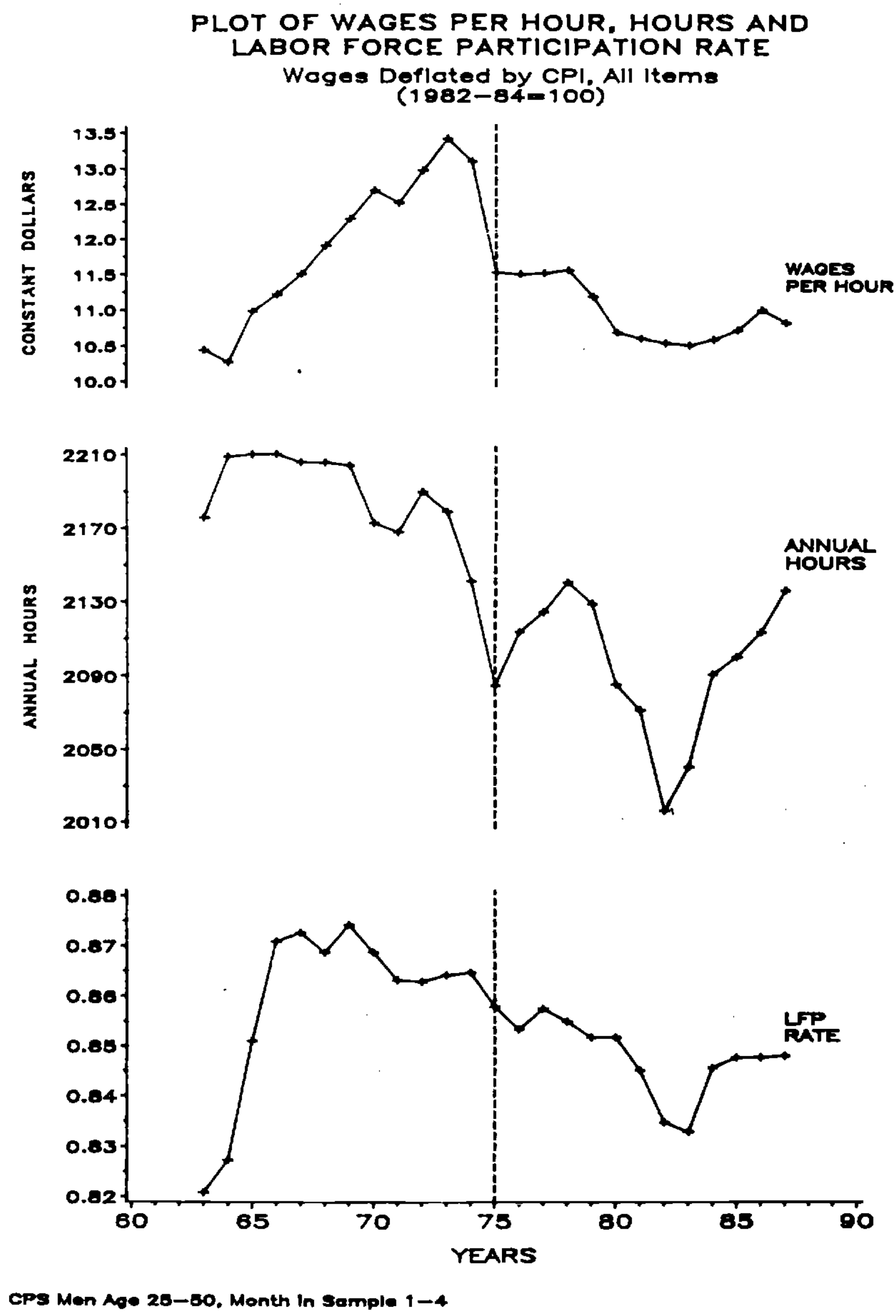
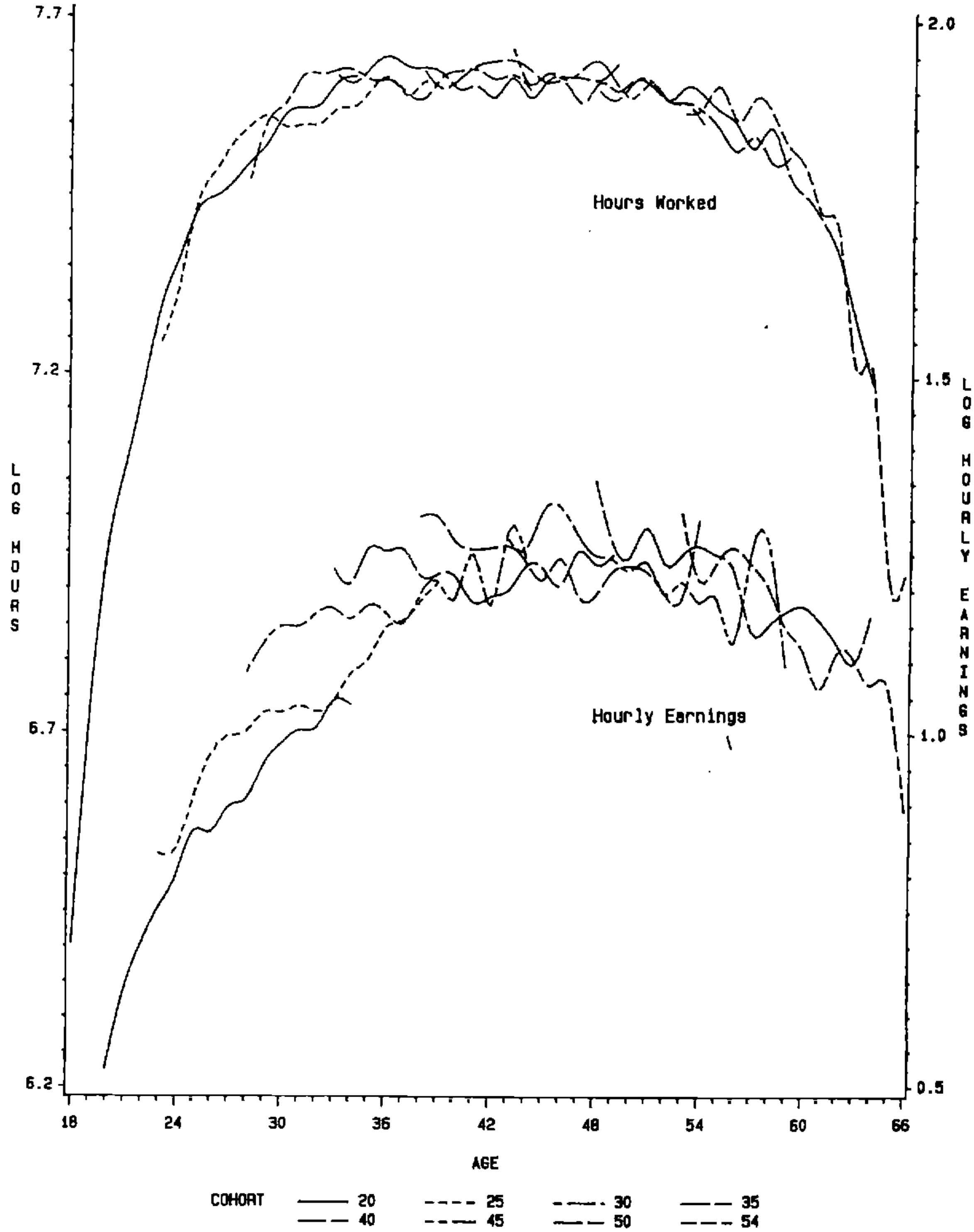

PLOT OF WAGES PER HOUR, HOURS AND
LABOR FORCE PARTICIPATION RATE
Wages Deflated by CPI, All Items
(1982–84=100)
CONSTANT DOLLARS
13.5
13.0
12.5
12.0
11.5
11.0
10.5
10.0
WAGES
PER HOUR
ANNUAL HOURS
2210
2170
2130
2090
2050
2010
ANNUAL
HOURS
0.88
0.87
0.86
0.85
0.84
0.83
0.82
LFP
RATE
60
65
70
75
80
85
90
YEARS
CPS Men Age 25–50, Month in Sample 1–4

Figure 1

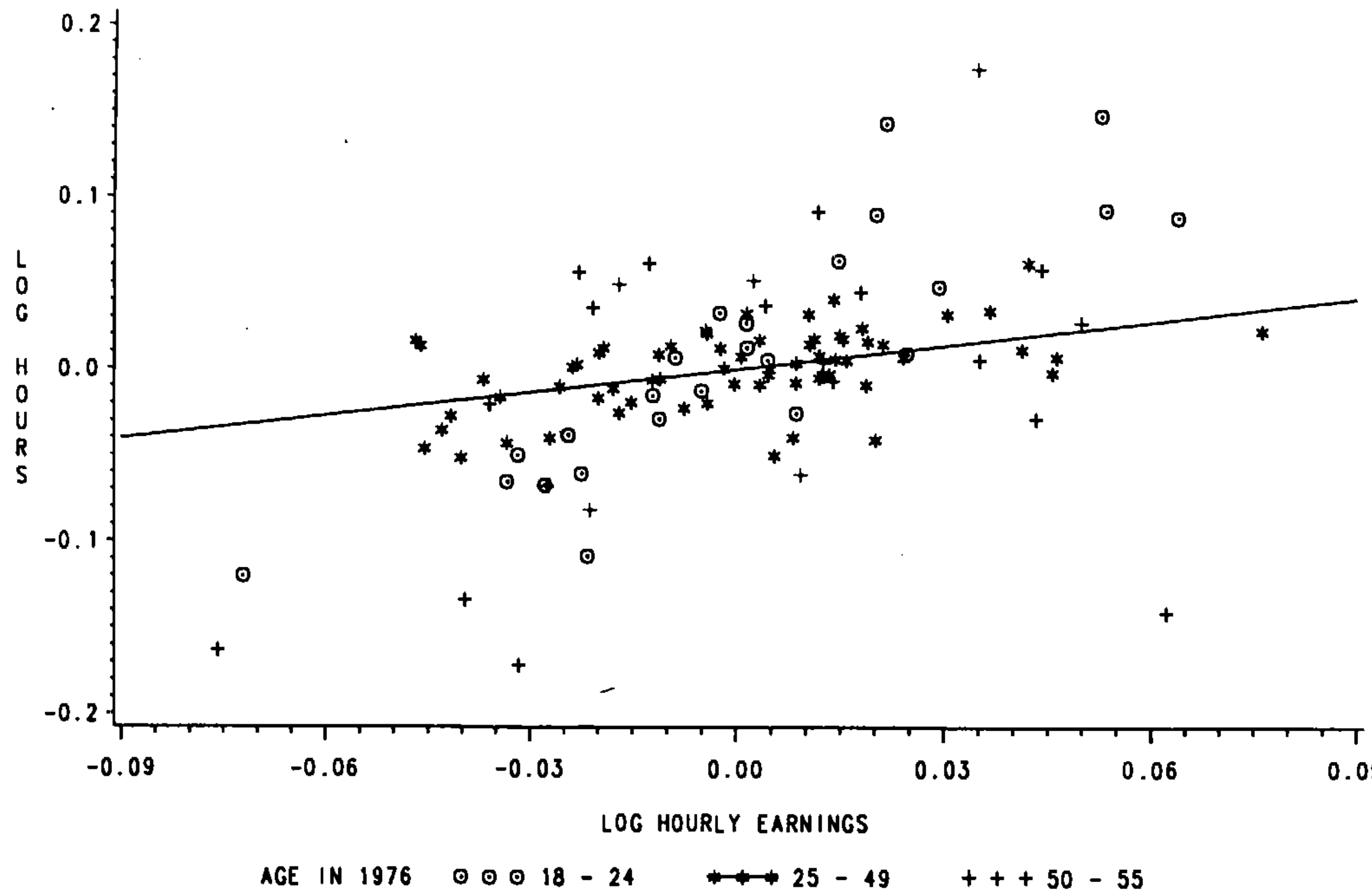
WAGES AND HOURS OF EMPLOYED MEN AGED 18-55 IN 1976



CPS AVERAGES FOR FIVE YEAR AGE GROUPS, MONTH IN SAMPLE 1-4
AVERAGE HOURLY EARNINGS IN 1967 DOLLARS

Figure 2

LABOR SUPPLY OF EMPLOYED MEN AGED 18–55 IN 76



CPS AVERAGES FOR FIVE YEAR AGE GROUPS
RESIDUAL FROM REGRESSION ON 5 YEAR COHORT SPECIFIC TREND

Table 1a - Labor Supply Equations 1975-87

Method	Year Dummies	θ_1	θ_2	χ^2(dof)
OLS	no	0.036 (0.002)	-	-
	yes	0.035 (0.002)	-	-
TSLS	no	0.460 (0.058)	-	160.7 (54)
	yes	0.289 (0.091)	-	53.3 (44)
OLS	no	-	0.435 (0.002)	-
	yes	-	0.433 (0.002)	-
TSLS	no	-	0.832 (0.087)	114.3 (54)
	yes	-	0.631 (0.130)	41.9 (44)

NOTES -- All models include a cohort specific linear trend for 5-year age groups.
Sample - men aged 25-50 in 1976 w/non-imputed earnings, month in sample 1-4, (n - 112,000)
Dependent variable - log (annual hours worked).

TSLS instruments are a full set of cohort and year main effects and interactions.

Table 1b - Labor Supply Equations 1963-74

Method	Year Dummies	θ_1	θ_2	χ^2(dof)
OLS	no	-0.163 (0.002)	-	-
	yes	-0.164 (0.002)	-	-
TSLS	no	0.018 (0.050)	-	138.6 (49)
	yes	-0.316 (0.076)	-	57.6 (39)
OLS	no	-	0.202 (0.003)	-
	yes	-	0.202 (0.003)	-
TSLS	no	-	0.357 (0.075)	108.4 (49)
	yes	-	0.164 (0.110)	78.0 (39)

NOTES -- See notes to Table 1a.

Sample - all men aged 25-50 in 1964, month in sample 1-4, (n - 85,000)

Table 2a - Labor Supply Elasticities 1975-87

	Trend (1) None	(2) Linear	(3) Quadratic
A. Sample 1 -- Men Aged 25-50 in 1976 (n = 125,000)			
θ_1	0.605 (0.089)	0.581 (0.088)	0.941 (0.139)
χ^2(dof)	96.4 (11)	94.6 (10)	32.7 (9)
θ_2	1.079 (0.144)	1.041 (2.141)	1.268 (0.188)
χ^2(dof)	61.2 (11)	60.8 (10)	24.4 (9)
B. Sample 2 -- Men Aged 25-50 Each Year (n = 149,000)			
θ_1	0.327 (0.028)	0.833 (0.074)	1.149 (0.139)
χ^2(dof)	254.4 (11)	63.1 (10)	31.4 (9)
θ_2	0.477 (0.032)	1.020 (0.088)	1.433 (0.176)
χ_2(dof)	237.4 (11)	53.2 (10)	25.0 (9)

NOTES -- Samples include men with positive earnings in 1976-88 CPS's, month-in-sample 1-4.

Estimation method is Two-Stage Least Squares. Instruments are a full set of year dummies.

θ_1 is from a regression of log annual hours on log hourly earnings.

θ_2 is from a regression of log annual hours on log annual earnings.

Table 2b - Labor Supply Elasticities 1963-74

	Trend (1) None	(2) Linear	(3) Quadratic
A. Sample 1 -- Men Aged 25-50 in 1964 (n = 85,000)			
θ_1	-0.005 (0.013)	0.245 (0.080)	-0.042 (0.101)
χ^2(dof)	65.6 (11)	35.7 (10)	38.7 (9)
θ_2	0.007 (0.014)	0.427 (0.049)	0.373 (0.165)
χ^2(dof)	65.6 (11)	29.5 (10)	29.7 (9)
B. Sample 2 -- Men Aged 25-50 Each Year (n = 91,000)			
θ_1	-0.065 (0.016)	0.316 (0.082)	-0.034 (0.144)
χ^2(dof)	84.2 (11)	28.6 (10)	38.3 (9)
θ_2	-0.042 (0.016)	0.463 (0.098)	0.789 (0.364)
χ^2(dof)	84.9 (11)	24.8 (10)	20.6 (9)

NOTES -- See notes to Table 2.

Table 3 - Labor Supply Elasticities: Models with Interest Rates

	Trend (1) one	(2) Linear	(3) Quadratic
	A. 1976-88 CPS, Men Aged 25-50 in 1976 (n = 125,000)		
θ_1	.530 (.093)	.603 (.110)	.814 (.134)
Interest Rate	-.130 (.071)	.049 (.139)	-.544 (.193)
χ^2(dof)	104.6 (10)	91.2	31.6
θ_2	1.12 (.171)	1.29 (.216)	1.13 (.182)
Interest Rate	.032 (.053)	.242 (.094)	-.184 (.122)
χ^2(dof)	59.6 (10)	48.2 (9)	23.5 (8)
	B. 1964-75 CPS, Men Aged 25-50 in 1964 (n = 85,000)		
θ_1	.029 (.016)	.075 (.107)	-.092 (.112)
Interest Rate	.610 (.141)	.522 (.248)	.242 (.246)
χ^2(dof)	44.6 (9)	42.0 (8)	38.9 (7)
θ_2	.040 (.016)	.519 (.184)	.445 (.208)
Interest Rate	.632 (.132)	-.168 (.248)	-.201 (.251)
χ^2(dof)	44.6 (9)	27.9 (8)	28.5 (7)

NOTES: Samples include men with positive earnings in 1976-88 CPS's, month-in-sample 1-4. Interest rates are annualized expected real rates on 3-month treasury bills from Barro and Sala-I-Martin (1990).

Estimation method of Two-Stage Least Squares. Instruments are a full set of year dummies.

θ_1 is from a regression of log annual hours on log hourly earnings.
θ_2 is from a regression of log annual hours on log annual earnings.

Table 4a - Labor Supply Elasticities 1975-87: By Education

Education		Trend (1) None	(2) Linear	(3) Quadratic
A. Sample 1 -- Men Aged 25-50 in 1976 n = (26,000; 44,000; 54,000)				
Less than high school	θ_1	.577 (.084)	.836 (.218)	1.21 (.335)
	χ^2(dof)	41.0 (11)	28.9 (10)	14.9 (9)
High school	θ_1	.630 (.088)	.702 (.161)	.789 (.180)
	χ^2(dof)	46.9 (11)	41.8 (10)	34.0 (9)
Some college	θ_1	.216 (.058)	.150 (.080)	.557 (.145)
	χ^2(dof)	65.9 (11)	69.1 (10)	19.0 (9)
B. Sample 2 -- Men Aged 25-50 Each Year n = (25,000; 55,000; 68,000)				
Less than high school	θ_1	.431 (.042)	1.10 (.218)	1.22 (.271)
	χ^2(dof)	64.5 (11)	22.0 (10)	18.2 (9)
High school	θ_1	.306 (.029)	1.20 (.183)	1.19 (.219)
	χ^2(dof)	158.0 (11)	22.3 (10)	22.5
Some College	θ_1	.221 (.044)	.392 (.056)	.634 (.137)
	χ^2(dof)	99.0 (11)	46.2 (10)	27.7 (9)

NOTES: Samples include men with positive earnings in 1976-88 CPS's, month-in-sample 1-4.

Estimation method is Two-Stage Least Squares. Instruments are a full set of year dummies.

θ_1 is from a regression of log annual hours on log hourly earnings.

Table 4b - Labor Supply Elasticities 1963-74: By Education

Education		Trend (1) None	(2) Linear	(3) Quadratic
A. Sample 1 -- Men Aged 25-50 in 1964 n = (31,000; 30,000; 24,000)				
Less than high school	θ_1	-.060 (.027)	.028 (.149)	-.229 (.171)
	χ^2(dof)	25.9 (10)	23.6 (9)	19.9 (8)
High school	θ_1	-.101 (.022)	.386 (.177)	-.137 (.204)
	χ^2(dof)	45.3 (10)	13.2 (9)	19.1 (8)
Some college	θ_1	.081 (.024)	.150 (.061)	-.059 (.080)
	χ^2(dof)	29.2 (10)	24.4 (9)	20.7 (8)
B. Sample 2 -- Men Aged 25-50 Each Year n = (28,000; 34,000; 29,000)				
Less than high school	θ_1	-.128 (.033)	.160 (.171)	-.548 (.298)
	χ^2(dof)	24.8 (10)	15.8 (9)	8.07 (8)
High school	θ_1	-.185 (.027)	.615 (.254)	-.005 (.208)
	χ^2(dof)	72.1 (10)	12.0 (9)	14.9 (8)
Some college	θ_1	-.076 (.041)	.063 (.059)	-.157 (.118)
	χ^2(dof)	45.9 (10)	29.2 (9)	29.3 (8)

NOTES: Samples include men with positive earnings in 1964-75 CPS's, month-in sample 1-4.

See notes to Table 4a.

Table 5a - Alternate Wages and Hours Measures

Method	Parameter	Annual Hours Construction (1)	(2)	(3)	(4)	(5)
		(n = 125,000)			(n = 112,000)	
OLS	θ_1	0.037 (0.002)	0.011 (0.002)	0.011 (0.002)	-0.086 (0.002)	-0.112 (0.002)
TSLS		0.941 (0.139)	0.898 (0.137)	0.660 (0.112)	0.699 (0.144)	0.667 (0.143)
$\chi^2(9)$		32.7	33.8	27.4	23.0	22.9
OLS	θ_2	0.435 (0.002)	0.399 (0.002)	0.271 (0.002)	0.292 (0.002)	0.280 (0.003)
TSLS		1.268 (0.190)	1.232 (0.189)	0.866 (0.143)	0.980 (0.192)	0.949 (0.194)
$\chi^2(9)$		24.4	24.8	21.1	17.4	17.3

Sample - Men Age 25-50 in 1976, month in sample 1-4.
All models contain a quadratic trend.

TSLS instruments are a full set of year dummies.

Annual Hours Construction

(1) (weeks worked last year) * (usual hours/week last year);
(2) (grouped weeks worked last year) * (usual hours/week last year);

Sample with positive hours last week only:

(3) (weeks worked last year) * (usual hours/week last year);
(4) (weeks worked last year) * (hours worked last week);
(5) (grouped weeks worked last year) * (hours worked last week).

Table 5b - Labor Supply Elasticities: Based on Weeks Worked

	Trend (1) None	(2) Linear	(3) Quadratic
	A. Sample 1 -- 1976-88 CPS, Men Aged 25-50 in 1976 (n = 125,000)		
θ_1	.292 (.044)	.283 (.045)	.477 (.061)
χ^2(dof)	116.0 (11)	117.0 (10)	39.5 (9)
θ_2	.465 (.055)	.466 (.056)	.578 (.071)
χ^2(dof)	94.0 (11)	94.0 (10)	34.2 (9)
	B. Sample 2 -- 1976-88 CPS, Men Aged 25-50 Each Year (n = 149,000)		
θ_1	.179 (.018)	.367 (.033)	.543 (.056)
χ^2(dof)	196.0 (11)	97.0 (10)	50.4 (9)
θ_2	.234 (.019)	.444 (.036)	.645 (.064)
χ_2(dof)	194.0 (11)	89.0 (10)	43.4 (9)
	A. Sample 1 -- 1964-75 CPS, Men Aged 25-50 in 1964 (n = 92,000)		
θ_1	.010 (.010)	.217 (.037)	.104 (.061)
χ^2(dof)	106.0 (10)	53.4 (9)	57.7 (8)
θ_2	.020 (.010)	.279 (.041)	.297 (.078)
χ^2(dof)	110.0 (10)	49.5 (9)	48.8 (8)
	B. Sample 2 -- 1964-75 CPS, Men Aged 25-50 Each Year (n = 99,000)		
θ_1	-.034 (.013)	.163 (.035)	.151 (.083)
χ^2(dof)	115.0 (10)	69.6 (9)	70.4 (8)
θ_2	-.016 (.013)	.237 (.038)	.377 (.148)
χ^7(dof)	118.0 (10)	66.4 (9)	42.0 (8)

Notes to Table 5b:

Samples include men with earnings, month-in-sample 1-4.

Estimation method is Two-Stage Least Squares. Instruments are a full set of year dummies.

θ_1 is from a regression of log weeks on log weekly earnings.

θ_2 is from a regression of log weeks on log annual earnings.

Weeks are tabulated from grouped weeks' midpoints

Table 6a - Labor Supply with Unemployment

Coefficient	(1)	(2)	(3)	(4)	(5)	(6)
a. 1975-87 Earnings						
Linear Trend	0.008 (0.001)	0.005 (0.004)	0.005 (0.001)	0.002 (0.001)	0.002 (0.004)	0.004 (0.003)
Squared Trend	-	-	-	-	0.0004 (0.0002)	-0.0001 (0.0001)
Unemployment Rate	-	-	-1.66 (0.16)	-1.14 (0.16)	-1.68 (0.18)	-1.02 (0.22)
ϕ_1	0.833 (0.074)	-	0.350 (0.071)	-	0.332 (0.120)	-
ϕ_2	-	1.020 (0.086)	-	0.399 (0.074)	-	0.475 (0.137)
χ^2(dof)	63.1(10)	53.2(10)	13.1(9)	12.8(9)	13.3(8)	12.4(8)
b. 1963-74 Earnings						
Linear Trend	-0.010 (0.002)	-0.009 (0.001)	-0.003 (0.002)	-0.006 (0.002)	-0.007 (0.007)	-0.012 (0.007)
Squared Trend	-	-	-	-	-0.0004 (0.0003)	0.0003 (0.0003)
Unemployment Rate	-	-	-1.02 (0.23)	-0.64 (0.25)	-0.93 (0.22)	-0.62 (0.25)
ϕ_1	0.316 (0.082)	-	0.085 (0.087)	-	-0.080 (0.142)	-
ϕ_2	-	0.462 (0.098)	-	0.227 (0.102)	-	0.408 (0.244)
χ^2(dof)	28.6(9)	24.8(9)	20.7(8)	19.1(8)	22.2(7)	17.6(7)

NOTES: Sample - men aged 25-50 all years;
Month-in-Sample 1-4;
Estimation method is Two-Stage Least Squares. TSLS instruments are a full set of year dummies.

Table 6b - Labor Supply with Demand-Side Variables

Coefficient	(1)	(2)	(3)	(4)	(5)	(6)
a. 1975-87 Earnings						
Linear Trend	.009 (.001)	.005 (.0004)	.006 (.001)	.005 (.0004)	.032 (.007)	.015 (.002)
Quadratic Trend					-.001 (.0004)	-.0006 (.0001)
% Change in M1	-.134 (.062)	-.080 (.034)	-	-	-.254 (.092)	-.118 (.038)
% Change in Defense	-	-	-.579 (.110)	-.023 (.095)	-	-
ϕ_1	.866 (.077)	-	.413 (.097)	-	1.34 (.171)	-
ϕ	-	1.05 (.092)	-	.984 (.172)	-	1.55 (.202)
χ^2(dof)	55.5 (9)	47.2 (9)	85.9 (9)	53.9 (9)	17.1 (8)	14.5 (8)
b. 1963-74 Earnings						
Linear Trend	-.010 (.002)	-.010 (.001)	-.009 (.002)	-.009 (.001)	.007 (.009)	-.021 (.007)
Quadratic Trend	-	-	-	-	-.0007 (.0003)	.0006 (.0004)
% Change in M1	.147 (.097)	.094 (.076)	-	-	.063 (.089)	.138 (.088)
% Change in Defense	-	-	.032 (.024)	.017 (.019)	-	-
ϕ_1	.307 (.082)	-	.298 (.082)	-	.011 (.160)	-
ϕ	-	.444 (.096)	-	.442 (.097)	-	.931 (.446)
χ^2(dof)	26.7 (8)	23.5 (8)	27.6 (8)	24.2 (8)	36.3 (7)	17.1 (7)

NOTES: Sample - men aged 25-50 all years;
Month-in-Sample 1-4;
Estimation method is Two-Stage Least Squares. TSLS instruments are a full set of year dummies.

Table 7 - Partial R^2's for Hours Worked

	Controlling for: Nothing	Linear Trend	Quad Trend
a. 1975-87			
Wages	.36	.67	.71
Earnings	.66	.91	.94
b. 1963-74			
Wages	.20	.41	.001
Earnings	.06	.72	.32
c. 1963-87			
Wages	.14	.11	.46
Earnings	.32	.28	.77

NOTES - Partial R^2's are from unweighted regressions of average log hours on average log wages or earnings. Sample includes men aged 25-50 each year.

Table A1 - Labor Supply Elasticities 1975-87: Uncertainty Model

	Trend (1) None	(2) Linear	(3) Quadratic
	A. Sample 1 -- Men Aged 25-50 in 1976 (n = 125,000)		
θ_1	.633 (.270)	.604 (.283)	.967 (.249)
χ^2(dof)	99.5 (11)	99.5 (10)	29.7 (9)
θ_2	1.120 (.353)	1.100 (.373)	1.250 (.284)
χ^2(dof)	61.5 (11)	62.2 (10)	22.1
	B. Sample 2 -- Men Aged 25-50 Each Year (n = 149,000)		
θ_1	.303 (.129)	.805 (.189)	1.140 (.248)
χ^2(dof)	239.2 (11)	62.8 (10)	29.6 (9)
θ_2	.445 (.144)	1.004 (.210)	1.400 (.277)
χ^2(dof)	233.6 (11)	54.5 (10)	24.0 (9)

NOTES: Samples include men with positive earnings in 1976-88 CPS's, month-in-sample 1-4.

Estimation method is White (1982) Two-Stage Least Squares. Instruments are a full set of year dummies.

θ_1 is from a regression of log annual hours on log hourly earnings.

θ_2 is from a regression of log annual hours on log annual earnings.

Table A2 - Labor Supply Elasticities 1963-74: Uncertainty Model

	Trend (1) None	(2) Linear	(3) Quadratic
	A. Sample 1 -- Men Aged 25-50 in 1964 (n = 85,000)		
θ_1	-.010 (.035)	.239 (.150)	-.039 (.224)
χ^2(dof)	66.2 (10)	35.3 (9)	39.9 (8)
θ_2	.012 (.039)	.323 (.123)	.327 (.231)
χ^2(dof)	66.2 (10)	27.3 (9)	28.0 (8)
	B. Sample 2 -- Men Aged 25-50 Each Year (n = 91,000)		
θ_1	-.065 (.046)	.304 (.145)	-.045 (.305)
χ^2(dof)	81.8 (10)	27.8 (9)	37.6
θ_2	-.028 (.053)	.397 (.113)	.700 (.335)
χ^2(dof)	86.2 (10)	18.8 (9)	13.8 (8)

Notes: See notes to table A1.

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Notes

1. Studies that test assumptions underlying intertemporal substitution models include Abowd and Card (1987, 1989), Ham (1986), and Ashenfelter (1984).

2. The assumption that future wages and prices are known is not restrictive. When future wages and prices are uncertain and consumers maximize expected utility, the log of the marginal utility of wealth is (approximately) a random walk with drift (See, e.g., Altonji 1986), and may still be eliminated by transformations such as differencing. The implications of uncertainty for grouping strategies are explored below.

3. This includes the work of Ashenfelter and Ham (1979), Heckman and MaCurdy (1980), MaCurdy (1981, 1985), Altonji (1986) and Abowd and Card (1987, 1989).

4. Pakes (1983) also makes this point. An early grouping strategy for estimating life-cycle labor supply models is Becker (1975), who groups a single cross-section by age. Other references to the instrumental variables interpretation of grouping are given by Angrist (1991).

5. Evidence on the extent of measurement error in labor market data has been presented by Duncan and Hill (1985) for the PSID and Bound and Krueger (1991) for the CPS. Solutions to the measurement error problem in panel data are cataloged by Griliches and Hausman (1986).

6. A general reference on overidentification testing is Newey (1985) or Hausman (1984). In the case of dummy variable instruments for a bivariate regression, the overidentification test may be interpreted as a test for equality of all the linearly independent Wald (1940) estimates that can be computed from T groups. See Angrist (1991) for details.

7. For models including trend terms, Durbin-Watson statistics show no evidence of serially correlated residuals in regressions using annual averages.

8. The White (1982) weighting matrix is $\Omega = \Sigma_i z_i' z_i \epsilon_i^2/N$, where z_i is the ith row of Z. The optimally weighted TSLS estimator is $(X'Z\Omega^{-1}Z'X)^{-1}X'Z\Omega^{-1}Z'y$. In the case where Z consists of mutually exclusive dummy variables, Ω is easily seen to be a diagonal matrix with elements $(n_t/N)\sigma_t^2$. Substitution into the TSLS formula establishes the equivalence to weighted least squares.

9. The exception is when the period mean of Z_{it} is orthogonal to average wages. As an empirical matter, the problem of sample selection may be somewhat less important than the theoretical discussion would imply. Many labor supply studies (including this one) are carried out using a sample of prime age males. Few members of this sample report zero hours worked over an entire year. More troubling, perhaps, is the practice of requiring continuous employment in all years in studies using panel data (e.g., Barsky and Solon 1988). Thus, someone who is out of the labor force for a single year, possibly because of sickness or schooling, is dropped from the sample for all years.

10. Pencavel (1986) offers a critique of the inclusion of aggregate unemployment rates in labor supply equations as a test of equilibrium. Heckman and MaCurdy (1988) discuss the complicating role of selection bias in the use of microeconomic labor supply elasticities for macroeconomic inferences. Card (1989) uses sample selection to justify the inclusion of unemployment rates in labor supply equations.

11. Although certain variables are missing from the Mare-Winship Extracts (most importantly, allocation flags), they are used for the earlier sample because they are a source of CPS micro data for 1964-67. CPS Micro data before 1964 are not available and CPS data for 1964-67 are not available from the Census Bureau (Allen 1973). Because allocation flags for person's wage and salary income are not included on Census Bureau tapes before 1972, little is lost by using the more convenient Mare-Winship Extracts to form consistent time series for 1963-75.

12. This R^2 is from a regression that includes period effects.

13. What is required is an estimate of the year to year correlation in individual hours and earnings. This information is available for a few CPS's from extracts containing matched rotation groups.

14. The 1988 Economic Report of the President (page 290) shows a one percentage point decline in labor force participation (as defined by the Census Bureau) for men aged 20 and over in the same period. As noted above, Allen (1973) documents problems with the early CPS tapes.

15. Degrees of freedom are calculated as follows. There are 65 instruments: 13 years of earnings * 5 cohorts = 65; there are 11 parameters: θ_1, 4 cohort dummies plus intercept, and 5 linear trend terms.

16. The sample used in Table 2 and all subsequent tables differs slightly from that in Table 1a in that it includes men for whom the Census Bureau imputed earnings. Results were insensitive to this variation.

17. The ranking of overidentification test statistics here is somewhat anomalous but theoretically possible. To see this, let Z be the matrix of instruments, P_z be the projection matrix for Z, $\hat{u}$ be the TSLS residuals, and σ^2 be the residual variance. Then the test statistic is $\hat{m} = \hat{u}'P_z\hat{u}/\sigma^2$ (Hausman 1984). The numerator of $\hat{m}$ is necessarily smaller in the quadratic than in the linear trend specification, but the residual variance estimate turns out to be substantially smaller as well.

18. The approximation may be rationalized by the assumption that people behave each period as if past interest rates were constant, but contemporaneous rates may differ.

19. See, e.g., Altonji (1986). Evidence that grouping eliminates measurement error in estimates based on variable (1) is presented in Angrist (1991).

20. Card (1989) provides a recent detailed analysis of the relationship between wages, weeks worked per year, and hours worked per week.

21. See, e.g., Ashenfelter and Ham (1979) and Ashenfelter (1980).

22. The unemployment rate is the civilian unemployment rate for all workers on p. 293 of the 1988 Economic report of the President. The M1 growth series, used below, is on p. 325. The growth of real expenditure on national defense is derived from calender year levels on p. 403 of the 1989 Report for 1967-87, and from p. 345 of the 1986 Report for 1963-66.

23. A formal argument is as follows. Assuming that $E(u|\nu)$ is linear and ν_{it} is uniformly distributed on [0,1], we have

$$E(u_{1it}|\ Z_{it}>\nu_{it}) = \xi_0 + \xi_1 E(\nu_{it}|Z_{it}\psi>\nu_{it}) = \xi_0 + \xi_1(Z_{it}\psi)/2.$$

If the hours residual is positively correlated with participation, then it is negatively correlated with ν_{it}, so that $\xi_1 < 0$. The bias from omitting $E(u_{1it}|\ Z_{it}>\nu_{it})$ is $\xi_1 COV(w_{it}, Z_{it})$. The covariance term is positive if wages are also positively correlated with participation, so that sample selection bias is negative.

24. Testing standards that account for sample size would accept models with a linear trend as well. For example, Schwarz (1978) critical values for these models are qln(n), where n is sample size and q is degrees of freedom. Schwarz critical values for the models in Table 2 are all greater than 100.