Journal of Econometrics 27 (1985) 273–298. North-Holland

DYNAMIC MODELS OF THE LABOR FORCE BEHAVIOR OF MARRIED WOMEN WHICH CAN BE ESTIMATED USING LIMITED AMOUNTS OF PAST INFORMATION *

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Received June 1983, final version received July 1984

Pure cross-sectional models cannot capture the observed continuity over time in the work behavior of wives. Proposed alternative models generally require panel data not available in most countries. We present simulation results for models incorporating more limited information about previous behavior which could be collected on a recall basis in cross-sectional surveys, and establish that these models yield good forecasts of employment, hours of work and earnings of wives over ten years. One of our models may be viewed as a difference transformation of a standard work behavior model incorporating an inequality decision rule and modified to include fixed effects.

1. Introduction

There is a growing consensus in the literature that standard cross-sectional models of labor force behavior cannot adequately capture the observed continuity in the employment behavior of married women.[1] It is often argued that this is because these models ignore unobservable fixed or persistent individual effects which are responsible for much of the observed continuity. Panel data are required to estimate most of the models which have been proposed as alternatives to standard cross-sectional models. This has been a discouraging development for those of us living outside the United States, since the United States is one of the few countries in the world where good quality panel data

* This research was supported in part by Grant Number 61A-8801, 'The analysis of retirement security issues using simulation models', from the U.S. Department of Health and Human Services to the Survey Research Center of the University of Michigan, and in part by Social Sciences and Humanities Research Council of Canada Research Grant 410-77-0339-R1. We are very grateful for the encouragement and written comments we received on this work from James Heckman. Earlier versions of this paper were presented at the meetings of the Canadian Economic Association in Ottawa, June 1982, and in Vancouver, June 1983, as well as at the Departments of Economics at Queens University and the University of British Columbia. We benefited from comments from the participants in these seminars, as well as from Martin Dooley, John Ham, Guy Orcutt and Paul Swain.

[1] Heckman (1978, 1981c) shows that a model which does not consider heterogeneity cannot properly capture the employment histories (the sequences of years of work and non-work) for married women.

0304-4076/85/$3.30

are available to the general research community. Moreover estimation of some of the alternative models which have been proposed is a forbidding task even when good quality panel data are available.[2]

Heckman (1978, p. 36) has suggested: 'It is plausible to conjecture that 'lagged participation' might serve as a good 'proxy' for the effect of heterogeneity.' In Heckman's terminology 'lagged participation' refers to whether or not a person worked for pay or profit in the previous year. Information on work status for the year prior to the year for which earnings data are reported could easily be collected as part of cross-sectional surveys like the Census of Canada.[3] Thus if Heckman's conjecture were correct, good quality empirical research on the work behavior of individuals could soon be carried out for countries like Canada where panel data are not likely to be available to the general research community for the foreseeable future. Heckman himself

[2] There are two formats for introducing person-specific, time invariant effects into a model. In random effects models the person-specific effects are assumed to be distributed over individuals in accordance with some probability distribution which is specified a priori. In this case, it is possible to write down a likelihood function to be maximized [see, for example, Heckman (1981b, p. 184, (4.6) or (4.7))]. In this case also, consistent parameter estimates may be obtained as n goes to infinity for fixed T, where n is the number of individuals in the panel and T is the number of time periods over which data are available on these individuals [see Heckman (1981a, p. 147, and 1981b, pp. 183–184)]. However, as Heckman (1981b, p. 184) points out, maximizing such a likelihood function is computationally forbidding.

In so-called fixed effects models on the other hand, the individual-specific effects are simply given parameters. These fixed effects can potentially be estimated along with the other parameters of interest in a model. Within the multivariate probit framework often adopted in studies of the labor force behavior of married women, fixed effects models are generally computationally more tractable than random effects models. There are problems, however. For the estimation methods which have been proposed in the literature for fixed effects multivariate probit models, consistency is typically proved for T approaching infinity and it is necessary to limit the sample used in estimation to wives who have changed their employment status at least once during the period over which the panel data were collected [see Heckman (1981a, pp. 133–134, and 1981b, pp. 186–187)]. For all existing panel data sets n is large but T is small. Moreover, we may never have good quality panel data over long periods of time since attrition biases become more and more severe as the length of a panel increases. Dropping out data for wives who do not change their employment state over the duration of a panel study may, of course, result in selection biases.

Further estimation problems arise if there are persistent (autocorrelated) as well as fixed person-specific unobservables.

[3] In the 1971 Census of Canada, for instance, respondents were asked: 'When did you last work at all, even for a few days?' The possible answers, from which the respondent was supposed to choose one, were 'in 1971', 'in 1970', 'before 1970', and 'never worked' (see question 32 in 1971 Census Questionnaire). This question could easily have been reworded to read: 'Indicate *all* of the following time periods in which you worked at all, even for a few days: in 1971, in 1970, in 1969, before 1969, never worked.'

If individuals had answered this question we would know the work status of each individual in the 'lagged' year of 1969, with 1970 being the year for which 'current' data were reported on weeks of work and earnings.

Likewise in the 1970 U.S. Census respondents were asked whether they *last* worked in 1970, 1969, 1968, 1964–1967, 1960–1963, 1959 or earlier, or never worked. The question could easily have been reworded to ask respondents to indicate *all* of the designated time periods in which they worked rather than just the last one. The relevant 'lagged' year for the 1970 U.S. Census is 1968, with 1969 being the year for which 'current' data were reported on weeks of work and earnings.

seemed to dash this hope, however, in a 1981 article. In this article, based on in-sample and out-of-sample simulation comparisons, Heckman (1981c, p. 118) concludes ' 'Proxy methods' for solving the problems raised by heterogeneity such as ad hoc introduction of lagged work experience variables lead to dynamic models that yield exceedingly poor forecast equations for labor force turnover. Models that neglect recent market experience and heterogeneity actually perform better in forecasting turnover on fresh data, but these forecasts are still poor, and considerably overestimate the amount of turnover in the labor market.'

The purpose of this paper is first of all to re-examine the extent of the inadequacy of standard cross-sectional models of labor force behavior. Cross-sectional models do contain a number of variables for attributes such as education, age and child status which change in a largely predictable manner, or not at all, from one year to the next. Variables like these surely must capture some of the observed continuity in the employment and earnings behavior of individuals. Nor do convincing arguments concerning the existence of heterogeneity allow us to judge the *extent* of the inadequacy of standard cross-sectional models. The only empirical evidence we are aware of on this topic is contained in Heckman's (1978, 1981c) simulation studies. Given the importance of the question, these results should be replicated. Also Heckman deals with only the zero-one employment decisions which lead to runs of work and non-work (that is, the employment histories). In many policy applications, however, it is the ability of a model to capture the distribution of the income of individuals cumulated over some number of years which really matters. This is true, for instance, in simulation studies of the accumulation of pension or Social Security benefits, and in studies of many questions concerning poverty. It has been shown that the relative abilities of alternative models to capture the cumulative income distribution for some sample of individuals cannot be reliably inferred from evidence concerning the relative abilities of these models to capture the employment histories of these individuals.[4] Thus in this study we consider the abilities of our alternative models to capture the observed continuity in the hours of work and earnings of individuals as well as in their employment histories.

The second purpose of this paper is to re-examine Heckman's finding that models which include lagged work experience variables, introduced to account for unobservable fixed or persistent individual factors in a proxy sense, perform more poorly than models which take no account of these unobservables and do not include any information about lagged work experience. Heckman himself (1981c, p. 105) finds for samples of data spanning a three-year period for wives included in the Michigan Panel Study of Income Dynamics: 'A noteworthy feature of the data is that roughly 80 percent of the

[4] This point is demonstrated in Nakamura and Nakamura (forthcoming, ch. 4).

women in the sample of older women either work all the time or do not work at all... The corresponding figure for younger women is 75 percent.' If this is the case, it is hard to understand how the use of information about work behavior in the previous year, in any manner however 'ad hoc', could lead to 'poorer' forecasts about work behavior in the current year.

Both of the alternatives to the standard cross-sectional model which we consider in this paper incorporate limited amounts of information about past work behavior that could easily be collected on a recall basis as part, for instance, of a national population census. In contrast to some of the more sophisticated methods proposed in the literature, both our alternative models can include time varying explanatory variables, and it is not necessary to restrict the sample for estimation to observations for wives who have changed employment status at least once over the period spanned by our data base. Although both these alternative models are shown to reproduce the observed continuity in the employment behavior, and in the hours of work and earnings behavior of individual wives over a ten-year period with considerable success, these models may be estimated using *pooled* data. Thus we do not require data on runs, nor do we need to deal with the problems of incomplete runs, in order to predict the runs behavior for individuals.

It may be difficult to interpret the parameter values for the first of the two alternative models we consider. This first alternative is a direct application of Heckman's conjecture that a dummy variable for work status in the previous year might serve as a good proxy for fixed or persistent unobservables. The second alternative model may be viewed as a first difference transformation of an important class of models of employment behavior developed by Heckman. This difference method allows postulated fixed and persistent person-specific unobservables to be eliminated from a model incorporating an inequality decision rule. No general transformation that eliminates person-specific fixed effects from a model incorporating an inequality decision rule has been presented in the literature, although such transformations are known for linear and logit models [see, for instance, Heckman (1981b, p. 187, fn. 9)]. This difference method utilizes the special behavioral structure of Heckman's model. However, a similar transformation could be applied to other models incorporating an inequality decision rule so long as some measure can be found for the strength or intensity of the dichotomous response of interest in the previous time period.

The accepted means of validating estimated models, and hence of validating the outputs of these models, is to show acceptable theoretical derivations for these models and to establish analytically that estimates for the parameters of the models are unbiased or consistent under certain precisely specified conditions. When a lagged endogenous variable is included in an equation as a proxy for heterogeneity, however, there may be no plausible conditions under which the estimates of the parameters of the model can be shown to be unbiased or consistent. This is probably the case for the first of our two alternative models. Conditions of this sort do exist for the second alternative model, but these conditions may not be fully satisfied in reality. Perhaps we might use specification error tests to determine whether various of these conditions are satisfied. Each of the available specification error tests only allows certain conditions of a model to be tested, however, under the assumption that the model is correctly specified in all other respects. Nor do these tests provide a convenient measure of how badly various assumptions of a model are violated when the null hypothesis of no misspecification is rejected, or for assessing in what way or to what extent the outputs of the model are likely to be distorted as a result of specification problems. We choose instead, therefore, to directly examine the simulation outputs of our models, which should reflect all the bias and specification problems of these models.[5] One might view this as a bottom line approach to model validation. Arnold Zellner (1983, p. 3) writes, for instance: 'I always like to learn about new ideas and approaches but the bottom line is how well they work... .' Certainly if an estimated model fails to be able to capture key features of the joint distribution of the dependent variables of interest, this casts doubt on the wisdom of using the model for policy studies. In this paper we present both in-sample and out-of-sample simulation results for our models.

We evaluate the models considered in this study solely on the basis of relative comparisons of the distributions for various simulated outputs of these models with the corresponding actual distributions for the women in our simulation populations. We follow Heckman (1978, 1981c) in this approach, and in our use of a chi-square statistic as a basis for ranking the relative performances of our alternative models.[6]

[5] If the simulated outputs of an estimated model properly reflect the distinguishing characteristics of the joint distribution of the dependent variables of the model, this does *not* prove that the model is properly specified or that the estimates of the parameters of the model are unbiased or consistent. It would be possible, for instance, for specification errors to lead to distortions in the outputs of a model which cancel out. If the simulated outputs of a model *fail* to reflect the key features of the joint distribution of the dependent variables, however, this is a strong indication of specification and/or estimation problems. For instance, the distributions of some of the model disturbance terms may be misspecified leading to poor fits between the simulated and actual distributions of some of the dependent variables of interest. Heckman and Singer (1984, p. 272) note: 'Economic theory... rarely offers guidance on the functional form of the distribution of unobservables. The choice of a particular distribution of unobservables is usually justified on the grounds of familiarity, ease of manipulation, and considerations of computational cost.' Of course, if the distributions of the disturbance terms of a model are incorrectly specified this may call into question claims concerning the unbiasedness or consistency of the parameter estimates for the model and the appropriateness of any parametric tests of significance for which results are presented including parametric tests for specific problems of specification error. For further discussion of these issues see Nakamura and Nakamura (forthcoming, secs. 2.5 and 2.6, and ch. 4).

[6] See Nakamura and Nakamura (forthcoming, ch. 4) also for extensive use of a chi-square type of statistic for ranking the relative performance of alternative models of work behavior.

In section 2 of this paper we describe the models for which estimation and simulation results are given in this paper. In section 3 we describe the data used and other details of the estimation of our models. In section 4 we evaluate these models on the basis of both in-sample and out-of-sample simulation results. The conclusions of our study are summarized in section 5. The estimation results for our models are presented in the appendix to this paper.

2. Alternative models

The model which is our starting point in this study was originally presented by Heckman.[7] In this model an individual's asking wage, the minimum wage at which the individual would be willing to work one more hour, is specified to be a function of various explanatory variables including the number of hours of work at which the asking wage function is being evaluated, and unobservable factors represented by a random error term. Also the individual's offered wage, the wage an employer would be willing to pay the individual for an hour of work, is assumed to be some function of explanatory variables and unobservable factors represented by another random error term. If the individual's offered wage exceeds the individual's asking wage evaluated at zero hours of work, then we would expect the individual to work sometime during the given time period. Those who work are assumed to choose their hours of work, through their choice of a job or some combination of jobs, so as to equate their offered wage and their asking wage evaluated at their actual hours of work. An apparent advantage of this model is that it allows us to consider the determination of the individual probabilities of work, and the wage rates and hours of work for those who do work, within an integrated framework.

This model has been applied in a number of pure cross-sectional studies of the employment and earnings of married women.[8] A typical formal expression of this model for a given individual in a pure cross-sectional setting is as follows. The log of the offered wage, w, is given by

$$\ln w = \alpha_0 + Z\alpha_1 + u, \tag{1}$$

where Z is a vector of predetermined personal and regional variables, the α's are parameters, and u is a disturbance term which is assumed to be independently and identically normally distributed with zero mean over individuals and time periods. The log of the asking wage, w^*, is given by

$$\ln w^* = \beta_0 + Z^*\beta_1 + \beta_2 h + \beta_3 \ln w + u^*, \tag{2a}$$

[7]See Heckman (1974, 1976).

[8]See, for instance, Heckman (1974, 1976), Rosen (1976), Nakamura, Nakamura and Cullen (1979), and Nakamura and Nakamura (1981, 1983).

when the annual hours of work, h, are positive, and by

$$\ln w^* = \beta_0 + Z^*\beta_1 + u^*, \tag{2b}$$

when h is zero, where Z^* is a vector of predetermined personal characteristics, the β's are parameters, and u^* is another disturbance term which is assumed to be independently and identically normally distributed with zero mean over individuals and time periods.[9] The condition for an individual to work in a given year is

$$\ln w > \ln w^*, \tag{3}$$

where the asking wage is evaluated at zero hours of work. Thus the probability that a given individual will work in a year is given by

$$\mathrm{P}(h > 0) = F(\phi), \tag{4}$$

where F denotes the cumulative standard normal density function, and the index for the probability of work is given by

$$\phi = \delta_0 + Z^*\delta_1 + Z\delta_2, \tag{5}$$

where the δ's are parameters which can be specified up to a constant of proportionality [the standard deviation of the random term for (4)] as functions of the parameters of (1) and (2b).

Under the assumptions of this model the parameters of (5) may be estimated using standard probit analysis. For those individuals found to work, the log wage equation to be estimated using ordinary or generalized least squares regression is given by

$$\ln w = \alpha_0 + Z\alpha_1 + \alpha_2\lambda + U, \tag{6}$$

where U is a disturbance term and the selection bias term is given by

$$\lambda = f(\phi)/F(\phi), \tag{7}$$

[9] The log of the offered wage belongs in the asking wage function of an individual, evaluated at positive hours of work, if the linearized asking wage function is derived by maximizing a standard utility function subject to a budget constraint which contains the earnings of the individual, and is linearized around the log wage and hours of work. See Heckman (1974, app.). For further comment on this issue, see also Heckman (1978) and Nakamura, Nakamura and Cullen (1979, p. 788 and p. 796, fn. 11). Both the offered wage variable and the annual hours of work drop out of the asking wage function when the hours of work, and hence the earnings of the individual, are zero.

and may be computed using the estimation results for the index for the probability of work given in (5).[10] Also for those found to work the equation to be estimated for the annual hours of work is given by

$$h = \gamma_0 + \gamma_1 \ln w + Z^* \gamma_2 + \gamma_3 \lambda + U^*, \tag{8}$$

where U^* is a disturbance term, the γ's are parameters which can be related mathematically to the parameters of (2a), and where the term $\ln w$ is usually replaced by the predicted log of the offered wage using the estimated version of eq. (6). After this substitution is made, the hours equation can be estimated using ordinary or generalized least squares regression.

Annual hours of work for each individual have been measured in this study as reported weeks of work in the given calendar year times the usual number of hours worked per year.[11] The wage variable, w, has been measured as the reported earned income for the relevant calendar year divided by the corresponding value for annual hours of work,[12] and then deflated using the Consumer Price Index. Hence the wage rate is measured in constant 1967 dollars. An individual has been counted as working in a given year if both h and w were positive for the individual in the given year.[13]

In this study the variables included in the Z vector are the age of the wife, the education of the wife (measured as years of schooling), the state average hourly wage in manufacturing measured in 1967 dollars, and the unemployment rate for the state in which the wife lives. The variables included in the Z^* vector are a dummy equal to one if there is a new baby in the wife's household, and set equal to zero otherwise; a dummy equal to one if the youngest child is less than six but not a new baby, and set equal to zero otherwise; the number of children in the wife's household who are younger than 18; the earned income of the husband measured in constant 1967 dollars; and the age of the wife. In specifying the components of Z and Z^* we were constrained by the information available (or which can be added from other sources) for wives for the ten-year period of 1969 through 1978 spanned by our data base. The data used in this study are from the Michigan Panel Study of Income Dynamics

[10] Basic references concerning problems of selection bias include Amemiya (1973), Gronau (1974), Lewis (1974), Heckman (1976, 1979), and Goldberger (1981). The particular correction for selection bias used in this study, sometimes referred to as Heckit analysis, is presented in Heckman (1976).

[11] This is the Hours Worked for Money by Individual variable, also referred to as Annual Hours Worked, in the PSID data base [see Institute for Social Research (1980, p. 287, variable 6826, and p. 496)].

[12] For a description of the average hourly earnings variable available for wives in the PSID data, see Institute for Social Research (1980, p. 267). This is the variable which we deflate using the Consumer Price Index.

[13] Thus the definition of work used in this study does not include unpaid work in a family business or as a volunteer.

(PSID).[14] All of the variables included in Z and Z^* have been included in numerous other studies of the labor force behavior of married women except the variable for the state average hourly wage in manufacturing and the dummy variable for a new baby.[15] The motivation for including the baby variable is obvious. The state wage variable requires some comment, however. The real offered wage distribution faced by an individual cannot be determined solely by characteristics of the individual such as the individual's level of education. Conditions in financial, factor and product markets will also affect the real offered wage distribution by affecting firm behavior. Our hope was that these macro conditions affecting the offered wage distributions of individuals would be reflected in the state averages for the hourly wage in manufacturing, as well as in the state unemployment rate.

In this paper we will refer to this pure cross-sectional version of the model proposed by Heckman as the *Standard Model.* This is the type of model which can be estimated with micro data from a cross-sectional survey, such as the Census of Canada.

Heckman (1978, p. 36) conjectured, as noted in the introduction, that a dummy variable set equal to one if a person worked in the previous year, and set equal to zero otherwise, might serve as a good proxy for unobservables which affect a person's work behavior year after year. We will refer to the model which results from introducing such a dummy variable for work in the previous year into eqs. (5), (6) and (8) of the Standard Model as the *Dummy Model.*

The proportion of women who work in the current year is much higher for those who worked in the previous year than for those who did not. Among those women who worked last year, moreover, the proportions found to work in the current year are higher for women who worked more hours in the previous year compared with those who worked smaller numbers of hours, and for women who received higher hourly wage rates in the previous year compared with those who were paid less per hour. These observations suggest that we might be able to improve our forecasts of a woman's employment and earnings behavior by using information about her hours of work and wage rate in the previous year, as well as information about whether or not she worked in the previous year. For instance, we could estimate eqs. (5), (6) and (8)

[14] Information for certain variables such as earned income is collected in the PSID for the calendar year preceding the survey year. Thus we obtain the current values of these variables for each individual from the next year's record for this individual. Also we obtain the values of certain lagged variables from the previous year's record for each individual. Thus our data for the calendar years of 1969 through 1978 have been extracted from the 1968 through 1979 waves for the PSID.

[15] From the information provided in the PSID we cannot tell directly whether a woman has a new baby. Our baby dummy is set equal to one if the reported number of children in the family unit aged zero to seventeen has increased by at least one since the previous year, and if there is a child twenty-three months of age or under in the family unit. See Institute for Social Research (1980, p. 146).

separately for women who did and women who did work in the previous year, incorporating information about hours of work and the wage rate in the previous year into the equations for those who worked in the previous year.

A model of this sort may also be derived theoretically as a modification of the Standard Model. Suppose that the constant terms of the asking and offered wage functions are individual-specific, and that the error terms of these functions follow random walks. Thus it is postulated that there are both fixed and persistent individual specific unobservable factors. A common way of coping with such problems in a linear model is to difference the model. Notice, however, that the inequality expression given by

$$\ln w - \ln w_{-1} > \ln w^* - \ln w^*_{-1}, \tag{9}$$

is *not* equivalent to our inequality decision rule given in (3). (A sub minus one denotes a one-year lag.) In general, as noted in the Introduction to this paper, we cannot difference a model containing an inequality decision rule in quite the same manner in which we might difference a linear model.

A first difference version of the Standard Model modified to incorporate fixed and persistent unobservables may be obtained in the following manner though. If we subtract the log of the lagged offered wage from both sides of expression (3), and add and subtract the log of the lagged asking wage evaluated at zero hours of work on the right-hand side of (3), we obtain the expression

$$\ln w - \ln w_{-1} > \left(\ln w^* - \ln w^*_{-1}\right) - \left(\ln w_{-1} - \ln w^*_{-1}\right), \tag{10}$$

which is equivalent to the inequality decision rule given in (3) because of the manner in which it has been derived.

The hours equation for the Standard Model given in (8) is derived using the equilibrium condition that individuals who work will choose their hours of work so as to equate their offered wage with their asking wage evaluated at the actual hours of work. From the log form of this equilibrium condition and eqs. (2a) and (2b) for the asking wage evaluated at some positive number and at zero hours of work, respectively, we see that within this model the second term on the right-hand side of (10) may be expressed as[16]

$$\ln w_{-1} - \ln w^*_{-1} = \beta_2 h_{-1} + \beta_3 \ln w_{-1}, \tag{11}$$

[16]Suppose we let $w^*(0)$ denote the asking wage evaluated at zero hours of work and $w^*(h)$ denote the asking wage evaluated at the actual hours of work. Then using (2b) we see from (2a) that we can write the log of the asking wage for the previous year for someone who worked in that year as

$$\ln w^*_{-1}(h) = \ln w^*_{-1}(0) + \beta_2 h_{-1} + \beta_3 \ln w_{-1}.$$

Using the equilibrium condition,

$$\ln w_{-1} = \ln w^*_{-1},$$

for those who worked in the previous year, we obtain the result shown in (11).

where the lagged asking wage in (11) is evaluated at zero hours of work in the previous year as in (10). Thus we may rewrite (10) as

$$\ln w - \ln w_{-1} > \left(\ln w^* - \ln w^*_{-1}\right) - \beta_2 h_{-1} - \beta_3 \ln w_{-1}. \tag{12}$$

The second term on the right-hand side of (10) can be thought of as a measure of the strength of the individual's attachment to the work force in the previous year. For those who worked in the previous year we evaluate this term as in (11). For those who did not work in the previous year, we approximate this term as a function of the proportion of years the individual has worked since eighteen years of age, denoted by *PROE*, as well as a dummy variable set equal to one if the person has never worked since eighteen and set equal to zero otherwise, with this dummy being denoted by *NW*. That is, we employ the approximation given by

$$\ln w_{-1} - \ln w^*_{-1} = a_0 + a_1 PROE + a_2 NW + e_{-1}, \tag{13}$$

where the a's are parameters and e is an error term which is assumed to be independently and identically normally distributed with a mean of zero for all individuals who did not work in the given year. Thus for those who did not work in the previous year (10) may be rewritten as

$$\ln w - \ln w_{-1} > \left(\ln w^* - \ln w^*_{-1}\right) - a_0 - a_1 PROE - a_2 NW - e_{-1}. \tag{14}$$

Based on (12) we see that for those who worked in the previous year we thus write the probability of work in the current year as

$$\mathrm{P}(h > 0) = F(\phi^{\mathrm{W}}), \tag{15}$$

where

$$\phi^{\mathrm{W}} = \Delta Z^* \xi_1 + \Delta Z \xi_2 + \xi_3 h_{-1} + \xi_4 \ln w_{-1}, \tag{16}$$

where the ξ's are parameters and where the first difference vector is denoted by Δ. For those who did not work in the previous year, based on (14) we write the probability of work in the current year as

$$\mathrm{P}(h > 0) = F(\phi^{\mathrm{N}}), \tag{17}$$

where

$$\phi^{\mathrm{N}} = \Delta Z^* \xi_1' + \Delta Z \xi_2' + \xi_3' + \xi_4' PROE + \xi_5' NW. \tag{18}$$

The ξ''s in (18) are parameters.

For those who worked in the previous year and who are also found to work in the current year, the appropriate wage and hours equations to be estimated are first difference versions of (6) and (8), with the selection bias term computed as in (7) using estimation results from (16) and with predicted values substituted for the first differences of the log wage variable in the first difference version of (8). For those who did not work in the previous year we simply estimate (6) and (8), with the selection bias term computed using estimation results from (18) and with predicted values substituted for the log wage variable in (8). We will refer to this model as the *Difference Model*. Notice that in the Difference Model the impacts of any fixed or persistent unobservables, including the values of the original constant terms of the model which we have now assumed are individual-specific, will be embedded in the lagged hours of work and wage variables for those who worked in the previous year, and in the variables for previous work experience for those who did not work in the previous year.

It is possible to mathematically relate the coefficients of the probit indices for the Difference Model, up to constants of proportionality [which will differ because the standard errors of the relevant error terms will differ for (15) and (16)], to the original parameters of the offered and asking wage functions. The coefficients for the wage and hours equations for the Difference Model can be related, as well, to the coefficients of the underlying offered and asking wage equations, respectively. We do not do so here because the focus of this paper is not on our estimation results.

If u and u^* obey random walk processes, and if our assumptions about the distribution of the errors of approximation represented by the disturbance term in (13) are correct, then the parameters of our Difference Model can be consistently estimated using standard probit analysis and regression analysis, except for the parameters of the wage rate and hours of work functions for working women who did not work in the previous year. In particular, in this case no further problem of selection bias will be introduced due to the estimation of separate indices for those who did and those who did not work in the previous year, except in the case of the wage rate and hours of work functions for working women who did not work in the previous year.

3. Estimation of our models

The basic data base for this study consists of data over the 10 year period of 1969 through 1978 from the Michigan Panel Study of Income Dynamics (PSID) for the 546 women who were twenty-one through sixty-four years of age and married over this period, and for whom data are available for all years for all of the variables included in our models. We randomly selected 364 out of the 546 wives for whom data were included in our basic data base. The data for these 364 wives were used in pooled form in the estimation of the Standard, Dummy and Difference Models presented in section 2, and in performing in-sample simulation checks on these models. It should be noted that since the estimation of our models is carried out using pooled data, there is no definitional reason why the simulated behavior of individual wives over the 1969–1978 period should mirror their actual behavior even in in-sample simulations. Nevertheless, we also present out-of-sample simulation results using data for the remaining 182 wives whose data were not used in estimating our models.

Theoretically all of the variables in Z and Z^* should enter the indices for the probability of work for the Difference Model in first difference form. This is also the case for the wage and hours equations for the Difference Model for those who worked in the previous year. Thus theoretically all of the variables in Z and Z^* which do not change from one year to the next, like race or like education for many adults, should be omitted from our empirical specifications for these indices and equations. Also the effects of all variables, like age, which change by some constant amount each year should be embedded in constant terms for these indices and equations. We have included these theoretically omitted variables along with the first differences called for in our Difference Model as a check on the theoretical specification of this model, and to allow for possible interactions between these variables and the age of the individual which changes by one each year.

For all our models we estimate separate relationships for wives twenty-one through forty-six and those forty-seven through sixty-four years of age. Thus we allow for the possibility that the response coefficients of our models may differ for younger versus older wives. For our Difference Model, we also hypothesize different responses to a change in the earned income of the husband for younger versus older wives. In particular, we hypothesize that younger wives will tend to increase their work effort when the husband's income falls, but that older wives will tend to reduce their work effort as the husband reduces his and eventually retires. Finally for all of the models defined in section 2 we have specified the current and lagged hours of work variables in log form. The advantages of this specification in a simulation context are that no negative values are generated for hours of work, and the residuals from the estimated hours equations have distributions which are closer to the normal distributions which they are assumed to obey in our simulations. We have found the implications of this change in specification to be generally minimal in terms of the signs or magnitudes of the estimated impacts of the explanatory variables included in our model.

Coefficient estimates for our Standard, Lag and Difference Models are given in the appendix. We turn our attention now to the continuity and distributional properties which are the focus of this study.

4. Simulation results

Our simulations for each of our models were carried out by calculating for each wife in each year the value of the appropriate probit index, finding the corresponding probability of work in the given year using a subroutine for the standard normal distribution, taking a random draw from an appropriate uniform distribution and comparing it with the probability of work to determine whether or not a wife will actually be simulated to work in a given year, and then calculating the predicted wage rate and annual hours of work for each wife simulated to work in a given year. Our in-sample simulation results are for the same group of 364 wives for whom pooled data were used in estimating our probit indices and wage rate and hours equations. Our out-of-sample simulation results are for an entirely different group of 182 wives over the same ten-year time period of 1969 through 1978. Since the data were used in pooled form in the estimation of our relationships, there is no reason why even the in-sample simulation results will necessarily capture the observed employment and earnings behavior of individuals over time. Moreover in the simulation, wage rates and hours of work are generated for the wives simulated to work, rather than for those who actually did work; and after the first

Table 1

Actual and simulated distributions of annual hours of work pooled over the ten-year period of 1969–1978.

		In-sample simulation		
Annual hours	Actual	Standard model	Dummy model	Difference model
0	0.45	0.44	0.46	0.53
1–500	0.08	0.00	0.03	0.09
501–1,000	0.10	0.14	0.09	0.10
1,001–1,400	0.08	0.27	0.25	0.08
1.401–1,700	0.07	0.11	0.08	0.04
1.701–2,000	0.17	0.03	0.05	0.04
> 2,000	0.04	0.00	0.02	0.11
Pseudo-chi-square values[a]		1175	891	455
		Out-of-sample simulation		
Annual hours	Actual	Standard model	Dummy model	Difference model
0	0.45	0.45	0.50	0.56
1–500	0.08	0.00	0.03	0.12
501–1,000	0.09	0.15	0.10	0.07
1,001–1,400	0.08	0.26	0.23	0.06
1,401–1,700	0.06	0.10	0.08	0.06
1,701–2,000	0.18	0.02	0.04	0.04
> 2,000	0.04	0.01	0.02	0.10
Pseudo-chi-square values[a]		1323	834	379

[a]See text for definition. Here $n = 1820$.

simulation period the lagged endogenous information used by the Dummy and Difference Models is the simulated rather than the actual information from the previous period for each individual. Thus there is no reason why even the distributions for our pooled in-sample simulation results must mirror reality.

The descriptive measure used in comparing the simulation results for our different models is a pseudo-chi-square statistic defined by

$$\chi^2 = \sum_{i=1}^{c} \frac{[(PA(i) - PS(i))(n)]^2}{(P(i))n}, \tag{19}$$

where i is the index for c mutually exclusive and exhaustive categories for the characteristics of interest, $PA(i)$ is the actual proportion of observations in category i, $PS(i)$ is the simulated proportion of observations in category i for

Table 2

Actual and simulated distributions of annual earned income pooled over the ten-year period of 1969–1978.

Annual earned income ($)[a]	In-sample simulation: Actual	Standard model	Dummy model	Difference model
0	0.45	0.44	0.46	0.53
1–1,000	0.07	0.00	0.03	0.09
1,001–2,000	0.11	0.08	0.07	0.10
2,001–5,000	0.26	0.46	0.40	0.19
5,000–10,000	0.10	0.01	0.03	0.07
> 10,000	0.01	0.00	0.00	0.02
Pseudo-chi-square values[b]		588	313	107
Annual earned income ($)[a]	**Out-of-sample simulation: Actual**	**Standard model**	**Dummy model**	**Difference model**
0	0.45	0.45	0.50	0.56
1–1,000	0.09	0.00	0.03	0.10
1,001–2,000	0.09	0.07	0.07	0.09
2,001–5,000	0.24	0.46	0.37	0.14
5,001–10,000	0.11	0.01	0.02	0.08
> 10,000	0.01	0.00	0.00	0.02
Pseudo-chi-square values[b]		723	371	160

[a] Measured in 1967 dollars.
[b] See text for definition. Here $n = 1820$.

Table 3

Actual and simulated distributions of years of work over the ten-year period of 1969–1978.

Years of employment out of ten	Actual	In-sample simulation		
		Standard model	Dummy model	Difference model
0	0.27	0.00	0.25	0.46
1–3	0.13	0.14	0.13	0.03
4–6	0.08	0.52	0.16	0.05
7–9	0.14	0.31	0.14	0.10
10	0.38	0.02	0.32	0.36
Pseudo-chi-square values[a]		587	16	43

Years of employment out of ten	Actual	Out-of-sample simulation		
		Standard model	Dummy model	Difference model
0	0.27	0.00	0.28	0.46
1–3	0.13	0.18	0.13	0.02
4–6	0.09	0.48	0.16	0.08
7–9	0.14	0.32	0.16	0.15
10	0.37	0.02	0.26	0.28
Pseudo-chi-square values[a]		462	16	46

[a]See test for definition. Here $n = 182$.

the given model, and n is the total number of observations for our out-of-sample simulations.[17] Lower values of this pseudo-chi-square statistic correspond to a better fit.

In table 1 we show the actual and simulated pooled distributions of annual hours of work. The Dummy Model performs better than the Standard Model in this respect, but the model which results in the best fitting simulated pooled distribution of annual hours of work, both in-sample and out-of-sample, is the Difference Model. In table 2 we show the actual and simulated pooled distributions for the annual earned income of the wives in our in-sample and out-of-sample simulation populations. The Dummy and Difference Models both do substantially better than the Standard Model, with the Difference Model performing best of all.

[17]If different weighting factors are used in the computation of the descriptive chi-square values for our in-sample and our out-of-sample simulation results, we will not be able to compare the goodness-of-fit of the in-sample versus the out-of-sample results. Massy, Montgomery and Morrison (1970, p. 36) note: 'The chi-square statistic may be more useful for comparing the fit of two different models than it is in evaluating the correctness of either model. The effect of the sample size on the significance of chi-square statistics should always be remembered when one interprets a chi-square (or any other goodness-of-fit) statistic.'

Table 4

Actual and simulated distributions of years of part-time versus full-time work over the ten-year period of 1969–1978.

Full-time years ($h \geq 1{,}400$)	In-sample simulation Part-time years ($0 < h < 1{,}400$)				
	0	1–3	4–6	7–9	10
0	0.27[a]	0.10	0.03	0.01	0.05
	0.00[b]	0.11	0.25	0.08	0.00
	0.25[c]	0.10	0.06	0.05	0.10
	0.46[d]	0.03	0.03	0.03	0.07
1–3	0.02	0.03	0.05	0.05	
	0.00	0.12	0.14	0.02	
	0.00	0.08	0.04	0.07	
	0.00	0.00	0.04	0.09	
4–6	0.00	0.04	0.08		
	0.05	0.09	0.02		
	0.01	0.04	0.06		
	0.00	0.00	0.08		
7–9	0.01	0.13			
	0.06	0.02			
	0.00	0.11			
	0.01	0.08			
10	0.10				
	0.00				
	0.01				
	0.07				

Full-time years ($h \geq 1{,}400$)	Out-of-sample simulation Part-time years ($0 < h < 1{,}400$)				
	0	1–3	4–6	7–9	10
0	0.27[a]	0.10	0.05	0.04	0.04
	0.00[b]	0.11	0.26	0.09	0.00
	0.28[c]	0.08	0.06	0.06	0.11
	0.46[d]	0.01	0.05	0.05	0.06
1–3	0.01	0.02	0.03	0.02	
	0.02	0.13	0.11	0.04	
	0.02	0.08	0.04	0.05	
	0.00	0.02	0.04	0.03	
4–6	0.00	0.04	0.10		
	0.02	0.12	0.00		
	0.00	0.09	0.07		
	0.00	0.02	0.08		
7–9	0.02	0.14			
	0.06	0.01			
	0.00	0.04			
	0.00	0.11			
10	0.09				
	0.01				
	0.02				
	0.05				

[a]Actual proportions.
[b]Simulated proportions for the Standard Model.
[c]Simulated proportions for the Dummy Model.
[d]Simulated proportions for the Difference Model.

Table 5

Actual and simulated distributions of individual income cumulated over the ten-year period of 1969–1978.

		In-sample simulation		
Cumulative income ($)[a]	Actual	Standard model	Dummy model	Difference model
0	0.27	0.00	0.25	0.46
1–12,000	0.23	0.34	0.20	0.13
12,001–20,000	0.19	0.53	0.24	0.14
20,001–32,000	0.12	0.11	0.22	0.09
> 32,000	0.19	0.02	0.08	0.18
Pseudo-chi-square values[b]		198	30	36

		Out-of-sample simulation		
Cumulative income ($)[a]	Actual	Standard model	Dummy model	Difference model
0	0.27	0.00	0.28	0.46
1–12,000	0.21	0.40	0.19	0.21
12,001–20,000	0.18	0.49	0.28	0.07
20,001–32,000	0.14	0.09	0.19	0.08
> 32,000	0.20	0.02	0.05	0.17
Pseudo-chi-square values[b]		210	34	42

[a]Measured in 1967 dollars.
[b]*See text for definition. Here $n = 182$.*

In table 3 we show the actual and simulated distributions of years of work over the ten-year period of 1969–1978. Compared with the Standard Model the in-sample and out-of-sample performances of the Dummy and Difference Models are now spectacularly better, with the Dummy Model outperforming the Difference Model. Whether a woman is simulated to work at all in a given year is important, of course, but how much she is simulated to work is also important. Thus in table 4 we show the actual and simulated distributions of part-time (less than 1,4000 hours) and full-time (at least 1,400 hours) years of work over the ten-years period of 1969–1978. The pseudo-chi-square values for our in-sample results are 691 for the Standard Model, 103 for the Dummy Model, and 74 for the Difference Model. The pseudo chi-square values for our out-of-sample results are 453 for the Standard Model, 106 for the Dummy Model, and 58 for the Difference Model. The value of n used in computing both these in-sample and out-of-sample chi-square values is 182.[18] Thus both

[18]This is the number of women in our out-of-sample simulation population.

the Dummy and Difference Models are again found to perform much better than the Standard Model, with the Difference Model performing best of all.

The actual and simulated distributions of annual earned income cumulated for each wife over the ten-year period of 1969–1978 are shown in table 5. According to this criterion the Dummy and Difference Models perform much better than the Standard Model with the Dummy Model having the higher pseudo-chi-square statistic. The Difference Model does a much better job than the Dummy Model, however, in terms of placing the correct proportions of wives in the over 32,000 dollars category for cumulated earnings over the 1969–1978 period. The results shown in table 5 are of particular interest since any systematic errors made in determining which individuals work, what they earn per hour, or how many hours they work should result in prediction errors of the same sort year after year in the computation of annual earnings. These errors should stand out particularly clearly when earnings for each individual are summed over the ten-year simulation period.

5. Conclusions

We have shown that a standard levels model of the work behavior of married women, of the sort which can be estimated using pure cross-sectional data available from sources such as the Census of Canada or the U.S. Census, cannot capture the observed continuity of the employment and earnings behavior of individual wives. Our findings with respect to years of work and non-work, years of part-time versus full-time work, and cumulative earnings over a ten-year period confirm and extend Heckman's (1978, 1981c) findings with respect to years of work and non-work. Thus forecasting models of the work behavior of individuals should not be estimated using pure cross-sectional data. The outputs of such models with respect to work behavior and earnings over time could be grossly misleading. These results also call into question behavioral inferences in the published literature based on pure cross-sectional models of the work behavior of women. The failure of an estimated model to capture key aspects of the distributions of the dependent variables of the model is a clear indication that the model is misspecified.

Incorporation of information about past work behavior, even in the form of a simple dummy variable for whether or not a woman worked in the previous year, is found to result in greatly improved forecasts of the employment and earnings behavior of wives over time. This finding supports Heckman's (1978) original conjecture concerning the possible usefulness of information about past work behavior as a proxy for heterogeneity, but overturns his later (1981c) rejection of this conjecture based on out-of-sample simulation comparisons. We believe that these simulation comparisons primarily reflect offsetting effects related to two of the variables included in Heckman's models. The first of these is a national unemployment variable which changed value only once over the period of 1968 through 1970 for which data were used in estimating these models. The second is a variable for recent work experience which can take on values ranging from zero to two over Heckman's in-sample period of 1968 through 1970, but which has a range of zero to five over his out-of-sample simulation period of 1971 through 1973.

Thus the bad news for those of us in countries where good quality panel data is not publicly available is that pure cross-sectional data cannot be used to estimate models of individual work behavior which will properly capture the employment and earnings behavior of wives over time. The good news though is that models of this sort could be estimated using cross-sectional data augmented by a small amount of information about previous work behavior which could easily be collected on a recall basis as part of future cross-sectional surveys. It might be worthwhile to collect recall information of this sort in future population censuses in the U.S. as well. Census data have the advantage over the panel data available in the United States of being self-weighting, and providing more liberal numbers of observations for minorities of various sorts within the population. Moreover recent political events have made it clear that even in the U.S. funding for the collection of panel data may not always be available.

The model which is found to perform best in terms of our simulation comparisons may be viewed as a first difference version of a model of the work behavior of individuals presented by Heckman, modified to incorporate fixed and persistent person-specific unobservable factors. This model could be estimated using more sophisticated methodologies which would provide consistent parameter estimates under more general assumptions about the autoregressive structure of the model disturbance terms than those contemplated in this study. We demonstrate, however, that the model as estimated in this study using standard packaged probit and regression programs does properly reflect a number of key features of the joint distributions of the dependent variables of the model. These results should at least provide one benchmark against which to judge the potential advantages of other models and estimation methods which are more demanding in their data requirements or their computational complexity.

Recent discussions in the literature concerning the importance of fixed and persistent person-specific unobservable factors may help to revive interest in models incorporating lagged dependent variables as explanatory variables. Although such models have been deemed acceptable for forecasting purposes, it has often been argued that meaningful estimates of behavioral responses cannot be obtained from such models. Rather, it is argued that behavioral work should be based on structural models which rarely are formulated to contain lagged dependent variables. The literature on bias problems resulting from correlations between fixed and persistent person-specific unobservables and explanatory variables included in a model has made us aware, however, that estimates of the parameters of structural models may be misleading if we fail to control for important fixed or persistent unobservable effects. Lagged endogenous variables embed these unobservable effects. Thus the reformulation of structural models so that lagged dependent variables appear as explanatory variables in these models may prove to be one of the more tractable ways of controlling for fixed and persistent unobservables.

In the context of a study of the work behavior of wives, models taking account of work behavior in the previous period help to focus our attention on factors which lead wives who are working to quit, or wives who have not been working to take a job. It is unclear to us whether a more limited focus of this sort can eventually help us, for instance, in understanding the origins of the large increase in the labor supply of wives since World War II in countries like the U.S. and Canada. We feel certain, however, that there is value in asking more limited questions about the work behavior of wives, as an alternative or complement to simultaneous life cycle approaches, just as it has been found to be fruitful to ask more limited questions in other branches of science. Cole (1984, p. 62) writes in *Discover* magazine, for instance: 'As long as people asked grand fundamental questions about the nature of the universe (What is life? What is matter?) they did not get very far. As soon as they began to ask more focused questions (How does blood flow? How do the planets move?) they were rewarded with more general answers.' Cole goes on to argue: 'Newton's understanding of gravity was no less valuable because it was incomplete. As he answered the critics... 'To understand the motions of the planets under the influence of gravity without knowing the cause of gravity is as good a progress... as to understand the frame of a clock, and the dependence of the wheels upon one another, without knowing the cause of gravity of the weight which moves the machine.' We believe it would be important if researchers could identify what observable factors, if any, increase the likelihood that wives will alter their work behavior from what it has been in the immediate past, even if we are not able to fully understand or explain this previous work behavior. The models and research methodology presented in this paper can be viewed as an initial attempt toward addressing questions of this nature.

Appendix

Our estimation results are presented in the following tables A.1–A.3. Discussions of these estimation results are given in Nakamura and Nakamura (1982, 1984).

Table A.1

Estimated coefficients for probit indices (asymptotic t-statistics shown in parentheses).[a]

	Standard model		Dummy model		Difference model: Worked in $t-1$		Difference model: Did not work in $t-1$	
	< 47	≥ 47	< 47	≥ 47	< 47	≥ 47	< 47	≥ 47
Constant	1.530 (5.77)	2.411 (3.97)	−0.788 (1.96)	−1.200 (1.23)	0.345 (0.38)	−1.984 (1.30)	0.530 (0.87)	1.997 (1.04)
Log of hours of work in $t-1$					0.289 (3.67)	0.569 (5.62)		
Log of hourly wage rate in $t-1$ (1967$)					0.406 (3.26)	0.258 (1.56)		
Dummy = 1 if wife worked in $t-1$; = 0 otherwise			3.011 (36.03)	3.211 (24.28)				
Proportion of years worked since 18 years of age					−0.015 (0.05)	0.442 (1.14)	0.554 (1.58)	1.303 (2.27)
Dummy = 1 if wife never worked since 18 years of age; = 0 otherwise							−1.401 (8.00)	−0.795 (2.25)
Dummy = 1 if baby in t; = 0 otherwise	−0.790 (5.38)		−0.708 (3.07)		−0.272 (0.78)		−1.332 (2.39)	
Dummy = 1 if youngest child is less than 6 but not a new baby; = 0 otherwise	−0.605 (8.77)		−0.150 (1.43)		0.335 (1.30)		−0.290 (2.02)	
Number of children younger than 18 living at home	−0.062 (3.44)	−0.083 (2.59)	−0.007 (0.27)	0.025 (0.47)	0.027 (0.49)	0.153 (1.52)	0.036 (0.89)	0.010 (0.10)
Age	−0.004 (0.86)	−0.059 (6.17)	−0.005 (0.69)	−0.012 (0.78)	0.017 (1.22)	0.002 (0.07)	−0.035 (3.04)	−0.047 (1.69)
Education	0.010 (1.05)	0.129 (7.24)	−0.000 (0.03)	0.042 (1.58)	−0.008 (0.33)	−0.001 (0.04)	0.021 (0.83)	0.046 (0.79)
Dummy = 1 if wife is black; = 0 otherwise	0.172 (2.49)	0.457 (3.80)	0.080 (0.76)	0.005 (0.02)	−0.217 (1.18)	−0.286 (0.95)	0.357 (2.24)	−0.326 (0.94)
Earned income of husband (1000's of 1967$)	−0.043 (9.28)	−0.012 (2.06)	−0.015 (2.23)	0.007 (0.95)	0.006 (0.39)	0.020 (1.10)	−0.022 (1.89)	0.22 (0.16)

Table A.1 (continued)

	Standard model		Dummy model		Difference model: Worked in $t-1$		Difference model: Did not work in $t-1$	
	< 47	≥ 47	< 47	≥ 47	< 47	≥ 47	< 47	≥ 47
Difference between earned income of husband in t and $t-1$ (1000's of 1967$)					−0.016 (0.57)		−0.018 (1.05)	
Difference between earned income of husband in t and $t-1$ if difference negative (1000's of 1967$); = 0 otherwise						−0.005 (0.09)		0.097 (1.36)
State average hourly wage in manufacturing (1967$)	−0.187 (2.83)	0.019 (0.21)	0.046 (0.46)	−0.050 (0.34)	−0.035 (0.14)	−0.116 (0.49)	0.126 (0.79)	−0.360 (1.36)
Difference between state average hourly wage in manufacturing in t and $t-1$ (1967$)					1.317 (1.55)	2.754 (2.33)	1.167 (1.38)	3.748 (1.84)
State unemployment rate	0.003 (0.22)	−0.000 (0.01)	−0.035 (1.67)	−0.004 (0.13)	−0.230 (5.90)	−0.108 (1.97)	−0.050 (1.40)	−0.054 (0.81)
Difference between state unemployment rate in t and $t-1$					0.118 (2.54)	0.055 (0.85)	−0.016 (0.36)	0.053 (0.69)
Pseudo-R^2 for model	0.146	0.128	0.796	0.828	0.198	0.235	0.317	0.185
Number of observations	2550	1090	2550	1090	1372	604	1178	486
Proportion of wives who worked in year t	0.56	0.54	0.56	0.54	0.96	0.94	0.10	0.05

[a] These t-statistics must be treated as descriptive statistics.

Table A.2

OLS coefficient estimates for our equations for the log of the offered wage rate (t-statistics shown in parentheses).[a]

	Standard model		Dummy model		Difference model			
					Worked in $t-1$[b]		Did not work in $t-1$	
	< 47	≥ 47	< 47	≥ 47	< 47	≥ 47	< 47	≥ 47
Constant	−0.238 (1.92)	0.105 (0.33)	−1.995 (3.43)	0.196 (0.15)	0.111 (0.85)	0.165 (0.58)	−0.854 (1.84)	3.262 (0.66)
Dummy = 1 if wife worked in $t-1$; = 0 otherwise			1.802 (3.25)	−0.464 (0.34)				
Proportion of years worked since 18 years of age					0.016 (0.29)	−0.028 (0.35)	0.408 (1.53)	2.287 (1.57)
Dummy = 1 if wife never worked since 18 years of age; = 0 otherwise							−0.919 (2.53)	−2.008 (1.41)
Age	0.001 (0.48)	−0.040 (5.54)	−0.001 (0.30)	−0.013 (2.18)	−0.000 (0.10)	−0.001 (0.15)	−0.010 (0.95)	−0.087 (1.10)
Education	0.034 (7.68)	0.132 (10.18)	0.031 (7.27)	0.073 (8.52)	0.001 (0.18)	−0.002 (0.43)	0.048 (2.82)	0.162 (1.63)
Dummy = 1 if wife is black; = 0 otherwise	−0.017 (0.50)	0.130 (2.05)	−0.013 (0.39)	0.018 (0.30)	−0.011 (0.34)	0.006 (0.10)	0.328 (2.19)	−2.151 (2.24)
State average hourly wage in manufacturing (1967$)	0.248 (7.25)	0.327 (6.48)	0.288 (9.01)	0.357 (6.98)	0.050 (1.53)	−0.054 (1.16)	0.116 (1.01)	−1.288 (1.61)
Difference between state average hourly wage in manufacturing in t and $t-1$ (1967$)					0.311 (1.71)	0.533 (1.59)		
State unemployment rate	−0.007 (1.01)	0.030 (2.66)	−0.013 (1.67)	0.025 (2.19)	−0.058 (5.26)	0.018 (1.56)	0.007 (0.26)	0.043 (0.42)
Difference between state unemployment rate in t and $t-1$					0.002 (0.16)	0.003 (0.25)		
Selection bias term (λ)	0.161 (2.41)	0.876 (5.00)	0.920 (2.73)	−0.294 (0.42)	1.252 (5.70)	−0.494 (2.55)	0.807 (2.62)	2.508 (2.24)
R^2	0.104	0.363	0.127	0.337	0.038	0.024	0.127	0.498
Number of observations	1437	594	1437	594	1319	570	118	24
Mean of dependent variable	0.73	0.77	0.73	0.77	0.03	0.01	0.47	0.63

[a] These t-statistics must be treated as descriptive statistics.
[b] The dependent variable for those who worked in $t-1$ is $\Delta \ln w_t$.

Table A.3

IV coefficient estimates for our equations for the log of annual hours of work (t-statistics shown in parentheses).[a]

	Standard model		Dummy model		Difference model			
					Worked in $t-1$[b]		Did not work in $t-1$	
	< 47	≥ 47	< 47	≥ 47	< 47	≥ 47	< 47	≥ 47
Constant	7.516	6.462	7.484	8.718	−0.193	−0.081	6.714	7.290
	(45.54)	(15.54)	(6.74)	(5.43)	(1.40)	(0.27)	(8.00)	(1.61)
Predicted log of hourly wage (1967$)[c]	−0.394	−0.239	−0.561	−0.000			0.033	−0.769
	(2.64)	(2.19)	(4.59)	(0.00)			(0.04)	(1.46)
Predicted difference between log of hourly wage in t and $t = 1$ (1967$)[c]					1.281	−1.338		
					(6.13)	(3.03)		
Dummy = 1 if wife worked in $t-1$; = 0 otherwise			0.137	−1.841				
			(1.12)	(1.20)				
Dummy = 1 if baby in t; = 0 otherwise	0.431		0.111		−0.215		0.553	
	(2.17)		(0.65)		(1.82)		(0.39)	
Dummy = 1 if youngest child is less than 6 but not a new baby; = 0 otherwise	0.364		0.077		0.058		−0.078	
	(2.84)		(1.33)		(1.10)		(0.26)	
Number of children younger than 18 living at home	−0.024	0.010	−0.048	−0.035	0.006	0.042	0.050	0.047
	(1.25)	(0.43)	(3.69)	(1.70)	(0.48)	(2.73)	(0.59)	(0.15)
Age	0.010	0.025	0.006	0.010	0.003	−0.003	−0.002	−0.040
	(2.60)	(2.99)	(1.73)	(1.50)	(0.84)	(0.60)	(0.06)	(0.48)
Earned income of husband (1000's of 1967$)	−0.000	0.009	−0.020	−0.003	0.002	0.014	−0.052	−0.012
	(0.04)	(1.46)	(4.30)	(0.74)	(0.55)	(3.87)	(1.96)	(0.37)
Difference between earned income of husband in t and $t-1$ (1000's of 1967$)					−0.002			
					(0.29)			
Difference between earned income of husband in t and $t-1$ if difference negative (1000's of 1967$); = 0 otherwise						0.025		
						(1.62)		
Selection bias term (λ)	−0.915	−0.905	−0.608	−1.939	1.115	1.578	−0.163	0.337
	(2.79)	(5.12)	(0.90)	(2.42)	(4.91)	(5.47)	(0.64)	(0.47)
R^2	0.073	0.055	0.182	0.250	0.075	0.201	0.053	0.190
Mean of dependent variable	7.04	7.06	7.04	7.06	0.07	0.03	6.10	5.25

[a] These t-statistics must be treated as descriptive statistics.
[b] The dependent variable for those who worked in $t-1$ is $\Delta \ln h_t$.
[c] See table A.2 for coefficient values used in obtaining the predicted wage rates.

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