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THE DYNAMICS OF PART-TIME WORK

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ABSTRACT

This paper uses 14 years of data from the PSID to explore dynamic labor supply choices among adult women between full-time, part-time, or no labor market work. A variety of models indicate that past choices should be important in predicting current labor supply choices. This paper compares the effectiveness of several estimation strategies which require more or less historical information. The results indicate that past history in labor supply choices among adult women is very important in predicting current labor supply; given the lack of such data in many cases, the paper explores how much is lost when limited or no longitudinal information is available. In addition, the paper explores the substantive question of the role of part-time work in the labor market. Part-time workers are a very heterogeneous group; different part-time workers are in the midst of very different labor supply patterns. Most women use part-time work as a temporary alternative to full-time work or to being out of the labor market; few women use it as a transitional step into full-time employment. Simulations suggest the potential impact on future labor supply of mandating that low-skilled women who are out of the labor market enter part-time work.

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The Dynamics of Part-Time Work

I
Introduction

The role of part-time work in the labor market is not well understood. Some argue that part-time work creates difficulties for workers, pointing to the lesser availability of health and pension plans among part-time workers, and to the lower average wage levels on part-time jobs. Others argue that part-time work provides labor market flexibility to workers who face other demands on their time, allowing workers who are currently unable or unwilling to work full-time to maintain their labor market connections and skills. Consistent with this last argument, there is increasing emphasis on placing public assistance recipients into mandatory part-time work, on the theory that this will aid their movement toward economic self-sufficiency by leading to future full-time employment.

This paper investigates dynamic labor supply choices among adult women, with a particular focus on the role of part-time work. The primary substantive question of the paper is, "How does part-time work fit into long-term patterns of labor supply?" I am particularly interested in knowing whether part-time work acts as an "intermediate state" that some women utilize as they move toward full-time work. This is important in evaluating the policy claim that putting non-working women into part-time jobs will assist them in moving toward full-time work. To answer this question, however, we need to understand the dynamic patterns underlying the choice of all labor market states utilized by adult women. Thus, this paper also provides an empirical investigation of labor supply choices among women, with more careful attention to the role of past history and of heterogeneity in preferences in determining current and future labor market status.

In addition to substantive questions about part-time work and female labor supply, this paper provides useful information for empirical researchers about the value of utilizing longitudinal data on past labor supply choices to predict current labor supply. Because I have a particularly long panel (14 years), I can compare the usefulness of controlling more or less completely for past labor market history, either by including more years of past history, or by modelling sequential patterns of past choices more fully. I can also compare lagged dependent variable estimates to random-effects estimates, which characterize in a different way the population heterogeneity that is presumably reflected in past history and which can be implemented on cross-sectional data without any past labor supply information.

The results of this analysis indicate that past labor market choices are critically important for understanding and predicting current labor market choices among women. This is particularly true for part-time workers; at any point in time, part-time work is used by women following very different dynamic labor supply patterns. While part-time work is used by many women for brief periods of time (highly correlated with changes in household demographics), it is only infrequently used as a stepping stone from out of the labor market into full-time work. It is much more likely to serve as a short-term alternative to someone who is predominantly out of the labor market, or to someone who is predominantly a full-time worker. There is also evidence of substantial heterogeneity among adult women in their labor supply behavior. Some women appear to be very stably attached to a particular labor market state, while other women are more likely to be frequent movers between multiple labor market states. Random effects models of this heterogeneity do not fit the data as well as models that include lagged information on past labor supply choices, but for some purposes random effects models may be almost as useful as lagged dependent variable models.

II

Part-time Work and Dynamic Labor Supply: What Do We Know?

Among the 19 percent of the workforce that worked part-time in 1992, over two-thirds were women. Figure 1 indicates that a relatively constant share of employed women have worked part-time over the past 25 years, between 25 to 30 percent of the female labor force.[1] Of course, the

[1]This is based on number of people working less than 35 hours per week on their main job, the official definition of part-time work.

growth in female labor force involvement means that the *number* of part-time female workers has expanded enormously. In contrast, there has been a slow increase in the share of part-time workers among employed men over the past 25 years, from about 8 percent to over 12 percent of male workers, as figure 1 shows. Part-time work among men is also more cyclical than among women, reflecting a greater amount of involuntary part-time work among men.[2]

Despite an ongoing public discussion about the problems and/or advantages of part-time jobs, labor supply research that has focused on part-time work is surprisingly scarce.[3] A few studies have investigated part-time work choices at a point in time, including Long and Jones (1981), Nakamura and Nakamura (1983), and Blank (1988). These studies indicate that women with younger children, more children, and higher levels of other income are more likely to work part-time.[4]

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[2]Involuntary part-time work occurs when workers indicate that they are working part-time even though they are available for and want full-time work. In 1992, 40 percent of male part-timers indicated they were involuntary, while only 25 percent of female part-timers sought full-time work.

[3]For a review of the literature, see Blank (1990b).

[4]A larger literature analyzes wage differentials between part-time and full-time workers (for instance, Nakamura and Nakamura, 1983, or Blank, 1990a). This research typically concludes that equivalent part-time workers earn less than their full-time counterparts, although the size of this effect varies across occupations and depends upon the correction for selectivity into part-time work. Non-wage compensation differentials are even larger. Jones and Long (1979), Corcoran et al. (1983) and Sundt (1987) control for the effect of past labor-market involvement on current wages. At least in the short run, part-time spells appear correlated with lower wage growth.

A number of "counting exercises" have investigated the use of part-time work in a more dynamic context. Moen (1985) includes simple spell tabulations of part-time and full-time spells over short periods of time. Main (1988) uses retrospective life histories of British women to display lifetime patterns of part-time and full-time work. Blank (1989) estimates the determinants of part-time spells using hazard rates.[5] These studies tend to show quite complex patterns of labor market movement among adult women and indicate that part-time work is a transitory labor market state for most women. But most of these studies are limited. Except for simple descriptive analysis, we know very little about the women's choices over time between part-time and full-time spells of work and spells out of the labor market.

III
Models of Dynamic Labor Supply

The standard static labor supply model conceptualizes hours of work as a function that can be written as:

$$\text{Hours} = f(S, Y_o, D, Z), \tag{1}$$

where S is a vector of human capital attributes of the individual that determine compensation and wages. Y_o is a vector of other income sources in the

[5]Attempts to estimate the determinants of women's spells of labor market participation and nonparticipation (without explicit attention to the issue of part-time work) include Heckman and Willis (1977) and Hill and O'Neill (1989).

household and includes both the earnings of other individuals as well as non-earned income. D represents a vector of labor market demand conditions that may constrain labor market choices. Z is a vector of household composition and demographic characteristics that is used to control for differences in the opportunity cost of market work and for differences in preferences across households. If labor market choices in each time period are independent of choices in all past and future years, then estimation of (1) using current information on all the variables will suffice.

A variety of labor supply models, however, predict time dependence in labor supply. First, human capital investment models suggest that current compensation will depend on past labor market experience, which in turn affects current labor supply. This implies that the human capital vector, S, should include information on accumulated experience. Second, there may be time dependence in labor supply options exclusive of compensation effects. If labor market involvement expands a woman's job networks and job search knowledge, she may be more likely to work if she has worked more in the past. A theory less accepted by economists but often raised in policy discussions about labor supply is that past labor market involvements may change women's preferences over time, so that the utility associated with work may increase (or decrease) over time as work experience changes.[6]

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[6]Eckstein and Wolpin (1989) make this point; their estimates indicate that the disutility of employment increases with experience.

Third, there may be heterogeneity in women's preferences with regard to how they evaluate their labor/leisure choices. In the absence of direct information on this phenomenon, past labor supply choices are often assumed to reveal evidence about this heterogeneity. In this case, past patterns of labor supply are important not because they directly affect current choices, but because they are correlated with other less measurable variables that influence both past and current choice. Fourth, life cycle models of labor supply predict that labor supply choices will depend not only on past but also on future expectations about labor supply and household demands. Since most data sets contain no information on future expectations, these are typically proxied by information on past behavior.

The point of this paper is not to try to distinguish between these competing explanations. Researchers who have estimated models designed to highlight each of these particular theories of labor supply have found evidence of time dependence. My interest is in conducting a less structural exploration of dynamic labor supply choice, although like all empirical papers I will have to make certain distributional and functional form assumptions.

Rather than estimating the static model in (1), I want to estimate a more general dynamic version. Specifically, I want to estimate the determinants of the sequential set of labor market choices, assuming these choices are correlated over time, starting in period 1 when a woman first enters the labor market and opts to work h_1 hours. These choices can be characterized as a series of probabilistic equations that evolve over time:

(2a) $\quad \text{Prob}(\text{Hours}_1 = h_1 \mid S_1, Y_{o1}, D_1, Z_1)$

(2b) $\quad \text{Prob}(\text{Hours}_2 = h_2 \mid h_1, S_2, Y_{o2}, D_2, Z_2)$

(2c) $\quad \text{Prob}(\text{Hours}_3 = h_3 \mid h_2, h_1, S_3, Y_{o3}, D_3, Z_3) \quad \ldots$

(2d) $\quad \text{Prob}(\text{Hours}_T = h_T \mid h_{T-1}, h_{T-2}, \ldots, h_1, S_T, Y_{oT}, D_T, Z_T)$

where the choice of hours in each period is assumed to be the result of all past optimizing choices among labor/leisure/home production options of the individual.[7] Unfortunately, unrestricted estimates of (2d) are impossible to compute when T becomes at all large, because of the difficulty of computing all of the necessary intercorrelations between periods.

One way to solve this problem is to parameterize the utility function in a way that assumes preferences are separable over time (Heckman and MaCurdy, 1980; MaCurdy, 1981; Browning, Deaton and Irish, 1985; and Altonji, 1986).[8] These models of life-cycle labor supply assume that people are able to fully adjust their labor supply in each time period. More recent work has estimated models that allow somewhat slower labor supply

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[7] Fertility decisions may also be endogenous. I do not deal with this, other than to control for cumulative past fertility decisions through the vector Z that characterizes household constraints.

[8] A somewhat different specification is provided by Eckstein and Wolpin (1989), although they also specify and estimate a particular form of the utility function, which is then used to simulate dynamic labor supply choices.

adjustment, typically assuming some type of habit adjustment model (Hotz, Kydland and Sedlacek, 1988; Bover, 1991). The focus of this work is to measure the intertemporal adjustment in labor supply that occurs as wages change along a given lifetime wage profile.

I choose a different approach to study the dynamics of labor supply, for a variety of reasons: First, the explicit parameterization of utility required to produce estimable specifications in the research cited above makes it difficult to determine how much the results depend on the parameterization. I do not want to impose a particular model of intertemporal labor supply on the data, but want to test for patterns of time dependence among labor supply choices in as nonparametric a manner as possible. Second, such specifications assume wages are not affected by labor supply choices, an assumption that the existing literature on part-time wages clearly indicates is incorrect. This is particularly important, given my interest in separating part-time and full-time work choices. Third, these models are primarily designed to estimate the elasticity of intertemporal male labor supply to wage variation over time, which is not the main concern of this study. Household characteristics should be far more important in determining women's labor supply decisions--particularly their movements in and out of part-time work--than are changes in short-run wage levels. I therefore want a model that allows me to estimate the effect of a wide range of time-varying variables on labor supply choice.

An alternative way to simplify the problem in (2) is to characterize the continuous hours of work variable by a few discrete labor market states. I will assume that a person's labor market involvement at any point in time can be adequately summarized by three discrete categories: (1) Out of the labor market (Hours = 0), referred to as OLM; (2) Part-time work (0 < Hours < 35), referred to as PT; and (3) Full-time work (Hours ≥ 35), referred to as FT. The result is a discrete version of (2) with three labor market states in each period. This simplification is consistent with existing evidence on how the labor market functions. First, firms explicitly define and advertise part-time jobs, so that this distinction is recognized institutionally in the labor market. Second, as noted above, there is a difference in the compensation of equivalent workers in part-time and full-time jobs, which indicates that these two categories embody real productivity differences.

With a three-way characterization of labor supply choices, I can investigate the dynamic model in (2) in three different ways. First, I can focus on the determinants of the duration of time spent in any one labor market state. This results in standard duration analysis of OLM, PT, and FT spells. The biggest drawback to this approach is that it does not allow me to estimate patterns of movement across multiple labor market states over time.[9]

[9]Theoretically, one can estimate a hazard model with multiple types of spells allowing for a full set of intercorrelations between the spells, but this sort of estimation is beyond current econometric abilities.

Therefore I also investigate a second approach, which ignores the issue of spells and estimates the discrete version of (2) in each time period, controlling for past labor market history. This means estimating a three-way multinomial logit of the choice between labor market states, including dummy variables to represent the full range of (discrete) labor market choices made in past periods. The third approach is to use a three-way multinomial logit to estimate current labor supply choices, but rather than including explicit information on past labor market history to instead characterize the heterogeneity across individuals with random effects. (This would be particularly consistent with the third model of time dependence described above, where past history merely proxies for underlying stable differences in preferences.) Because this approach requires only cross-sectional data to implement, it is interesting to compare the goodness of fit properties between the lagged dependent variable estimates and the random effects estimates. All three of these models are developed in more detail below.

IV
The Data

The data used in this paper are from the Panel Study of Income Dynamics (PSID) from 1976 to 1989. Data prior to 1976 are not usable for my purposes, since labor supply information on wives was not available before this year. This provides 14 years of information. Included in my sample are all women between the ages of 18 and 50 in 1976, who are spouses or family heads in all 14 years.[10] Thus, I have attempted to select a sample of women who, for the entire time period, are in a position to make labor supply choices. Explicitly omitted are women who are in school or living with their parents during any of these years, or women who are old enough to have reached the usual retirement age. I also omit those persons who were part of the oversample of low-income families in the PSID. There are 1463 women who meet these criteria, which provides 20,482 observations (1463 times 14 years). Where I make comparisons to men, they are sampled in an identical way.

Throughout this paper, a part-time worker is someone who reports working less than 35 hours per week on her longest job last year. This ignores differences in annual weeks of work among women. The alternative is use a full-time definition based on annual hours of work (such as 1680 hours per year—35 hours per week times 48 weeks per year.) This would seriously overestimate the incidence of part-time work, however. For most of these years I only have information on "main job last year." Any full-time worker who enters or leaves the labor market during the middle of the year will show an annual hours figure that will look like part-time work, even though it

[10] I use "family heads" loosely here to refer to women who are both unrelated individuals as well as the head of a group of related individuals.

actually reflects the end (beginning) of a spell of non-work and the beginning (end) of a spell of full-time work.[11]

Figure 2 presents the range of labor supply choices among both men and women over these 14 years. Plotted is the cumulative share of the population as hours of work increase, based on data from the entire 14 year period. The solid line is based on the adult women sample described above and the dashed line shows hours choices among an equivalent sample of adult men. As the graph shows, substantially more women are out of the labor force (at zero hours), and their cumulative share between 0 and 40 hours rises more rapidly than men's. Both groups show a large spike at 40 hours. The number of men working over 40 hours is much higher, and men's cumulative share rises quickly above 40 hours, while women's is more flat. Few women or men work less than 20 hours per week. An average, 28 percent of the women in our sample are out of the labor market at any point in time during these years, another 23 percent are working part-time, and 51 percent are

[11]Experimentation with an annual hours of work definition of "part-time" confirms this problem. In the most recent years of the PSID, there is monthly information on labor supply, but the short period over which this is available limits its usefulness. An alternative approach would be to define five labor market states instead of three: OLM, Part-time/Part-year; Part-time/Full-year; Full-time/Part-year; and Full-time/Full-year.

working full-time. In contrast, only 3 percent of the men are out of the labor market, 4 percent work part-time and 93 percent work full-time.[12]

V

Observed Transitions and Labor Supply Patterns in the Raw Data

Because of the scarcity of information on dynamic labor supply choices, it is interesting to start by looking at simple tabulations of the patterns of labor market change in the raw data. Table 1 presents the average transition matrix for adult women and men between the three labor market states over the 14-year period. Table 1 indicates that a substantial number of women remain in the same labor market state over any two-year period: 79 percent of the sample lies on the diagonal of the transition matrix. Much greater stability is present among full-time and OLM women than among part-time women, however. While 86 percent of the women who work full-time in year t are observed to work full-time in year t+1; only 66 percent of the part-timers in year t will remain part-time workers in year t+1. Twenty percent of part-time workers will move up to full-time work, and 14 percent will move out of the labor market. Thus, table 1 indicates that part-time work

[12]Realize that these data are based on hours of work in the longest job held last year. The share of men who are out of the labor force is quite low compared to weekly labor force participation data, since a person would have to be out of the labor market all year in order to be placed in this category.

is clearly a more transitional category than either of the other two labor market states.

While the adult women's transition matrix looks relatively stable, the men's transition matrix is extremely stable. Ninety-four percent of the men stay in the same labor market state (are on the diagonal) over a two-year period, mostly in full-time work. Of those working part-time, over half will be in full-time work in the next year.

Table 1 emphasizes the differences between the male and female labor force and indicates that dynamic labor supply estimates for men are of much less interest than for women. Most men work full-time at some point during the year. Women show much greater variance in their labor supply choices, both at a point in time and in their movements over time.

Given an interest in the dynamic role of part-time work in women's labor supply choices, it is interesting to look at a three-year transition matrix, to see whether any frequent patterns of movement between the OLM, PT and FT categories occur. Table 2 presents the three-year transition matrix for adult women, showing the probability of being in one of the three labor market states in year t+2, conditional upon all possible patterns in years t and t+1.

Table 2 indicates that over a three-year period 66 percent of women stay in the same labor market state for all three years. The transitional nature of part-time work is even more apparent in table 2. Among all women who worked part-time in year t, 66 percent were still in part-time work after 1 year, while only 49 percent (11.4 percent out of 23.3 percent) are still there after 2 years. Those who move between labor market states are distributed widely throughout all the cells in the matrix.

Table 3 presents information on aggregate labor supply patterns over the entire 14-year period. For comparison purposes, table 3 also shows the equivalent patterns among adult men (who one would expect to show more stable patterns than adult women), and among all adult women in my sample who are married 10 or more of the 14 years (who one would expect to show less stable patterns if married women are more prone to changing labor market status).

With 14 years of data and 3 labor market states, there are 3^{14} (approximately 4.8 million) possible data patterns. Among the 1463 women in the sample, I observe only 931 of these patterns, with a substantial minority of the women located in only a few patterns. Twenty-two percent of all adult women never change labor market states over a 14 year period, as part 1 of table 3 indicates. The bulk of these are full-time workers. Only 1 percent of the sample is permanently attached to part-time work. In comparison, 68 percent of the men remain in one labor market state for 14 years, almost all of them working full-time.

Part 2 of table 3 indicates that over half of the women are in the same labor market state at least 10 of the 14 years. Yet, it is also true that most women have some experience with multiple labor market states. As part 3 indicates, 64 percent of the women have spent at least one year out of the labor market, 69 percent have worked part-time at least one year, and 85 percent have worked full-time at least one year. A substantial minority of women seem to be "movers"—40 percent have spent time in all three labor market states over the 14 year period. Interestingly, as column 3 indicates, there are not large differences between those women who are stably married over this period and all women.

The last two parts of table 3 investigate the prevalence of any sort of "stepping-stone" pattern between OLM, PT and FT moves. Part 6 tabulates the share of women who ever show a pattern of OLM to PT to FT work (regardless of the number of years spent in each state). Part 7 tabulates the reverse stepping stone pattern, moving from FT to PT to OLM. The results indicate that few women in part-time work are in a transitional state between OLM and full-time employment.[13] The majority of part-time workers enter part-time work from a full-time spell and return to full-time work, or they enter part-time work from OLM and return to OLM. This suggests that part-time work is used as a temporary alternative to another (more permanent) labor market state, not as a transitional state.

The results in tables 1 through 3 confirm that women show a great deal of movement in their labor supply choices over time. Much more so than

[13]It is possible that a larger proportion of women work part-time for a month or two before finding full-time work and that higher frequency data would show more "stepping stone" patterns.

among men, there are frequent changes in labor supply among many women, implying that dynamic analysis of labor supply decisions may be more interesting for women than for men. Although women appear to be a heterogeneous group, a substantial minority seem stably attached to a particular labor market state. Part-time work is clearly a more short-term and transitional state than OLM or full-time work, but it is used less as a transitional state into or out of the labor market than as an alternative to either OLM or full-time work.

VI
Estimating the Determinants of Spells in a Labor Market State

A. Competing Risk Duration Models of OLM, PT, and FT Spells

An obvious way to investigate dynamic labor market movements is to focus on the observed spells in part-time and full-time work and out of the labor market. This section introduces a competing risk multiple-spell estimation model that I will use to investigate both what moves women into spells of part-time work from full-time work or OLM, as well as the determinants of the length of part-time spells. The analysis of time-dependent data is by now relatively standard and does not require much introduction.[14]

[14]For a discussion of duration models, see Lancaster (1990).

Let $F(t,X_t,\beta)$ be the cumulative distribution function of time spent in part-time work, with $f(t,X_t,\beta)$ as its related density function. X_t represents the vector of independent variables $[S_t, Y_{ot}, D_t, Z_t]$, with β as the vector of related coefficients. One can characterize the probability of leaving part-time work at any point in time as the hazard rate, $h(t,X_t,\beta)$, which is the probability that a spell ends in period t, given that it lasted to t-1. For any completed spell of part-time work, the likelihood that an individual is observed to work part-time from time 0 to time t is simply $f(t,X_t,\beta)$.

The probability that an individual spends a particular amount of time in any labor market state can be straightforwardly estimated, once a hazard function is chosen. A semi-parametric hazard, where the data essentially determines the shape of the hazard function in each period, is often preferred.[15] Time-varying covariates (such as number of children, household non-earned income, etc.), can be readily included in the estimation, as can any number of right-censored spells.

A few particular issues are important in implementing spell duration estimates with this data. First, because of the lack of any retrospective information, I have to omit all left-censored spells. While this is a standard procedure, it is particularly worrisome in this case, because the most stable

[15]Depending on the data, freeing up the hazard in each period is not always possible. Flinn and Heckman (1982), for instance, suggest a particularly flexible form of the time variable. The approach used here is similar to that suggested in Meyer (1988).

individuals—those who remain working full-time or part-time, or who are out of the labor market in all observed years—are all left-censored. By throwing these individuals out, I may be throwing out a very important part of my sample. Concern about this issue is one reason I turn to alternative explorations of the data in the next section.

Second, I am particularly interested in estimating competing risk models of labor force movement. Ending a spell of part-time work to move out of the labor market is almost surely a very different type of spell ending than is moving into full-time work. In addition, to the extent that I want to estimate the determinants of the start of part-time spells, I need to distinguish between full-time and OLM spells that end in part-time work and those that end in other activity. Competing risk models can be implemented in a straightforward manner.[16] I simply assume that at any point in time, an individual in labor market state j is "at risk" of ending a spell in the labor market by either moving to labor market state k or by moving to labor market state l. Each of these moves has an underlying hazard rate, $h_k(t,X_t, \beta_{jk})$ and $h_l(t,X_t, \beta_{jl})$. The aggregate hazard of leaving labor market state j can be characterized as a simple additive function:

$$(3) \qquad h_j(t,X_t, \beta_j) = h_k(t,X_t, \beta_{jk}) + h_l(t,X_t, \beta_{jl}).$$

[16]For a discussion of the issues involved in estimating competing risk models, see the above references on duration analysis, as well as Heckman and Honore (1989), Han and Hausman (1990), and Narendranathan and Stewart (1991).

With only minor complications, this additive hazard can be readily estimated.

Third, I observe a substantial number of individuals who experience multiple spells in the same labor market state over 14 years. This is particularly true of spells of part-time work, which tend to be of short duration. The best way to work with data which contain multiple spells is to include information on past labor market spells in the estimation (Honore, 1991). For instance, I can include information on the type of spell immediately preceding the current one. In a competing risk model for part-time spells, including a control variable for whether the prior spell was an OLM spell lets me determine whether people who move into part-time work from out of the labor market are more likely to leave the labor market again or to move on to full-time work. I can also include information on the observed spell number, on the length of previous spells in the same labor market state, and on the length of time since a previous spell was last observed.

Given the frequency of multiple spells in the data, including these multiple spells in the estimation procedure is probably quite important to the analysis. The cost of including multiple spells, however, is that it makes traditional adjustments for population heterogeneity impossible to carry out. Once characteristics on past spells are included in the estimation, the assumptions needed to estimate standard heterogeneity models no longer hold (Honore, 1991). This is not necessarily a major concern, however.

Heterogeneity adjustments try to control for unmeasured population differences; including information on past labor market choices should also control for these differences. In the following section, I control for heterogeneity in several alternative ways.

B. Estimation Results

Table 4 summarizes the spell data in my sample. I observe up to five spells of OLM and part-time work over 14 years, although the higher-sequence spells tend to be quite short. First observed spells in full-time work average close to 4 years, out of the labor market spells average 3.2 years, and part-time spells average only 2.6 years, again indicating the more transitory nature of part-time work. Second spells in all labor market states average between 2 and 3 years. When the sample is limited to non-censored spells, the spell lengths are shorter. Table 4 indicates that there are a substantial number of second and higher spells in this data, making the use of multiple-spell estimation techniques particularly attractive.

Table 5 presents the results of three multiple-spell competing risk estimates, as described above. The first two columns of table 5 present the estimates for spells out of the labor market. The third and fourth columns present the estimates for spells of part-time work, and the last two columns present the estimates spells of full-time work. Hazard rates are estimated semiparametrically, with dummy variables included for each time period.[17] Positive coefficients in table 5 indicate that higher values of a variable make it more likely that a current spell type will end in an exit to the indicated labor market state. Thus, the coefficients in row one imply that older workers are likely to have longer OLM spells because they are less likely to terminate a spell OLM and move into either full-time or part-time work, although the probability of moving into full-time work is lower. Older workers in part-time spells are also less likely to terminate their spell and move into full-time work, but are more likely to move out of the labor market.

The first group of variables in table 5 presents the coefficients on personal and household characteristics from these three competing risk models. A few results stand out. First, older women are less likely to end a spell out of the labor market or to move into full-time work. Second, black women are more likely to move into full-time work. Third, less educated women are more likely to terminate spells of full- or part-time work and leave the labor market. Fourth, an increase in the total number of children increases the propensity of a woman to move into full- or part-time work, while an increase in the number of preschoolers decreases the propensity to move into full-time work and increases the propensity to leave the labor market. Part-time spells

[17] Because of the sparsity of spells above 6 years, a single dummy variable is used to control for spells of 6 to 7 years length, and another for all spells of 8 or more years. This means that 7 dummy variables estimate the hazard rate in each "competing risk" branch of the three models in table 5.

are little affected by the number of children but strongly affected by the number of preschoolers. Fifth, women with higher other income in their family are less likely to become full-time workers. Sixth, local unemployment rates increase the length and probability of OLM spells, but have little effect on part-time or full-time spells.

The second group of variables in table 5 controls for previous spells. These variables are very significant for all types of spells, and underscore the importance of past history on current spell duration. The length and type of spell ending is strongly influenced by the previous spell type. For instance, women who enter a part-time spell from out of the labor market are much more likely to leave the labor market again than move into full-time work. Women who enter a part-time spell from full-time work are much more likely to return to full-time work than to move out of the labor market. These results are consistent with the data tabulations above, which indicated that few people use part-time work as a stepping stone between OLM and full-time employment.

The observed spell number has weaker effects on spell lengths.[18] Higher number spells of OLM or part-time work (which tend to be shorter spells) are less likely to end in full-time work. To the extent that full-time

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[18]The inclusion of a variable to control for observed spell number may be somewhat problematic, since the observed first spell after 1976 may not be the first spell of the woman in this type of work. The omission of this variable has little effect on other covariates.

work is a more stable category for many women, this may reflect the fact that women who have higher sequence spells in this data are frequent movers, and thus more likely to be in OLM or part-time spells.[19,20]

Figure 3 plots the hazard rates estimated in table 5 for each of the three competing risk models for a specific woman.[21] Because the woman is assume to have a preschooler, she has a high (41 percent) probability of leaving a full-time spell after one year (the sum of the two hazard functions among full-time workers), but this declines steeply over time. In contrast, if this woman work part-time the probability of ending her spell is 47 percent in the first year and remains high over time. After 5 years, almost all part-time workers have exited part-time work. If this woman is out of the labor market, she has a 47 percent chance of going to work after one year. The probability that this woman will enter part-time work from out of the labor market is everywhere higher than the probability that she will move into full-time work.

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[19]In other estimates (not shown here), based only on second and higher spells, I included controls for the length of the previous spell in the same labor market state and the length of time since that spell occurred. Both of these variables were highly significant. The longer a previous spell and the more recent that spell, the more likely that the current spell will continue.

[20]Other specifications included occupational controls and controls for changes in variables as well as their level values. While some of these had significant coefficients, their inclusion had little effect on the coefficients reported here. An important excluded variable in all the models is a control for involuntary part-time work, but the PSID has no data on this.

[21]The base individual whose hazard rates are calculated in Figure 3 is a white married women with a high school degree, two children (one a preschooler) whose non-earned income is $25,000, in a county with a 6.9 percent unemployment rate.

These hazard rates underscore the differences between part-time and full-time workers and, together with the results of table 5, indicate the importance of looking at women's labor supply choices in a dynamic context. Spells of either OLM, part-time, or full-time work are strongly influenced both by the nature of the previous spell as well as by the type of spell exit that occurs (the use of a competing risk model significantly increases the explanatory power of the model). In addition, these hazard models indicate the importance of personal, household, and environmental variables in determining the length and nature of labor market spells. Part-time workers, in particular, are a very heterogeneous group, at risk of either increasing or decreasing their labor market efforts. The differential effects of control variables in influencing the movement into and out of part-time work indicates that, depending on their personal and environmental characteristics, women observed working part-time in any particular period may be in the midst of very different routes through the labor market.

VII
Modelling a Complete Set of Labor Market Patterns Over Time

While the duration estimates just discussed provide useful information about women's dynamic movements through the labor market, they have at least two problems. First, they focus only on spells in a single labor market state. To the extent that my primary interest is in the full pattern of labor market behavior over 14 years, the duration models do not estimate this. In fact, as noted, those patterns that are most striking—persons who remain in the same labor market state for the entire 14-year period—must be thrown out of the data as left-censored spells. Second, these duration estimates may not fully account for heterogeneity across women. Although two limited measures of spell count and past spell type are included in the estimates, one might believe that past patterns of labor involvement have a much greater impact on current choices than these duration models allow. For both of these reasons, this section presents an alternative way to analyze women's movement through the labor market.

A. Multinomial Logit Lagged Dependent Variable Models

I am interested in developing a technique that will measure the probability that a woman follows any sequence of labor market choices over time. The dynamic model of labor supply in (2) provides a starting point for this analysis. In this section I estimate a simplified version of (2) which assumes that the probability an individual is observed in any particular labor market state can be denoted as

$$(4) \qquad \text{Prob}(LMS_t = I_t) = f(X_t,\ g(LMS_{t-1},\ LMS_{t-2},\ \ldots\ LMS_{t-j})),\ I=1,\ 2,\ 3$$

where LMS_t is a discrete variable indicating labor market state that takes on

three values $I_t = 1$ if $Hours_t = 0$ (OLM)
$I_t = 2$ if $0 < Hours_t < 35$ (PT)
and $I_t = 3$ if $Hours_t \geq 35$ (FT).

X is the vector of personal, household, and economic environment variables discussed above and g(.) is a function that describes past labor market patterns. Written this way, the probability of observing an individual in any particular labor market state can be estimated as a multinomial logit, with controls for the labor market patterns observed in past periods. For example, this implies that the probability a person is of out of the labor market in time period t can be written as

$$(5) \qquad Prob(LMS_t{=}1) = \frac{\exp(X_t\beta_1 + L_t\gamma_1)}{1+\exp(x_t\beta_1 + L_t\gamma_1) + \exp(x_t\beta_2 + L_t\gamma_2)}$$

where L is the vector of dummy variables representing past labor market history. β_1 and β_2 are coefficient vectors that indicate the effect of the X variables on OLM and part-time work, respectively. γ_1 and γ_2 describe the effects of past labor market patterns on the probability of choosing OLM or part-time work, respectively. Full-time work is the residual category. Using the standard multinomial logit format, equivalent equations can be written for the probability of being in part-time and in full-time work.

The characterization of labor market history is important in this model. I will compare results from three different lag specifications:[22]

(1) *Full Lag Specification*: If there are j lag periods in the model, there are j^3 potential patterns of history that an individual could follow, given three different labor market states. A separate dummy variable specifying each of these possible patterns provides the fullest possible set of controls for past labor market patterns. Of course, this specification is only feasible at relatively low levels of j.

(2) *Simple Lag Specification:* One of the simplest specifications for j lag periods is to include a dummy variable for each independent labor market state in each past year, which results in 2j lag parameters. For each lag period, this means including a dummy variable that controls for whether an individual was OLM and a dummy variable that controls for whether an individual was a part-time worker (full-time work status can always be derived from these two dummy variables). This specification assumes that the effect of each past labor market choice is independent of the pattern of choices that precede or follow it, so that multiple years in one state of the labor market have a simple additive effect on current labor market choices.

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[22]None of these lag structures interact past labor market choices with the other control variables, due to constraints on the number of parameters I can feasibly estimate. For instance, the effect of past education on the probability of working full-time may be different for someone who has been out of the labor market for the past three years.

(3) *Complex Lag Specification:* An alternative between the full and the simple lag specification is to control for the labor market state at each past point in time (the simple specification) as well as past patterns over time. With j lag periods, one can specify a set of 2(2j-1)+(j-2) dummy variables that completely distinguishes all possible past patterns, but imposes some adding up constraints. In particular, this means including all of the 2j dummies from the simple specification, as well as controlling for the total number of times that each state was observed over the past j periods (2(j-1)+(j-2) independent dummies). For example, with three lags, the complex lag specification would include 11 dummy variables:

$OLM_{t-1} = 1$ if person OLM in period t-1, 0 otherwise;
$OLM_{t-2} = 1$ if person OLM in period t-2, 0 otherwise;
$OLM_{t-3} = 1$ if person OLM in period t-3, 0 otherwise;
$PT_{t-1} = 1$ if person PT in period t-1, 0 otherwise;
$PT_{t-2} = 1$ if person PT in period t-2, 0 otherwise;
$PT_{t-3} = 1$ if person PT in period t-3, 0 otherwise;
$2OLM = 1$ if $OLM_{t-j} = 1$ in two of three past periods;
$3OLM = 1$ if $OLM_{t-j} = 1$ in three of three past periods;
$2PT = 1$ if $PT_{t-j} = 1$ in two of three past periods;
$3PT = 1$ if $PT_{t-j} = 1$ in three of three past periods;
$2FT = 1$ if $FT_{t-j} = 1$ in two of three past periods.

These 11 dummy variables can be used to uniquely characterize every one of the 27 possible past labor market states within a three period lag structure.

B. *Estimation Results*

Table 6 presents estimates of labor force choices, using two quite different lag specifications. Columns 1 and 2 present the results from a multinomial logit model with three lag periods, using a complex lag specification (11 lag parameters in each branch of the logit.) It will become clear below why I elect to focus particularly on this 3-lag structure. For comparison, columns 3 and 4 choose a very different lag structure, which uses information from the largest possible number of lags (13). As one adds lag periods, the number of usable observations shrinks. Thus, with 13 lags, I can use only the 1463 observations on labor market choices in 1989, while with 3 lags I can use 16,093 observations, using information from 11 years of labor market choices for each person. By necessity with this smaller number of observations, I use the simple lag specification for the 13-lag model. Thus, between these two models, we can see the trade-off between more lags (but a simpler lag structure and fewer observations) versus fewer lags (but more observations and a more complex lag structure.)

Many of the coefficients on the explanatory variables are similar in sign and magnitude between the first two and second two columns in table 6, although the coefficients estimated from the 3-lag model are much more significant. In both cases, older persons with less education, fewer total children, more preschoolers, more non-earned income, and in areas with higher unemployment rates are more likely to be out of the labor market than working full-time (the omitted category). Compared to full-time workers, part-timers are less likely to be black, and more likely to be older, married, and have more preschoolers.

Table 7 simulates the estimated effect of past labor market history on current labor market choices, using the coefficients from the 3-lag model estimated in columns 1 and 2 of table 6. Using a "typical" woman (age 25, white, high school education, married, 2 children, 1 preschooler, and $25,000 in non-earned income, with a county unemployment rate of 6.9 percent), the table simulates the probability that this women is currently out of the labor market, or working part-time or full-time, given all possible patterns of labor force involvement over the last three years.

Note three things in table 7. First, the most recent year's history is most important in determining current labor force status. For instance, women who were out of the labor market in the most recent past year (row 1 and rows 4-11) have over a 50 percent probability of being out of the labor market next year. Second, those persons with stable past labor market histories (rows 1-3) are strikingly more likely to continue in the same labor market state than even persons who have been in the same labor market state for the past 2 years (rows 4-5, 12-13, and 20-21). Third, in these estimates as in the simple tabulations, part-time work is a much more transitory state than OLM or full-time work.

The conclusion from table 7 is that time dependence in labor supply choices among adult women appears to be extremely strong, even after controlling for the standard set of household, skill, and economic factors. Further tests of the extent and nature of this time dependence are provided in table 8. Table 8 shows the likelihood function values that result from a series of increasingly more complex lag specifications, testing two different hypotheses about the importance of time dependence on labor supply choices. Part 1 of table 8 looks at the effect of controlling for longer lag periods, while part 2 looks at the effect of controlling more fully for all possible lag patterns within a given lag period.

Part 1 presents the log likelihood values and the related likelihood ratio tests that result as an increasing number of lag periods are included in the data set. For instance, the first row of part 1 indicates that going from a 7-period lag structure (using the complex lag model described above, with 32 lag parameters in each logit branch) to an 8 period lag structure—implemented on the same data--results in no significant increase in the likelihood function. This is true for 8 lags versus 7 lags, as well as for 7 lags versus 6 lags. Below 6 lags, however, dropping a lag period results in significantly worse explanatory value, particularly when moving from 3 to 2 lags or from 2 to 1 lags, as measured by the likelihood ratio test. This suggests that a great deal of past labor supply information is necessary (at least 6 years) before further past lag periods become unimportant in explaining current labor supply.

Part 2 of table 8 investigates the effect of controlling more completely for all past lag patterns, given a preset lag length. For models that include from 2 to 8 lags, the simple model (which assumes the effect of past labor market choices are additive over time) fits the data significantly worse than the complex model, which also includes controls for multiplicative effects. In turn, the complex model fits less well than the full interactive model for models that include 2 to 4 lags.[23] This section indicates that there is no "simple" specification of past lag patterns that fully captures their effects. Rather, increasingly complex models that control for as many past patterns as possible fit the data increasingly better.

The short summary of table 8 is that there does not appear to be any "short-cut" to dealing with time dependence in labor supply estimation, at least among adult women. The more lag periods (up to at least 6 years), and the more complex the lag specification, the better the model fits the data. The time dependence in labor supply is both "deep" (in the sense that past labor supply choices continues to affect current choices for many years), and "wide" (in the sense that all unique past patterns of labor supply choices appear to affect current choices; past patterns cannot be conveniently grouped together into only a few significant patterns.)

[23]The full model, with controls for every possible past lag pattern, cannot be readily implemented for more than 4 lags.

Taken together, the results in tables 7 and 8 also indicate that past labor market histories are crucially important in determining current labor market location for adult women. The coefficients on these past histories are large and significant in most cases. Simply observing information from a current labor market spell provides little predictive information about next year's labor market choices since different past labor market histories have such a strong effect on future choices. I return to this point below.

With respect to part-time work, tables 6 and 7 confirm many of the results noted above. The use of part-time work is heavily affected by personal and household characteristics. Even after controlling for these, however, part-time work remains a labor market state which women are more likely to leave. Among other things, this implies that the use of part-time work is harder to predict than are other labor market choices. Past use of part-time work is less likely to lead to future part-time work than are other types of labor market choices.

C. *Multinomial Logit Random Effects Models*

As noted above, one reason to include past lag histories in labor supply models is because they may reflect endogenous differences in women's preferences that create heterogeneous choices. This suggests that an alternative to a multinomial logit model of labor supply with lagged dependent variables is a multinomial logit model that controls for heterogeneity in the population through random effects.[24] In addition, it is worth noting that a random effects model may be the only feasible model when only cross-sectional data on labor supply are available. In this case, one interpretation of heterogeneity adjustments is that they are a way of controlling for the unmeasured (in cross-sectional data) differences in past labor market histories.

Assume there are two types of women, not fully accounted for by the control variables in these logit equations. A standard way of characterizing heterogeneity is assume that the constant term in the multinomial logit estimates differs across heterogeneous groups of individuals. The result is that the probability of being out of the labor market now becomes the more complicated expression:

$$(6)\quad Prob(LMS_t = O) = \begin{array}{c} P\dfrac{\exp(X_t\beta_1 + C_{11})}{1 + \exp(X_t\beta_1 + C_{11}) + \exp(X_t\beta_2 + C_{12})} + \\ (1-P)\dfrac{\exp(X_t\beta_1 + C_{21})}{1 + \exp(X_t\beta_1 + C_{21}) + \exp(X_t\beta_2 + C_{22})} \end{array}$$

[24]Both controlling for heterogeneity and including lagged dependent variables results in biased estimates of the heterogeneity, for the same reason that it is not appropriate to include heterogeneity corrections in duration models with information on past spells. The assumptions under which random effects models produce unbiased estimates do not hold in the presence of lagged dependent variables.

where P is an estimated coefficient equal to the probability of being a type 1 person,[25] while C_{11}, C_{12}, C_{21}, and C_{22} are the random effects parameters associated with being a type 1 or type 2 person in each branch of the logit.

In estimating this model, there is one additional complication. I have 14 observations on each person. In estimating the likelihood function for each individual, I need to take account of the fact that the probability of being a type 1 person is applied similarly to all 14 data periods. This implies that the likelihood function for any individual is maximized by estimating

$$(7)\ LLH= \begin{array}{l} P\left[\prod_{i\epsilon z}\frac{\exp(X_i\beta_1 + C_{11})}{DEN1}\prod_{j\epsilon p}\frac{\exp(X_j\beta_2 + C_{12})}{DEN1}\prod_{k\epsilon f}\frac{1}{DEN1}\right] + \\ (1-P)\left[\prod_{i\epsilon z}\frac{\exp(X_i\beta_1 + C_{21})}{DEN2}\prod_{j\epsilon p}\frac{\exp(X_j\beta_2 + C_{22})}{DEN2}\prod_{k\epsilon f}\frac{1}{DEN2}\right] \end{array}$$

where $DEN1 = 1 + \exp(X_t\beta_1 + C_{11}) + \exp(X_t\beta_2 + C_{12})$ and
$DEN2 = 1 + \exp(X_t\beta_1 + C_{21}) + \exp(X_t\beta_2 + C_{22})$ for any $t \in (z,p,f)$.

z is the set of all time periods during which this person is out of the labor market; p is the set of all time periods during which this person works part-time and f is the set of all time periods during which this person works full-time. Maximizing the log of this likelihood function across all individuals in

[25]This form of heterogeneity is admittedly quite arbitrary. I experimented with interacting the control variable coefficients and the random effects, but had problems making this more complex model converge.

the sample results in estimates for the vectors β_1, β_2, for the random effects terms C_{11}, C_{12}, C_{21}, C_{22}, and for the probability parameter, P. In the results below I estimate three random effects rather than two, which is a straightforward extension of the above model.

D. *Estimation Results from Random Effects Logit*

Columns 5 and 6 of table 6 presents the results from maximizing the log of a likelihood function similar to (7) for all individuals, but with three rather than two random effects. The coefficients indicate the effect of the relevant variable relative to the omitted (full-time) category. Thus, the first row indicates that older workers are more likely to be found out of the labor market or in part-time work, although the likelihood of being out of the labor market is higher than the likelihood of being in part-time work.

Compared to the estimated coefficients on the two lagged dependent variables models, shown in columns 1 through 4 of table 6, the random effects coefficients are different in a number of cases, in terms of size and significance. Lower education levels and more preschool children have particularly strong effects in keeping women out of the labor market in the random effects model.

Table 9 summarizes these estimates by simulating the probability of being in each labor market state for a typical woman of either type 1, 2, or 3, using the coefficients reported in columns 5 and 6 of table 6. Taking the same set of base personal and household characteristics as were used in the simulation in table 7, table 9 shows the differences in labor market choices predicted by the random effect model for women of each of the three types.

The probability of being a type 1 worker is estimated at 27 percent. Type 1 workers are mobile across all three labor market states, and have a significant probability of working part-time, working full-time or being out of the labor market. In contrast, type 2 workers have a very high probability of being out of the labor market (79 percent in the simulation in table 9) with less chance of working either part-time or full-time. The probability of being a type 2 worker is 30 percent. Finally, type 3 workers are almost always found working full-time. The probability of being a type 3 worker is estimated at 43 percent.

The broad characterization coming out of this random effects model is that there are three distinct labor market types: "workers," who typically work full-time; "non-workers," who are typically out of the labor market; and "movers" who migrate between all three of these states. There is a substantial probability mass associated with each of these three types. These results clearly suggest that some number of women appear permanently attached to full-time work, and some appear permanently out of the labor force. But a significant number (27 percent) are more mobile across labor market states.[26]

E. *How Do These Models Compare?*

The three models estimated in table 6 are based on three different conceptions of how to characterize female labor force choices. The 3-lag model assumes that a complex but relatively short lag specification is adequate, the 13-lag models opts for many lag periods but a simple lag specification, while the random-effects model ignores past labor market history and attempts to estimate the unmeasured heterogeneity in labor supply choices among women at any point in time. This section compares the advantages and disadvantages of each of these models.

Table 10 presents three different measures of the goodness of fit among these three models, based on a comparison of the actual data for 1463 women in 1989 (the last year of my sample) versus the estimated data from each of the three models for this year. Part 1 compares the aggregate predicted weight in each labor market category. In the actual data in 1989, 24 percent of the women are out of the labor market, 23 percent work part-time, and 52 percent work full-time. Taking the average predicted probabilities for

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[26]Although there are problems with interpreting the coefficients as noted above, I also estimated a multinomial logit model with both three years of lag information and with two random effects, allowing all of the lag parameters to vary in the random effects. This model indicates that even after controlling for three years of lags, some heterogeneity appears to remain in the data. In general, the two random effects indicate a group of "stayers" who remain in the same labor market state over time, and "movers" who change labor market states frequently.

each woman in the sample for each labor market state indicates that the 3-lag model predicts almost identical aggregate probability weights, while the 13-lag model is exactly right (to 1 decimal place.) The random effects model comes in third, but doesn't do too badly. A chi-squared test comparing each of these three model predictions to the actual data indicates that the null hypothesis that the predicted numbers are identical to the actual numbers cannot be rejected at a 10 percent level of significance for any of the three models.

In contrast to predicting the aggregate probability in each category, part 2 of table 10 compares how well each model predicts labor supply choices for each woman in the sample. The numbers indicate how many cases are predicted accurately by the model for each labor market category, where "accuracy" is defined as a predicted probability of 67 percent or greater that the woman will be in the labor market state where she is actually found. Among the 1463 observations, the 13-lag model accurately predicts the labor supply choices of 78 percent of the sample, while the 3-lag model is correct 74 percent of the time. The random effects model is substantially worse, with only 7 percent of the observations correctly predicted. This is because the random effects model assigns *every* woman some probability of being either type 1, type 2, or type 3. The result is that the predicted probabilities for each woman are a mix of the predicted types. While its aggregate probability weights are not too far off, the individual predictive ability of this model is extremely bad. In all three models, the probability that these individual predictions are identical to the null hypotheses can be rejected with 99 percent confidence. The chi-squared statistic for the random effects model is particularly large.

Finally, part 3 of table 10 does a more standard goodness of fit test, based on Heckman's (1984) suggested procedure for comparing a set of estimated sample values to a set of actual observations. Consistent with the other results, one cannot reject the null hypothesis that either the 13-lag model or the 3-lag model are similar to the actual data, while the null hypothesis that the random effects model is similar to the actual data is rejected with 99 percent certainty.

Two very important conclusions emerge from table 10. First, although the results in tables 7 and 8 emphasized the significance of extensive and fully specified lag patterns in fitting current labor supply choices, table 10 suggests that such complete specifications may not be necessary for good predictive value. In fact, the 3-lag model, estimated with a complex lag specification, predicts both the aggregate probability weight in each labor market state as well as actual individual choices almost as well as a model that includes another 10 lag periods. While there may be significant differences in the likelihood functions of these two models, the difference in their predictive values is quite small. I compared a number of alternative models, and the predictive value of including only two lags is noticeably worse, as is the predictive value of including three lags but with only a simple lag specification. In contrast, the value of including more than three lags, or of specifying that lag structure beyond the complex specification in table 6, columns 1 and 2, has little additional predictive value. Thus, having data on only a few lag periods is adequate for specifying time dependence in labor supply choices if one's primary intent is to predict labor supply choices at some future time or for some alternative sample of persons.

The second major conclusion from table 10 is that the value of controlling for past labor supply history depends heavily upon the purpose of the exercise. If you want to estimate the aggregate population weights, all three of these models are generally effective. In this case, using cross-sectional data with a random effects specification may be entirely satisfactory. If, however, you want to predict individual labor supply choices, then the availability of longitudinal and lagged information on labor supply is much more important, and the lagged models are far superior to random effects models.

VIII
Implications for Women's Labor Market Behavior: Some Simulated Results

Any of the estimates derived above can be used to simulate the behavior of women over time, estimating the probability that they will follow a particular sequence of labor market choices. This type of simulation may be particularly interesting with regard to the question "How do women move from out of the labor market into full-time work?" A number of policies in recent years have focused on moving women who receive public assistance into employment. In most cases, this means placing them in a part-time job. For instance, the welfare reform plan proposed by President Bill Clinton in summer 1994 requires eligible welfare recipients who do not find private sector work to work between 15 and 35 hours in an assigned public sector job. The hope is that this part-time work will increase their labor market connections and experience and, over time, will result in their moving into full-time self-sufficient employment. This section estimates a series of simulations that test whether moving women into part-time work is a reasonable approach, based on the historical experiences of adult women over the past two decades.

Table 11 presents simulation results for several low-skilled women. Assuming these women have been out of the labor market for the past two years, the simulations estimate the effect of moving into part-time or full-time work this year (as opposed to spending another year out of the labor force) on the probability of working part-time or full-time next year. All of these simulations are based on the coefficients estimated in the 3-lag model and shown in columns 1 and 2 in table 6. The first simulation is for a black woman without a high school degree, with two grade-school-age children, who is unmarried, age 25, and has only $2500 in non-earned income. The second simulation is for the same women but assumes that both of her two children are preschoolers. The third simulation assumes that the woman has a high school degree.

The first simulation indicates that if this woman stays out of the labor market one more year, the probability she will move into full-time or part-time work the following year is quite low (26 percent). If, however, she works part-time this year, there is almost a 50 percent probability she will remain a part-time worker next year and a 29 percent probability she will move into full-time work next year. If she works full-time this year, there is a 78 percent chance she will remain in full-time work next year.

Comparing the results in these simulation, there are two major conclusions. First, the personal and household characteristics of the individual matter enormously in her labor supply choices. The woman with preschoolers has a much lower probability of working full-time in the future, regardless of what she does this year. I emphasize this point because much of this paper has focused on coefficients other than those on the control variables. While past labor market histories are very important in predicting future labor market choices, the control variables are also important, particularly education level and number and age of children.

Second, if a woman has been out of the labor market for three years, moving into part-time work will substantially increase her probability of staying in the labor market the next year, but it will only somewhat increase her probability of moving into full-time work. The only way to substantially increase her future probability of full-time work is for her to work full-time this year. This is consistent with all of the evidence above: Few women use part-time work as a way to move from out of the labor market toward full-time work. Women who have been out of the labor market and move into part-time work are much more likely to leave the labor market or stay in part-time work than to move on to full-time work.

These simulations are only suggestive of the effects of a policy that mandates welfare recipients move into part-time work. They show the expected future labor market patterns among women over the past 14 years who have voluntarily moved into part-time work from an extended spell out of the labor force. As a result, one might believe that they substantially overstate the effect on future labor supply choices of mandatorily demanding that a woman take a part-time job. They do, however, underscore policy issues that deserve more consideration: According to these simulations, moving into part-time work substantially increase a woman's probability of being in the labor market in the future. If the goal of welfare-to-work programs is increased labor force participation, these simulations support the idea that current part-time work increases future labor force participation. If, however, the goal is to move women into economic self-sufficiency, which almost always requires full-time work, then it is less clear that mandating part-time work will help as much. Rather, the results in this paper suggest that women who move from out of the labor market into full-time work tend to make that leap immediately. At least historically, few women have either chosen or been able to put together a sequence of jobs that lets them move sequentially from out of the labor market, into part-time work, into full-time work.

IX
Conclusions

This paper analyzes the dynamics of adult women's labor market behavior over a 14-year period between 1976 and 1989. It uses several different techniques to investigate the nature and the pattern of labor supply choices made by women over time. The results indicate there is a substantial amount of labor market movement among individual women over these years, which is strongly correlated with personal characteristics and household demographic changes. The results also indicate the importance of analyzing longitudinal data in order to understand current labor supply choices among women. Women's current choices are strongly affected by their past labor market choices. Even information on labor supply choices as far back as 6 years helps explain current labor market behavior.

Yet, for those with more limited longitudinal data from which to explore labor supply choices, this paper indicates that models with only 3 years of lag information can predict individual and aggregate labor market involvement almost as well as models with more lag periods, if a relatively full specification of lag patterns is used. Models with less than 3-year lags or with only very simple controls for past lag structure are less adequate. In addition, random effects models, based only on current labor supply information, are also quite effective in predicting aggregate labor supply patterns, although they are very ill-suited for predicting individual labor supply decisions and do not fit the data as well as models controlling for past labor supply choices.

With regard to the use of part-time work in the labor market, this paper indicates that it is rarely used by women as a transitional labor market state. Most women use part-time work as an alternative to full-time work and return to full-time work after some period of part-time employment, or they enter part-time work from out of the labor market and then leave the labor market again after a part-time spell. There is little evidence here that placing women in part-time jobs will greatly increase their probability of moving into full-time employment over time.

Women show a far greater diversity in their labor supply choices than do men, and move between labor market states more frequently. This is the result of two groups of women in the labor market: A substantial number of women are extremely constant in their labor supply decisions, either working full-time or not working at all over many years. This heterogeneity in long-term behavior is one primary cause of diversity in labor supply choices among women. Another group of women, however, can be more readily characterized as "movers," and change labor market states with greater frequency. Thus, the diversity observed in female labor supply at any point in time is the result of both underlying stable heterogeneity in behavior among some, as well as extensive mobility across labor supply choices over time among others.

Further analysis of these issues might usefully focus in three areas. First, this paper contains little information on the nature of the jobs that women are taking. Given the evidence here on the heterogeneity among the part-time work force, it would be interesting to see what types of jobs are used by different groups of part-time women. Second, this paper necessarily aggregates labor supply decisions into three discrete labor market categories. By doing this, a great deal of information on labor supply choices is thrown away. Third, the econometric models used in this paper are limited in the extent to which they estimate intercorrelations between different labor market choices and in the ways in which labor market history is fed into the estimates. Attention to more complete econometric estimation procedures could provide a better understanding of the full set of interactions between past and present labor supply choices.

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TABLE 1
Two-Step Labor Market Transition Patterns

Year t	Year t+1: Out of Labor Market	Part-time	Full-time	Row Totals
	I. Adult Women			
Out of labor market				
% of total	21.6	4.0	2.4	28.0
% of row	77.1	14.3	8.7	
Part-time				
% of total	3.2	15.5	4.7	23.3
% of row	13.5	66.4	20.1	
Full-time				
% of total	2.7	4.2	41.8	48.7
% of row	5.6	8.7	85.7	
Column totals				
% of total	27.4	23.7	48.9	100.0
	II. Adult Men			
Out of labor market				
% of total	1.8	0.3	0.6	2.6
% of row	68.3	10.3	21.4	
Part-time				
% of total	0.2	1.7	2.2	4.0
% of row	4.1	42.1	53.8	
Full-time				
% of total	1.0	2.1	90.3	93.4
% of row	1.1	2.2	96.7	
Column totals				
% of total	3.0	4.1	93.0	100.0

Based on the sum of 13 two-year transition matrices, PSID data, 1976-1989. 19,019 observations on adult women; 16,523 observations on adult men.

TABLE 2

Three-Step Labor Market Transition Patterns Among Adult Women

Patterns in Years t and t+1	Year t+2			Row Totals
	Out of Labor Market	Part-time	Full-time	
Out of LM, Out of LM				
% of total	17.8	2.4	1.4	21.7
% of row	82.4	11.1	6.6	
Out of LM, Part-time				
% of total	1.2	2.3	0.6	4.1
% of row	29.5	55.6	14.9	
Out of LM, Full-time				
% of total	0.5	0.5	1.6	2.5
% of row	19.4	17.8	62.8	
Part-time, Out of LM				
% of total	1.9	1.0	0.4	3.2
% of row	58.2	29.9	12.0	
Part-time, Part-time				
% of total	1.5	11.4	2.5	15.4
% of row	9.6	73.9	16.5	
Part-time, Full-time				
% of total	0.4	1.1	3.2	4.7
% of row	8.1	23.8	68.1	
Full-time, Out of LM				
% of total	1.7	0.6	0.6	2.8
% of row	59.4	20.9	19.7	
Full-time, Part-time				
% of total	0.5	2.2	1.6	4.3
% of row	11.7	51.6	36.7	
Full-time, Full-time				
% of total	1.6	2.5	37.3	41.4
% of row	3.9	6.1	90.1	
Column Totals				
% of total	27.0	23.9	49.1	100.0

Based on the sum of 12 three-year transition matrices, PSID data on adult women, 1976-1989. 17,556 observations.

TABLE 3

Patterns of Labor Market Involvement Over 14 Years

(PSID data, 1976–1989)

	Adult Women	Adult Men	Adult Women Married 10 or More of 14 Years
1. Non-movers			
Percentage spending all 14 years			
Out of labor mkt	5.0	0.2	5.8
Part-time	1.1	0.2	1.3
Full-time	16.1	67.7	12.7
Total	22.2	68.1	19.8
2. Infrequent movers			
Percentage spending at least 10 years			
Out of labor market	14.5	0.9	16.3
Part-time	8.7	0.4	10.0
Full-time	37.0	93.3	31.0
Total	60.2	94.6	57.3
3. Percentage ever spending at least 1 year			
Out of labor market	64.5	13.9	69.5
Part-time	69.2	24.7	72.2
Full-time	84.6	99.5	82.3
4. Percentage in all 3 labor market states over 14 years			
	40.5	6.3	43.8
5. Percentage in exactly 2 labor market states over 14 years			
OLM/Part-time	9.3	0.1	10.6
OLM/Full-time	9.7	7.3	9.3
Part-time/Full-time	18.3	18.2	16.5
6. Percentage ever moving OLM → Part-time → Full-time			
Total percentage	20.9	1.3	21.7
Percentage of those who ever work part-time	30.2	5.1	30.1
7. Percentage ever moving Full-time → Part-time → OLM			
Total percentage	17.7	3.2	19.4
Percentage of those who ever work part-time	25.6	13.1	26.8
Number of observations	1,463	1,271	1,156

TABLE 4

Characteristics of Spells of Out of Labor Market, Part-time, and Full-time Work Among Women

(All Non-Left-Censored Spells Within the 14-Year Period)

	Spells Out of the Labor Market		Part-time Spells		Full-time Spells	
	All	Non-Censored	All	Non-Censored	All	Non-Censored
I. First Spells						
Number	731	571	925	801	859	584
Average length (years)	3.22	1.85	2.60	1.67	3.87	2.04
Ending in 1 year	43.0	62.9	49.0	70.9	36.7	60.6
2 years	16.8	15.9	17.9	12.0	17.6	17.0
3 years	11.5	9.3	10.2	7.5	8.4	7.2
4 years	5.6	5.1	6.6	4.1	6.9	5.0
5 years	3.8	2.6	5.7	3.1	5.4	2.9
6-8 years	10.3	4.2	6.0	2.01	0.4	6.0
9-13 years	8.0	—	4.0	0.2	11.9	1.3
II. Second Spells						
Number	286	202	436	333	379	197
Average length (years)	2.53	1.50	2.19	1.42	2.98	1.55
III. Third Spells						
Number	84	52	164	87	101	40
Average length (years)	2.10	1.21	2.14	1.33	2.37	1.13
IV. Fourth Spells						
Number	15	7	33	15	14	5
Average length (years)	1.00	1.00	.79	1.13	2.29	1.00
V. Fifth Spells						
Number	2	0	3	1	1	0
Average length (years)	1.50	—	1.67	1.00	1.00	—

TABLE 5

Determinants of Spell Length

Based on Semi-Parametric Competing Risk Models Using All Non-Left-Censored Spells

Personal and Family Variables:	Spells Out of the Labor Market		Part-time Spells		Full-time Spells	
	Exiting to		Exiting to		Exiting to	
	Part-time	Full-time	Out of LM	Full-time	Out of LM	Part-time
Age	-.013*	-.032**	.010*	-.009*	.005	.003
	(.007)	(.009)	(.007)	(.006)	(.008)	(.006)
Race (1=black)	-.226	.387*	.164	.131	.077	-.037
	(.199)	(.185)	(.203)	(.178)	(.190)	(.173)
Education less than high school	-.423**	-.097	.340*	-.130	.766**	-.233*
	(.159)	(.173)	(.158)	(.138)	(.166)	(.160)
Education equal to high school	-.176*	-.107	.240*	-.101	.195	-.080
	(.124)	(.155)	(.119)	(.107)	(.162)	(.117)
Married (1=yes)	.160	-.198	.081	-.229*	.377*	.071
	(.190)	(.178)	(.192)	(.129)	(.204)	(.134)
Total number of children	.117*	.151**	-.014	-.015	-.128*	.026
	(.051)	(.060)	(.051)	(.041)	(.061)	(.047)
Number of children under age 5	-.082	-.424**	.411**	-.268**	.480**	.152*
	(.078)	(.101)	(.078)	(.081)	(.104)	(.086)
Other (non-earned) income	-.002	-.006**	.001	-.004**	.003*	.001
	(.002)	(.001)	(.001)	(.001)	(.002)	(.002)
County unemployment rate	.039*	-.008	.010	.018	.047*	.034*
	(.018)	(.023)	(.016)	(.015)	(.021)	(.017)
Spell History Variables:						
Previous spell type (Col 1&2: P-Time, Col 3-6: Out of LM)	.272**	-.362**	.675**	-.596**	.882**	-.252*
	(.108)	(.132)	(.111)	(.095)	(.136)	(.111)
Number of spell	.056	-.149*	-.100*	-.149**	-.139	-.149*
	(.079)	(.109)	(.072)	(.063)	(.110)	(.080)
Number of shape parameters	7	7	7	7	7	7
Likelihood value	-2360		-3250		-2563	
Number of observations	1118		1561		1354	

* Significant at 10% level; **Significant at 1% level. Standard errors in parentheses.

TABLE 6
Logit Models of Dynamic Labor Market Choices

	Logit Model with 3 Lags		Logit Model with 13 Lags		Logit Model with 3 Random Effects	
	Out of Labor Market	Part-Time	Out of Labor Market	Part-Time	Out of Labor Market	Part-Time
Age	.032**	.006*	.073**	.014	.047**	.027**
	(.004)	(.004)	(.019)	(.016)	(.002)	(.002)
Race (1=black)	-.030	-.244**	.903*	-.581*	.080*	-.460**
	(.102)	(.096)	(.456)	(.379)	(.057)	(.057)
Education less than high school	.575**	.099	.201	.201	1.294**	.137**
	(.088)	(.083)	(.428)	(.340)	(.049)	(.049)
Education equal to high school	.248**	- .014	.504*	.290	.970**	.193**
	(.073)	(.065)	(.333)	(.251)	(.040)	(.039)
Married (1=yes)	.438**	.344**	.071	.355	.521**	.247**
	(.094)	(.077)	(.418)	(.303)	(.055)	(.050)
Total number of children	-.074**	.017	-.155	-.004	.275**	.295**
	(.031)	(.026)	(.175)	(.128)	(.015)	(.015)
Number of children under age 5	.698**	.277**	.345	.474*	1.127**	.363**
	(.053)	(.049)	(.393)	(.318)	(.030)	(.031)
Other (non-earned) income	.006**	.004**	.003	-.001	.018**	.015**
	(.001)	(.001)	(.003)	(.002)	(.001)	(.001)
County unemployment rate	.025**	.007	.058	.024	.043**	.028**
	(.011)	(.009)	(.094)	(.079)	(.007)	(.007)
Constant	-5.758**	-3.635**	-7.557**	-4.196*	3 separate constants estimated in each column, for each of three random effects	
	(.230)	(.180)	(1.160)	(.975)		
Number of parameters for past lag patterns	11	11	26	26		
					Prob(type 1) = .271 (.013)	
					Prob(type 2) = .299 (.013)	
					Prob(type 3) = .430 (.014)	
Number of observations	16093		1463		20482	
Likelihood function	-9223		-667		-15111	

Standard errors in parentheses.

**Significant at the 1 percent level.

* Significant at the 10 percent level.

TABLE 7

Simulated Probabilities of Labor Market Choices Conditional on Past Labor Market Patterns

(Based on coefficients estimated in columns 1 and 2 of table 6)

Labor Supply Pattern in Years t-3, t-2, and t-1	Probability in Year t That Woman is		
	Out of Labor Market	Part-Time	Full-Time
1. OOO	82.3	11.7	6.0
2. PPP	6.6	78.4	15.0
3. FFF	3.0	6.1	90.9
4. POO	65.6	25.0	9.4
5. FOO	69.4	16.9	13.7
6. OPO	58.2	31.6	10.3
7. PPO	51.1	38.6	10.2
8. FPO	50.7	31.1	18.1
9. OFO	61.4	19.0	19.6
10. FFO	57.6	19.9	22.5
11. PFO	49.4	27.3	23.2
12. OPP	17.6	69.9	12.5
13. FPP	8.9	68.2	22.9
14. OOP	28.5	57.0	14.5
15. POP	22.9	63.9	13.2
16. FOP	23.2	52.7	24.0
17. FFP	9.9	54.2	35.9
18. PFP	8.9	61.0	30.1
19. OFP	18.0	52.0	30.0
20. OFF	14.2	14.6	71.1
21. PFF	5.8	18.0	76.2
22. OOF	23.5	17.0	59.5
23. POF	16.6	21.4	62.0
24. FOF	20.4	16.4	63.1
25. PPF	6.9	29.6	63.5
26. FPF	6.9	24.0	69.1
27. OPF	13.5	24.6	61.9

Estimates based on coefficients reported in columns 1 and 2 of table 7. The base individual for these simulations is a 25 year old married white women, with a high school degree and two children, 1 under the age of 5, with other income of $25,000 and a county unemployment rate of 6.9 percent.

O: Out of Labor Market
P: Part-time Work
F: Full-time Work

TABLE 8

Effect of Including more Lag Information on the Fit of a Multinomial Logit Model

1. Effect of including more years of lagged information

t= Number of Lag Years	Log Likelihood Function[1] Controlling for		Likelihood Ratio Test[2]	Number of Observations
	t Lags	t-1 Lags		
8	-4659.6	-4662.1	5.0	8778
7	-5504.9	-5507.9	6.0	10241
6	-6381.6	-6405.8	48.4**	11704
5	-7294.6	-7316.3	43.4**	13167
4	-8225.3	-8283.9	117.2**	14630
3	-9222.6	-9378.0	310.8**	16093
2	-10325.0	-10776.1	902.2**	17556

2. Effect of controlling more fully for the lag pattern

t= Number of Lag Years	Log Likelihood Function Based On			Likelihood Ratio Test[3]	
	Simple Model	Complex Model	Full Model	Simple-Complex	Complex-Full
8	-4690.4	-4659.6	—	61.6**	—
7	-5542.6	-5504.9	—	75.4**	—
6	-6340.2	-6381.6	—	82.8**	—
5	-7342.5	-7294.6	—	95.8**	—
4	-8271.4	-8225.3	-8187.5	92.2**	75.6**
3	-9272.9	-9222.6	-9202.8	100.6**	39.6**
2	-10334.5	-10325.0	-10316.1	19.0**	17.8**

SIMPLE MODEL includes 2t lag parameters, with a dummy variable for the labor market state in each past year (only two dummy variables per year are needed, since the third state is known once the first two states are known.) For a 3-lag model, this means including a dummy variable for OLM_{t-1}, OLM_{t-2}, OLM_{t-3}, PT_{t-1}, PT_{t-2}, and PT_{t-3}.

COMPLEX MODEL includes 2(2t-1)+(t-2) lag parameters, with a dummy variable for the labor market state in each past year [2t parameters] plus a dummy variable for the number of total times each state occurs [2(t-1)+(t-2) independent parameters]. This model is able to distinguish between all possible past patterns, although it imposes certain adding up constraints. For a 3-lag model, this means including the same dummies as in the simple model, as well as dummies variables if two of the three years are OLM, if three of the three years are OLM, if two of the three years are PT, if three of the three years are PT, and if two of the three years are FT.

FULL MODEL includes t^3 lag parameters, with a dummy variable for each possible past pattern.

[1]Uses complex model, described above.

[2]Chi-squared with 5 degrees of freedom.

[3]Chi-squared, with varying degrees of freedom for each row and column.

**Significantat the 1 percent level.

TABLE 9

Simulated Probabilities of Labor Market Choices From Random Effects Model

(Based on coefficients estimated in columns 5 and 6 of table 6)

Estimated Type	Probability in Year t that Woman is: Out of Labor Market	Part-Time	Full-Time	Probability Associated This Type
Type 1	22.3	56.4	21.3	27.1
Type 2	79.2	10.6	10.2	29.9
Type 3	9.1	8.7	82.1	43.0
Aggregate Probabilities	33.7	22.2	44.1	

Estimates based on coefficients reported in columns 1 and 2 of table 7. The base individual for these simulations is a 25 year old married white woman, with a high school degree and two children, 1 under the age of 5, with other income of $25,000 and a county unemployment rate of 6.9 percent.

TABLE 10
Comparison of Model Effectiveness

1. Aggregate predicted weight in each labor market state

	Out of Labor Market	Part-Time	Full-Time	χ^2 Test of Similarity Between Actual and Predicted
a. Actual data	24.5	23.2	52.2	
b. 3-lag model	24.4	23.5	52.0	a vs b: 0.01
c. 13-lag model	24.5	23.2	52.2	a vs c: 0.00
d. Random effects model	25.7	24.5	49.7	a vs d: 0.25

2. Number of accurately predicted individual data points (Of 1463 observations, number where the model predicted a greater than 67 percent probability that the individual would be in the correct labor market state.)

	Total	Out of Labor Market	Part-Time	Full-Time	χ^2 Test of Similarity
a. Actual data	1463	359	340	764	
b. 3-lag model	1087	264	170	653	a vs b: 126.3**
(percentage correct)	(74.3)	(73.5)	(50.0)	(85.4)	
c. 13-lag model	1136	279	193	664	a vs c: 94.5**
(percentage correct)	(77.6)	(77.7)	(56.8)	(86.9)	
d. Random-effects model	108	6	0	102	a vs d: 1260.7**
(percentage correct)	(7.4)	(1.7)	(0.0)	(13.4)	

3. Goodness-of-fit test (Heckman)

	χ^2 Test of Similarity to Actual Data
a. 3-lag model	0.19
b. 13-lag model	0.03
c. Random-effects model	13.85**

Based on estimates from the three models shown in table 6, using the 14th year of data (1989) with 1463 observations.

**Significantlydifferent at 1 percent level.

TABLE 11

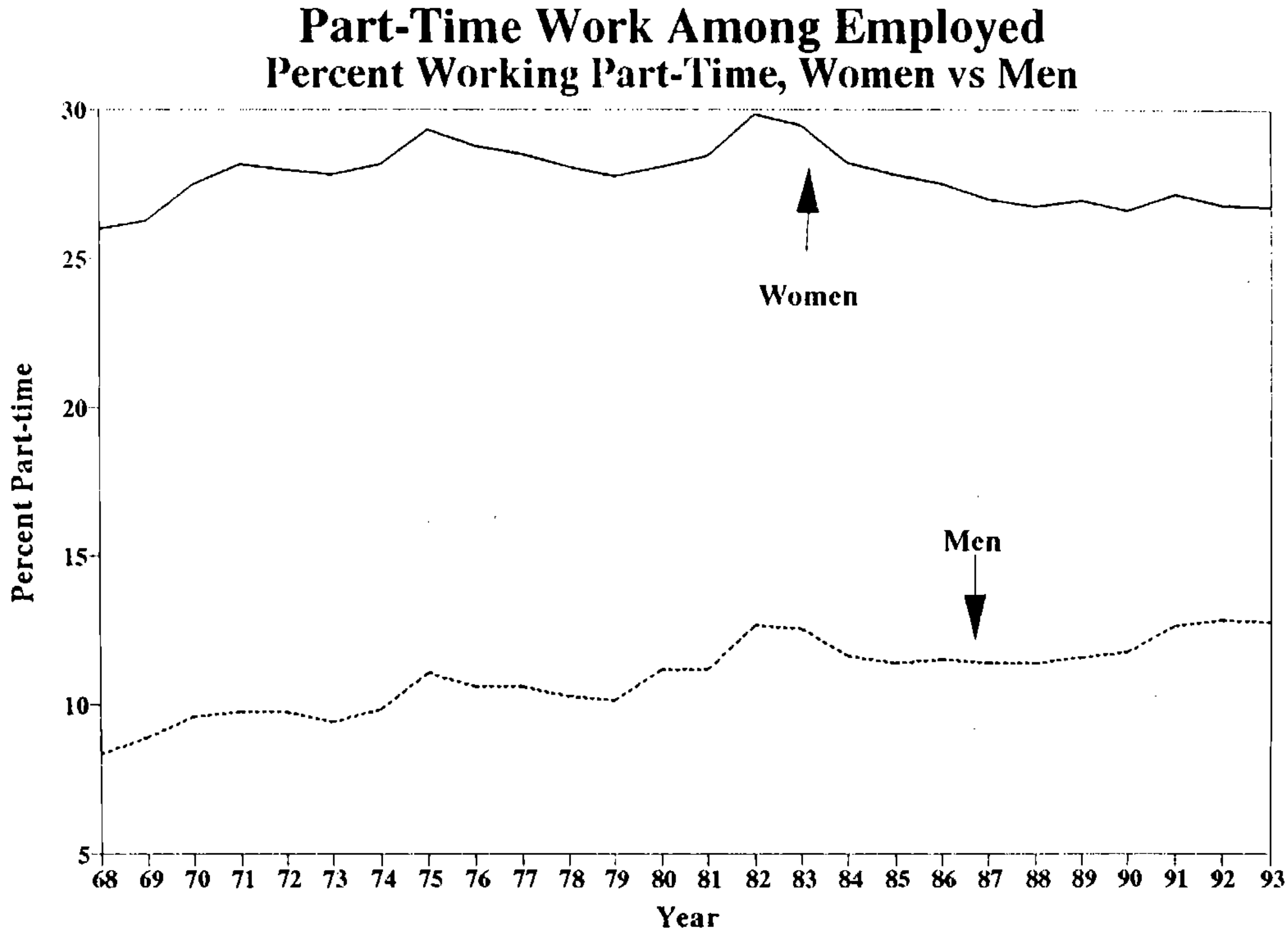
Simulated Probabilities of Moving from Out of the Labor Market into Full-Time Work for a Low-Skilled Woman

For a woman who has been out of the labor market two years, her probable labor market status next year depends on what she does this year:

Past 2-Year Pattern	Elected Pattern This Year	Probabilities for Next Year Conditional on Status this Year		
		Out of Labor Market	Part-Time	Full-Time
1. Person 1 Characteristics: Black woman, age 25, unmarried, 2 children, no preschoolers, high school dropout, non-earned income=$2500, county unemployment rate=6.9.				
OLM-OLM	OLM	73.8	12.0	14.2
OLM-OLM	PT	21.6	49.4	29.0
OLM-OLM	FT	11.8	9.7	78.5
2. Person 2 Characteristics: Same as person 1, but both children are preschoolers.				
OLM-OLM	OLM	89.5	6.3	4.3
OLM-OLM	PT	43.1	42.5	14.3
OLM-OLM	FT	33.3	11.8	54.9
3. Person 3 Characteristics: Same as person 1, but with high school education.				
OLM-OLM	OLM	68.1	13.8	18.2
OLM-OLM	PT	17.5	49.8	32.7
OLM-OLM	FT	8.9	9.1	82.0

Simulations based on coefficients from the 3-lag model shown in columns 1 and 2 of table 6.

Figure 1



Part-Time Work Among Employed
Percent Working Part-Time, Women vs Men
Percent Part-time
30
25
20
15
10
5
68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93
Year
Women
Men

Figure 2

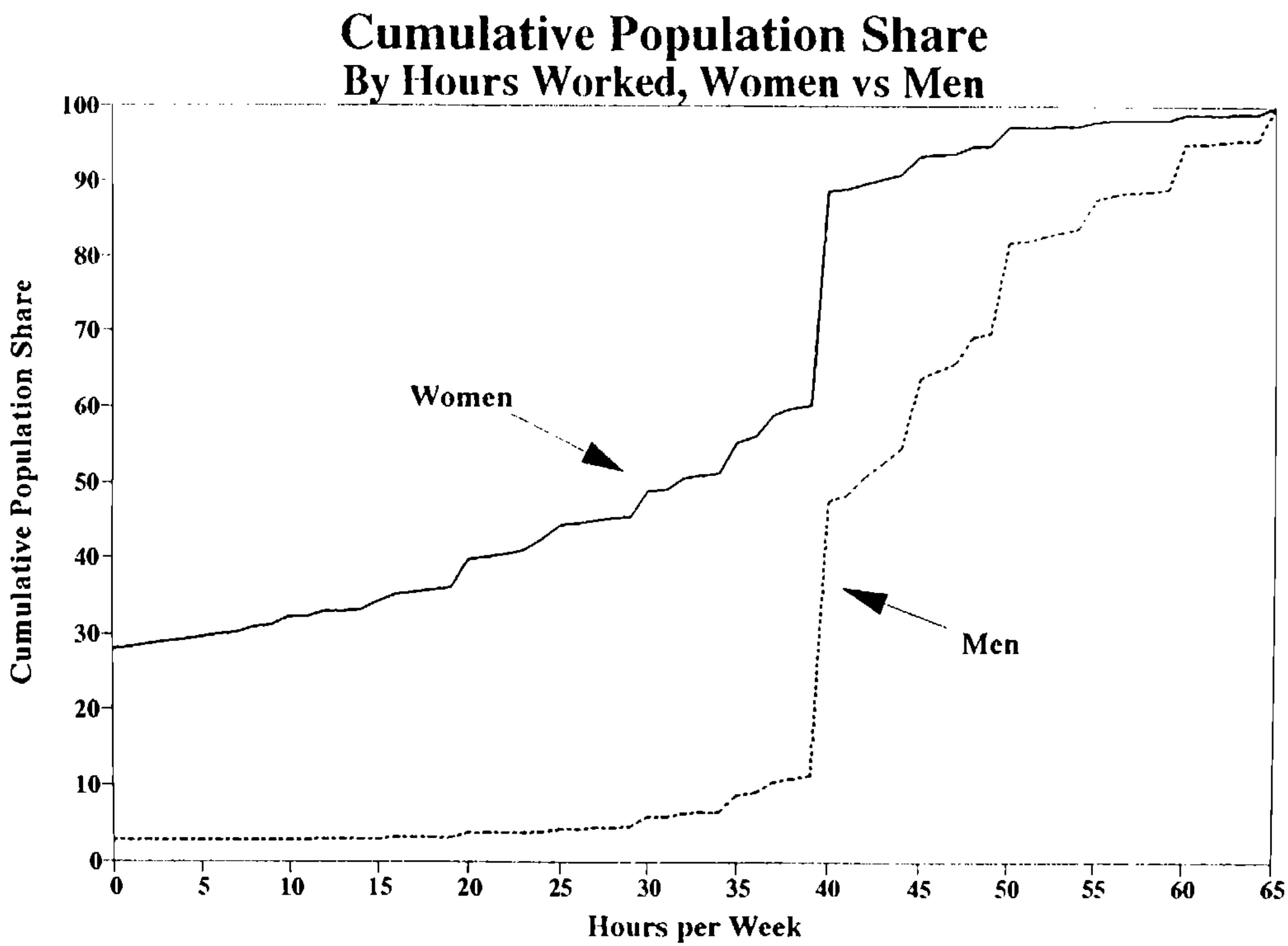
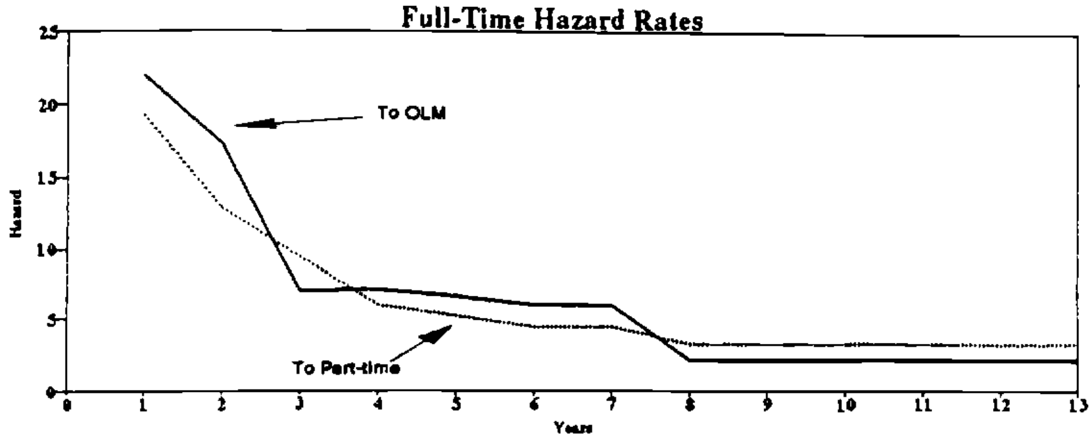
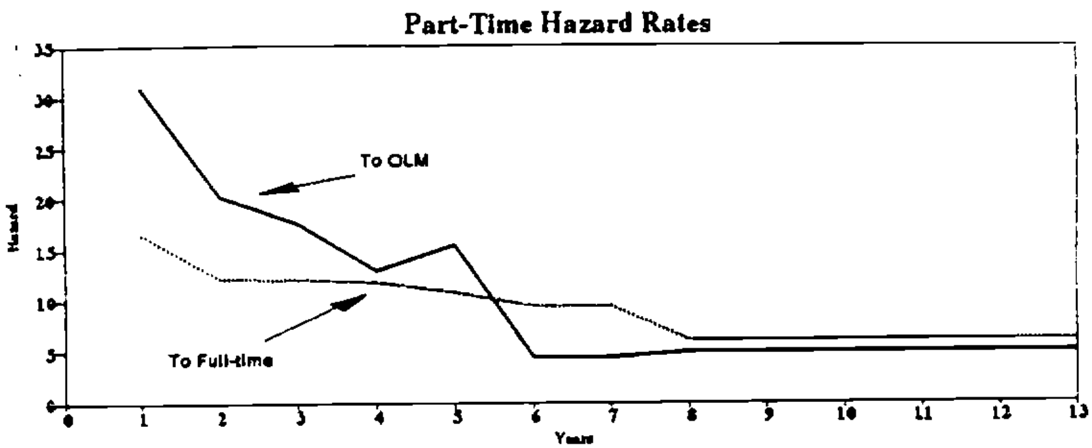
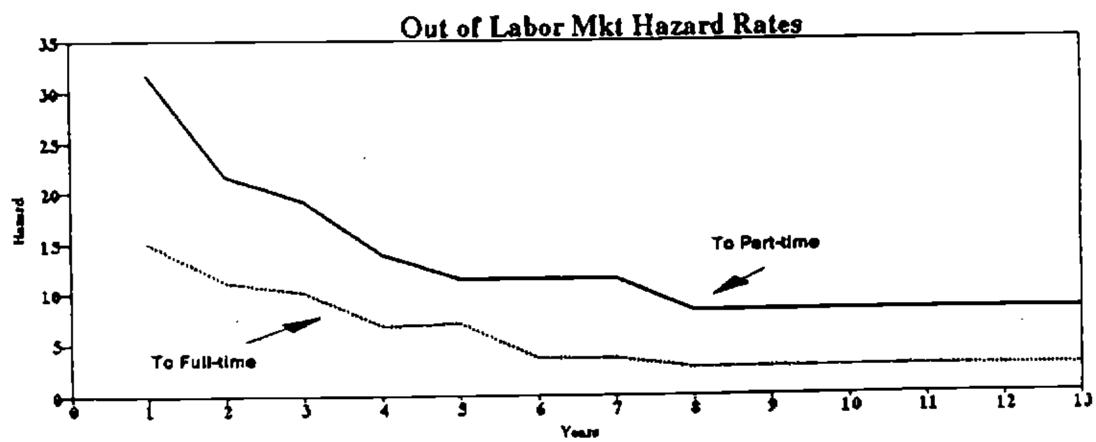

Cumulative Population Share
By Hours Worked, Women vs Men
Cumulative Population Share
Hours per Week
Women
Men
0
10
20
30
40
50
60
70
80
90
100
0
5
10
15
20
25
30
35
40
45
50
55
60
65

Figure 3


Full-Time Hazard Rates
To OLM
To Part-time
Hazard
Years
25
20
15
10
5
0
0
1
2
3
4
5
6
7
8
9
10
11
12
13


Part-Time Hazard Rates
To OLM
To Full-time
Hazard
Years
35
30
25
20
15
10
5
0
0
1
2
3
4
5
6
7
8
9
10
11
12
13


Out of Labor Mkt Hazard Rates
To Part-time
To Full-time
Hazard
Years
35
30
25
20
15
10
5
0
0
1
2
3
4
5
6
7
8
9
10
11
12
13

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