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THREE PAPERS ON ECONOMIC JUSTICE AND FAIRNESS

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Abstract

This dissertation comprises three essays on economic justice and fairness. The first chapter investigates the effect of job continuity on new mothers' labor supply following their first childbirth. The second chapter studies the impact of wages and other factors on women's work duration after childbirth. The third chapter analyzes the effect of disability within the family on the financial satisfaction of the female head or spouse.

Chapter 1 investigates the effect of job continuity on the supply of labor of new mothers for the five-year period after their first childbirth. Using the National Longitudinal Survey of Youth 1997 (NLSY97), we extend the beta-logistic model of Heckman and Willis (1977) to a higher-dimensional Dirichlet generalized ordered logit (DGOL) model. This approach considers heterogeneity in employment choices. The DGOL model nearly doubles the predictive accuracy of the standard generalized ordered logit model. Our study finds that working full-time in any given period increases the likelihood of continuing full-time work in the next year by 65 percent. The findings also suggest the importance of job continuity: a higher job continuity probability increases full-time employment rates by over 10 percent, offsetting potential drawbacks of lower education and older age.

Chapter 2 incorporates a control function approach to study the duration of women's work after childbirth. Maternity leaves allow mothers to return to the labor force after giving birth without having to find a new job at a potentially lower wage rate. Contrary to expectations, recent research, such as Bailey et al. (2019), suggests that California's paid leave program has had limited impact on women's labor market outcomes. Traditional labor

market models often suffer from bias due to the endogeneity of wages and unobserved variables. Building on the methodological framework set by Petrin and Train (2005, 2006), this chapter introduces an innovative duration analysis technique. This approach incorporates instrumental variables via control functions to examine job attachment after childbirth using U.S. data from NLSY97. Our empirical findings reveal a that the effect of wages on job attachment and the baseline hazard for leaving the job both increase substantially when we use information about maternity leave as an instrument for missing employment conditions.

In Chapter 3, we examine the effect of disability in the family on financial satisfaction of the female head or spouse using the Panel Study of Income Dynamics. This empirical work is based on the theoretical work on the capability approach developed primarily by Amartya Sen and Martha Nussbaum, which emphasizes the presence of capabilities as opposed to actual outcomes. Following the empirical work of Kuklys (2005), we estimate a probit of financial satisfaction on log income, disability variables, and variables representing other capabilities. We find that the loss in financial satisfaction due to disability in the United States is substantially greater than the corresponding loss in Britain. Point estimates suggest that conversion factors for disability reduce effective income by as much as 60 percent for male heads and 70 percent for female heads. These figures are over and above the direct income loss due to reduced labor market opportunity.

THREE PAPERS ON ECONOMIC JUSTICE AND FAIRNESS

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Chapter 1

A Dirichlet Generalized Ordered Logit Analysis of Women's Labor Supply after Childbirth

1.1 Introduction

Labor force participation rates of women decline after the birth of their first child (Bianchi 2000; Gornick and Meyers 2003). New mothers may need to balance career with increased domestic responsibility. Maternity leave legislation can help with this task by replacing lost wages and salary and by providing job continuity, which maintains firm-specific human capital. This study investigates how job continuity affects future labor market outcomes for new mothers. We take into account that labor supply displays significant persistence at the individual level (Heckman and Willis 1977; Heckman 1981; Alison L Booth, Stephen P Jenkins and Carlos Garcia Serrano 1999; Hyslop 1999; Francesconi 2002; Seetharaman 2004; Haan 2010; Jia and Vattø 2021).

Persistence in labor market outcomes may arise because of true state dependence, where an individual's past employment outcomes determine current labor supply. Observed persistence may also arise because of unobserved heterogeneity, also called spurious state dependence, where the presence of factors not observed in the data determine labor force participation through time. Ignoring the presence of persistence in labor market outcomes may lead to erroneous inferences about the population and faulty design of policy[1] (Prowse 2012).

Observed outcomes (Figure 1.1) in the National Longitudinal Survey of Youth 1997 (NLSY97) show that, in the year after the birth of the first child, 40 percent of women work full-time, 40 percent work part time, and 20 percent do not work. The data show that 80 percent of new mothers who worked full-time in the year after the birth of their first child continued to work full-time in the second year after the birth, 56 percent who worked part-time in the first year also worked part-time in the second year, and 68 percent who did not work in the first year also did not work in the second year.

To capture the impact of unobserved heterogeneity, our empirical analysis builds on the beta-logistic framework developed by Heckman and Willis (1977), who study the two choices of participating and not participating. A bete-logistic model is discussed by Kennan (1985) in the context of contract strikes in US manufacturing and is mentioned by Even (1987), who study the effect of interruptions in women's careers. Since the balancing of career and care of the child may involve a choice that combines labor force participation and care of child at home, we construct a Dirichlet generalized ordered logit (DGOL) model to be able to include three ordered choices: full-time work, part-time work, and no work.

We hypothesize that job continuity for working new mothers is an important determinant of these labor market outcomes. Mincer and Polachek (1974) analyze family investiment in human capital and specially discuss a new mother's time spent home after birth of the first

[1] The United States is the only member of the Organisation for Economic Co-operation and Development (OECD) that does not have a national paid family leave program. As of now, nine states and the District of Columbia have established or are on the path to implement paid family and medical leave programs. Nonetheless, barriers to access these benefits remain. A few states have strict eligibility criteria based on work tenure, hours worked, or the size of the employer. Some states offer limited benefits that don't sufficiently address the needs of low-wage workers. Several state programs do not provide robust job protection for paid family leave. Consequently, job protection after childbirth may assist career-oriented women in returning to work and accumulating more human capital.

child. They examine two important aspects of the new mother's wage, the depreciation of human capital during the time spent home and the loss of human capital accumulation while looking for a new job, recognizing that these potential decreases in human capital must be compared to the benefits of staying at home with the child.

Martha J Bailey, Tanya S Byker, Elena Patel and Shanthi Ramnath (2019) analyze the 2004 California Paid Family Leave Act (PFLA) and find little evidence that PFLA increased women's employment, wage earnings, or attachment to employers. For new mothers, taking up PFLA reduced employment by 7 percent and lowered annual wages by 8 percent six to ten years after giving birth. The absence of job protection within the legislation (Julia Isaacs, Olivia Healy and H Elizabeth Peters 2017) is a possible explanation for this. Women who give up their jobs after childbirth must take the time to find satisfactory re-employment before they can continue with their careers. Failure to do so may result in these new mothers dropping out of the labor force entirely.

In a pre-sample analysis we estimate the probabilities of returning to the same employer and returning to a different employer within the first year after childbirth. We use these estimates in a DGOL model of choosing to work full-time, part-time, or not at all for the five subsequent years. To preview the results, our findings indicate that engaging in full-time work increases the likelihood of maintaining full-time employment in the following year by 65 percent. Our study also reveals that maintaining job continuity within the first year after childbirth significantly increases full-time employment rates by over 10 percent. Additionally, full-time employment rates for low-educated mothers and older mothers are lower than the average population. Nevertheless, a higher probability of returning to previous employer mitigates these adverse effects on their full-time employment.

Compared to the existing literature, our study makes four primary contributions. First, we extend the consideration of state dependence and unobserved heterogeneity to a high-dimensional framework for ordered choices. Second, we apply this newly-developed methodological approach to evaluate women's labor force participation after childbirth and the connection between job continuity and employment decisions, addressing issues of reverse causality and correlated unobserved heterogeneity. Our DGOL model reveals significant unobserved heterogeneity among women following childbirth resulting in substantial state dependence in employment status. Additionally, the DGOL significantly outperforms traditional models like generalized ordered logit and ordered logit in predictive accuracy, with an accuracy rate approximately twice as high as those of the latter two models. Third, given the impracticality of conducting random experiments, our structural model allows us to separately identify the causal impact of previous employment on current employment decisions, thus complementing the reduced-form literature. We find that engaging in full-time work in any period enhances the probability of continuing full-time employment in next year by 65 percent. Finally, we use the estimated parameters to simulate a variety of policy counterfactuals in different scenarios and for various groups of mothers. These policy counterfactuals shed light on the importance of existing maternity leave, paid family leave policies, and corresponding job protection policies.

The remainder of this figure is organized as follows. Section 1.2 presents the econometric theory. Section 1.3 presents the data. The empirical results are given in section 1.4 which also includes counterfactual experiments on the effect of job continuity on women's subsequent employment. Conclusions are given in section 1.5.

1.2 Methodology

1.2.1 The Ordered Logit and Generalized Ordered Logit Models

Techniques such as ordinary least squares regression require that outcome variables have interval or ratio level measurement. The most exact measurement of labor force participation is hours of work, which is a ratio level variable. Because the ratio of values are meaningful (for example, working 1000 hours per year means working twice as much as 500 hours per year), we prefer to use desired hours of work rather than actual hours of work. Shorter periods of non-employment or unemployment should not distinguish the level of labor force attachment. Therefore, we will create an ordinal variable based on ranges of hours of work. When the outcome variable is ordinal, the most popular method is the ordered logit model, also known as the proportional odds model (Williams 2016).

In mathematical terms, let Y represent an ordinal dependent variable with J levels of labor force participation. The ordered logit model assumes that Y changes when an unobserved continuous latent variable, Y^* crosses certain thresholds. In our study, we categorize women's employment status as full-time ($Y_i = 3$), part-time ($Y_i = 2$), or not working ($Y_i = 1$), underpinned by the latent variable of their utility, which is determined by their anticipated working hours and characteristics. So, we have three levels ($J = 3$) and two thresholds:

$$\mathrm{P}\left(Y_i > j\right) = \frac{\exp\left(\alpha_j + z_i'\beta\right)}{\left(1 + \exp\left(\alpha_j + z_i'\beta\right)\right)}, \; j = 1, 2 \quad , \tag{1.1}$$

where z_i is a vector of covariates. Using equation (1), we can write the three probabilities as:

$$\begin{aligned} P(Y=1) &= \frac{1}{\left(1 + \exp\left(\alpha_1 + z_i'\beta\right)\right)} \\ P(Y=2) &= \frac{\exp\left(\alpha_1 + z_i'\beta\right)}{\left(1 + \exp\left(\alpha_1 + z_i'\beta\right)\right)} - \frac{\exp\left(\alpha_2 + z_i'\beta\right)}{\left(1 + \exp\left(\alpha_2 + z_i'\beta\right)\right)} \quad . \\ P(Y=3) &= \frac{\exp\left(\alpha_2 + z_i'\beta\right)}{\left(1 + \exp\left(\alpha_2 + z_i'\beta\right)\right)} \end{aligned} \tag{1.2}$$

The ordered logit model relies on a strong assumption known as the parallel lines or proportional odds assumption. This assumption dictates that the relationship between the predictor variables and the ordinal response variable is consistent across all levels of the response variable. In other words, the coefficient vector is assumed to be constant across all thresholds.

Violating this assumption could lead to inconsistnet estimates. To illustrate this with our labor-force participation example, one could conceptualize two binary logit submodels: 1) ‘no work’ versus ‘some work’, and 2) ‘less than full-time’ versus ‘full-time’. The ordered logit model assumes that the odds ratios are equal across these submodels. But in reality, the odds ratios could differ between these scenarios. For example, the level of education might have a different influence on transition from ‘no work’ to ‘some work’ than when moving from ‘less than full-time’ to ‘full-time’ employment.

The generalized ordered logit model relaxes the parallel lines assumption. The proportional odds are allowed to vary across submodels. The formulation of this model is given by:

$$\mathrm{P}\left(Y_i > j\right) = \frac{\exp\left(\alpha_j + z_i'\beta_j\right)}{\left(1 + \exp\left(\alpha_j + z_i'\beta_j\right)\right)}, \; j = 1, 2. \tag{1.3}$$

A test devised by Brant (1990) can be used to determine whether the observed deviations from what the proportional odds model predicts are larger than what can be attributed to chance alone.

1.2.2 The Dirichlet Generalized Ordered Logit Model

Although the generalized ordered logit model relaxes the parallel lines assumption, it still has some limitations and drawbacks. Both the ordered logit and generalized ordered logit models assume that the odds are homogeneous within the population for a given set of covariate values. If the homogeneity of odds assumption is violated, it can lead to inconsistent estimates.

One remedy is to consider higher order moments. Let the probabilities of women’s labor force participation of no work, part-time job and full-time job be $\pi_1,\ \pi_2, \pi_3$ with $\pi_1 + \pi_2 + \pi_3 = 1$. Then the probabilities that a woman does not work for x_1 years, works part time for x_2 years, and works full time for x_3 years out of total T years are:

$$P\left(x_1, x_2, x_3, T\right) = \frac{T!}{x_1! x_2! x_3!} \pi_1^{x_1} \pi_2^{x_2} \pi_3^{x_3} \quad . \tag{1.4}$$

The expected probability of women's labor supply, taking into account their prior labor force participation is:

$$E\left[P\left(x_1, x_2, x_3, T\right)\right] = \int \frac{T!}{x_1!x_2!x_3!}\pi_1^{x_1}\pi_2^{x_2}\pi_3^{x_3}f(\boldsymbol{\pi})d\boldsymbol{\pi} \quad , \tag{1.5}$$

where $f(\boldsymbol{\pi})$ represents the density function of $(\pi_1,\ \pi_2,\ \pi_3)$, In this work, we assume $f(\boldsymbol{\pi})$ is the Dirichlet distribution density:

$$f(\boldsymbol{\pi}) = \frac{1}{B(\alpha_1, \alpha_2, \alpha_3)}\pi_1^{\alpha_1-1}\pi_2^{\alpha_2-1}\pi_3^{\alpha_3-1} \quad , \tag{1.6}$$

where the parameter vector $(\alpha_1, \alpha_2, \alpha_3)$ has positive components, $B(\alpha_1, \alpha_2, \alpha_3) = \frac{\Gamma(\alpha_1)\Gamma(\alpha_2)\Gamma(\alpha_3)}{\Gamma(\alpha_1+\alpha_2+\alpha_3)}$ is the beta function, and $\Gamma(\cdot)$ is the gamma function with $\Gamma(\alpha) = \int_0^1 t^{\alpha-1}e^{-t}dt$.

The Dirichlet distribution is an attractive choice of functional form for the responding probability of $(\pi_1,\ \pi_2,\ \pi_3)$ for several reasons. First, the range of the Dirichlet distribution is from 0 to 1. Second, it has relatively few parameters, one for each of the random components. The parameters $\alpha_1,\ \alpha_1,\ \alpha_3$ govern the shape of the distribution. When $\alpha_1 = \alpha_2 = \alpha_3 = 1$, the data points are uniformly distributed across the simplex, corresponding to a three-dimensional uniform distribution (as shown in 1.2(a)). When $\alpha_1 < 1$, $\alpha_2 < 1$, $\alpha_3 < 1$, the data points tend to cluster at the corners and edges of the simplex, creating ageneralized U-shaped distribution in three dimensions (see Figure 1.2(b)). When $\alpha_1 > 1$, $\alpha_2 > 1$, $\alpha_3 > 1$, the distribution exhibits a concentration of points at the simplex's center, forming a generalized bell-shaped pattern in three dimensions (see Figure 1.2 (c)). Figures 1.2 (d) - 2 (f) illustrate other shapes generated by different $(\alpha_1,\ \alpha_2,\ \alpha_3)$ combinations, each with a generalized J-shape in three dimensions.

We now derive the expected probability of labor supply from equation (1.5) under the assumption that the probabilities $(\pi_1,\ \pi_2,\ \pi_3)$ follow a Dirichlet distribution:

$$
\begin{aligned}
E\left[P\left(x_1,x_2,x_3,T\right)\right] &= \int \frac{T!}{x_1!x_2!x_3!}\pi_1^{x_1}\pi_2^{x_2}\left(\pi_3\right)^{x_3} \times \frac{1}{B(\alpha_1,\alpha_2,\alpha_3)}\pi_1^{\alpha_1-1}\pi_2^{\alpha_2-1}\pi_3^{\alpha_3-1}d\boldsymbol{\pi} \\
&= \frac{T!}{x_1!x_2!x_3!}\frac{1}{B\left(\alpha_1,\alpha_2,\alpha_3\right)}\int \pi_1^{x_1+\alpha_1-1}\pi_2^{x_2+\alpha_2-1}\left(\pi_3\right)^{x_3+\alpha_3-1}d\boldsymbol{\pi}
\end{aligned} \tag{1.7}
$$

Define

$$
\begin{aligned}
p &= Pr(y>2) = \pi_3 \\
q &= Pr(y>1) = \pi_2+\pi_3
\end{aligned} ,
$$

and

$$
\begin{aligned}
\pi_1 &= 1-q \\
\pi_2 &= q-p \\
\pi_3 &= p
\end{aligned} .
$$

Then

$$
E\left(P\left(x_1,x_2,x_3,T\right)\right) = \frac{T!}{x_1!x_2!x_3!}\frac{1}{B\left(\alpha_1,\alpha_2,\alpha_3\right)}\int_0^1\int_0^q (1-q)^{x_1+\alpha_1-1}(q-p)^{x_2+\alpha_2-1}p^{x_3+\alpha_3-1}dpdq \tag{1.8}
$$

By the generalized binomial theorem:

$$
(q-p)^{x_2+\alpha_2-1} = \sum_{k=0}^{\infty}(-1)^k \left(\begin{array}{c} x_2+\alpha_2-1 \\ k \end{array} \right) q^{x_2+\alpha_2-k-1}p^k
$$

Therefore

$$
\begin{aligned}
E\left(P\left(x_1,x_2,x_3,T\right)\right) &= \frac{T!}{x_1!x_2!x_3!}\frac{1}{B\left(\alpha_1,\alpha_2,\alpha_3\right)}\sum_{k=0}^{\infty}(-1)^k\left(\begin{array}{c} x_2+\alpha_2-1 \\ k \end{array}\right) \\
&\times \int_0^1\int_0^q (1-q)^{x_1+\alpha_1-1}q^{x_2+\alpha_2-k-1}p^k p^{x_3+\alpha_3-1}dpdq \\
&= \frac{T!}{x_1!x_2!x_3!}\frac{1}{B\left(\alpha_1,\alpha_2,\alpha_3\right)}\sum_{k=0}^{\infty}(-1)^k\left(\begin{array}{c} x_2+\alpha_2-1 \\ k \end{array}\right) \\
&\times \int_0^1 (1-q)^{x_1+\alpha_1-1}q^{x_2+\alpha_2-k-1}\int_0^q p^{x_3+\alpha_3+k-1}dpdq \quad .
\end{aligned} \tag{1.9}
$$

The first integral in the last line above is a standard beta-logistic model, while the second integral is:

$$
\begin{aligned}
&\int_0^q p^{x_3+\alpha_3+k-1}dp \\
&= \left.\frac{p^{x_3+\alpha_3+k}}{x_3+\alpha_3+k}\right|_{p=0}^{p=q} = \frac{q^{x_3+\alpha_3+k}}{x_3+\alpha_3+k}
\end{aligned}
$$

So

$$
\begin{aligned}
E\left(P\left(x_1,x_2,x_3,T\right)\right) &= \frac{T!}{x_1!x_2!x_3!}\frac{1}{B\left(\alpha_1,\alpha_2,\alpha_3\right)}\sum_{k=0}^{\infty}(-1)^k\left(\begin{array}{c} x_2+\alpha_2-1 \\ k \end{array}\right) \\
&\times \frac{1}{x_3+\alpha_3+k}\int_0^1 (1-q)^{x_1+\alpha_1-1}q^{x_2+\alpha_2-k-1}q^{x_3+\alpha_3+k}dq \\
&= \frac{T!}{x_1!x_2!x_3!}\frac{1}{B\left(\alpha_1,\alpha_2,\alpha_3\right)}\sum_{k=0}^{\infty}(-1)^k\left(\begin{array}{c} x_2+\alpha_2-1 \\ k \end{array}\right) \\
&\times \frac{1}{x_3+\alpha_3+k}\int_0^1 (1-q)^{x_1+\alpha_1-1}q^{x_2+x_3+\alpha_2+\alpha_3-1}dq \\
&= \frac{T!}{x_1!x_2!x_3!}\frac{1}{B\left(\alpha_1,\alpha_2,\alpha_3\right)} \\
&\times \sum_{k=0}^{\infty}(-1)^k\left(\begin{array}{c} x_2+\alpha_2-1 \\ k \end{array}\right)\frac{B\left(x_1+\alpha_1,x_2+x_3+\alpha_2+\alpha_3\right)}{x_3+\alpha_3+k} \\
&= \frac{T!}{x_1!x_2!x_3!}\frac{B\left(x_1+\alpha_1,x_2+x_3+\alpha_2+\alpha_3\right)}{B\left(\alpha_1,\alpha_2,\alpha_3\right)} \\
&\times \sum_{k=0}^{\infty}(-1)^k\frac{\Gamma(x_2+\alpha_2)}{\Gamma(k+1)\Gamma(x_2+\alpha_2-k)}\frac{1}{x_3+\alpha_3+k} \\
&= \frac{T!}{x_1!x_2!x_3!}\frac{B\left(x_1+\alpha_1,x_2+x_3+\alpha_2+\alpha_3\right)}{B\left(\alpha_1,\alpha_2,\alpha_3\right)}\Gamma(x_2+\alpha_2) \\
&\times \sum_{k=0}^{\infty}(-1)^k\frac{1}{\Gamma(k+1)\Gamma(x_2+\alpha_2-k)(x_3+\alpha_3+k)} \quad .
\end{aligned}
\tag{1.10}
$$

Note that

$$
\begin{aligned}
&\lim_{n\to\infty}\sum_{k=0}^{n}(-1)^k\frac{1}{\Gamma(k+1)\Gamma(x_2+\alpha_2-k)(x_3+\alpha_3+k)} \\
&= \lim_{n\to\infty}\frac{\frac{(-1)^n{}_3F_2(1,a+n+1,-b+n+2;n+2,a+n+2;1)}{\Gamma(n+2)\Gamma(b-n-1)}+\frac{n\Gamma(a+1)}{a\Gamma(a+b)}+\frac{(a+1)\Gamma(a+1)}{a\Gamma(a+b)}}{a+n+1} \quad ,
\end{aligned}
\tag{1.11}
$$

where $a=x_3+\alpha_3$ and $b=x_2+\alpha_2$. Given that a and b are constants, as n goes to infinity, the third term of the limit goes to zero. We will now show the limit of the first term also equals zero. ${}_3F_2(1, a+n+1, -b+n+2; n+2, a+n+2; 1)$ is a generalized hypergeometric function defined from the hypergeometric series, ${}_3F_2(1, a+n+1, -b+n+2; n+2, a+n+2; 1) = \sum_{k=0}^{\infty} c_k$, for which $c_0 = 1$ and

$$\begin{aligned}\frac{c_{k+1}}{c_k} &= \frac{P(k)}{Q(k)} \\ &= \frac{(k+1)(k+a+n+1)(k-b+n+2)}{(k+n+2)(k+a+n+2)(k+1)} \\ &= \frac{(k+a+n+1)(k-b+n+2)}{(k+a+n+2)(k+n+2)} < 1 \quad .\end{aligned}$$

So,

$${}_3F_2(1, a+n+1, -b+n+2; n+2, a+n+2; 1) = \sum_{k=0}^{\infty} c_k < \sum_{k=0}^{\infty} c_0 = \sum_{k=0}^{\infty} 1 = \lim_{n\to\infty} \sum_{k=0}^{n} 1 = \lim_{n\to\infty} n$$

Hence,

$$\begin{aligned}&\lim_{n\to\infty} \frac{\frac{(-1)^n {}_3F_2(1,a+n+1,-b+n+2;n+2,a+n+2;1)}{\Gamma(n+2)\Gamma(b-n-1)}}{a+n+1} \\ &= \lim_{n\to\infty} \frac{\frac{(-1)^n \lim_{n\to\infty} n}{\Gamma(n+2)\Gamma(b-n-1)}}{a+n+1} \to 0 \quad .\end{aligned}$$

So the limit of the first term in the numerator of the last line of equation (1.11) also equals zero, and

$$\begin{aligned}&\lim_{n\to\infty} \frac{\frac{(-1)^n {}_3F_2(1,a+n+1,-b+n+2;n+2,a+n+2;1)}{\Gamma(n+2)\Gamma(b-n-1)} + \frac{n\Gamma(a+1)}{a\Gamma(a+b)} + \frac{(a+1)\Gamma(a+1)}{a\Gamma(a+b)}}{a+n+1} \\ &= \frac{\Gamma(a+1)}{a\Gamma(a+b)} = \frac{\Gamma(a)}{\Gamma(a+b)} \quad .\end{aligned}$$

Therefore,

$$
\begin{aligned}
E\left(P\left(x_1,x_2,x_3,T\right)\right) &= \frac{T!}{x_1!x_2!x_3!}\frac{B\left(x_1+\alpha_1,x_2+x_3+\alpha_2+\alpha_3\right)}{B\left(\alpha_1,\alpha_2,\alpha_3\right)}\frac{\Gamma(x_2+\alpha_2)\Gamma(x_3+\alpha_3)}{\Gamma(x_2+x_3+\alpha_2+\alpha_3)} \\
&= \frac{T!}{x_1!x_2!x_3!}\frac{\Gamma(\alpha_1+\alpha_2+\alpha_3)}{\Gamma(\alpha_1)\Gamma(\alpha_2)\Gamma(\alpha_3)} \\
&\times \frac{\Gamma(x_1+\alpha_1)\Gamma(x_2+x_3+\alpha_2+\alpha_3)}{\Gamma(x_1+x_2+x_3+\alpha_1+\alpha_2+\alpha_3)}\frac{\Gamma(x_2+\alpha_2)\Gamma(x_3+\alpha_3)}{\Gamma(x_2+x_3+\alpha_2+\alpha_3)} \\
&= \frac{T!}{x_1!x_2!x_3!}\frac{\Gamma(\alpha_1+\alpha_2+\alpha_3)}{\Gamma(\alpha_1)\Gamma(\alpha_2)\Gamma(\alpha_3)}\frac{\Gamma(x_1+\alpha_1)\Gamma(x_2+\alpha_2)\Gamma(x_3+\alpha_3)}{\Gamma(x_1+x_2+x_3+\alpha_1+\alpha_2+\alpha_3)} \quad .
\end{aligned}
\tag{1.12}
$$

The model is complted by adding individual heterogeneity[2]:

$$
\begin{aligned}
\alpha_1 &= \frac{exp(z'\beta_1)exp(z'\beta_3)+exp(z'\beta_1)exp(z'\beta_4)}{exp(z'\beta_1)+exp(z'\beta_2)} \\
\alpha_2 &= \frac{exp(z'\beta_2)exp(z'\beta_3)-exp(z'\beta_1)exp(z'\beta_4)}{exp(z'\beta_1)+exp(z'\beta_2)} \quad . \\
\alpha_3 &= exp(z'\beta_4)
\end{aligned}
$$

Then for $T=1$:

$$E\left(P\left(1,0,0,1\right)\right) = \frac{exp(z'\beta_1)}{exp(z'\beta_1)+exp(z'\beta_2)}$$

$$E\left(P\left(0,1,0,1\right)\right) = \frac{exp(z'\beta_2)}{exp(z'\beta_1)+exp(z'\beta_2)} - \frac{exp(z'\beta_4)}{exp(z'\beta_3)+exp(z'\beta_4)}$$

$$E\left(P\left(0,0,1,1\right)\right) = \frac{exp(z'\beta_4)}{exp(z'\beta_3)+exp(z'\beta_4)} \quad ,$$

[2]We can also parametry $\alpha_1,\alpha_2,\alpha_3$, as follows

$$
\begin{aligned}
\alpha_1 &= exp(z'\beta_1) \\
\alpha_2 &= \frac{exp(z'\beta_2)exp(z'\beta_3)-exp(z'\beta_1)exp(z'\beta_4)}{exp(z'\beta_3)+exp(z'\beta_4)} \quad . \\
\alpha_3 &= \frac{exp(z'\beta_1)exp(z'\beta_4)+exp(z'\beta_2)exp(z'\beta_4)}{exp(z'\beta_3)+exp(z'\beta_4)}
\end{aligned}
$$

with respective variances:

$$\sigma_1^2 = E[(p(1,0,0,1))^2] - E[(p(1,0,0,1))]^2$$
$$= \frac{\alpha_1(\alpha_2+\alpha_3)}{(\alpha_1+\alpha_2+\alpha_3)^2(1+\alpha_1+\alpha_2+\alpha_3)}$$

$$\sigma_2^2 = E[(p(0,1,0,1))^2] - E[(p(0,1,0,1))]^2$$
$$= \frac{\alpha_2(\alpha_1+\alpha_3)}{(\alpha_1+\alpha_2+\alpha_3)^2(1+\alpha_1+\alpha_2+\alpha_3)}$$

$$\sigma_3^2 = E[(p(0,0,1,1))^2] - E[(p(0,0,1,1))]^2$$
$$= \frac{\alpha_3(\alpha_1+\alpha_2)}{(\alpha_1+\alpha_2+\alpha_3)^2(1+\alpha_1+\alpha_2+\alpha_3)} \quad .$$

This defines the Dirichlet generalized ordered logit model. With cross-section data (i.e., data on participation for only one year), β_1 and β_2 (β_3 and β_4) cannot be identified separately. Hence, the traditional generalized ordered logit function can be used only to identify $\beta_2 - \beta_1$ and $\beta_4 - \beta_3$ in a population conditional on the z's, but cannot determine the higher moments of the distribution of participation probabilities. However, with participation data on the same individuals for 2 or more years, both β_1 and β_2 (β_3 and β_4) can be identified.

The spurious state dependence induced by heterogeneity may be seen by comparing the conditional probability of full time work in year t of women who worked full time in year $t-1$ with that of women who did not work in $t-1$ or worked part time in $t-1$. Let y_t represent the labor force participation decision at time t: y_t equals 1 for not working at time t, y_t equals 2 for working part-time at time t and y_t equals 3 for working full-time at time t.

$$P(y_t = 3|y_{t-1} = 3) - P(y_t = 3|y_{t-1} = 1)$$
$$= \frac{\alpha_3+1}{1+\alpha_1+\alpha_2+\alpha_3} - \frac{\alpha_3}{1+\alpha_1+\alpha_2+\alpha_3}$$
$$= \frac{1}{1+\alpha_1+\alpha_2+\alpha_3}$$
$$= \frac{exp(z'\beta_1)+exp(z'\beta_2)}{exp(z'\beta_1)+exp(z'\beta_2)+exp(z'\beta_1+z'\beta_3)+exp(z'\beta_1+z'\beta_4)+exp(z'\beta_2+z'\beta_3)+exp(z'\beta_2+z'\beta_4)} \ ,$$

and

$$P(y_t = 3|y_{t-1} = 3) - P(y_t = 3|y_{t-1} = 2) = \frac{1}{1+\alpha_1+\alpha_2+\alpha_3} \quad .$$

This difference ranges from zero (i.e. $\sigma^2 \to 0$ as $\alpha_1, \alpha_2, \alpha_3 \to \infty$) to one under extreme heterogeneity (i.e. $\sigma^2 \to \infty$ as $\alpha_1, \alpha_2, \alpha_3 \to 0$).

The conditional probability of working full-time given previous full-time work increases with the amount of previous full-time work. Thus,

$$\begin{aligned}
&P(y_t = 3|y_{t-1} = 3, \ldots, y_1 = 3) \\
&= \frac{P(y_t = 3, y_{t-1} = 3, \ldots, y_1 = 3)}{P(y_{t-1} = 3, \ldots, y_1 = 3)} \\
&= \frac{\alpha_1 + t - 1}{\alpha_1 + \alpha_2 + \alpha_3 + t - 1} \\
&= \{exp(z'\beta_1 + z'\beta_3) + exp(z'\beta_1 + z'\beta_4) + (exp(z'\beta_1) + exp(z'\beta_2))(t-1)\} \Big/ \\
&\quad \Big\{exp(z'\beta_1 + z'\beta_3) + exp(z'\beta_1 + z'\beta_4) + exp(z'\beta_2 + z'\beta_3) + exp(z'\beta_2 + z'\beta_4) \\
&\quad + (exp(z'\beta_1) + exp(z'\beta_2))(t-1)\Big\} \quad ,
\end{aligned}$$

which is a positive monotonic function of t that approaches unity as t approaches infinity. Similar equations can be derived for the conditional probabilies of not working and working part-time.

The predictive probability of the labor force participation decision at time t, based on the previous pattern of job participation behavior up to time $t-1$, can be expressed as:

$$
\begin{aligned}
f_{1t} &= P(y_t = 1 | x_{1,t-1}, x_{2,t-1}, x_{3,t-1}, t-1) \\
&= \frac{E[p(x_{1,t-1}+1, x_{2,t-1}, x_{3,t-1}, t)]}{E[p(x_{1,t-1}, x_{2,t-1}, x_{3,t-1}, t-1)]} \\
&= \frac{x_{1,t-1}+\alpha_1}{t-1+\alpha_1+\alpha_2+\alpha_3} \\
&= \{(exp(z'\beta_1)+exp(z'\beta_2))x_{1,t-1} + exp(z'\beta_1+z'\beta_3) + exp(z'\beta_1+z'\beta_4)\} \Big/ \\
&\quad \Big\{(exp(z'\beta_1)+exp(z'\beta_2))(t-1) + exp(z'\beta_1+z'\beta_3) \\
&\quad + exp(z'\beta_1+z'\beta_4) + exp(z'\beta_2+z'\beta_3) + exp(z'\beta_2+z'\beta_4)\Big\} \\
f_{2t} &= P(y_t = 2 | x_{1,t-1}, x_{2,t-1}, x_{3,t-1}, t-1) \\
&= \frac{E[p(x_{1,t-1}, x_{2,t-1}+1, x_{3,t-1}, t)]}{E[p(x_{1,t-1}, x_{2,t-1}, x_{3,t-1}, t-1)]} \\
&= \frac{x_{2,t-1}+\alpha_2}{t-1+\alpha_1+\alpha_2+\alpha_3} \\
&= \{(exp(z'\beta_1)+exp(z'\beta_2))x_{2,t-1} + exp(z'\beta_2+z'\beta_3) - exp(z'\beta_1+z'\beta_4)\} \Big/ \\
&\quad \Big\{(exp(z'\beta_1)+exp(z'\beta_2))(t-1) + exp(z'\beta_1+z'\beta_3) \\
&\quad + exp(z'\beta_1+z'\beta_4) + exp(z'\beta_2+z'\beta_3) + exp(z'\beta_2+z'\beta_4)\Big\} \\
f_{3t} &= P(y_t = 3 | x_{1,t-1}, x_{2,t-1}, x_{3,t-1}, t-1) \\
&= \frac{E[p(x_{1,t-1}, x_{2,t-1}, x_{3,t-1}+1, t)]}{E[p(x_{1,t-1}, x_{2,t-1}, x_{3,t-1}, t-1)]} \\
&= \frac{x_{3,t-1}+\alpha_3}{t-1+\alpha_1+\alpha_2+\alpha_3} \\
&= \{(exp(z'\beta_1)+exp(z'\beta_2))x_{3,t-1} + exp(z'\beta_1)^2 + exp(z'\beta_1+z'\beta_2)\} \Big/ \\
&\quad \Big\{(exp(z'\beta_1)+exp(z'\beta_2))(t-1) + exp(z'\beta_1+z'\beta_3) \\
&\quad + exp(z'\beta_1+z'\beta_4) + exp(z'\beta_2+z'\beta_3) + exp(z'\beta_2+z'\beta_4)\Big\} \ ,
\end{aligned}
\tag{1.13}
$$

where $x_{i,t-1}$ is the cumulative number of times that choice i has been selected in the preceding $t-1$ periods. Note that $\sum_i x_{i,t-1} = t-1$. These equations demonstrate that the predictive probabilities of women's labor force participation behavior at time t depends not only on exogenous factors but also on their past behavior.

1.3 Data

1.3.1 Data Description

This research uses data from waves 1 through 19 (1997-2019) of the NLSY97 cohort. The NLSY97, a part of the US Department of Labor's survey series, explores workforce entry patterns and transitions for youth. The content of the survey includes extensive information about youths' employment history, educational experiences, marital status, etc. over time. It is a nationally representative panel study tracking individuals aged 12 to 16 on December 31, 1996. The initial 1997 survey covered 8,984 respondents, with 51 percent men (4,599) and 49 percent women (4,385).

We analyze NLSY97 women who gave birth to their first child and had employment status data for the five years following their childbirth, starting from the first year after. Similar to Deza (2023), we categorize employment into three levels based on employment status and work hours: non-working, part-time worker, and full-time worker. The NLSY97 provides a comprehensive employer roster for each respondent at every wave, detailing all employers they worked for since the last interview. This roster differentiates between types of jobs, such as employee roles, freelance positions, self-employment, or military service. Using information on whether the respondent is matched to at least one employer and the number of work hours, we determine whether the respondent worked since the last interview and compute the total number of hours. We define not working as reporting zero hours of work in this year. Part-time workers are defined as those who worked at most 1500 hours a year. Finally, full-time workers are those that report working more than 1500 hours in this year.

Table 2.1 presents the definitions of the main variables. The explanatory variables consist of education in years at childbirth, age one year after childbirth, having a spouse or partner at childbirth, logarithm of the partner's annual real income, logarithm of the mother's hourly real wage for the job at childbirth or immediately preceding it, religion indicators, and indicators for US region. Additionally, two extra variables are included. The first one comprises missing value indicators for the logarithm of the spouse or partner's real income, while the second pertains to missing values for the logarithm of the mother's real wage. The estimated coefficients for these two variables are not presented in the regression table.

Table 1.2 displays the summary statistics: 21.5 percent of women choose not to work after childbirth, while 43.8 persent work full time and 34.8 percent work part time. The average age at the birth of their first child is 24 years. Figure 1.3 indicates that most women give birth between the ages of 20 to 30. The average education level exceeds high school, with women having an average of 12.4 years of education. Figure 1.4 presents a detailed distribution of different education levels. Additionally, 63.1 percent of women have a partner at the time of childbirth.

1.3.2 Pre-sample Analysis

Figure 1.5 shows the number of weeks women take to return to work, truncated at 104 weeks. The data shows that 25 percent of women return within four weeks, 50 percent within three months, and 75 percent within around a year. This distribution further justifies our choice to commence our study from one year post-childbirth. Because women may experience different health conditions and job search capabilities immediately after childbirth, a one-year window allows for the accommodation of individual differences during this transition period. Additionally, the distribution indicates that about 75 percent of women resume work within a year, which further confirms the suitability of this one-year window for our selection.

We use a nested logit model to estimate the probability of women returning to employment and returning their previous employer in the year after childbirth. We include the woman's personal characteristics and three other variables in the model: education of the woman's mother, work duration and percentage of time in the labor force. The nested logit model is displayed in Figure 1.6. Initially, we categorize employment decisions into two primary groups: choosing not to work and deciding to return to work. For those in the second category, we further distinguish between two scenarios: returning to the same employer and returning to work with a new employer.

The nested logit results are presented in Table 1.3. Women with higher education and wages are more likely to work and return to their previous employers, while older women tend to not work or seek a different employer. Having a partner increases the likelihood of returning to work and to a previous employer. Women work less when the income of their partner is higher. The education level of a woman's mother does not directly influence her work decisions. A longer duration of work before childbirth reduces the probability of returning to work within a year after childbirth. Conversely, a greater percentage of time working before childbirth increases the likelihood of returning to work and to the previous employer. Figures 1.7 and 1.8 show the distribution of the probability of returning to work and returning to the same employer within one year. We will include these two probabilities in our second stage ordered logit model.

1.4 Empirical Results

1.4.1 Parameter Estimates

Table 1.4 and 1.5 present the results of the ordered logit, generalized ordered logit, and DGOL models with only the two probabilities as regressors. The probability of women working is given by $j = 1$ in equation (1) of section 1.2.1 for the ordered logit model and in equation (3) of section 1.2.1 for the generalized ordered logit model. The coefficient estimates in Table 1.4 suggest that a higher probability of returning to work and returning to the same employer within a year after childbirth both increase the probability of women working and working full time in subsequent years for both the ordered logit and generalized ordered logit models. The same qualitative result can be seen in Table 1.5 by subtracting the coefficient in the first column from the coefficent in the second column for the comparison of no work and some work, and by subtracting the coefficient in the third column from the coefficent in the fourth column for the comparison of not full time and full time.

In Tables 1.6 through 1.8, we extend our analysis by including woman's characteristics. Our goal is to compare the results of the generalized ordered logit model (Table 1.7) with those of the DGOL model (Table 1.8). In the case of the generalized ordered logit model, the baselines are set to zero, so there is only one column for each comparison. For example, in the comparison of working and not working, not working is the baseline, and in the comparison of full time and not full time, not full time is the baseline.

Analyzing the DGOL results in Table 1.8 involves four columns,[3] as in Table 1.5. The signs of most variables are consistent across the generalized ordered logit and DGOL models and align with our expectations. Similar to the results in Table 1.4 and 1.5, a higher probability of returning to work and returning to the same employer within a year increases the probability of women working and reduces the probability of not working. Furthermore, women with more education are more likely to work, and less likely to not work. Older women are less likely to return to work after childbirth.

For some varaibles, the results change across models. In the generalized ordered logit estimation, partnership, partner income, and hourly wage have insignificant effects on women's employment decisions. This finding is counter-intuitive, as numerous studies emphasize the importance of wage levels and partnership status on women's labor force participation (Hausman 1979; Treas 1987; Bradbury and Katz 2002; Bowen and Finegan 2015). In contrast, in the DGOL model, partnership and higher partner income are associated with a decreased probability of women working after childbirth. Moreover, higher wages significantly increase the labor force participation of women after childbirth, both full time and part time. Fi-

[3]In the next subsection, we will analyze the average partial effects (APEs) to obtain more insight into state dependence.

nally, regions have an insignificant effect on women's labor force participation decisions in the generalized ordered logit model, but a significant effect in the DGOL.

1.4.2 Model Accuracy

We present the accuracy rates for three models in Figure 1.9. We begin by comparing the performance of the ordered logit and generalized ordered logit models. The generalized ordered logit outperforms the ordered logit slightly. The accuracy rates of these three models are nearly identical in the first year. However, in the second year, the Dirichlet generalized ordered logit, which considers heterogeneity, exhibits significant predictive improvement with an accuracy rate of 0.83, substantially surpassing the accuracy rates of 0.55 for the generalized ordered logit and 0.53 for the ordered logit models. This higher accuracy persists in subsequent years.

The accuracy rate indicates whether the predicted category is correct or not, without considering the size of the error. This problem is corrected by using the mean absolute error (MAE) for all three models.[4] The MAE takes into account the order of the categories and the magnitude of the errors. A lower MAE value suggests superior predictive accuracy. As depicted in Figure 1.10, all three models exhibit similar MAE values in the first year. However, in the second year, the DGOL's MAE drops from 0.50 to 0.18, notably outperforming the generalized ordered logit model's 0.53 and the ordered logit model's 0.55. The MAE values for DGOL remains small in the following years.

1.4.3 Heterogeneity

Figure 1.11 suggests the presence of considerable heterogeneity in the response probability. In a homogeneous population, the response probability distribution should be centered around the simplex's midpoint. However, the figure reveals an asymmetrical Dirichlet dis-

[4]The MAE formula is: MAE $= \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$, where y_i is the actual dependent variable value, and $\hat{y}_i$ is the predicted dependent variable value. In our study, y_i and $\hat{y}_i$ represent the actual and predictive employment status.

tribution concentrated tightly on one side of the simplex. This skewed distribution indicates that only a few women are likely to consider switching their employment status near the response mean of the entire sample. The mean response probability in the (generalized) ordered logit model fails to adequately capture the nuances of women's labor force participation decisions. This is due to the model's assumption of homogeneity within the women's population, which overlooks the diversity of experiences and factors influencing each individual's choice.

Next, we use the parameter estimates to compute the average partial effects (APEs), which quantify the change in predicted probability of full-time employment that is driven by prior full-time employment relative to prior non-full-time employment, holding other condition no change: $P(y_t = \text{full time}|y_{t-1} = \text{full time}) - P(y_t = \text{full time}|y_{t-1} = \text{not full time})$, the causal effect of lagged employment on the current full-time employment decision. Given that individuals are only observed in one possible scenario ($\{y_{t-1} = \text{full time}\}$ or $\{y_{t-1} = \text{not full time}\}$), observed data would only allow us to compute either $P(y_t = \text{full time}|y_{t-1} = \text{full time})$ or $P(y_t = \text{full time}|y_{t-1} = \text{not full time})$. One method to get the APEs is to take the difference of these two probabilities.

However, the group of people who work full time in time $t-1$ may be different from the group of people who do not work full time in time $t-1$, so the difference will be biased and this selection bias may mask the real APEs (Angrist and Pischke 2009). We simulate 100,000 artificial observations, ensuring that every variable has a distribution similar to that of the observed data. We randomly assign their employment status in the first period based on the proportion of each employment type in the observed data. Then, we use the estimated parameters from our structural DGOL model and equation (1.13) to predict their choice in subsequent years. Next, we estimate this difference in probabilities separately for each respondent and period. Finally, we take the average over all individuals and periods after the initial period to compute the APE.

The results for the APEs from the DGOL model, presented in Table 1.9, can be summarized as follows. The estimates indicate that if all respondents are employed full time in any given period, their probability of full time employment in the next period would increase by 64.8 percentage points relative to the counterfactual scenario where they are not employed full time, i.e., $P(y_t = \text{full time}|y_{t-1} = \text{full time}) - P(y_t = \text{full time}|y_{t-1} = \text{not full time}) = 0.648$. Given the existing literature on state dependence in employment (e.g. Deza 2023), it is unsurprising that $P(y_t = \text{full time})$ more than quadruples when we change the lagged employment outcome from not full time to full time employment (increasing from 0.191 to 0.839).

1.4.4 Policy Consequences of Job Continuity

In this subsection, we simulate full-time employment and non-employment under several different simulated policy counterfactual scenarios. Figures 1.12 and 1.13 indicate that the DGOL model closely simulates actual full-time employment patterns over the sample period. We predict full-time employment by changing actual partner income levels to high, low, and no income scenarios. As shown in Figure 1.14, women with partners who have low or no income are more likely to work full time. The simulated full-time employment rate increases by approximately 5 percent for women with no partner income.

Using the parameters estimates for the DGOL model, we simulate full-time employment and non-employment by changing the probability of returning to the same employer within a year after childbirth. Figures 1.15 and 1.16 present the simulated changes in the employment in each scenario. Surprisingly, increasing the probability of returning to the same employer to a high level significantly increases the full-time employment rate from 0.44 to 0.55. Conversely, a low probability of returning to the previous employer reduces the full-time employment rate from 0.44 to 0.35. As seen in Figure 1.16, both low and moderate probabilities of returning to the same employment increase the non-employment rate by approximately 1 percent and 3 percent respectively, while a high probability of returning to the same employment decreases the non-employment rate by approximately 3.5 percent.

Figure 1.17 presents the simulated effect of policies related to job continuity for women with lower educational attainment. The green dotted line represents women with less than a high school education, showing that their full-time employment rate is lower than that of the actual sample. However, if we increase the probability of returning to the same employment to a high level, this policy can mitigate the negative effect of low education on their full-time employment. The red dashed line demonstrates that the full-time employment rate will be slightly higher than the rate in the original simulated data.

Figure 1.18 presents the simulated effect of policies related to job continuity for older new mothers. The green dotted line shows the decreased labor market outcome for older new mothers, with a full-time employment rate approximately 5 percent below that of the actual sample. However, the red dashed line demonstrates that implementing a job continuity policy, which increases their probability of returning to the same employer, can offset this decrease and result in a full-time employment rate similar to that of the actual sample.

These policy counterfactuals hold significant value and offer insights into potential negative or positive outcomes related to existing job continuity policies, such as maternity leave and paid family leave. Our findings indicate the importance of job protection after childbirth. Returning to one's previous employer after childbirth exerts a significant influence on women's subsequent employment choices. Policies aimed at promoting job continuity can substantially increase the labor supply of new mothers.

1.5 Conclusion

This study examines the effect of job continuity and other factors on the labor force participation of new mothers in the United States. It is important for policymakers to understand the relationship between job continuity and women's labor market outcomes. We control for unobserved heterogeneity by developing a Dirichlet generalized ordered logit (DGOL) model. The predictive accuracy achieved by this model surpassing previous models in the literature.

The empirical results demonstrate the presence of substantial unobserved heterogeneity in the models of the labor force participation of new mothers. Our findings indicate working full time increases the probability of full-time work in the next year by 65 percent. Moreover, the estimation results from the DGOL model allow us to simulate policy counterfactuals. The simulations imply that the elasticity of full-time employment with respect to the probability of returning to the same employer after childbirth is 0.437.

First time mothers who are older are more likely to face health risks that delay their return to the labor force. Women with less education have lower levels of human capital that make them less competitive in the labor market. Policies that increase the probability of returning to the same employer will offset decreases in labor force participation and family income for these two groups.

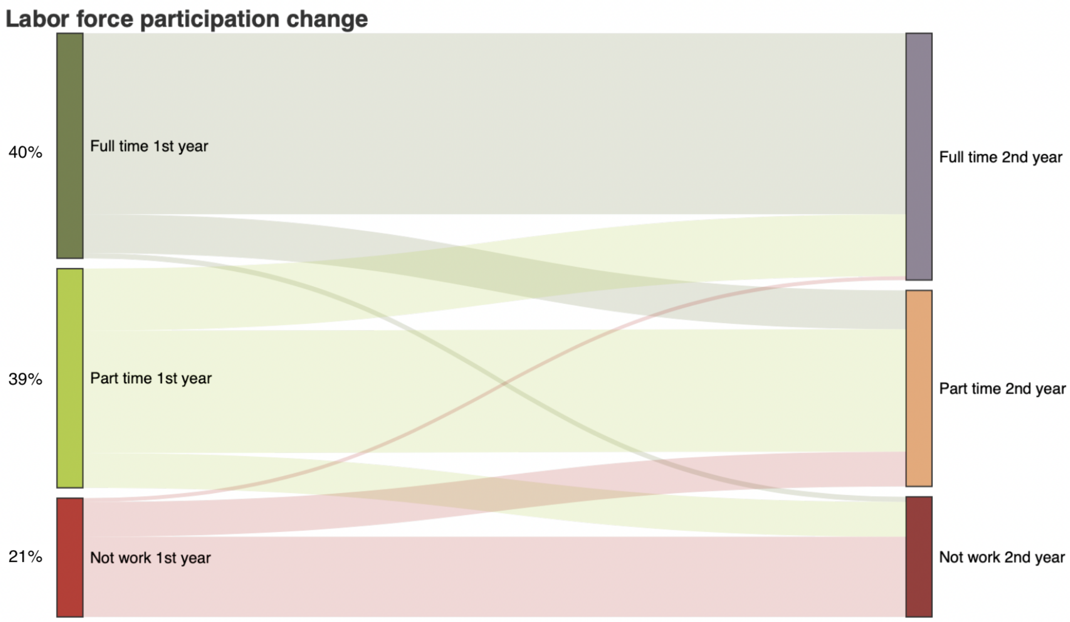

Figure 1.1: Women's Labor Force Participation: First to Second Year Transitions

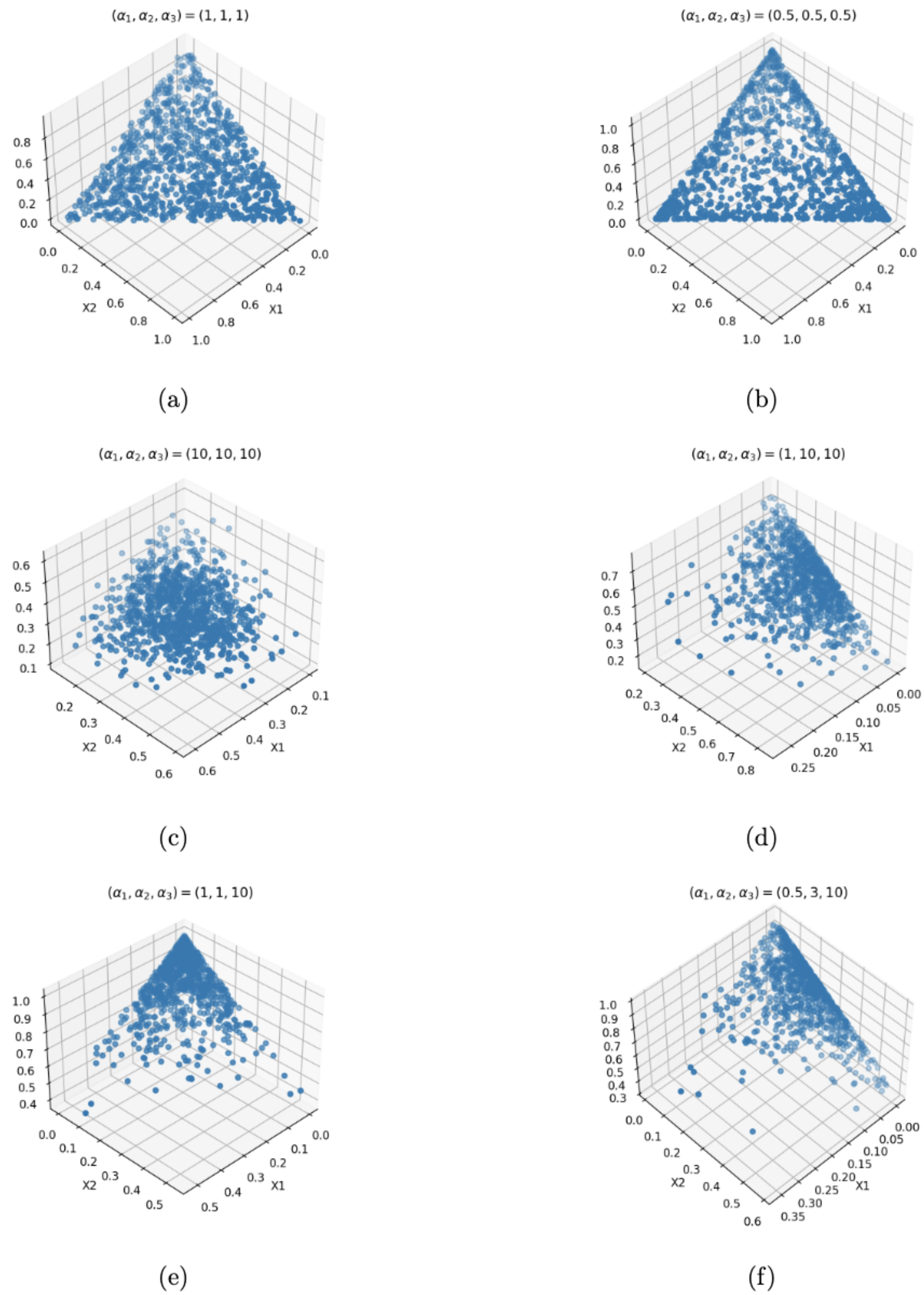

Figure 1.2: Scatter Plots of the Dirichlet Distribution

Notes: This figure shows the Dirichlet distributions under different shape parameters (α_1 α_2 α_3) for $K = 3$. Those shape parameters govern the shape of the distribution.

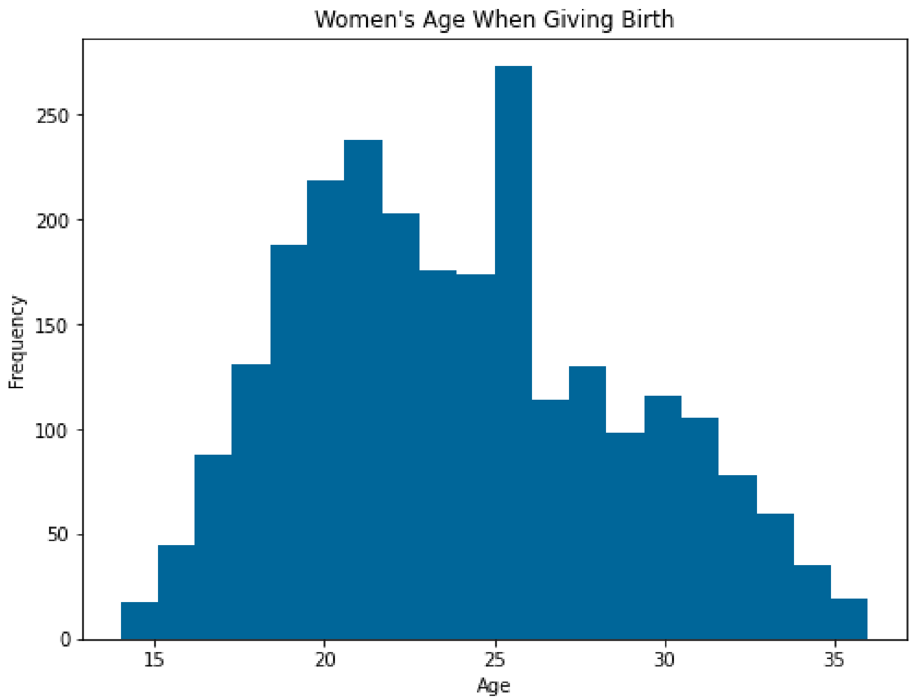

Figure 1.3: Women's Age When Giving Birth

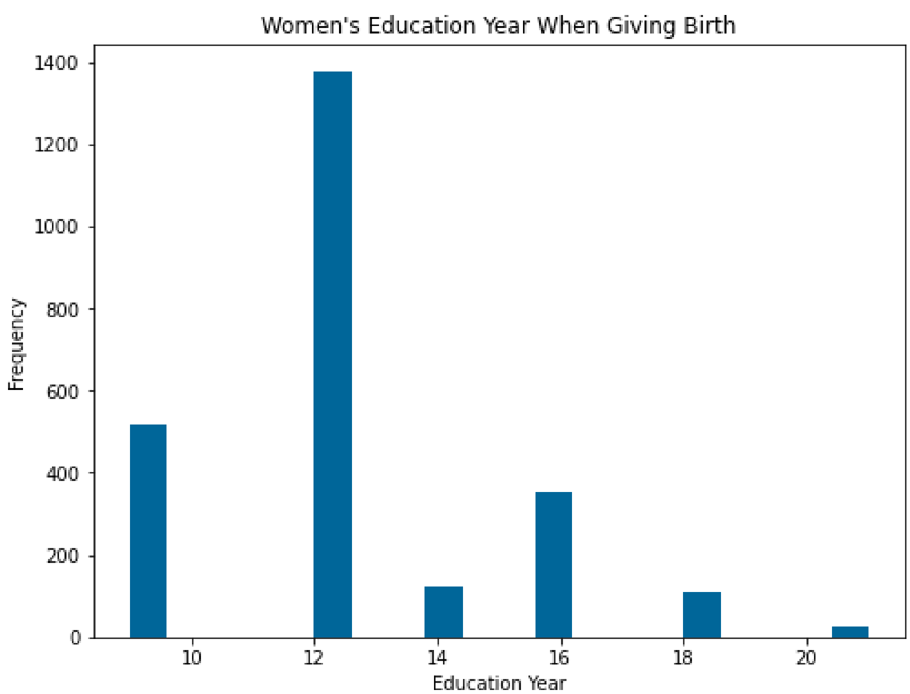

Figure 1.4: Women's Education Level (year) When Giving Birth

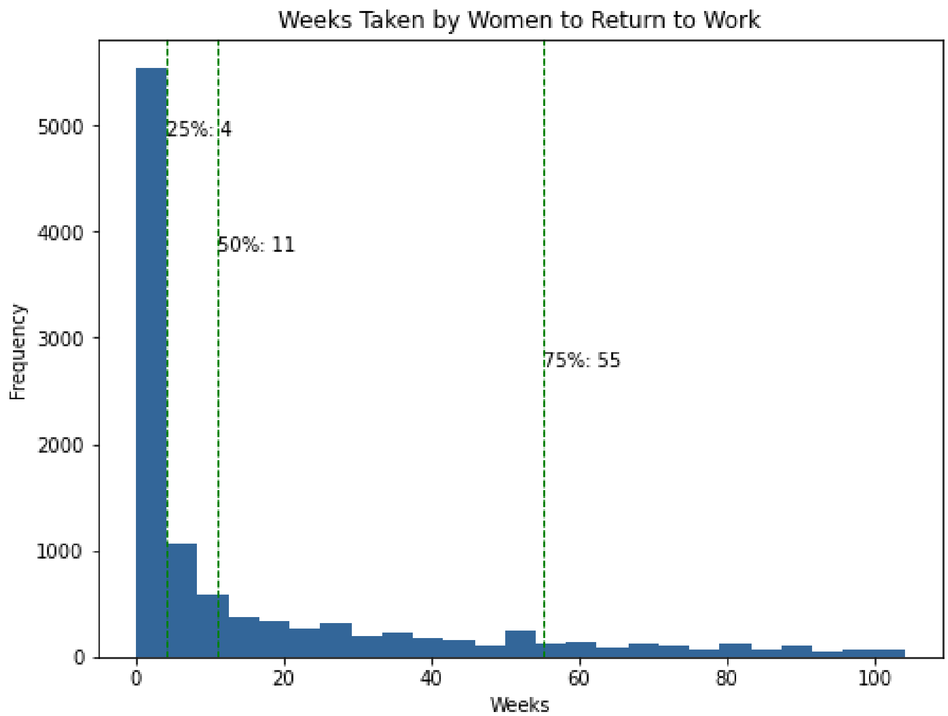

Figure 1.5: Weeks Taken by Women to Return to Work

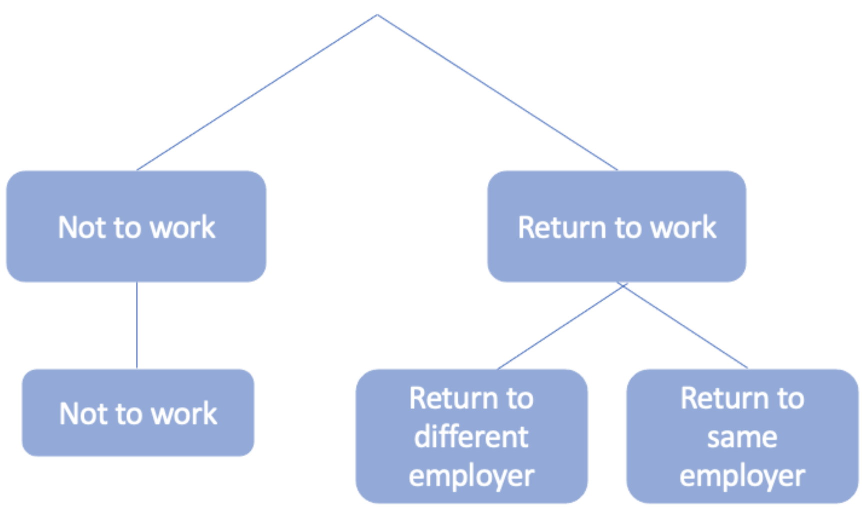

Figure 1.6: Nesting Structure for Pre-sample Employment

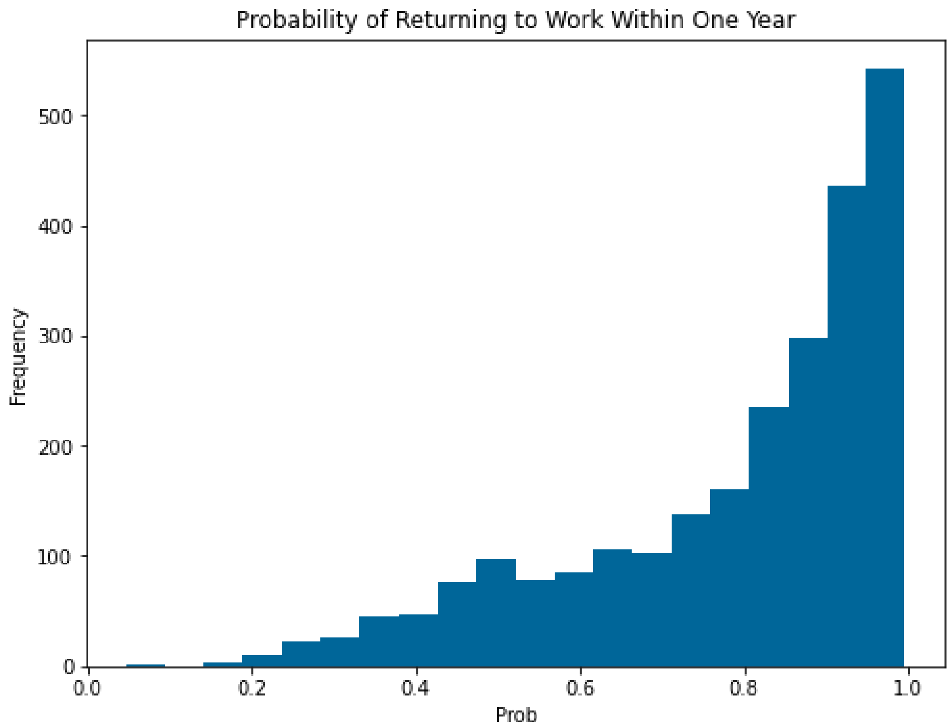

Figure 1.7: Probability of Returning to Work within One Year

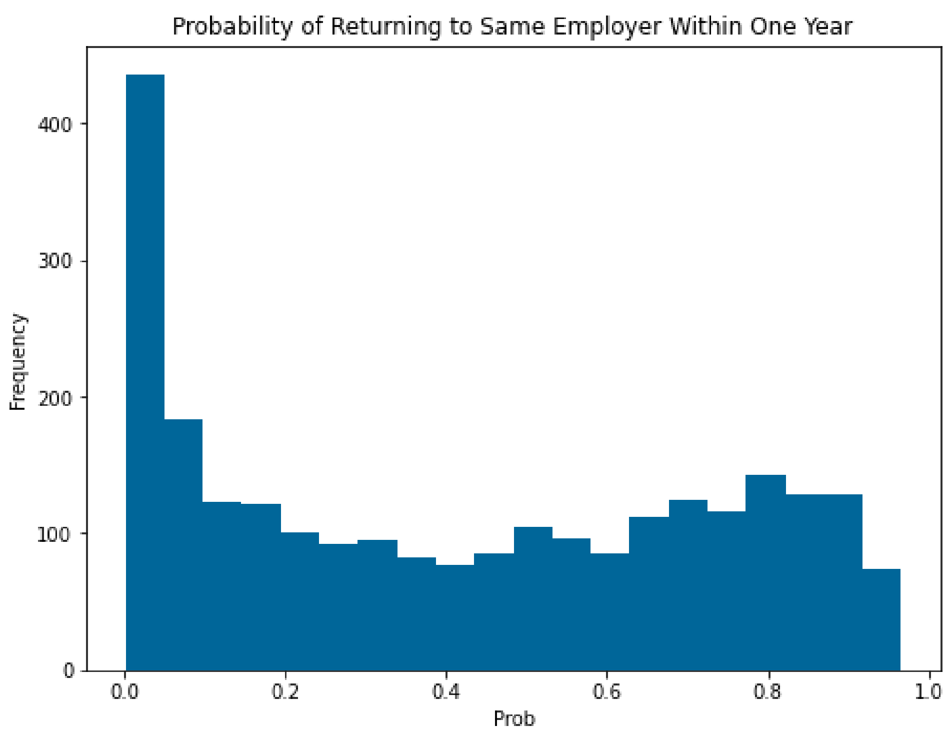

Figure 1.8: Probability of Returning to Same Employer within One Year

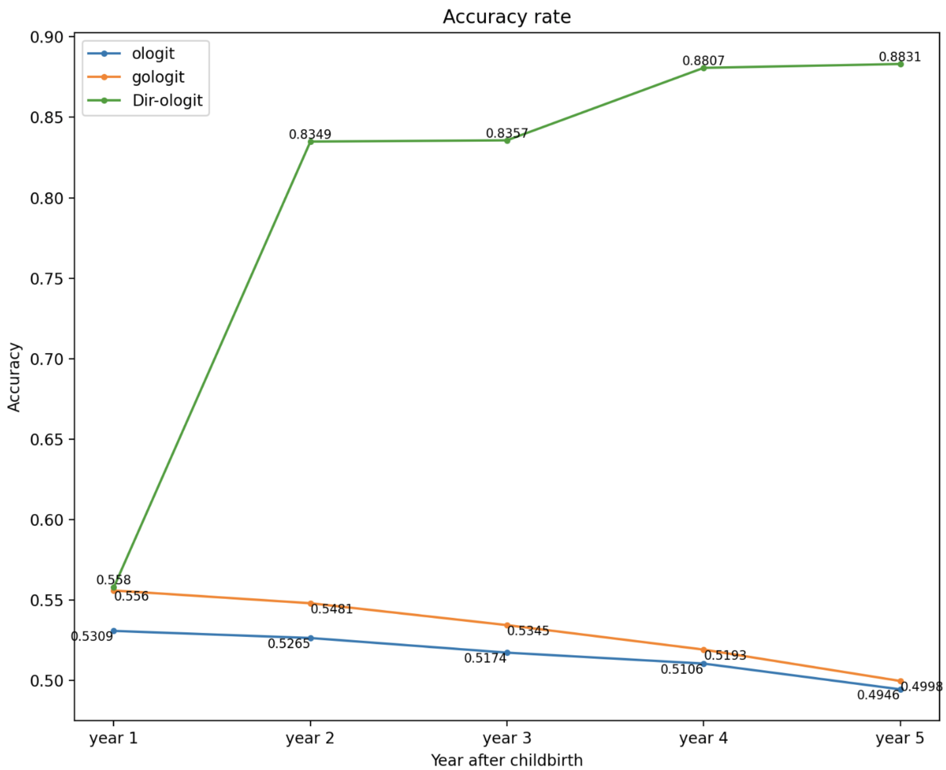

Figure 1.9: Model Comparison: Accuracy Rate

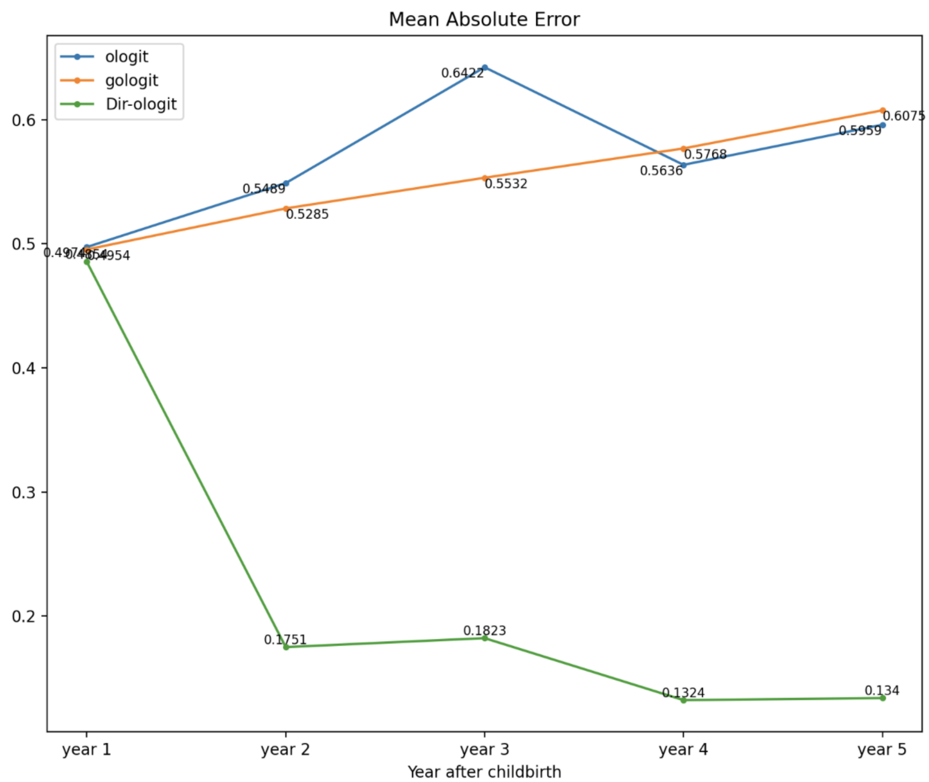

Figure 1.10: Model Comparison: Mean Absolute Error

Notes: The formula for MAE is given by: $\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$, where y_i is the actual value, and $\hat{y}_i$ is the predicted value.

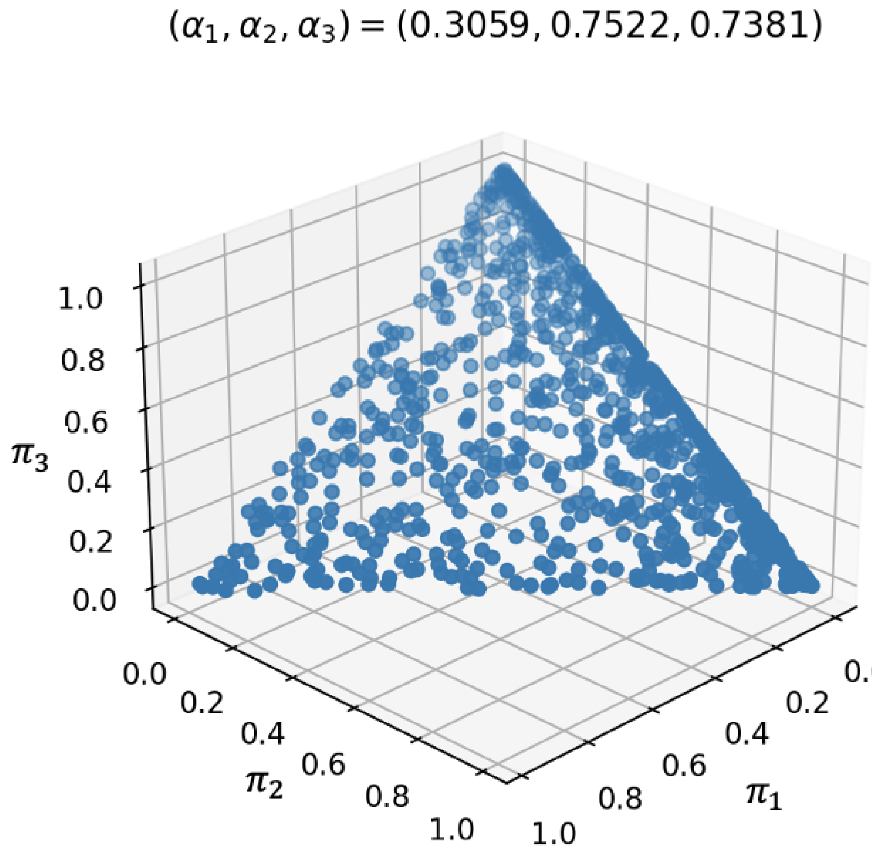

Figure 1.11: The Dirichlet Distribution for the DGOL Model 2

Note: This figure shows the Dirichlet distribution of full population with average characteristics for women. The definition of shape parameters $(\alpha_1, \alpha_2, \alpha_3)$ in the Dirichlet distribution are from Section 2.2. $\alpha_1 = \frac{exp(z'\beta_1)exp(z'\beta_3)+exp(z'\beta_1)exp(z'\beta_4)}{exp(z'\beta_1)+exp(z'\beta_2)}$, $\alpha_2 = \frac{exp(z'\beta_2)exp(z'\beta_3)-exp(z'\beta_1)exp(z'\beta_4)}{exp(z'\beta_1)+exp(z'\beta_2)}$ and $\alpha_3 = exp(z'\beta_4)$.

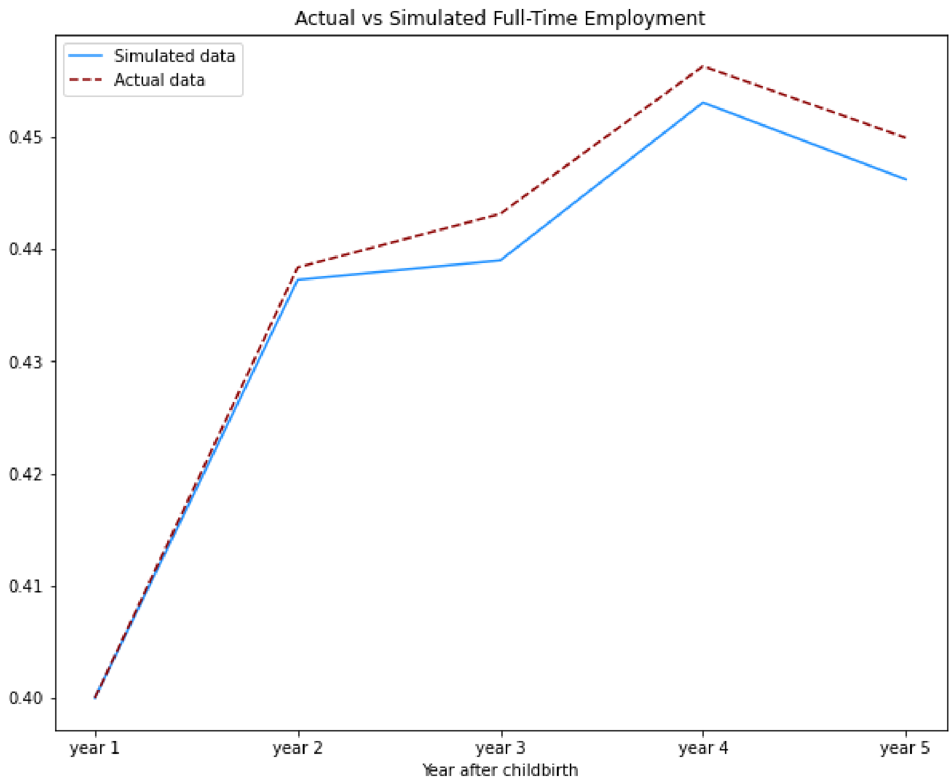

Figure 1.12: Actual vs Simulated Full-Time Employment

Notes: This figure presents the observed and simulated probability of full-time employment using the parameters estimated by the Dirichlete generalized ordered logit model.

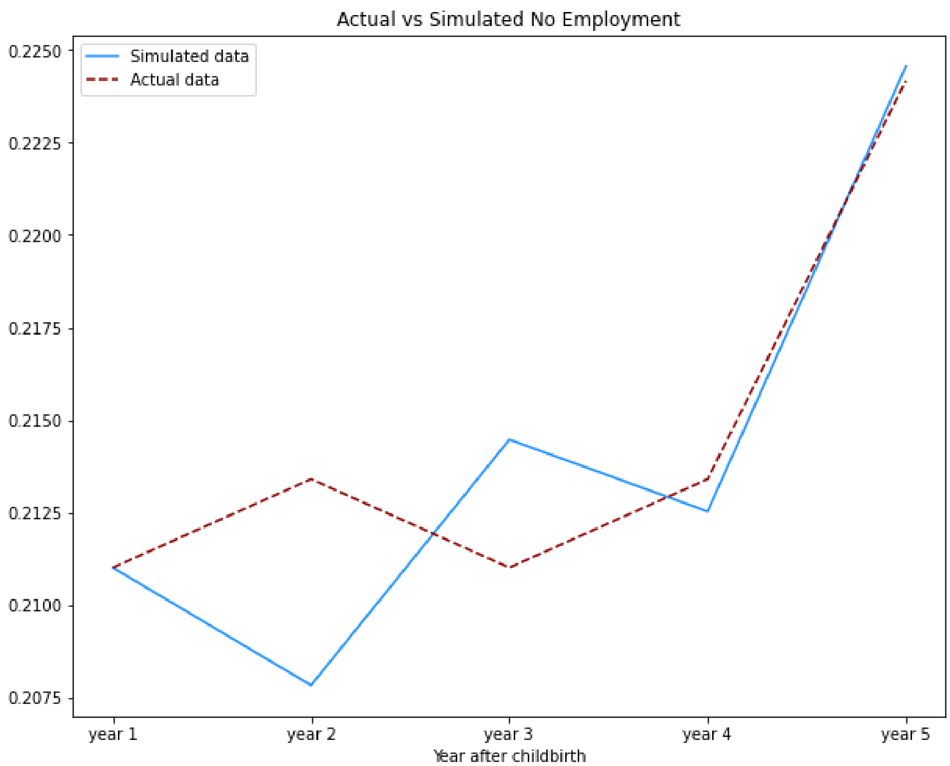

Figure 1.13: Actual vs Simulated Non-Employment

Notes: This figure presents the observed and simulated probability of non-employment using the parameters estimated by the Dirichlete generalized ordered logit model.

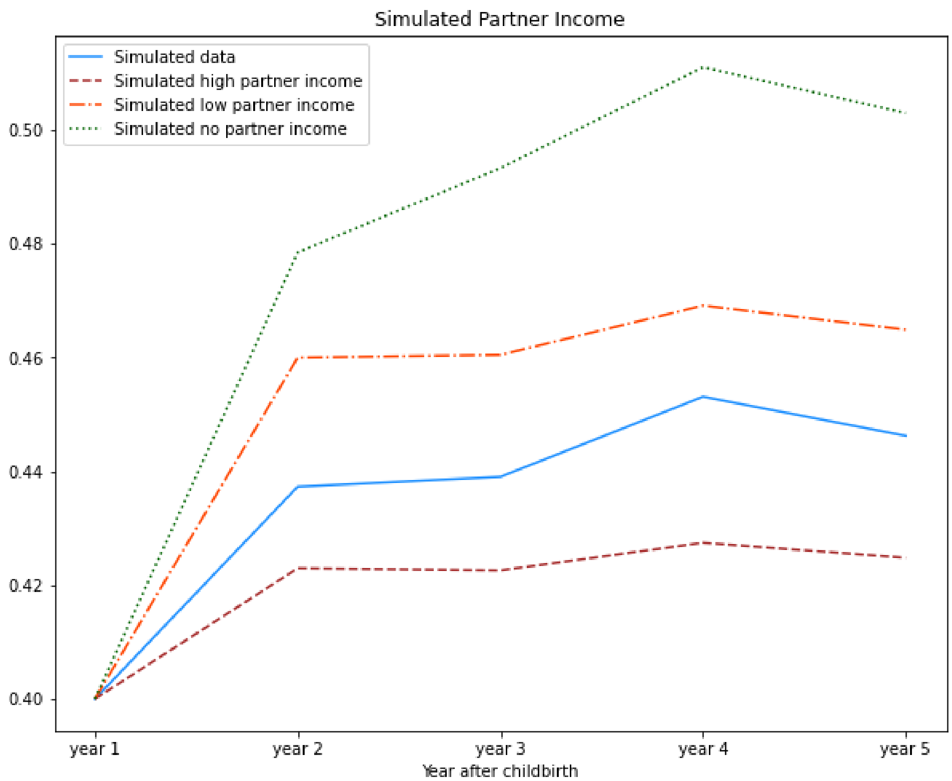

Figure 1.14: Simulated Partner Income impact (full time)

Notes: This figure presents the simulated probability of full-time employment using the parameters estimated by the Dirichlet generalized ordered logit model. In addition, it shows the simulated probability of full-time employment under three counterfactual scenarios, where I hold all other variables unchanged and artificially change the partner income for all respondents who have partner before simulating full-time employment in the next period: (i) A scenario with a high partner income (log (partner income) = 8) given they have partner, (ii) a scenario with partner income (log (partner income) = 5) given they have partner, and (iii) a scenario with no partner income (log (partner income) = 0).

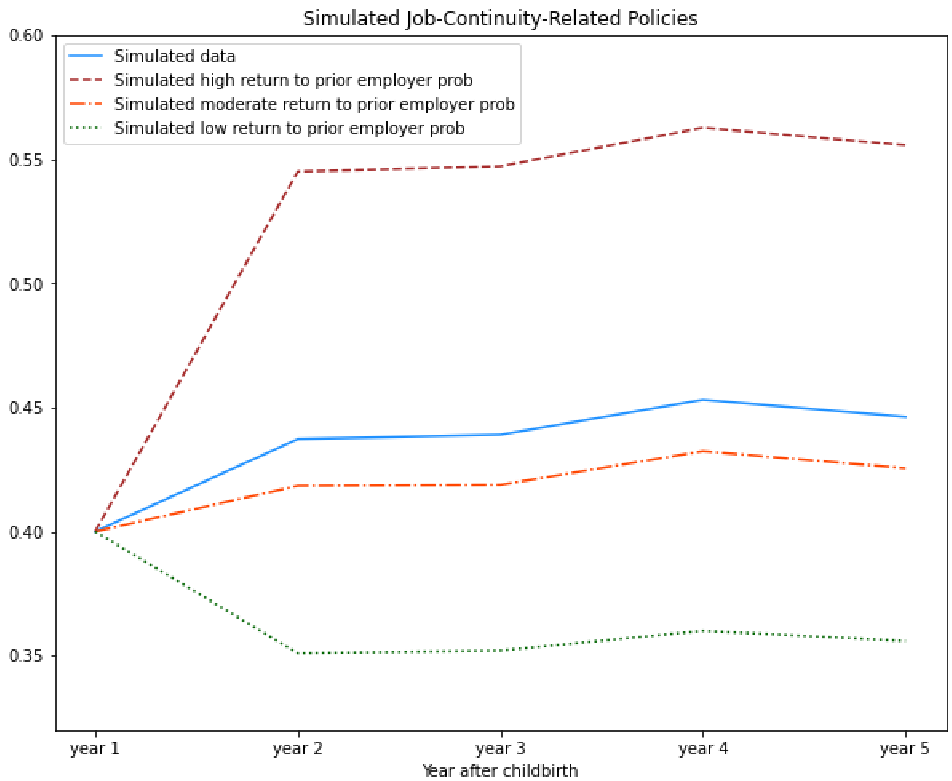

Figure 1.15: Simulated Job Continuity-Related Policy (full time)

Notes: This figure presents the simulated probability of full-time employment using the parameters estimated by the Dirichlet generalized ordered logit model. In addition, it shows the simulated probability of full-time employment under three counterfactual scenarios, where I hold all other variables unchanged and artificially change the probability of returning to the previous employer for all respondents before simulating full-time employment in the next period: (i) A scenario with a high probability (0.7) of returning to the same employer given they return to work within a year after childbirth, (ii) a scenario with a moderate probability (0.4) of returning to the same employer given they return to work within a year after childbirth, and (iii) a scenario with a low probability (0.1) of returning to the same employer given they return to work within a year after childbirth.

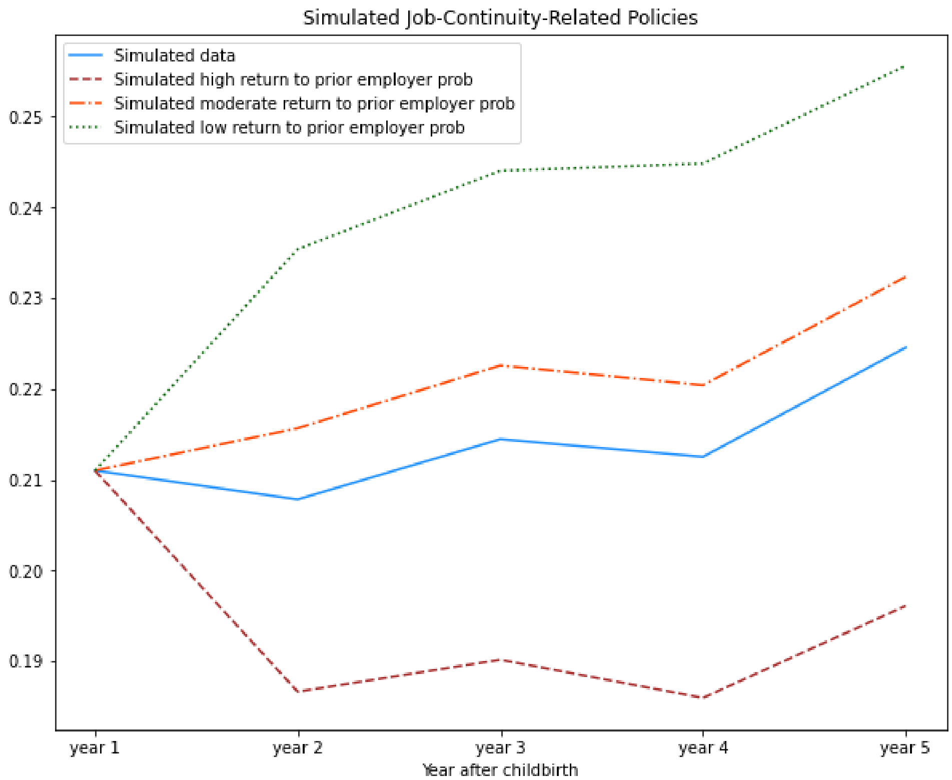

Figure 1.16: Simulated Job Continuity-Related Policy (non-employment)

Notes: This figure presents the simulated probability of non-employment using the parameters estimated by the Dirichlet generalized ordered logit model. In addition, it shows the simulated probability of full-time employment under three counterfactual scenarios, where I hold all other variables unchanged and artificially change the probability of returning to the previous employer for all respondents before simulating full-time employment in the next period: (i) A scenario with a high probability (0.7) of returning to the same employer given they return to work within a year after childbirth, (ii) a scenario with a moderate probability (0.4) of returning to the same employer given they return to work within a year after childbirth, and (iii) a scenario with a low probability (0.1) of returning to the same employer given they return to work within a year after childbirth.

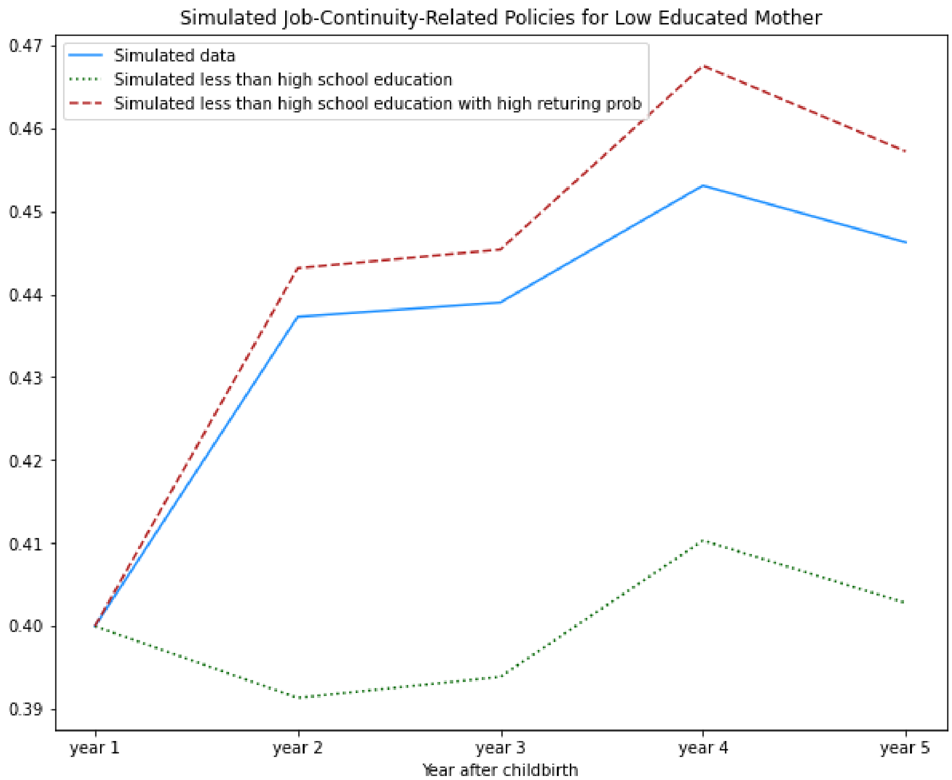

Figure 1.17: Simulated Job Continuity-Related Policy for Low Educated Mother (full time)

Notes: This figure presents the simulated probability of full-time employment using the parameters estimated by the Dirichlet generalized ordered logit model. In addition, it shows the simulated probability of full-time employment under two counterfactual scenarios, where I hold all other variables unchanged and artificially change the probability of returning to the previous employer for mothers with low education levels before simulating full-time employment in the next period: (i) A scenario for women with low education levels (8 education years), and (ii) A scenario for women with low education levels (8 education years) but having a high probability (0.7) of returning to the same employer given they return to work within a year after childbirth.

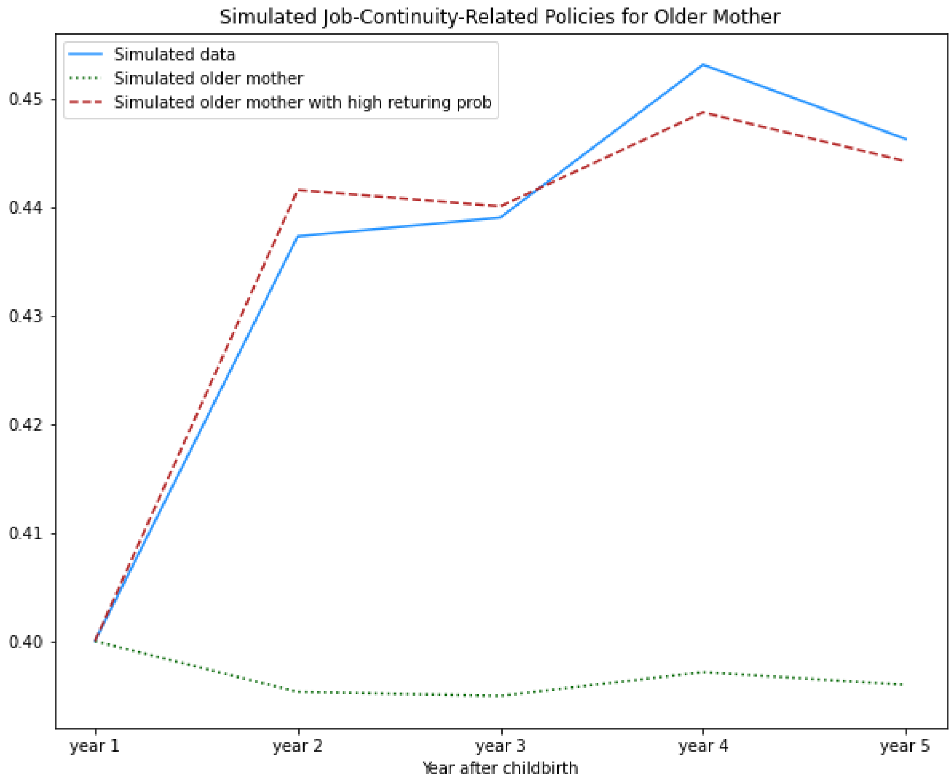

Figure 1.18: Simulated Job Continuity-Related Policy for Older New Mother (full time)

Notes: This figure presents the simulated probability of full-time employment using the parameters estimated by the Dirichlet generalized ordered logit model. In addition, it shows the simulated probability of full-time employment under two counterfactual scenarios, where I hold all other variables unchanged and artificially change the probability of returning to the previous employer for mothers aged 30 years before simulating full-time employment in the next period: (i) A scenario for 30-year-old women, and (ii) A scenario for 30-year-old women with a high probability (0.7) of returning to the same employer given they return to work within a year after childbirth.

Table 1.1: Definition of Variables

Variables	**Definition**
Labor-Force Attachment	The labor-force attachment of women, which is divided into three categories: full-time workers (FW), part-time workers (PW), and those who are not working (NW).
Education	Women's education in years.
Age	The age of the women one year after giving birth.
Partner	The dummy variable denotes whether the woman is in a partnership (married or cohabiting).
Log Partner Income	The logarithm of the partner's actual annual income (measured in \$100 units) ($log(patner\ income + 1)$). If the woman is without a partner, the variable is zero.
Log Wage	The logarithm of real hourly wage of the woman (hourly wage in cents).
Religion	The religion preference of the woman, which is divided into four categories: Roman Catholic (baseline), Protestant, other religion and no religion.
Region	The region of the woman, which is divided into four categories: Northeast (baseline), North Central, South and West.

Table 1.2: Summary Statistics

Variable	**N**	**Mean**	**S.D.**
Full-time Workers	12,535	0.438	0.50
Part-time Workers	12,535	0.348	0.48
Not Working	12,535	0.215	0.41
Education	12,535	12.40	2.56
Age	12,535	23.95	4.72
Partner	12,535	0.631	0.48
Log Partner Income	12,535	2.286	2.87
Log Wage	12,535	5.936	2.57
Religion			
Catholic	12,535	0.221	0.41
Protestant	12,535	0.544	0.50
Other Religion	12,535	0.099	0.30
No Religion	12,535	0.136	0.34
Region			
Northeast	12,535	0.147	0.35
North Central	12,535	0.203	0.40
South	12,535	0.433	0.50
West	12,535	0.216	0.41

Table 1.3: Nested Logit Results

	No Work vs Return to Work	Different Employer vs Same Employer
Constant	0.6373***	-4.9495***
	(0.793)	(0.986)
Education	0.0934**	0.1741***
	(0.038)	(0.039)
Age	-0.1145***	-0.0848**
	(0.029)	(0.037)
Partner	0.7800*	1.2073**
	(0.461)	(0.463)
Log Partner Income	-0.2266**	-0.3093***
	(0.083)	(0.082)
Log Wage	0.1921**	0.2744***
	(0.075)	(0.071)
Education of Women's Mom	-0.0145	-0.0308
	(0.016)	(0.020)
Total Work	-0.0034***	-0.0004
	(0.001)	(0.001)
Percent Work	3.7605***	7.8853***
	(0.384)	(0.507)
Religion		
Protestant	0.0628	0.1318
	(0.169)	(0.187)
Other Religion	-0.2147	-0.1656
	(0.234)	(0.266)
No Religion	-0.0671	-0.4523*
	(0.211)	(0.232)
Region		
North	-0.4523**	-0.3270
	(0.223)	(0.255)
South	-0.3917**	-0.2861
	(0.195)	(0.223)
West	-0.5823**	-0.5969**
	(0.211)	(0.241)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.4: Ordered logit and Generalized Ordered Logit for Job Continuity

	Ordered logit model	Generalized ordered logit model	
		No Work vs Work	Not Full Time vs Full Time
Prob Return Work	2.728***	2.873***	2.505***
	(0.11)	(0.12)	(0.13)
Prob Same Employer	1.417***	1.482***	1.435***
	(0.06)	(0.10)	(0.06)
cut1	1.033**	-1.139***	
	(0.08)	(0.09)	
cut2	2.841***		-2.658***
	(0.08)		(0.10)
AIC	24111.76	24105.94	
Log likelihood	-12053.88	-12048.97	
N	12535	12535	

Table 1.5: DGOL for Job Continuity

Variable	Work or Not		Full Time or Not	
	No Work	Some Work	Not Full Time	Full Time
Constant	-1.823^{***}	-2.958^{***}	0.784^{***}	-1.866^{***}
	(0.06)	(0.06)	(0.17)	(0.19)
Prob Return Work	-1.525^{***}	1.448^{***}	-0.696^{**}	1.731^{***}
	(0.09)	(0.09)	(0.23)	(0.25)
Prob Same Employer	5.249^{***}	6.488^{***}	-0.911^{***}	0.515^{***}
	(0.07)	(0.07)	(0.12)	(0.13)
AIC	20764.13			
Log likelihood	-10370.06			
N	12535			

Table 1.6: Ordered logit for Job Continuity and Women Characteristics

Variable	Coefficient
Prob Return Work	2.328***
	(0.12)
Prob Same Employer	1.568***
	(0.07)
Education	0.089***
	(0.01)
Age	-0.052***
	(0.01)
Partner	-0.215
	(0.13)
Log Partner Income	0.018
	(0.02)
Log Hourly Wage	0.041
	(0.02)
Religion	
Protestant	-0.041
	(0.05)
Other Religion	0.084
	(0.07)
No Religion	0.047
	(0.06)
Region	
North	-0.003
	(0.06)
South	0.113**
	(0.05)
Wes	0.028
	(0.06)
cut1	0.877**
	(0.20)
cut2	2.698***
	(0.21)
AIC	24004.58
Log likelihood	-11987.29
N	12535

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Generalized Ordered Logit for Job Continuity and Women Characteristics

Variable	No Work vs Work	No Full Time vs Full Time
Prob Return Work	2.465^{***}	2.355^{***}
	(0.15)	(0.15)
Prob Same Employer	2.027^{***}	1.274^{***}
	(0.10)	(0.07)
Education	0.077^{***}	0.091^{***}
	(0.01)	(0.01)
Age	-0.096^{***}	-0.015^{**}
	(0.01)	(0.01)
Partner	-0.216	-0.214
	(0.18)	(0.14)
Log Partner Income	-0.000	0.031
	(0.03)	(0.03)
Log Hourly Wage	0.006	0.028
	(0.03)	(0.03)
Religion		
Protestant	0.050	-0.097
	(0.06)	(0.05)
Other Religion	0.186	0.039
	(0.08)	(0.07)
No Religion	0.203	-0.055
	(0.08)	(0.07)
Region		
North	-0.005	-0.014
	(0.08)	(0.07)
South	0.068	0.140^{*}
	(0.07)	(0.06)
West	0.090	0.004
	(0.08)	(0.07)
Constant	0.417	-3.456^{***}
	(0.25)	(0.24)
AIC	23712.30	
Log likelihood	-11826.15	
N	12535	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.8: DGOL for Job Continuity and Women Characteristics

Variable	Work or Not		Full Time or Not	
	No Work	Some Work	Not Full Time	Full Time
Prob Return Work	-1.311***	1.234***	-0.763***	1.518***
	(0.06)	(0.06)	(0.24)	(0.27)
Prob Same Employer	4.974***	6.763***	-0.391**	0.885***
	(0.06)	(0.06)	(0.13)	(0.15)
Education	0.041***	0.120***	-0.083***	0.009
	(0.01)	(0.01)	(0.02)	(0.02)
Age	-0.064***	-0.160***	-0.041***	-0.056***
	(0.01)	(0.01)	(0.01)	(0.01)
Partner	-0.064	-0.289***	0.294***	0.215
	(0.05)	(0.05)	(0.10)	(0.13)
Log Partner Income	-0.270***	-0.264***	-0.072***	-0.066**
	(0.01)	(0.01)	(0.02)	(0.03)
Log Hourly Wage	-0.294***	0.279***	-0.042	0.032
	(0.02)	(0.02)	(0.04)	(0.05)
Religion				
Protestant	-0.019	-0.007	0.058	-0.043
	(0.04)	(0.04)	(0.08)	(0.08)
Other Religion	-0.094	0.007	0.031	0.063
	(0.05)	(0.05)	(0.10)	(0.11)
No Religion	0.064	0.182***	0.224**	0.152
	(0.05)	(0.05)	(0.10)	(0.12)
Region				
North	0.285***	0.225***	-0.035	-0.109
	(0.04)	(0.04)	(0.10)	(0.11)
South	-0.290***	-0.254***	-0.172*	-0.049
	(0.03)	(0.03)	(0.10)	(0.09)
West	-0.051	-0.001	-0.163	-0.188*
	(0.04)	(0.04)	(0.11)	(0.11)
Constant	-2.677***	-2.103***	3.241***	-0.071
	(0.11)	(0.11)	(0.39)	(0.45)
AIC	20608.32			
Log likelihood	-10240.16			
N	12535			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.9: Average Partial Effects

	APE	
	Actual	Simulated
$P(y_t = \text{full time} \vert y_{t-1} = \text{full time})$	0.794	0.839
$P(y_t = \text{full time} \vert y_{t-1} = \text{not full time})$	0.181	0.191
$P(y_t = \text{full time} \vert y_{t-1} = \text{full time}) - P(y_t = \text{full time} \vert y_{t-1} = \text{not full time})$	0.613	0.648

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Chapter 2

Estimating the Determinants of Return to Work Durations after Childbirth: A Control Function Approach

2.1 Introduction

Women's labor force participation has increased dramatically over the past 60 years. Between 1940 and 1998, the participation rate of women in the U.S. labor force rose from 27% to 60% (U.S. Bureau of the Census, 1999). Between 1970 and 2000 alone, the proportion of married mothers with preschool children in the labor force doubled from 30% to 63% (Hayghe, 2000; U.S. Bureau of the Census, 1999). However, the most dramatic increase has been in the labor force participation of mothers of infants. Smith, Downs and O'connell (2001) shows that 52% of new mothers in 1991 to 1994 were working six months after childbirth, increasing to 60% by the 12th month.

Although female labor market participation has increased everywhere, women are still likely to interrupt their career when they have a child (Pronzato 2009). U.S. policies implemented during the 1990s may have changed the incentives for employment among mothers of young children. The Family and Medical Leave Act of 1993 represents the first Federal legislation concerning parental leave (Ondrich et al. 2003). It guaranteed job protection and a maximum of 12 weeks of unpaid leave to care for a new-born child or a family member who is ill (Ruhm and Teague 1997).

Several American studies provide a general perspective on women's return to work after childbirth. Klerman and Leibowitz (1995) find no significant effect of state maternity leave statutes on the employment of mothers. Joesch (1997) uses duration analysis to show that women appear to increase their attachment to the labor force when given the opportunity to take paid leave. Waldfogel (1997) finds that maternity leave is associated with higher pay for working mothers, at least in part because returning to the prior employer leads to gains in work experience and job tenure.

An important feature of the studies by Ruhm and Teague (1997) and by Ruhm (1998) is the use of data from many different nations. Ruhm and Teague study the effects of changes in federal leave legislation using data for 17 industrialized nations, including the United States, between 1968 and 1988. They find that a federal leave period of moderate length is positively related to macro-level labor market outcomes. Ruhm (1998) uses a differences-in-differences approach to show that the female employment-to-population ratio is higher when there are rights to paid leave; moreover, the effect is substantial even for short leaves.

On the other hand, lengthier leave entitlements are associated with relative wage reductions. Blau and Robins (1991) uses panel data from the National Longitudinal Survey of Youth (NLSY) to analyze jointly fertility, employment, and child care decisions of young women over time. Baum and Ruhm (2016) suggest that California's paid family leave program (CA-PFL), financed by contribution from wages, raised the leave-taking of new mothers and fathers.

Recent results by Bailey, Byker, Patel, and Ramnath (2019) are more negative. They use

IRS tax data to evaluate the short- and long-term effects of CA-PFL on women's careers. They find little evidence that CA-PFL increased women's employment, wage earnings, or attachment to employers. For new mothers, taking up CA-PFL reduced employment by 7 percent and lowered annual wages by 8 percent six to ten years after giving birth. Overall, CA-PFL tended to reduce the number of children born and increase time spent with children.

This study introduces a conditional expectation correction approach to control for endogeneity in the Cox partial likelihood. In our application, we use data from NLSY97 and find that standard Cox model techniques that do not control for the omitted job match quality variable underestimate the sensitivity of women's job duration to wages after childbirth.

The paper is organized as follows. Section 2.2 introduces the hazard model and conditional expectation correction approach, as well as the consistency proof of control function estimation. Section 2.3 describes the data set and provides the definition and analysis of the variables. Section 2.4 shows the results we find from our models. Section 2.5 talks about the conclusion.

2.2 Model

2.2.1 The Control Function Approach

A common concern in labor market participation studies is the possibility that wages and unobserved characteristics are not independent, so that standard econometric techniques that require exogenous covariates produce biased estimates. Petrin and Train (2005, 2006) illustrate how to correct the omitted variables problem in a multinomial logit using a control function. A control function is a term added to an econometric specification to correct the conditional expectation. The consistency of the control function approach was first established by Dubin and McFadden (1984) in the context of the appliance portfolio choice models. They called the control function approach conditional expectation correction and cite Heckman (1978).

The method proceeds in two steps. The first step is a linear regression of the endogenous variable on all exogenous variables and appropriate set of instruments. The residual μ_i from this regression is used to construct the control function, $f(\mu_i, \lambda)$, where λ is a vector of estimated parameters. The random utility function for choice i can now be written as:

$$U_i = \alpha + \beta' Z_i + f(\mu_i, \lambda) + (\beta_\zeta \zeta_i - f(\mu_i, \lambda)) + \epsilon_i$$

The new error term is the difference between the effect of the omitted variable $\beta_\zeta \zeta_i$ and the control function, plus the idiosyncratic error. In the second step, the likelihood function is maximized with the control function as an additional explanatory variable.

2.2.2 The Cox Proportional Hazard Model

The proportional hazard model (PHM) was introduced by Cox (1972). The proportional hazard model provides a method for exploring the association of covariates with failure rates and survival distributions and for studying the effect of a primary covariate, such as a treatment, while adjusting for other variables. The model is neither fully parametric nor fully nonparametric, and inference for the model is based on a likelihood type function that, in censored data, only approximates the probability or density function of any observed set of values (Fleming and Harrington 2011).

The Cox proportional hazard model assumes that the hazard function λ_j for spell j has the following form:

$$\lambda_j(t) = \lambda_0(t) exp\{\beta' Z_j(t)\} \ ,$$

where $\beta = (\beta_1, \ldots, \beta_p)'$ is a p vector of unknown regression coefficients and $\lambda_0(t)$ is an unspecified baseline hazard function.

Suppose we have n distinct failure times $t_i = 1, \ldots, n$ ranked from smallest to largest, for J spells $j = 1, \ldots, J$. Let $Z_1, ..., Z_J$ be the corresponding covariate vectors. Initially we assume there is one and only one failure at each failure time. Therefore, $J - n$ spells are censored on the right. At each failure time i, The censoring is assumed to be noninformative.

At each failure time i, the contribution to the Cox partial likelihood is

$$L_i(\beta) = \frac{\sum_{j \in R_i} \delta_{ij} exp\{\beta' Z_j(t_i)\}}{\sum_{j \in R_i} exp\{\beta' Z_j(t_i)\}} \ ,$$

where δ_{ij} is the indicator for spell j failing at failure time i and R_i is the set of spells that are at risk for failure at time i. In another words, R_i is the set of spells that have not previously failed and that have not been censored before failure time i.

Then the maximum partial likelihood estimator $\hat{\beta}$ is the value that maximizes the partial likelihood function:

$$\hat{\beta} =_{\beta} \prod_{i=1}^{n} \frac{\sum_{j \in R_i} \delta_{ij} exp\{\beta' Z_j(t_i)\}}{\sum_{j \in R_i} exp\{\beta' Z_j(t_i)\}} \ .$$

2.2.3 Consistency of the Control Function Estimation of Partial Likelihood

To examine the consistency of the control function estimation, we start by presenting a lemma and standard regularity conditions that are required in the proof.

Lemma: Let E be an open convex subset of $\mathbb{R}^p$, and let $F_1, F_2, \ldots,$ be a sequence of random concave functions on E and f a real-valued function on E such that, for all $x \in E$,

$$\lim_{n \to \infty} F_n(x) = f(x)$$

in probability. Then:

1. The function f is concave.

2. For all compact subsets A of E,

$$\sup_{x \in A} |F_n(x) - f(x)| \to 0$$

in probability, as $n \to \infty$.

3. If F_n has unique maximum at X_n and f has one at x, then $X_n \to x$ in probability as $n \to \infty$.

Regularity Conditions:

Let $(N_i, Y_i, Z_i), i = 1, \ldots, n$, denote n independent triplet processes from the multiplicative intensity model, with possibly time-dependent p-dimensional covariates $Z = \{Z(u) : 0 \le u < \infty\}$. Let $Y_i(t) = 1$ if item i is at risk and under observation at time t, and zero otherwise, and let

$$\widehat{S}^{(0)}(\beta, t) = n^{-1} \sum_{i=1}^{n} Y_i(t) \exp\left\{\beta' \widehat{Z}_i(t)\right\}$$

$$\widehat{S}^{(1)}(\beta, t) = n^{-1} \sum_{i=1}^{n} \widehat{Z}_i(t) Y_i(t) \exp\left\{\beta' \widehat{Z}_i(t)\right\}$$

and

$$\widehat{S}^{(2)}(\beta, t) = n^{-1} \sum_{i=1}^{n} \left\{\widehat{Z}_i(t)\right\}^{\otimes 2} Y_i(t) \exp\left\{\beta' \widehat{Z}_i(t)\right\} \ ,$$

where $\widehat{Z}_i(t)$ is $Z_i(t)$ with $\hat{f}_i(t)$ replacing $f_i(t)$ and for any vector $X, X^{\otimes 2}$ denotes the outer product XX'.

The regularity conditions are:

(1) For all τ, $\int_0^\tau \lambda_0(x)dx < \infty$.

(2) For $\widehat{S}^{(j)}, j = 0, 1,$ and 2, there exists a neighborhood $\mathcal{B}$ of β_0 and, respectively, scalar, vector, and matrix functions $s^{(0)}, s^{(1)}$ and $s^{(2)}$ defined on $\mathcal{B} \times [0, \tau]$ such that, for $j = 0, 1, 2$,

$$\sup_{x \in [0,\tau], \beta \in \mathcal{B}.} \left\| \widehat{S}^{(j)}(\beta, x) - s^{(j)}(\beta, x) \right\| \to 0$$

in probability as $n \to \infty$.

(3) The functions $s^{(j)}$ are bounded and $s^{(0)}$ is bounded away from 0 on $\mathcal{B}\times$ $[0, \tau]$; for $j = 0, 1, 2$, the family of functions $s^{(j)}(\cdot, x), 0 \le x \le \tau$, is an equicontinuous family at β_0.

Theorem: Let $\hat{\beta}$ denote the MPLE of β in a Cox Partial Likelihood with an endogenous regressor and let β_0 be the true value of β. Then

$$\lim_{n\to\infty} \hat{\beta} = \beta_0$$

in probability, i.e., $\hat{\beta}$ is consistent.

Proof: Let $nX_n(\beta, \cdot)$ denote the process which, at time t, is the difference in log partial likelihoods over $[0, t]$, evaluated at an arbitrary β and the true value β_0,

$$\begin{aligned} X_n(\beta, t) =& n^{-1} \left\{ \mathcal{L}(\beta, t) - \mathcal{L}(\beta_0, t) \right\} \\ =& n^{-1} \left[\sum_{i=1}^{n} \int_0^t (\beta - \beta_0)' \widehat{Z}_i(x) dN_i(x) \right. \\ & \left. - \int_0^t \log \left\{ \frac{\sum_{i=1}^n Y_i(x) e^{\beta' \widehat{Z}_i(x)}}{\sum_{i=1}^n Y_i(x) e^{\beta_0' \widehat{Z}_i(x)}} \right\} d\bar{N}(x) \right] . \end{aligned}$$

If

$$\begin{aligned} A_n(\beta, t) =& n^{-1} \left[\sum_{i=1}^{n} \int_0^t (\beta - \beta_0)' \widehat{Z}_i(x) Y_i(x) \exp\left\{ \beta_0' \widehat{Z}_i(x) \right\} \lambda_0(x) dx \right. \\ & \left. - \int_0^t \sum_{i=1}^{n} \log \left\{ \frac{\widehat{S}^{(0)}(\beta, x)}{\widehat{S}^{(0)}(\beta_0, x)} \right\} Y_i(x) \exp\left\{ \beta_0' \widehat{Z}_i(x) \right\} \lambda_0(x) dx \right] , \end{aligned}$$

then

$$\begin{aligned} & X_n(\beta, t) - A_n(\beta, t) \\ & \quad = n^{-1} \left[\sum_{i=1}^{n} \int_0^t \left\{ (\beta - \beta_0)' \widehat{Z}_i(x) - \log \frac{\widehat{S}^{(0)}(\beta, x)}{\widehat{S}^{(0)}(\beta_0, x)} \right\} dM_i(x) \right], \end{aligned}$$

where $\widehat{S}^{(0)}(\beta, t) = n^{-1} \sum_{i=1}^n Y_i(t) \exp\left\{ \beta' \widehat{Z}_i(t) \right\}$.

The process $X_n(\beta, \cdot) - A_n(\beta, \cdot)$ is then a locally square integrable martingale (it is trivial that the integrand in above equation is locally bounded and predictable) with predictable variation process at t:

$$
\begin{aligned}
&\langle X_n(\beta,\cdot)-A_n(\beta,\cdot),X_n(\beta,\cdot)-A_n(\beta,\cdot)\rangle(t)\\
&=n^{-2}\sum_{i=1}^{n}\int_0^t\left[(\beta-\beta_0)'\widehat{Z}_i(x)-\log\left\{\frac{\widehat{S}^{(0)}(\beta,x)}{\widehat{S}^{(0)}(\beta_0,x)}\right\}\right]^2 Y_i(x)\exp\left\{\beta_0'\widehat{Z}_i(x))\right\}\lambda_0(x)dx\\
&=n^{-1}\int_0^t\left[(\beta-\beta_0)'\widehat{S}^{(2)}(\beta_0,x)(\beta-\beta_0)-2(\beta-\beta_0)'\widehat{S}^{(1)}(\beta_0,x)\log\left\{\frac{\widehat{S}^{(0)}(\beta,x)}{\widehat{S}^{(0)}(\beta_0,x)}\right\}\right.\\
&\left.+\left[\log\left\{\frac{\widehat{S}^{(0)}(\beta,x)}{\widehat{S}^{(0)}(\beta_0,x)}\right\}\right]^2\widehat{S}^{(0)}(\beta_0,x)\right]\lambda_0(x)dx\ .
\end{aligned}
$$

By Conditions (1), (2), and (3),

$$
n\langle X_n(\beta,\cdot)-A_n(\beta,\cdot),X_n(\beta,\cdot)-A_n(\beta,\cdot)\rangle(\tau)
$$

converges to a finite limit, and hence the second condition of the Lemma implies

$$
\lim_{n\to\infty}X_n(\beta,\tau)-A_n(\beta,\tau)=0
$$

in probability. Since $A_n(\beta,\tau)$ converges to

$$
A(\beta,\tau)=\int_0^\tau\left[(\beta-\beta_0)'s^{(1)}(\beta_0,x)-\log\left\{\frac{s^{(0)}(\beta,x)}{s^{(0)}(\beta_0,x)}\right\}s^{(0)}(\beta_0,x)\right]\lambda_0(x)dx
$$

$X_n(\beta,\tau)$ must convenge in probability to the same limit, as long as $\beta\in B$. It is not difficult to show that $X_n(\beta,r)$ is a concave function of β with a unique maximum, and (using Conditions (2) and (3)) that $A(\beta,\tau)$ has a unique maximum at $\beta=\beta_0$. The Theorem now follows from the Lemma.

2.2.4 Maximum Likelihood Estimation for Tied Survival Data in the Cox Model

In some datasets ties may result due to measurement error. Breslow suggested that the partial likelihood function can still be used when there are ties. Efron suggested an alternative estimator:

$$\widehat{\beta} =_\beta \prod_{i=1}^{n} \Bigg(\sum_{j \in R_i} \delta_{ij} exp\{\beta' Z_j(t_i)\} / \\ \Big(\prod_{r=1}^{d_j} (\sum_{j \in R_i} exp\{\beta' Z_j(t_i)\} - \frac{r-1}{d_j} \sum_{j \in R_i} \delta_{ij} exp\{\beta' Z_j(t_i)\}) \Big) \Bigg) ,$$

where d_j is the number of ties in spell j.

In our study of the duration of the return to work with the same employer, $\beta' Z_j(t_i)$ should be given by

$$\beta_E E_j(t_i) + \beta_A A_j(t_i) + \beta_W W_j(t_i) + \beta_Q Q_j(t_i),$$

where E_j is the education year of the mother when she gives birth; A_j is the age of the mother when she gives birth; W_j is the log weekly wage of the mother's job; and Q_j is an indax of job characteristics that we will call job quality.

However, job quality is unobserved. Let $X_j(t_i)$ be the vector of observed variables. We replace $Q_j(t_i)$ with the control function $f_j(t_i)$ in $Z_j(t_i)$,

$$Z_j(t_i) = \begin{bmatrix} X_j(t_i) \\ f_j(t_i) \end{bmatrix}$$

and

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_f \end{bmatrix} ,$$

we assume that $E[\beta_f' f_j(t_i)] = E[\beta_Q' Q_j(t_i)]$ for each t_i.

If f_j's are known and do not have to be estimated, the control function estimator would be consistent given the assumptions of the theorem in Fleming and Harrington, (2013, pp. 297-8). Because f_j is unknown, we include $\hat{f}_j$ in our partial likelihood. A set of sufficient conditions for the consistency of the feasible partial likelihood estimator is that $(f_j - \hat{f}_j)$ is orthogonal to the included regressors along with the assumptions of Fleming and Harrington theorem.

In our application for the Cox partial likelihood, for each of the first two years after returning to work, we use as the control function the residual from the first stage regression of $W_j(t_i)$ on the remaining observed covariates and a set of instruments describing the conditions and mother's behavior during her leave. The residual is time-varying across years and new mothers. And there is an orthogonality condition in the second year as well as first year. For mothers who continue their employment with the same employer into the second year, the residual $f_j - \hat{f}_j$ for the second year is required to be orthogonal as well as the first year.

2.3 Data

This study uses data from Waves 1 through 18 (1997–2017) of the National Longitudinal Survey of Youth 1997 cohort (NLSY97). The National Longitudinal Survey of Youth (NLSY97) is the latest in a series of surveys sponsored by the U.S. Department of Labor, Bureau of Labor Statistics to examine issues surrounding youth entry into the workforce and subsequent transitions in and out of the workforce (Moore et al., 2000). It is an ongoing nationally representative panel study of youths ages 12 to 16 on December 31, 1996. At the initial survey in 1997, 8,984 respondents were interviewed. Men accounted for 51 percent (4,385), and Women accounted for 49 percent (4,385). The NLSY97 documents the transition from school to work and into adulthood (Haas and Fosse 2008). After deleting women without children and pregnancies without a work absence before childbirth, the pooled sample of return to work durations has 3157 observations.

This paper uses a sample composed of women who return to work with the same employer after they give birth. For all women, we record the length of employment with the same employer after they return to work, education in years, age, and their weekly wage. We choose the length of the work absence due to the current childbirth and the total number of work absences due to childbirth for current and previous employers as instrumental variables. Complete descriptions and summary statistics for all variables are provided in Table 2.1 and Table 2.2.

2.4 Results

2.4.1 IV Estimation for the Wage Equation

Table 2.3 presents the estimation of the log wage regression including the instrumental variables. For each year, we estimate the log wage if the woman still works with the same employer when she returns to work. All coefficients have their expected signs. Higher education indicates higher wages. Age also has a positive relation with the return-to-work wage. The instrumental variables, work absence length and the total number of work absences, negatively influence the wage. When we compare the first year and second year wage equations, we can see that the impact of education and age slightly increase, while the effects of the work absence length and the total number of work absences decline.

Table 2.4 presents the estimation of the interaction of age and log wage using instrumental variables. Similar to log wage, for each year, we include an observation if the woman still works with the same employer when she returns to work. Again, the impact of the year of education and age are positive and significant. In contrast, the work absence length and the total number of work absences have negative and significant influences on the log wage$\times$ age. When we compare column 1 (year 1) and column 2 (year 2) in Table 2.4, we also observe the increasing impact of education and age and the decreasing impact of the work absence length and the total number of work absences.

2.4.2 Cox Regression Results

Table 2.5 displays the results estimated using the Cox model with time-varying covariates. Here, we use Breslow's approximation to deal with ties. For the Cox regression coefficients sign, a positive sign means that the hazard (risk of leaving the job) is higher for new mothers with higher values of that variable. In the first column, we use the actual (raw) log weekly wage. The result in column 1 shows that women with more education have a lower risk of leaving their jobs than lower educated women. Age also has a significant impact on employment length; young women are more likely to leave their job. The wage effect is also as expected – the higher the wage, the lower the probability of departure. Column 2 adds the residual from the first-stage regression to the Cox model to control for unobserved job quality. The coefficients of education and age are almost unchanged. The wage coefficient remains negative and highly significant. However, it increases sharply in absolute value, providing an estimate of the downward bias with the standard method. Comparing model 1 with model 2, we find that the coefficient of -0.580 estimated with the control function is 483% larger than the coefficient of -0.120 estimated without the residual. Figure 2.1 plots the baseline hazard for the Cox model in model 1 and model 2. The plot shows that the standard Cox model techniques underestimate the true baseline hazard dramatically.

In Table 2.6, we add the interaction of log wage and age into the Cox model. Except for the log wage varible, the signs and magnitudes of coefficients in model 3 do not significantly differ from the corresponding coefficients in model 1. The estimate of the sum of the impact of log wage and log wage$\times$age is -0.133 (the coefficient of log wage plus the product of the mean of age and the coefficient of log wage$\times$age), which is close to the coefficient in model 1. Model 4 has two control functions. Control function 1 is the residual from the wage equation in the first stage regression (Table 2.3). Control function 2 is the residual from the log wage×age equation (Table 2.4). The estimate of the sum of the impact of log wage and log wage×age changes to -0.582 ($\beta_{wage} + \beta_{logwage \times age} \times mean(age)$), which is 438% larger than the estimation in model 3. Again, this estimate demonstrates the downward bias when there are no controls for unobserved job quality. Figure 2.2 plots the baseline hazard for the Cox model in model 3 and model 4. The plot also shows that the standard Cox model techniques underestimates the baseline hazard largely.

2.4.3 Prototype Results

In our prototype Cox model, we have selected three predictor variables: education, log wage, and age. Education is divided in two levels, high school (12 education years) or college (16 education years). We have chosen two levels of log wage based on the 75th and 25th percentiles of the log wage distribution. Finally, age is also a classified into two levels, 22 and 27 years old. We believe that these variables may have an impact on the cumulative hazard of the individuals in our study population. We will fit the model using these variables and assess the predicted cumulative hazard.

Figure 2.3 displays the cumulative hazard for model 1 and model 2 using prototype data. The prototype data features a woman with a high school degree (12 years of education), a young mother who gave birth at 22 years old, and varying wage levels. The plots reveal that the traditional Cox model tends to overestimate the cumulative hazard for this woman. As seen in the left panel of Figure 2.3, the traditional hazard model's cumulative hazard at the end of the second year (104 weeks) is 0.277, indicating a survival probability of 0.758 for this individual. In contrast, the Cox model with the control function suggests a lower cumulative hazard of 0.174 and a higher survival probability of 0.841. As previously noted, the standard Cox model underestimates the impact of wage on a woman's work duration. Even with a low wage, women are more likely to remain employed. Comparing the left panel with the right panels of Figure 2.3, women with higher wages have a lower likelihood of quitting their jobs, with a cumulative hazard of 0.111 and a survival probability of 0.895, which is in line with our expectations.

In Figure 2.4, we observe the cumulative hazard for model 3 and model 4 using prototype data that represents a woman with a college degree (16 years of education), an older mother who gave birth at 27 years old, and different wage levels. Similar to Figure 2.3, the plots show that the traditional Cox model overestimates the cumulative hazard for this woman. Our new model also reveals that women have a higher probability to continue working than the standard Cox model results and higher wage workers are more likely to stay in the labor market than lower wage workers, consistent with our expectations.

2.5 Conclusion

Recent work by Bailey, Byker, Patel and Ramnath (2019) finds little evidence that California's paid leave program increased women's employment, wage earnings, or attachment to employers. In Germany federal law has increased the potential duration of maternity leave five times. Ondrich, Spiess, Yang and Wagner (2003) use the German Socio-Economic Panel to estimate cumulative return to work probabilities for new mothers in the period 1984–1991. Their results are consistent with the hypothesis that employment conditions or career expectations frequently change for mothers taking longer leaves.

This study presents a new type of duration analysis that incorporates instrumental variables through control functions to examine job attachment up to two years after childbirth with U.S. data from NLSY97. We find that the effect of wages on job attachment increases fivefold when we use information about the maternity leave to instrument for missing employment conditions. Additionally, in the standard estimation without the control function the baseline hazard is relatively flat over the two year period. But when the control function is incorporated into the estimation, the baseline hazard triples after two years. The prototype result shows that there are significant divergences between the standard Cox model and the new model. The standard Cox model underestimates the probability of women's survival in the labor market. Overall, this study presents a novel approach to duration analysis and provides new insights into the determinants of job attachment for new mothers. Further research is needed to explore the implications of these findings for labor market policies and practices.

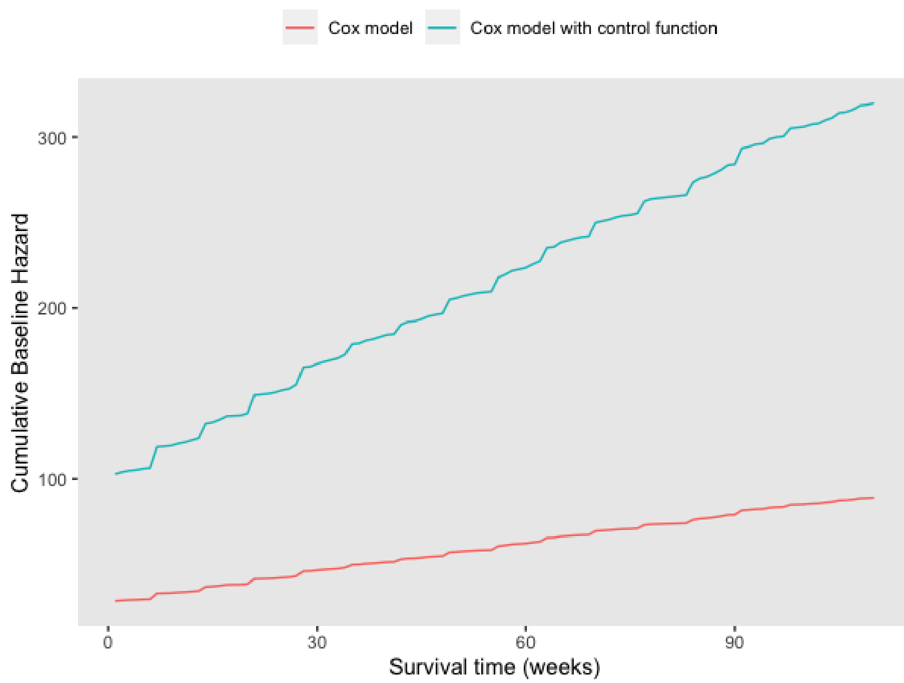

Figure 2.1: Cumulative Baseline Hazard for Cox Model

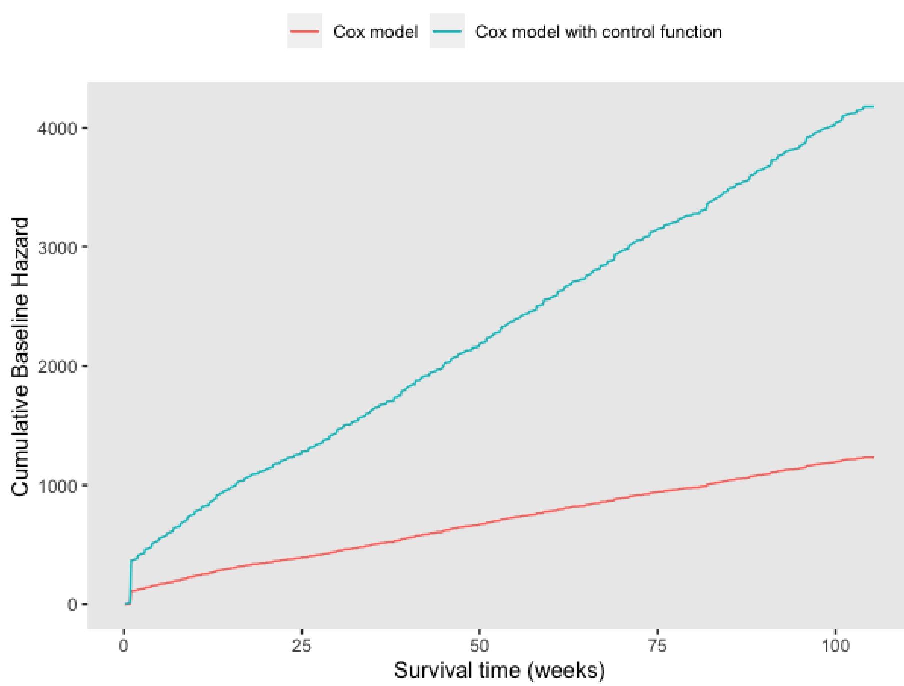

Figure 2.2: Cumulative Baseline Hazard for Cox Model (adding log wage×age)

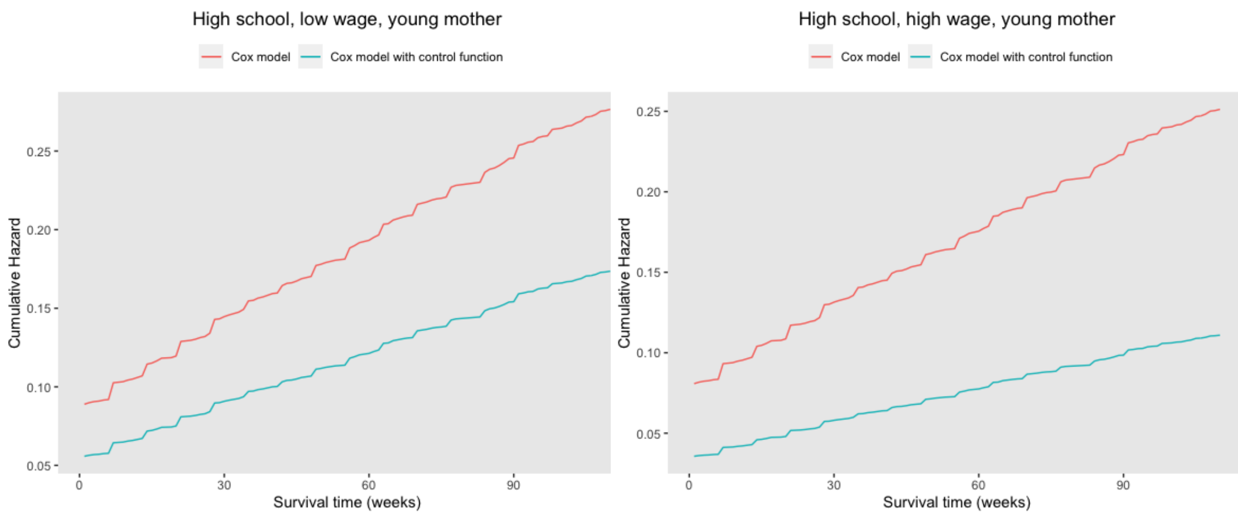

Figure 2.3: Cumulative hazard for high school, young mother with different wage

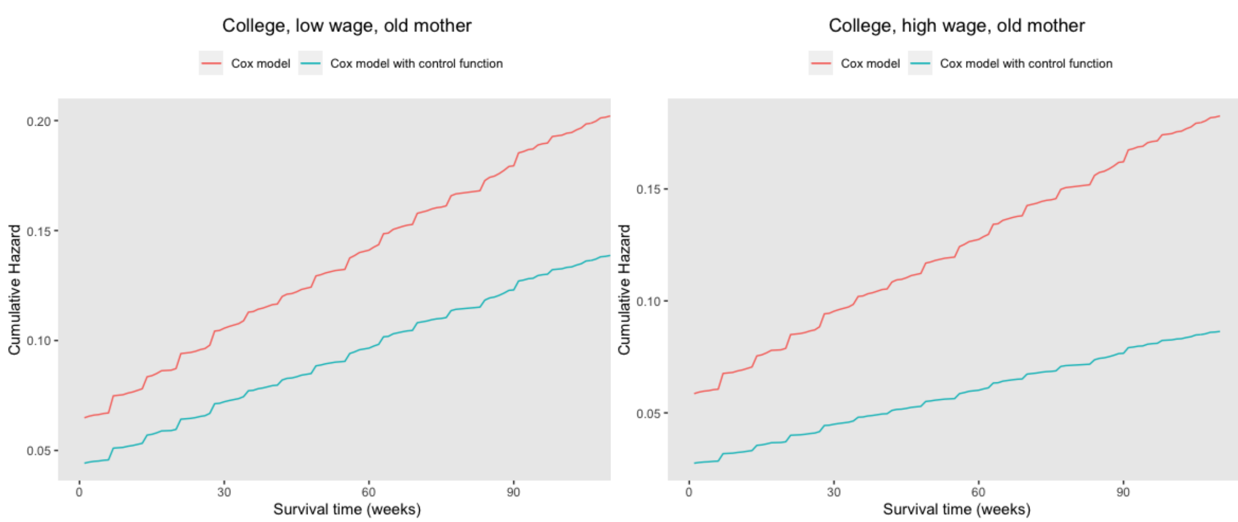

Figure 2.4: Cumulative hazard for college, old mother with different wage

Table 2.1: Definition of Explanatory Variables

Variables	Definition
Return to Work Duration	The duration in days of the remainder of the duration of the employment spell with the same employer after the work absence.
Education	Education in year.
Age	The age of the woman when she returns to work.
Log Wage Year 1	The log of weekly real wage in the first year after the woman returns to work.
Log Wage Year 2	The log of weekly real wage in the second year after the woman returns to work.
Instrumental Variables	
Work Absence Length	The length of the work absence due to the current childbirth.
Total Number of Work Absences	The total number of work absences due to childbirth for current and previous employers.

Table 2.2: Summary Statistics

Variable	N	Mean	S.D.
Return to Work Duration	3,157	105.123	127.07
Education (years)	3,157	12.825	2.99
Age	3,157	27.294	4.81
Log Wage Year 1	3,157	5.873	1.22
Log Wage Year 2	1,551	6.136	1.03
Instrumental Variables			
Work Absence Length	3,157	2.677	5.77
Total Number of Work Absences	3,157	0.881	1.05

Table 2.3: Instrumental Variable Estimation for Log Wage

Variable	**Year 1**	**Year 2**
Constant	2.111	2.100
	(0.63)	(0.95)
Education	0.543	0.584
	(0.08)	(0.10)
Age	1.852	1.980
	(0.48)	(0.71)
Age Squared	−0.241	−0.268
	(0.09)	(0.12)
Work Absence Length	−0.093	−0.066
	(0.05)	(0.06)
Total Number of Work Absences	−0.130	−0.116
	(0.02)	(0.03)
Work Absence Length ×	0.037	−0.032
Total Number of Work Absences	(0.04)	(0.05)
N	3157	1575
R^2	0.091	0.108
Adj. R^2	0.089	0.105

Table 2.4: Instrumental Variable Estimation for Log Wage × Age

Variable	**Year 1**	**Year 2**
Constant	−5.085	−6.370
	(1.80)	(2.77)
Education	1.630	1.724
	(0.23)	(0.28)
Age	7.087	8.152
	(1.38)	(2.07)
Age Squared	0.030	−0.130
	(0.25)	(0.38)
Work Absence Length	−0.271	−0.192
	(0.14)	(0.18)
Total Number of Work Absences	−0.375	−0.349
	(0.07)	(0.08)
Work Absence Length ×	0.101	−0.106
Total Number of Work Absences	(0.10)	(0.13)
N	3157	1575
R^2	0.543	0.569
Adj. R^2	0.542	0.568

Table 2.5: Cox model for the return to work duration

Variable	Cox Model 1	Cox Model 2 (with control function)
Education	−3.537	−2.885
	(0.46)	(0.49)
Age	−1.736	−1.379
	(0.19)	(0.22)
Education × Age	1.183	1.046
	(0.16)	(0.16)
Log Wage	−0.121	−0.564
	(0.02)	(0.13)
Control Function		0.448
		(0.13)
N	3157	3157
Log Likelihood	−16069.46	−16064.14
Log Likelihood Ratio	194.6	205.2

Table 2.6: Cox model for return to work duration with control functions

Variable	Cox Model 3	Cox Model 4 (with control function)
Education	−0.327	−0.264
	(0.05)	(0.05)
Age	−0.218	−0.178
	(0.02)	(0.03)
Education×Age	0.010	0.009
	(0.00)	(0.00)
Log Wage	−0.406	−0.828
	(0.09)	(0.16)
Log Wage×Age	0.010	0.009
	(0.00)	(0.00)
Control Function 1		0.434
		(0.14)
Control Function 2		0.001
		(0.00)
N	3157	3157
Log Likelihood	-16064.29	-16034.87
Log Likelihood Ratio	203.5	214.8

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Chapter 3

Disability and Financial Satisfaction

3.1 Introduction

Three of the most frequently analyzed sources of inequality that demand social justice are inequality due to race, inequality due to gender, and inequality due to disability. Inequality due to race has historical and possibly sociological causes that are at least conceptually straightforward to overcome, even if difficult to overcome in practice. The latter two sources, inequality due to gender and inequality due to disability, cannot be completely overcome even conceptually. To see that this is likely to be the case, one need only recognize that in both of these latter cases there is usually temporary or permanent alienation from the labor force.

This paper examines the effect of disability in the family on financial satisfaction of the female head or spouse using the Panel Study of Income Dynamics (PSID) 2016 Wellbeing and Daily Life Supplement merged with information from the PSID 2015 Family and Individual files. This empirical work is based on the theoretical work on the capability approach developed primarily by Amartya Sen and Martha Nussbaum (see, for example, Nussbaum and Sen 1993, Sen 1999, Nussbaum 2003, and Sen 2011). Nussbaum and Sen believe that researchers should focus on what individuals, families, or nations are capable of achieving under a given set of circumstances or policies, rather than examining what they actually achieve.

The first econometric work employing the capability framework is in the doctoral dissertation of Kuklys (2005). Her dissertation work will be described in more detail below. One piece of analysis uses British data to regress and qualitative income satisfaction on disability and capability variables. While there have been subsequent studies examining income satisfaction using German data (see Ferrer-i Carbonell and Van Praag 2003), we are not aware of any studies examining the situation in the United States. One of the apparent problems in doing so is the lack of data availability concerning income or financial satisfaction in U.S. data sets. (While there are many sources for U.S. data on life satisfaction, Kuklys 2005 demonstrates that life satisfaction is fundamentally different than income or financial satisfaction.) The PSID 2016 Wellbeing and Daily Life Supplement is the only source of income or financial satisfaction for the United States with a sufficient number of observations to undertake meaningful empirical work.

The remainder of this paper is organized as follows. Section 3.2 presents the theoretical basis for the capability approach. Section 3.3 discusses the econometrics of capability, which is largely a review of the work of Kuklys (2005). Section 3.4 describes the construction of the data used in this analysis and Section 3.5 presents the empirical results. Section 3.6 concludes.

3.2 The Capability Approach

The utilitarian approach to ethics, pioneered by Jeremy Bentham, takes the position that individual happiness or pleasure or utility is the best way of assessing how advantaged a person is. Proponents of utilitarianism typically focus on maximizing total social welfare without regard to its distribution. Amartya Sen, together with liberal philosophers Bernard Williams and John Rawls, among others, argue that the implied sum-ranking completely ignores relevant individual heterogeneity in the ability to convert resources into welfare.

A disabled person may need expensive equipment to achieve the same level of welfare as someone who is able-bodied. Maximizing total social welfare implies that the marginal utility of the last dollar spent is equal across individuals. As a result, resources are distributed away from the disabled.

Another approach, the resource-based approach, maintains that individual advantage can be assessed by an individual's income, wealth, or resources, which Rawls (1971) calls primary goods. But Sen points out that differential ability to convert resources into welfare is again a problem with resourcism. Two people with the same vision of the good life and the same bundle of resources may not be equally able to achieve that life. Specifically, Sen disputes Rawls' argument that a social contract should be the starting point and that the extension to difficult individual cases, such as the disabled, can be worked out later. Sen believes that social contracts essentially proclaim resources to be the source of advantage, rather than focusing on the relationship between resources and people.

Instead of focusing on resources, Sen's capability approach focuses on the quality of life that individuals are able to achieve. This quality of life is measured by the individual's capability to choose between different kinds of life, described by sets of states of affairs for the individual, such as having enough food, having adequate housing, and being able to get around.[1] These states of affairs are called functionings.

Resources are inputs, the value of which depend on the individual's ability to convert them into functionings. The ability of individuals to convert resources into functionings is constrained by individual characteristics, social norms, and physical environment. Figure 3.1 describes the methodology of the capability approach.

[1]More recently, the literature talks about an individual's capabilities rather than using the term capability in the singular. When this is done, capabilities should be viewed as different subsets of Sen's original capability set.

3.3 The Econometrics of Capability

In Kuklys' doctoral dissertation at Cambridge University, under the supervision of Amartya Sen, later published by Springer as "Amartya Sen's Capability Approach," Wiebke Kuklys (2005) presents two innovative empirical essays. The first describes a structural equation model of functioning achievement (presented in Section 3.3.1) and the second describes a method of conversion factors for disability (presented in section 3.3.2).

3.3.1 Structural Equation Modeling of Functioning Achievement

Kuklys presents a multiple-cause multiple-indicator (MIMIC) model of capability characterized by a latent endogenous variable and no measurement error in the independent variables. She estimates two models, one for being well sheltered (housing) and one for being healthy (health) for the 1991 and 2000 waves of the British Household Panel Survey (BHPS). Health is described by visits to the doctor in the past year, health limits to daily activities, and self-assessed health status over the past 12 months. Housing is described by housing conditions: presence of condensation, cold, rot in wood, and lack of space. Causal factors include gender, job status, marital status, and level of education. Kuklys compares her results for achievements in the functionings of health and housing to welfare achievements in the income space and concludes the resource-based measures do not capture what is happening in the functioning space.

3.3.2 Conversion Factors for Disability

Sen (2011) writes that "the magnitude of the global problem of disability in the world is truly gigantic. More than 600 million people – about one in 10 of all human beings – live with some sort of significant disability. More than 400 million of them live in developing countries. Furthermore, in the developing world, the disabled are quite often the poorest of the poor in terms of income, but in addition, their need for income is greater than that of able-bodied people, since they require money and assistance to try to lead normal lives and to attempt to alleviate their handicaps. The impairment of income-earning ability which can be called 'the earning handicap', tends to be reinforced and much magnified in its effect by the 'conversion handicap', the difficulty in converting incomes and resources into good living, precisely because of disability."

Kuklys finds that 17.9 percent of individuals in the United Kingdom live in families with income below the poverty line. Restricting attention to those who live in families with a disabled member, the percentage rises to 23.1 percent. The difference here reflects the income handicap associated with disability. Further taking into account the need for more income to ameliorate the disadvantages of disability, the proportion of individuals and families with disabled members living below the poverty line for the respective families rises to 47.4 percent, a gap of nearly 30 percentage points over the share of individuals below the poverty line.

Kuklys' econometric methodology involves estimating a random-effects probit model of income satisfaction. She uses four years of data (1996-1999) from the British Household Panel Survey in her empirical analysis. She chooses the head of household income satisfaction level as the relevant one for her analysis. She retains in her sample only those households where a household head does not change from 1996 to 1999. These restrictions result in a sample of 3000 households observed over four years. Her sample includes information on the number and age group of children, the number of adults, the number of disabled individuals, and preference shifters relating to age, sex, marital status, housing tenure, education, region of living, and job status. She also includes fixed time effects.

Kuklys' four indicator variables for job status are unemployed, family care, student, and long-term sick. The omitted category is employed. The estimated coefficients for the four indicator variables are all significantly negative at the 1 percent level.

Her four indicator variables for marital status are cohabiting, divorced, separated, and never married. The omitted category is married. The coefficient estimates were divorced, separated, and never married are all significantly negative at the 1 percent level. The point estimates of the effects of divorced and separated are roughly twice the size of never married. Surprisingly, the coefficient estimate for cohabiting, which is significantly negative at the 1 percent level, is similar in size to that of never married.

Her five indicator variables for housing tenure are own with mortgage, social housing, housing assistance, private rent, and other rent. The omitted category is own outright. Here the results are not completely as expected. The coefficient estimates for all five indicator variables are significantly negative at the 1 percent level except for private rent, which is significantly positive, although only at the 5 percent level. This suggests that privately renting is superior to owning outright, which seems unlikely. Also, owning with the mortgage has the same qualitative negative effects as social housing and housing assistance.

Kuklys' five indicator variables for education are A level, O level, commercial, apprentice, and no qualification. The omitted category is first or higher degree. The results are somewhat surprising. The coefficient estimates for all five indicator variables are significantly negative, but those for commercial and apprentice are significant at only the 5 percent level. These results may have been expected from a Mincerian wage equation, but in the current case, there are already controls for household income and job status.

3.4 Data

The data used in this paper come from merging information from the Panel Study of Income Dynamics (PSID) 2016 Wellbeing and Daily Life Supplement with information from the PSID 2015 Family and Individual files. The financial satisfaction variable comes from the Wellbeing and Daily Life Supplement. There are 8,341 respondents to the questions in the supplement. The respondents are either male heads, female heads, or female spouses in households. For some households both the male head and female spouse are respondents, while in other households where both male head and female spouse are present, one of the two might not be respondents. There were 3,641 male head respondents and 4,700 female head or spouse respondents.

The main use of the Wellbeing and Daily Life Supplement is to obtain the financial satisfaction variable. This variable is obtained from a group of questions in the supplement, the preamble for which is:

How satisfied are you with each of the following?

One question is labeled “My financial situation.” Possible answers are:

1. Completely satisfied
2. Very satisfied
3. Somewhat satisfied
4. A little satisfied
5. Not at all satisfied
6. Does not apply to me
7. NA; not answered.

Because there were substantially more female respondents than male respondents, we decided to use the female responses rather than the male responses, in contradistinction to Kuklys. After discarding the 70 female responses which were either ”does not apply to me” or ”NA,” we were left with 4,630 observations. The variable definitions are given in Table 3.1. Summary statistics are given in Table 3.2.

In principle, it may have been possible to have used an ordered logit or ordered probit model for the estimation, but we were concerned about the small number of families with disabled children and decided to use a simple binary probit. Unlike Kuklys, we have only one observation per family on financial satisfaction and therefore cannot use fixed effects or random effects specification. We experimented with different groupings for satisfied and unsatisfied and present the results for two such groupings in the tables at the end. In the first grouping, the responses from the questionnaire "completely satisfied" and "very satisfied" take on the value 1 and the remaining responses (3-5) take on the value 0. We call this variable Financial Satisfaction 1 and it has a mean of 0.37. In the second grouping, the responses from the questionnaire “completely satisfied,” “very satisfied,” and “somewhat satisfied” take on the value 1 and the remaining responses (4 and 5) take on the value 0. We call this variable Financial Satisfaction 2 and it has a mean of 0.72.

Like Kuklys, we log total family income in the probit. The mean of total family income is roughly $86,000 in the sample. We work with three family type variables: presence of male head, number of children in the household, and number of adults in the household.

As far as disability in the family is concerned, we work with two distinct groupings of disability for the head and spouse. In the first grouping, there are twelve disability variables for the head and/or spouse: separately, for male and female, presence of a mental disability, presence of an activity of daily living restriction, presence of an instrumental activity of daily living restriction, and finally, presence of the work limitation. Additionally, the four variables for the female head or spouse are interacted with the male head indicator so that we may obtain different results for female disability depending on whether or not she is the head. In the second grouping, we have three indicator variables, one for any male disability or work limitation, one for any female disability or work limitation, and one that interacts the second indicator with male head. Each of the first two is set equal to 1 for a mental disability, activity of daily living restriction, instrumental activity of daily living restriction, or work limitation. Only one of the two groupings is used in each estimation.

The child disability variable will miss some families with a disabled child because it is based on SSI receipt for the child. SSI receipt for disabled children has an upper family income limits and therefore we will be able to identify families with a disabled child only if the family is relatively poor.

We use five housing tenure indicators. The three ownership variables are: ownership with or without mortgage, paying mortgage, and mortgage amount. The two renter variables are renter and rental amount. Finally, we have four family education indicator variables: for each of head and spouse whether their highest degree is a bachelor degree and whether they hold a postgraduate degree.

3.5 Empirical Results

The empirical results are presented in Tables 3.3 and 3.4. Table 3.3 presents the results for estimations with Financial Satisfaction 1 and Table 3.4 presents the results for estimations with Financial Satisfaction 2. There are two models in each of these two tables corresponding to the two groupings for the head and spouse disability variables. The models in Table 3.3 are labeled Model 1 and Model 2, and the models in Table 3.4 are labeled Model 3 and Model 4. Table 3.4 is presented for completeness, and we will discuss the results only for Table 3.3.

Both specifications in Table 3.3, namely Model 1 and 2, have the log of total family income significantly positive at the 1 percent level. The coefficient of the male head indicator is insignificant in both cases, which is not surprising since we are conditioning on family income. In Model 1, coefficients for a mental disability for the household head are significantly negative for both sexes; however, the coefficient for a mental disability for the female spouse is significantly positive, which means that the total effect for the female spouse is lower in absolute value than for a female head. No other disability variable has a coefficient significant at the 5 percent level. In Model 2, the results for disability of the household head are both significantly negative at the 1 percent level. In both models, the coefficient result for a disabled child is insignificant.

Moving to the housing tenure variables, the results for home ownership are significantly positive at the 1 percent level when there is no mortgage and insignificant in the presence of a mortgage.

The higher education variables for the male head have coefficients that are significantly positive at the 1 percent level in both models, but the higher education results for the female head or spouse are insignificant. A disappointing feature of the results presented above is the insignificance of coefficients for a disabled child. More work needs to be done on this issue.

To help understand the results of this study, we developed the idea of converted income. This is defined to be the level of income that produces the same value of the probit in the absence of disability. Since disability typically has a negative effect on financial satisfaction, converted income will typically be less than actual income. It is straightforward to see that the function is linear and given by $Y^C = f^* Y$, where Y^C is converted family income, Y is actual family income, and f is the conversion factor. The formula for f is given by

$$f = \exp\left(\beta_D / \beta_Y\right),$$

where β_D is the coefficient on the disability indicator in the probit and β_Y is the coefficient on log family income.

In Model, $1 f$ equals 42 percent in the case of a mental disability for the male head, 28 percent in the case of a mental disability for the female head, and 52 percent in the case of a mental disability for the female spouse. In Model 2, conversion factors can be calculated for the presence of any disability. Conversion factor f equals 39 percent in the case of any disability for the male head, 34 percent in the case of any disability for the female head, and 50 percent in the case of any disability for the female spouse.

The numbers for Model 1 are similar to the corresponding numbers for Model 2. And even though our specifications are not identical to those of Kuklys, it is clear that our conversion factors are substantially smaller than hers. Although the difference in the magnitudes is striking, the direction of the difference is what is to be expected. Medical costs are an important consideration in the face of disability, and these costs in Britain are zero or infinitesimal when compared to those in the United States. Income replacement policy in Britain is similarly more generous than in the United States.

3.6 Conclusion

This paper examines the effect of disability in the family on financial satisfaction of the female head or spouse using the Panel Study of Income Dynamics (PSID) 2016 Wellbeing and Daily Life Supplement merged with information from the PSID 2015 Family and Individual files. This empirical work is based on the theoretical work on the capability approach developed primarily by Amartya Sen and Martha Nussbaum, which emphasizes the presence of capabilities as opposed to actual outcomes. Following the empirical work of Kuklys (2005), we estimate a probit of financial satisfaction on log income, disability variables, and variables representing other capabilities. We find that the loss in financial satisfaction due to disability in the United States is substantially greater than the corresponding loss in Britain. Point estimates suggest that conversion factors for disability reduce effective income by as much as 60 percent for male heads and 70 percent for female heads. These figures are over and above the direct income loss due to reduced labor market opportunity.

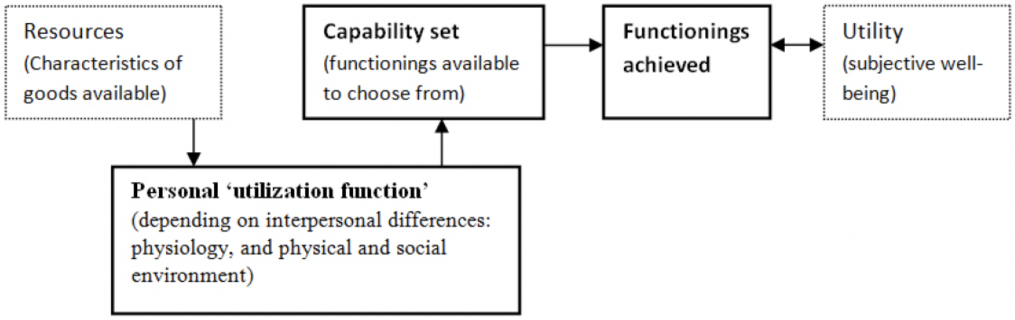

Figure 3.1: Methodology of the Capability Approach

Table 3.1: Definition of Explanatory Variables

Variable Name	**Definition**
Financial Satisfaction 1	Female head or spouse completely/very satisfied (indicator)
Financial Satisfaction 2	Female head or spouse completely/very/somewhat satisfied (indicator)
Log Income	Log of total family income
Family Type	
Male Head	Head and spouse both present (indicator)
Number of Children	Number of children under age 17 in household
Number of Adults	Number of adults in household
Family Disability	
Male Mental Disability	Mental disability for male head (indicator)
Male ADL	Activity of daily living restriction for male head (indicator)
Male IADL	Instrumental activity of daily living restriction for male head (indicator)
Male Work Limitation	Work limitation for male head (indicator)
Female Mental Disability	Mental disability for female head or spouse (indicator)
Female ADL	Activity of daily living restriction for female head or spouse (indicator)
Female IADL	Instrumental activity of daily living restriction for female head or spouse (indicator)
Female Work Limitation	Work limitation for female head or spouse (indicator)
Male Disabled	Male disabled (indicator)
Female Disabled	Female disabled (indicator)
Child Disabled	At least one child disabled (indicator)
Housing Tenure	
Owner	Family owns home (indicator)
Renter	Family rents (indicator)
Mortgage	Family owns home with mortgage (indicator)
Mortgage Amount	Mortgage amount
Rent Amount	Rent amount
Family Education	
Male Bachelor Degree	Male's highest degree is bachelor degree (indicator)
Male Postgraduate Degree	Male has postgraduate degree (indicator)
Female Bachelor Degree	Female's highest degree is bachelor degree (indicator)
Female Postgraduate Degree	Female has postgraduate degree (indicator)

Table 3.2: Summary Statistics
(N=4,630)

Variable	Mean	S.D.
Financial Satisfaction 1	0.372	0.48
Financial Satisfaction 2	0.716	0.45
Family Income	85964	115653
Log Income	10.895	1.31
Family Type		
Male Head	0.639	0.48
Number of Children	0.814	1.19
Number of Adults	1.929	0.73
Family Disability		
Male Mental Disability	0.106	0.31
Male ADL	0.056	0.23
Male IADL	0.053	0.22
Male Work Limitation	0.092	0.28
Female Mental Disability	0.090	0.28
Female ADL	0.127	0.33
Female IADL	0.147	0.35
Female Work Limitation	0.176	0.38
Female Mental Disability × Male Head	0.032	0.18
Female ADL × Male Head	0.057	0.23
Female IADL × Male Head	0.078	0.27
Female Work Limitation × Male Head	0.098	0.29
Male Disabled	0.176	0.38
Female Disabled	0.274	0.45
Female Disabled × Male Head	0.140	0.35
Child Disabled	0.041	0.19
Housing Tenure		
Owner	0.652	0.48
Renter	0.310	0.46
Mortgage	0.458	0.50
Mortgage Amount	538.021	776.59
Rent Amount	243.404	492.90
Family Education		
Male Bachelor Degree	0.140	0.35
Male Postgraduate Degree	0.081	0.27
Female Bachelor Degree	0.204	0.40
Female Postgraduate Degree	0.125	0.33

Table 3.3: Probit Results for Financial Satisfaction 1

Variable	**Model 1**	**Model 2**
Constant	-2.605	-2.594
	(0.33)	(0.33)
Log Income	0.236	0.233
	(0.03)	(0.03)
Family Type		
Male Head	0.009	0.046
	(0.06)	(0.07)
Number of Children	-0.082	-0.085
	(0.02)	(0.02)
Number of Adults	-0.169	-0.167
	(0.04)	(0.04)
Family Disability		
Male Mental Disability	-0.207	
	(0.07)	
Male ADL	0.023	
	(0.12)	
Male IADL	-0.111	
	(0.12)	
Male Work Limitation	-0.035	
	(0.10)	
Female Mental Disability	-0.306	
	(0.10)	
Female ADL	-0.145	
	(0.13)	
Female IADL	-0.119	
	(0.13)	
Female Work Limitation	-0.091	
	(0.11)	
Female Mental Disability × Male Head	0.152	
	(0.16)	
Female ADL × Male Head	0.066	
	(0.17)	
Female IADL × Male Head	0.093	
	(0.16)	
Female Work Limitation × Male Head	-0.001	
	(0.15)	
Male Disabled		-0.218
		(0.06)
Female Disabled		-0.253
		(0.07)
Female Disabled × Male Head		0.092
		(0.10)
Child Disabled	0.034	0.005
	(0.11)	(0.11)

Table 3.3 cont.

Housing Tenure		
Owner	0.511	0.527
	(0.12)	(0.12)
Renter	-0.302	-0.297
	(0.12)	(0.12)
Mortgage	-0.524	-0.528
	(0.07)	(0.07)
Mortgage Amount	0.000	0.000
	(0.000)	(0.000)
Rent Amount	0.000	0.000
	(0.00)	(0.00)
Family Education		
Male Bachelor Degree	0.389	0.389
	(0.06)	(0.06)
Male Postgraduate Degree	0.492	0.483
	(0.08)	(0.08)
Female Bachelor Degree	-0.023	-0.024
	(0.05)	(0.05)
Female Postgraduate Degree	0.001	0.006
	(0.07)	(0.07)
Log Likelihood	-2728.097	-2734.440

Table 3.4: Probit Results for Financial Satisfaction 2

Variable	**Model 1**	**Model 2**
Constant	-1.301	-1.254
	(0.31)	(0.31)
Log Income	0.162	0.156
	(0.03)	(0.03)
Family Type		
Male Head	0.069	0.093
	(0.07)	(0.07)
Number of Children	-0.052	-0.056
	(0.02)	(0.02)
Number of Adults	-0.119	-0.113
	(0.03)	(0.03)
Family Disability		
Male Mental Disability	-0.184	
	(0.07)	
Male ADL	0.061	
	(0.13)	
Male IADL	-0.246	
	(0.13)	
Male Work Limitation	-0.015	
	(0.10)	
Female Mental Disability	-0.529	
	(0.09)	
Female ADL	-0.069	
	(0.12)	
Female IADL	-0.073	
	(0.12)	
Female Work Limitation	-0.122	
	(0.10)	
Female Mental Disability × Male Head	0.365	
	(0.15)	
Female ADL × Male Head	0.194	
	(0.17)	
Female IADL × Male Head	-0.003	
	(0.16)	
Female Work Limitation × Male Head	-0.149	
	(0.14)	
Male Disabled		-0.179
		(0.06)
Female Disabled		-0.362
		(0.07)
Female Disabled × Male Head		0.065
		(0.09)
Child Disabled	-0.136	-0.154
	(0.101)	(0.10)

Table 3.4 cont.

Housing Tenure		
Owner	0.781	0.803
	(0.11)	(0.11)
Renter	0.112	0.109
	(0.11)	(0.11)
Mortgage	-0.246	-0.260
	(0.08)	(0.08)
Mortgage Amount	-0.000	-0.000
	(0.00)	(0.00)
Rent Amount	-0.000	-0.000
	(0.00)	(0.00)
Family Education		
Male Bachelor Degree	0.272	0.275
	(0.07)	(0.07)
Male Postgraduate Degree	0.462	0.453
	(0.10)	(0.10)
Female Bachelor Degree	0.033	0.029
	(0.06)	(0.06)
Female Postgraduate Degree	0.070	0.069
	(0.08)	(0.08)
Log Likelihood	-2459.003	-2474.586

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