National Longitudinal Surveys

U.S. Department of Labor
Bureau of Labor Statistics

Discussion Paper

Characterizing Leave for Maternity:
Modeling the NLSY Data

Jacob Alex Klerman

December 1993

Report: NLS 95-21

Characterizing Leave for Maternity: Modeling the NLSY Data

Jacob Alex Klerman
Rand Corporation

December 1993

This project was funded by the U.S. Department of Labor, Bureau of Labor Statistics under Grant Number 2-P-50-HD-12639. Opinions stated in this paper do not necessarily reflect the official position or policy of the U.S. Department of Labor. Sally Carson, Larry Painter, Natasha Kostan, and Sharon Koga provided excellent assistance.

EXECUTIVE SUMMARY

Characterizing Leave for Maternity

Jacob Alex Klerman

During the last three decades the "working mother" has become the norm rather than a rarity. Today, rather than dropping out of the labor force for a period of years after childbirth, many women spend only a few weeks away from the workplace. This shorter time away from the work-place has allowed employers and employees to arrange for formal or informal leave in which women remain employed, but take leave of a few weeks. For some women this leave is paid, for others it is unpaid. For some women such leave is not an option or not chosen; they either quit their jobs or return to their jobs less than a week after childbirth. For some women, such leave lasts only a few weeks; for others a few months. Relatively little is known about the distribution of work leave and non-employment during the weeks immediately preceding and following the birth of a child.

Part of the problem has been one of data availability. Most standard labor supply surveys do not record age of the youngest child in months nor collect complete labor market histories. An exception is the National Longitudinal Survey-Youth (NLS-Y). Unlike other datasets, the NLS-Y dates most events (births and labor market transitions) to the day. It can, therefore, be used to examine timing of return to work to the week (or day). Since most return to work that will occur over the first two years of the newborn's life occurs in the first two months after childbirth, timing within this period immediately after childbirth is of considerable importance.

To model leave and return to work, we specify a model of the timing of leaving work during pregnancy and returning to work after childbirth which is disaggregated into quitting work, taking unpaid leave, and taking paid leave. The baseline hazards are specified as exponentiated cubic splines. The different decisions are linked by a random effect. The resulting parameter estimates strongly support the use of a flexible baseline hazard (as provided by the cubic splines) and correlation across the decisions within a given birth and across births to a given mother as provided by the random effects. Furthermore, with multiple decisions (hazards and probits), the data clearly identify a (complicated) baseline hazard in a model which allows for unobserved heterogeneity.

 - 2 -

The model was specifically constructed to include a class of "can't tell" women. The NLS-Y's continuous Work History Data uses an employment concept. Women who are employed, but on paid leave (whether or not it is formal "maternity leave") are instructed to consider that time as time employed. Thus, for some women it is not possible to tell if they took an extended (i.e. several weeks) paid leave or worked through childbirth (taking leave of under a week). This ambiguity has been a significant stumbling block for researchers wishing to investigate the relation between earlier maternal presence (i.e. not at work) and subsequent child development. However, the NLS-Y includes several other sets of questions (the Employment Status Recode questions at each interview, a set of Maternity Leave Questions in 1983, and an additional set of questions about maternity leave as part of the Employer Supplements since 1988) which make it possible to reconstruct the distribution of time employed, on paid leave, and on unpaid leave, despite the missing data problems. The estimates presented here exploit all of the information on work in the NLS-Y data.

The estimated model is used to characterize leave for maternity for all recent mothers. It does so using regression standardization. The NLS-Y is a cohort sample of about six thousand women aged 14 to 21 in 1979. To extrapolate to the sample of all recent mothers, the econometric model includes controls for how the NLS-Y sample differs from a random sample of recent mothers (age, year of delivery, race/ethnicity, marital-status, education, parity). The model is then simulated for the characteristics of a representative sample of recent mothers drawn from the Fertility Supplement to the June 1990 Current Population Survey.

We find that as of 1990, before the passage of the federal Family Leave Act, leave for maternity was quite common. About a third of women never worked during pregnancy (33 percent) . Another third (34 percent) quit their jobs at or before childbirth. The remaining third took leave. Thus, in total about half of the women who worked during pregnancy did not quit their jobs at delivery. For about 19 percent of women the leave was paid, and for about 14 percent the leave was unpaid. However, many of these paid leaves were quite short, well under a week. Among all new mothers, 25 percent took longer leaves (more than a few days); 14 percent unpaid and 11 percent paid. Even excluding very short leaves, for half of the women who took paid leave and for half of the women who took unpaid leaves, the leave is over by eight weeks post-partum. This is considerably shorter than the 12 weeks guaranteed by the federal Family Leave Act.

 - 3 -

Proponents of maternity leave legislation and the Federal Family Leave Act have argued for the importance of maternal presence in the period immediately after the birth of a child for the child's emotional and intellectual development. During that debate, developmental psychologists argued for leaves of two to six months. The results presented here suggest that in the absence of maternity leave legislation the vast majority of women, even among those who had worked during pregnancy (and would return to work before the child's second birthday) take some leave after delivery. However, among women who would return to work before the child was two years old, the modal leave was only about six weeks and few women took as much as 12 weeks of leave.

ABSTRACT

JEL Classification: J22-Time Allocation and Labor Supply

Major changes in women's labor force behavior over the last two decades imply that while time away from the workforce after the birth of a child was once measured in years, it is now measured in weeks or even days. Concentrating on the weeks immediately following childbirth, this paper characterizes the labor force behavior of women immediately before and after the birth of a child. The timing of labor market exits (during pregnancy) and entrances (after childbirth) are estimated to the day, and reported to the week. Quits, exits to unpaid leave, and exist to paid leave are separately identified. The estimates reveal the most women who work before the birth of a child return to work relatively quickly after the birth of a child. The modal time to return occurs only about six weeks fter childbirth. Those who work long into pregnancy return to work more quickly after childbirth. The empirical work uses the National Longitudinal Survey-Youth. The estimates are generating using a system of probit and hazard models. The system includes unobserved heterogeneity to capture the correlation between decisions. The econometric model is specified to correct for the focus of the NLS-Y protocol (in some years) on employment, so that it is not possible to distinguish paid from unpaid leave.

During the last three decades the "working mother"has become the norm rather than a rarity. Today, rather than dropping out of the labor force for a period of years after childbirth, many women spend only a few weeks away from the workplace. Relatively little is known about just how long this period is — when it begins or ends, whether it involves quitting a job or taking leave, paid or unpaid. This paper characterizes leave for maternity using data from the National Longitudinal Survey-Youth (NLS-Y) and appropriate statistical models.

Two findings consistently emerge from the previous literature on work patterns around the birth of a child. First, women who work during pregnancy (at all, and longer into their pregnancy) return to work faster after childbirth (Sweet, 1972; Even, 1987; O'Connell, 1990; Desai and Waite, 1991; Wenk and Garrett, 1992). Second, neither the distribution of times to return to work after childbirth, nor the associated hazard function have the simple shapes implied by the standard parametric hazard functions (Even, 1987; Desai and Waite, 1992).

To model the correlation between work during pregnancy and work after childbirth, earlier studies have constructed models which give the first empirical regularity (that women who work later into pregnancy return to work earlier) a causal interpretation (Even, 1987; O'Connell, 1990). They include work during pregnancy (at all or its duration) as a regressor in models for work after childbirth and then interpret the results causally. Alternately, the correlation could reflect stable "tastes for work." (Browning, 1992). Consistent with the second interpretation, this paper presents an alternative approach which accounts for the strong inter-temporal correlation in labor supply using a random effects strategy. The "tastes for work" are modeled as random effects in the decision to work before pregnancy, the decision of how long to work during pregnancy, and the decision of when to return to work after childbirth.

Most earlier studies have chosen not to model the shape of the hazard itself, instead they apply the Cox proportional hazard models which treat the baseline hazard as a nuisance parameter (Greenstein, 1989; O'Connell, 1990; Desai and Waite, 1992; Wenk and Garrett, 1992; but see Even, 1990). This paper treats the distribution of times to return to work (and the underlying baseline hazards) as the fundamental parameter of interest. The paper seeks to describe the distribution of times away from the workplace and the mechanisms used to do so. Specifically, the paper jointly models the decision of whether to work at all during pregnancy, how long to work into pregnancy, when to return to work after childbirth; and whether the time spent not working is spent not employed (the woman quit her pregnancy job), on unpaid leave, or on paid leave. Consistent with this focus on the distribution of times away from work, the paper specifies and estimates a flexible cubic spline approximation to the log hazard and a flexible specification for tastes for work.

The results demonstrate the importance of both of these modeling decisions. The tastes for work are important in explaining the joint distribution of the labor supply decisions. The estimated baseline hazards (without the random effects) are far from monotonic. They are high in the days immediately after childbirth. They fall considerably for the next two weeks, rising to a peak about six weeks after childbirth, and fall thereafter. This overall pattern hides divergent shapes for the hazard across the three options: no work, unpaid leave, and paid leave.

The paper begins with an overview of the historical context and previous research on women's labor force behavior in the period immediately before and after childbirth. The next two sections then describe the NLS-Y data and our econometric model. The penultimate section presents the parameter estimates, describes the baseline hazards, and (using the June CPS data) generates population estimates of the distribution of time away from the workplace in days since the birth of the child (overall and separately by mother's status immediately after the birth: employed, on unpaid vacation, and on paid vacation). The paper concludes with a review of the results and directions for future research.

I. HISTORICAL TRENDS AND PREVIOUS RESEARCH

The broad outline of the history of work among women in general, and mothers in particular, is well known. At least from World War II through about 1970, the modal labor market pattern for women was to work until marriage or the birth of a first child (which usually followed shortly after marriage) and to remain out of the labor force until the last (of several) children entered school (Cherlin, 1990). Taking this pattern as given (and providing empirical evidence from the National Longitudinal Survey of Mature Women), Polacheck and others (Mincer and Polachek, 1974; Polacheck, 1975; Mincer and Polachek, 1978, Polachek, 1980; Gronau, 1988) built a theory of female earnings and male-female earnings differentials.

As Mincer and Polachek were writing in the early 1970s, female labor supply patterns were beginning to change. Cherlin (1990) summarizes the changes:

> *In the 1950s, larger numbers of married women began to join the labor force after their children were in school; in the 1960s and 1970s, the largest increases were among women with preschool-aged children; and more recently the largest rate of increase has occurred among mothers of infants. In fact, 51 percent of all mothers of infants - children under age 1 - are now in the labor force. During the postwar period, then, the trend for women has been towards a nearly continuous attachment to the labor force throughout adulthood.*

Using a time-series of cross-sections from the June Current Population Survey (CPS)[1], Klerman and Leibowitz (1994) explore labor supply among mothers of infants. They find that from the early 1970s to the late-1980s labor force participation (LFP) at all ages (through 36 months) has risen by between 25 and 30 percentage points. Since LFP has been (and continues to be) lower for mothers of younger children, the percentage increase in LFP is highest for the youngest children. For mothers of one month old children, LFP has more than doubled – from less than twenty percent to over forty percent.

These high levels of LFP among new mothers have made possible alternative mechanisms for juggling work and family. Polacheck's work assumed that women would quit their jobs when they had children. When time away from the work place is measured not in years but in months, other mechanisms are possible.

Results from the National Longitudinal Survey-Young Women (NLS-YW; covering the mid-1970s) suggest that other mechanisms were actually in use. Using the NLS-YW, Mott and Shapiro (1978, 1979) noted that LFP is a misleading measure of labor force patterns. Their data allow them to distinguish work from employment for the week preceding the interview. They note "in the months immediately surrounding the birth event, actual work activity is distinctly less than the measured labor force participation rates (Mott and Shapiro, 1979, p. 201)." Klerman and Leibowitz (1994) quantify these effects using a nationally representative sample of new mothers (the NLS-YW is a cohort sample) for the late-1980s. That paper computes the number of mothers

[1]The June survey is used because it includes a Fertility Supplement. The basic CPS monthly questionnaire only records age in years. The June Fertility Supplement asks age of the child in months (or month of birth) for the youngest child.

in each of the components of labor force participation - work, unpaid leave, paid leave, and unemployment - by age of the youngest child in months.

These changing patterns of work of new mothers emphasize the importance of three issues in our understanding of labor supply around childbirth. First, much of the action today takes place well within the first year after childbirth. Maternity leave legislation at the state and federal level is phrased in terms of weeks. However, most previous studies (to a great extent limited by data problems) characterize behavior in terms of quarters (Sweet, 1972, using the 1960 Census; Even, 1988, using the NSFG) or months (Klerman and Leibowitz, 1994, using the June CPS).

Second, LFP is a poor measure. It aggregates the unemployed and those on leave, with those at work. We want to describe separately patterns of employment and patterns of work (where the difference is leave).

Third, with time away from work now measured in months or weeks, we would like to cross-classify return to work after childbirth, by work patterns during pregnancy. Nakamura and Nakamura (1981, 1985, 1994), following an older literature in labor economics (e.g. Heckman and Willis, 1977, 1979; Clark and Summers, 1982; Mott and Shapiro, 1982; Shapiro and Mott, 1992), emphasize the importance of such conditional analyses (see also the more recent work of Duleep and Sanders, 1994; Mott and Shapiro, 1994; and Shaw, 1994). When compared to women who did not work during pregnancy, labor supply patterns of women in the months immediately after the birth of a child are markedly different for women who worked during pregnancy. For employers concerned about return to work of their employees (and governments setting policy to affect that return), the conditional analysis is the appropriate one.

Finally, we would like to make population level statements. Doing so is difficult given the sampling structures of previously used datasets. The NLS-YW (Mott and Shapiro, 1978; Shapiro and Mott, 1980; Greenstein, 1989) and the NLS-Y (Klerman and Leibowitz, 1988; Desai and Waite, 1992; Wenk and Garrett, 1992) are longitudinal cohort samples. Thus in many of the datasets used in previous studies, births occur over a

---

[2]Since the CPS is a cross-sectional survey, Klerman and Leibowitz (1994) could not do this.

range of years to a non-representative sample of women (many cohorts are excluded). Similarly, in retrospective surveys (e.g. NSFG used by Even, 1987; and the SIPP maternity leave questions used by O'Connell, 1990,[3]).births occur over a range of years. Finally, either by sample design (e.g. the SIPP; O'Connell, 1991) or by the analysis decisions of the authors (e.g. Desai and Waite, 1992; Klerman and Leibowitz, 1990; Mott and Shapiro, 1977; Shapiro and Mott, 1979) many papers only look at first births.

II. DATA: THE NATIONAL LONGITUDINAL SURVEY - YOUTH

For characterizing leave for maternity, an ideal dataset would have several characteristics. First, it would precisely date birth events and work events (unlike the CPS where we only have age of the child in months and there is a seven week ambiguity as to exactly when an *m* month old child was born). Second, it would allow us to distinguish work, from unpaid leave and from paid leave at each point in time (unlike the CPS and the NLS-YW where we only have behavior at the interview date). Third, it would contain a representative sample of all recent births (unlike the data in the SIPP on the first birth,[4] or in the NLS-YW[5] and NLS-Y on a cohort of women). Fourth, it would be a panel dataset, so we could stratify work after childbirth by work during pregnancy (unlike the Decennial Census or the CPS). Finally, a large sample size would allow precise estimates.

No dataset meets all of these requirements. In this paper, we analyze the National Longitudinal Survey-Youth (NLS-Y). The NLS-Y is a cohort panel dataset. The original sample was drawn in 1978 from among 14-21 year olds. The sampling scheme deliberately over-sampled blacks, Hispanics, and poor whites. The sampled individuals have been reinterviewed annually.

The NLS-Y is an attractive dataset for these analyses because the interview protocol was specifically designed to collect a continuous labor market history for the

---

[3]O'Connell's SIPP sample is large enough for him to stratify by birth year, mitigating this problem.

[4] Used by O'Connell, 1990.

[5] Used by Greenstein, 1989; Mott and Shapiro, 1978; Shapiro and Mott, 1979.

entire period since the previous interview (usually a year). Employment is recorded to the day. Since the NLS-Y is a panel dataset, we can track work before and after childbirth.

In addition, the NLS-Y includes copious information on each sampled woman's fertility history and the subsequent development of the child. Births are precisely dated (to the day). The sample is large. There have been over 6,000 births to sampled women during the period covered by the work history data. Finally, labor supply of these women is of special interest. Since 1986, children of sample women have been administered carefully designed developmental batteries. Exploiting this rich psychological status data, the NLS-Y has been used extensively to explore the relation between maternal work and child development (Desai, Chase-Lansdale and Michael, 1989; Chase-Lansdale, Mott, Brooks-Gunn and Phillips, 1991; Baydar and Chase-Lansdale, 1991; Blau and Grossberg, 1992). Therefore, modeling the labor market patterns of these specific women is of special importance.

There remain, however, two problems with the NLS-Y. First, it is a cohort sample based on a stratified sample of women aged 14-21 in 1978 (when the sample was drawn). We can correct for the stratified sampling (which oversampled blacks and Hispanics) using the initial sampling weights. However, the cohort and panel structure implies that—compared to a sample of recent births—NLS-Y births are spread out over more than a decade and the mothers are disproportionately young. We handle this problem by regression standardization. We discuss the details of that procedure below.

The second problem is more serious and induces much of the complication in our econometric methods. The NLS-Y's basic continuous Work History Data uses an employment concept. Therefore, NLS-Y respondents are explicitly instructed to consider paid vacation and paid sick leave as time employed. This problem is noted in the *NLS-Y Child Handbook*:

> *Users should note that the NLS-Y main questionnaire defines respondents who are on vacation, on sick leave, on unpaid leave of less than one month, or on maternity leave of less than 90 days as still attached to an employer. Therefore a mother with this kind of status would be considered working, even though she was on leave around the time of the birth of a child. ...* Researchers cannot use these variables for the period close to the birth if their actual concern is real hours of

> employment immediately before or after the birth.[6] *However, this caveat applies principally to the last quarter before the birth and the first quarter after the birth.*

As we discuss below in detail (and see Appendix A with the exact question wording), the problems with identifying unpaid leave can be remedied; the problems with identifying paid leave are more difficult.

We call this the *fundamental missing data problem,* and it is severe. Using the standard employment variables on the NLS-Y Merged Mother-Child file for 1990, fully 18 percent (unweighted) of all women report continuous employment. They are 29 percent of all women who ever worked during pregnancy.

This problem with the NLS-Y data has been cited in the maternity leave literature (Klerman and Leibowitz, 1990; Desai and Waite, 1991). However, in much of the literature on the relation between maternal work and child outcomes, it is not mentioned (Desai, Michael and Chase-Lansdale, 1990; Belsky and Eggebeen, 1991, and the other papers in the symposium; Baydar and Brooks-Gunn, 1991). An exception is Blau and Grossberg (1992), who explicitly note the problem:

> *Unfortunately, in the NLSY, women who are on vacation, sick leave, unpaid leave of less than one month, or maternity leave of less than 90 days are considered employed. To the extent that this is a problem, it would mainly affect the first year labor supply variable, biasing its coefficient toward zero and thus strengthening our confidence in the finding of a significant effect.*

This fundamental missing data problem probably does not seriously bias results on the relation of maternal work to child development when maternal work is being aggregated over the whole first year (even when the concept being measured is weeks worked in the first year). However, Belsky (1988) identifies maternal work in the first year as particularly deleterious. He then surveys several papers which suggest that there are differential effects depending on when during the first year the mother returns to work. Following this line of research, Baydar and Brooks-Gunn (1991) using the NLS-Y, disaggregate work by quarters since birth. They find (and interpret in terms of attachment theory) no negative effects of work in the first quarter after birth. The

---

[6] Emphasis in the original.

fundamental missing data problem calls into question these results. Some of the women coded in the NLS-Y Work History Data as "employed" were actually on leave caring for their newborns themselves. The model we develop below estimates the probability of each behavior for each woman, given what we know about her behavior, despite the missing data problem. Appendix E shows how to use the econometric model and the parameter estimates to impute the the probability that a given woman was not working, given the model and her recorded information..

Thankfully, the implications of this fundamental missing data problem for using the NLS-Y to characterize leave for maternity are not as negative as it appears from simple tabulations of the percentage of women who report continuous employment. There are five sources of information about labor market behavior around childbirth in the NLS-Y (Appendix A gives the exact question wording and skip patterns). They are:

- **Work History Data**: Continuous record of employment since January 1978 collected through employer supplements. Records jobs to the day (reported to the week on the Work History Tape). As discussed above, considers paid leave (on unpaid leave, see below) to be time employed.

- **Gap Data**: The Employer Supplements ask about periods "with an employer, but not paid." Covers the period 1978 to the present, records gaps in employment to the day of the beginning and end of leave. Women should (and do) report unpaid pregnancy/maternity leave here.

- **Maternity Leave Supplement**: In 1983, the NLS-Y included a set of retrospective questions on leave during pregnancy (in months) and leave after childbirth (in weeks or months, at the respondents choice). The questions refer to the most recent birth.

- **Maternity Leave Questions**: Since 1988 (covering the period since 1987), the Employer Supplements have included questions on the beginning and ending dates for maternity leave (paid or unpaid).

- **CPS Questions**: At each interview, the NLS-Y asks the standard battery of CPS labor force questions for the week preceding the survey. From that battery, the NLS-Y constructs the ESR (Employment Status Recode). This battery includes information on employment, work, and whether leave was unpaid or paid.

Thus, we have some information to the day (the Work History Data, the Gap Data, the Maternity Leave Questions), some information to the week or month (the Maternity Leave Supplement), and some information on the half line (was the woman working or on leave as of a date; the CPS Questions).

Table 1 summarizes for which births which data are available. As shown in the column heads, there are basically four regimes: Pre-1983 births not covered by the 1983 Maternity Leave Supplement, pre-1983 births covered by the Maternity Leave Supplement, births between the 1983 Maternity Leave Supplement and the post-1988 Maternity Leave Questions, and births covered by the post-1988 Maternity Leave Questions.

For birth covered by the 1983 Maternity Leave Supplement we have information on paid leave to the month or week. For births covered by the post-1988 Maternity Leave Questions, we have information on paid leave to the day. For the entire period, we have three pieces of information: the work history data, the gap data, and the CPS questions. In the periods for which we have only these basic three pieces of information, we have a sizable number of cases for which we "can't tell" when (or if) the mother took leave.

Table 1

Typology and Frequency of Available and Missing Information

Labor Force Pattern	Not in 1983 Suppl	1983 Suppl	Between ML Qs	Post-1988 Battery	Row Total	Row %
Never Worked During Pregnancy	236	717	961	558	2472	37.9%
Quit Pregnancy Job	148	579	838	653	2218	34.0%
Unpaid Leave	32	164	328	293	817	12.5%
Paid Leave	0	167	0	364	531	8.1%
Can't tell	52	0	434	0	486	7.4%
Col. Total	468	1627	2561	1868	6524	
Col. %	7.2%	24.9%	39.3%	28.6%		100.0%

NOTE: "Can't tell"s reported continuous employment; we can not tell if or when paid leave began.

"Not in 1983 Supplement - Child was not youngest or mother did not answer 1983 Maternity Leaves supplement.

"1983 Supplement" - Mother answered 1983 Maternity Leave Supplement for this child.

"Between ML Q's" - Child was born after 1983 Maternity Leave Questions and before 1988 Maternity Leave Battery.

"Post-1988 Battery" - Child covered by post-1988 Maternity Leave Battery.

Earlier, we noted that from the work history data alone 18 percent of the women are subject to the "fundamental missing data problem" (labeled "can't tell" in Table 1); they report continuous employment. The 1983 Maternity Supplement and the post-1988 Maternity Leave Battery resolve this ambiguity for over half of the sample women. Of the remaining "can't tells" (apparently working through delivery; no known date for beginning paid leave), the range of possible last date of work during pregnancy and first date of work after childbirth is further bounded by the ESR data from the CPS questions. For the "can't tells" in 18.3 percent of the cases, the ESR is informative regarding work prior to delivery[7]. After childbirth, the ESR variables are almost always informative (96.1 percent of the "can't tells")[8].

The challenge is to devise an econometric model to optimally combine each of these types of information in order to describe labor supply patterns during pregnancy and in the weeks following childbirth. This model can then be extrapolated to recent births by regression standardization, and used to impute labor market behaviors in analyses of the effect of maternal work on child outcomes.

III. ECONOMETRIC METHODS

Conceptually, we want to model the date of last work during pregnancy and the date of first work after childbirth. The richness of the data allow (and the weaknesses of the data require) that we model these work decisions in a disaggregated fashion. All mothers are assumed to be not working at the moment of childbirth. At that moment, we allow the new mother to be in one of three states: Without a job (either because she did not work during pregnancy or because she quit her pre-childbirth job), on unpaid leave (from job held during pregnancy), or on paid leave (from job held during pregnancy).

---

[7]For 3.3 percent of the cases the woman is already on leave, providing an upper bound on the last day of work. For 15.0 percent of the cases the woman is still working, providing a lower bound on the last day of work.

[8]For 94.2 percent of the cases the woman is already working by the second post-delivery interview, providing an upper bound on the return-to-work-date: For 1.9 percent of the cases, the woman is still on leave, so the ESR provides a lower bound. For some cases (included in the first group), the two ESR responses provide a lower and an upper bound.

Figure 3 schematically depicts the labor market dynamics of women from before the conception of the child through the time the child ceases being a toddler. At conception, a woman can be in or out of the labor force. Those women who are out of the labor force may begin working at some time after the child is born.

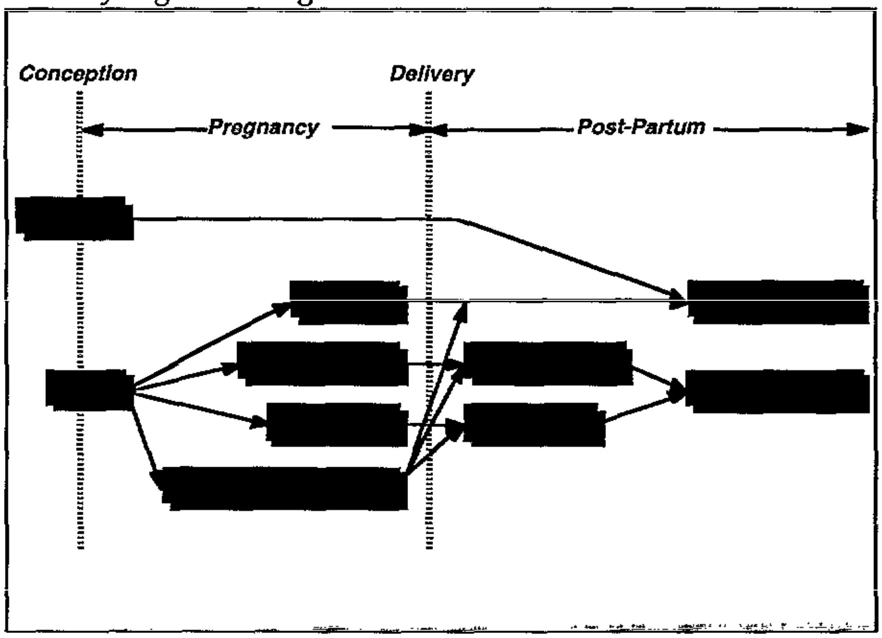

Fig. 1—Paths for Labor Market Near Childbirth.

Those women who are in the labor force at conception have several options. From most to least attached to the labor force, they can: work until delivery, take paid leave, take unpaid leave, or quit their job. Those who work until delivery can then begin: paid leave, unpaid leave, or quit their jobs.

We model these work dynamics as follows. The No Work/Work decision at conception is modeled as a probit. The Quit Job/Unpaid Leave/Paid Leave decision is modeled in a hazard framework as competing risks. Work Until Childbirth is modeled as simultaneous censoring of all three competing risks at 270 days (the 9 months of pregnancy). The Quit/Leave (whether paid or unpaid) decision after delivery for women who work until childbirth is modeled as a probit. The Unpaid Leave/Paid Leave decision after delivery for women who work until childbirth and do not quit at delivery is modeled as a probit. Finally, the time from delivery to New Job (for those who did not work during pregnancy or quit their pregnancy jobs), the time to the end of the Unpaid Leave (Return to Work at pre-delivery job), and the time to the end of the Paid Leave (Return to Work at pre-delivery job) are modeled as three separate hazards. Thus in total, we model nine vectors of regression coefficients: three binary probits, three competing risks (during pregnancy), and three simple hazards (after childbirth).

III.A The Shape of the Hazard

Unlike much of the rest of the literature which treats the underlying hazard and the timing of return to work as a nuisance parameter (at least in estimation, using the Cox Proportional Hazards model), understanding the timing of return to work is the explicit aim of this paper. Previous work with this data suggests a highly non-monotonic hazard (see Klerman and Leibowitz, 1992; and Desai and Waite, 1992). To model potentially varying rates of leaving work and returning to work with time since conception/childbirth, we use proportional hazards models with flexible cubic splines for the baseline hazard. This flexible characterization of the baseline hazard allows us to relax the strong parametric assumptions which characterize conventional hazard model approaches.

The use of cubic splines in estimation of non-linear models has been widely discussed in the statistical literature (see Poirier, 1973; Engle, et al., 1986 for a regression applications; and Grummer-Strawn, 1992 for a hazard application). Specifically, we model the log spline using a B-spline representation for the cubic spline with natural (unconstrained) endpoint conditions (de Boor, 1973; Press, et al., 1992). Appendix B presents a detailed discussion of our parameterization and the computational formulae. Here, we merely summarize the approach.

We a priori chose cubic-spline basis points (See Table 2). These knot locations correspond roughly to the distribution of failures; stopping work during pregnancy (and the knots characterizing the splines during pregnancy) becomes more common as pregnancy progresses; return to work after childbirth (and the knots characterizing the splines for return to work after childbirth) becomes less common as the child ages.[9]

---

[9]Most of the knots for the cubic spline were chosen at round dates (multiples of weeks). The spacing between knots is smallest in the weeks immediately before and after childbirth progresses/the child ages (when the probability of stopping work during pregnancy/returning to work after delivery is higher). The knots at 273, 315, 456, 547 and 648 days in the unpaid

Table 2

Knot Locations, by hazard (in days)

Period	Hazard	N. Knots	Knot Locations (in days)
During Pregnancy	Quit	8	0 , 90, 135, 210, 240, 250, 260, 270
During Pregnancy	Unpaid Leave	8	0 , 90, 135, 210, 240, 250, 260, 270
During Pregnancy	Paid Leave	8	0 , 90, 135, 210, 240, 250, 260, 270
After Childbirth	Quit	22	0, 3, 7, 14, 21, 28, 35, 42, 49, 56, 63, 70, 84, 98, 112, 182, 273, 315, 456, 547, 648, 730
After Childbirth	Unpaid Leave	18	0, 7, 14, 21, 28, 35, 42, 49, 56, 63, 70, 84, 98, 112, 140, 182, 730
After Childbirth	Paid Leave	19	0, 3, 7, 8, 14, 21, 28, 25, 42, 49, 56, 63, 70, 84, 98, 112, 140, 182, 730

In estimation, the value of the log hazard at each knot is estimated. The values of the log hazard between the basis points is interpolated by the associated cubic spline (see Press, et al., 1992). Modeling the log hazard as a cubic spline forces the non-negativity of the hazard.[10]

and paid leave after childbirth hazards were dropped because there are so few returns to work from leave after six months. The knot at 3 days in paid leave after childbirth was added to keep the unreported leaves from biasing leaves of just over a week.

[10]Grummer-Strawn (1992) takes an alternative approach. He models the hazard directly. However, when the hazard changes quickly, his estimated hazard is often negative. This forces him to use penalized likelihood approaches to forcing the non-negativity of the hazard.

Instead, we model the log hazard as a cubic spline. This forces the estimated hazard to always be positive. In doing so, we lose an advantage of approximating by splines. There exists a closed form for the integrated spline (it is after all locally a cubic polynomial). There does not exist a closed form expression for the integral of the exponential of a cubic spline.

In practice, the additional computational burden due to the lack of a closed form for the integrated hazard, is not large. The proportional hazards assumption implies that we need perform only a single integration for each iteration. In practice, we perform this integration numerically using a simple trapezoidal rule with the interval set equal to a day. This appears to be numerically sufficient.

III.B Regression Standardization

The NLS-Y is a cohort sample. To estimate leave patterns for all recent mothers, we use regression standardization.

In the estimation step, we include regressors to capture how the NLS-Y sample differs from the sample of all recent mothers: calendar year (and its square), age (and its square), black, Hispanic, education (dummies for high school drop-out, at least some college, and college graduate), never married, and not married (widowed or divorced). We then simulate the model for a sample of recent mothers. We draw the sample of recent mothers from all women who gave birth within the last 36 months from the June 1990 Current Population Survey. The regressors are specifically chosen so that they exist (and are comparable) in both surveys; making the simulations possible.

Table 3 presents sample statistics for the NLS-Y (unweighted and weighted) and for the CPS sample of NLS-Y recent mothers. Both samples exclude births to women before their eighteenth birthday. Normatively such women "should" still be in school, and we do not consider them as at risk for work (or return to work) before or after childbirth.

Table 3

Regressor Descriptive Statistics

	NLS-Y			CPS	
	Unweighted		Weighted	Unweighted	
	Mean	Std. Dev.	Mean	Mean	Std. Dev.
Age	24.274	3.408	24.667	27.550	5.242
Age Squared	600.837	13.004	620.018	786.482	50.754
Black	0.272	0.445	0.163	0.131	0.338
Hispanic	0.196	0.397	0.080	0.103	0.304
Year	84.538	3.174	84.728	90.000	0.000
Year Squared	7156.743	10.447	7189.020	8100.000	0.000
High School Drop-out	0.330	0.470	0.248	0.162	0.368
Some College	0.258	0.438	0.297	0.426	0.494
College Graduate	0.086	0.280	0.108	0.204	0.403
Second or later Child	0.354	0.478	0.357	0.653	0.476
Third or later Child	0.222	0.415	0.188	0.303	0.460
Never Married	0.292	0.455	0.210	0.138	0.345
Divorced or Widowed	0.779	0.268	0.070	0.101	0.301
N	6524			5994	

NOTE: NLS-Y sample is all births 1978-1990 to women over age 18 at birth. NLS-Y weights are 1979 sampling weights for population 14-21 in 1978 (at sample selection). CPS sample is all women with youngest child under 36 months old at June 1990, CPS interview (i.e., approximately births July 1987 - June 1990).

III.C Estimating the Model: Random Effects

In the introduction, we noted that previous studies have often included characterizations of work during pregnancy as regressors in their models characterizing work after childbirth. We noted that this implicitly implies a causal relationship. Common unmeasured tastes seem as plausible. Another disadvantage of including regressors is that the included work during pregnancy models will soak up much of the variation due to observed covariates. Instead, we adopt an alternative approach to modeling this correlation in the multiple dimensions of maternal labor supply.

To account for the possibility that maternal behaviors are correlated – (how long worked into pregnancy, how long until return to work after childbirth) – we link each of the decisions by a random effect. Specifically, each of the decisions (the probits, the competing risks, and the hazards) are assumed to be independent conditional on a "taste for work". We model these tastes for work as a random effect. The random effect is assumed normally distributed. Each of the decisions includes a factor loading.[11]

III.D Estimating the Model: Approach

If we had complete data this would be a straightforward estimation problem. Leaving aside concerns about sample size (a non-trivial problem), we could estimate the quantities of interest from simple cross-tabs (on a very large frequency table) and then reweight the cells for current births. However, because for a large fraction of births we have answers in weeks or months and for another large fraction we can not distinguish paid maternity leave from work; the problem is more complex.

In brief, we specify a probability model for the continuous time data. We then derive the implied probabilities of the recorded (often fuzzy or incomplete) responses. We estimate the model using all of the data by maximum likelihood. Finally, we simulate the model on a representative sample of all recent mothers.

For the complete data cases (i.e., except for the "can't tell"s) we proceed as follows: When the work history/gap data record that a woman quit her job or took unpaid leave, then we know we have the exact dates of the event. In those cases, we build up the likelihood directly (following Figure 1). Appendix C, Case 1 to Case 6 and Case 9 to Case 12 give the formal definition of the likelihood given our parameterization of the decision process. Similarly, for women reporting continuous employment and whose deliveries were covered by the 1983 Maternity Leave Supplement or the post-1988 Maternity Leave Batteries, we can date the events - including paid leave (to the week or month for the earlier Supplement; to the day for the later Battery). The exact likelihoods are Case 7 to Case 8, and Case 13 to Case 14 of Appendix C.

To simplify the estimation problem, we do not model entry into work or multiple exits from work during pregnancy; we only model the last day worked. This allows us

---

[11]We also explored a two factor heterogeneity, where the second factor linked all choices by a given mother (across multiple births). For reasons we were unable to determine, the estimator consistently converged to parameter values implying that almost all women who quit their jobs had returned to work by their child's second birthday. This was at clear variance with the observed data (and not a problem in the one-factor model).

to ignore the hazard of resuming work during pregnancy. In addition, we model the type of leave as of the beginning of the leave. Woman who begin by taking paid leave and then use unpaid leave are considered (for the purposes of the hazards) to be continuously on paid leave. Leaves which end before childbirth are ignored.

All durations are modeled using interval hazards. In the interval hazard formulation, instead of assuming we know exactly when the woman stopped working we assume that we know the date only to an interval. We then compute the likelihood as the probability that the event occurs over the interval (according to the underlying continuous time hazard). In this formulation, the interval can be of arbitrary length. For most cases this interval is a day. However, NLS-Y accepts fuzzy answers to dating questions (to the week or the month, rather than to the day). The interval hazard representation allows for easy handling of these fuzzy responses. Similarly, the 1983 Maternity Leave Supplement allowed responses in weeks or months. These cases are again easily handled by the interval hazards.

Even without the fundamental missing data problem, some women would report working continuously. This is possible in at least three cases. First, a woman could have gone to work on Friday morning, delivered Friday afternoon, and returned to work on Tuesday after a legal three-day weekend. She would not have missed a work day. Alternatively, since the post-1988 Maternity Leave Battery only asks for leaves of a week or more, some women undoubtedly take leaves of less than a week. Therefore, we censor all work during pregnancy three days before the birth of the child (the woman could already be in labor). At that time, women who are still working are assumed to have begun their post-delivery status (quit their job, or on unpaid leave, or on paid leave). After childbirth, women who report no leave are assumed to have returned from paid leave sometime within a week of delivery (because of the shape of the estimated cubic spline). Again, this "within a week" specification is easily handled by the interval hazard formulation.

The problem cases are those where a woman reports that she was continuously *employed*, from pregnancy through after childbirth without taking unpaid leave, and to whom neither the 1983 Maternity Leave Supplement, nor the 1988 Maternity Leave Battery apply. Even if these women took paid maternity leave, these women should have reported continuous *employment*. We simply cannot tell when a paid leave began and ended. The correct specification of the likelihood of occurrence of such a problem cases is the probability that *either* the woman worked continuously—(see the previous paragraph for how we interpret that behavior) or that she took paid leave (but the work history data provides no information as to when it began or ended).

As noted above for some cases, the Employment Status Recode questions (ESR) provide some information concerning when the paid leave could have begun. Any leave for the "can't tells" is assumed to begin in the third trimester (after week 26) of pregnancy.[12] For about a quarter of the cases the week preceding the interview (the week to which the ESR questions refer) occurs during the last tri-mester of pregnancy. Using this information we know for sure that a woman was working or not working as of that date. Similarly, after childbirth, if the answer to the ESR question (usually asked once or twice in the 24 months after childbirth) "not working", then we know that she took leave, the only problem is the unknown timing of the leave.

Beyond this ESR information, we simply do not know. The general approach is as follows: The correct formulation for the likelihood is the sum of the probability that the woman truly worked through childbirth and, for the probability that the leave actually began on that day each day of the pregnancy including delivery. As has been noted in the literature on simple competing risks models in discrete time, this is not simply the interval hazard (Allison, 1989). It is instead the joint probability for each possible moment that the paid leave began, that the leave began at that instant and that the woman would neither have quit her job nor begun unpaid leave before that date. We approximate this integral by sums at a daily frequency.

In all, there are 18 possible cases. For the complete data cases, we have: Never worked, quit during pregnancy, unpaid leave beginning during pregnancy, paid leave beginning during pregnancy, quit at delivery, unpaid leave beginning at delivery, and

---

12 This represents a major computational savings. About half of the computational effort is expended on the "can't tells"; computational effort is cut by about two-thirds with this restriction (rather than allowing for the possibility that leaves began on the first day of pregnancy).

This restriction can be justified by examination of the 364 cases of paid leave among those eligible for the post-1988 Maternity Leave Battery. In that sub-sample, only two cases—less than one half of one percent of the sample — begin leave before day 180 of pregnancy. (i.e., before the last three months).

paid leave beginning delivery, (seven paths); each of which can be censored (denoting return to work) or uncensored after childbirth (total of fourteen cases, two times seven). In addition, there are four "can't tell" cases: Certainly did not work until childbirth, and may have worked until childbirth; again with censored (denoting paid leave, then quit) and uncensored work after childbirth. Four of the censored cases do not occur in the data. Appendix C gives the formal likelihoods for each of the 18 cases. It also gives the distribution of births across cases.

III.E Estimating the Model: Computational Methods

Estimation proceeds by maximum likelihood using analytic derivatives and the outer-partial approximation to the Hessian. The standard errors are computed according to robust Huber formulae from the analytic first derivatives and numerical second derivatives (computed from the analytic first derivatives; White, 1982). From good starting values the estimation on the sample of 6524 birth events takes about half a day (on a Sun SPARC 10), and the computation of standard errors (for about 200 parameters) using numerical differentiation of the analytic first derivatives about a day. The formulae for the computation of the analytic derivatives are given in Appendix D.

The model was estimated without and with heterogeneity. As was noted earlier, the model (with heterogeneity) includes nine vectors of regression coefficients (one for each of the three competing risks during pregnancy, one for each of the three hazards after childbirth, and one for each of the three probit models), plus a parameter for each knot of the spline and constants in the probit equations. Even without heterogeneity, there are 203 parameters. For each of the three competing-risk and three hazard functions, there is a parameter for each spline knot. That accounts for 83 parameters. The remainder are demographic coefficients of the regressions for each of the competing-risk and hazard functions and of the three probits. (See Appendix F.) The nine factor loadings bring the parameter count to 212.

The random effect, assumed distributed normally, is approximated by three-point Gaussian-Quadrature (Butler and Moffitt, 1986). This three-point approximation is probably not sufficient to correctly approximate the normal distribution. However, we have no a priori reason to specify the normal. The three discrete mass points seem to capture the correlation between the outcomes relatively well.

IV. RESULTS

The primary goal of this paper is to describe the leave status of women (quit their jobs, unpaid leave, paid leave) and the timing of the beginning and ending of that leave. We begin our discussion of the results with an examination of the parameter estimates themselves and the implied shape of the underlying hazards. These parameter estimates are difficult to interpret. We then simulate the implied labor market patterns for the sample of new mothers in the June 1990 CPS.

IV.A The Parameter Estimates

Appendix F contains the full set of parameter estimates for the random effects model. In interpreting the results, it is useful to remember that more work is associated with positive coefficients in each of the probits (any work during pregnancy, did not quit at delivery, took paid leave at delivery); negative regression coefficients in the competing risks for leaving work during pregnancy (smaller/more negative coefficients imply that a woman works longer into pregnancy); and positive regression coefficients in the hazards for returning to work after childbirth (larger/more positive hazards imply that a woman returns to work sooner after delivery).

The results are generally consistent with the previous literature. Older women and those with at least some college (the College Grad effect is in addition to the Some College effect) are more likely to have worked during pregnancy. High school drop-outs, those with a child already at home, and those who have never married are less likely to work during pregnancy. Hispanics and blacks are less likely to work during pregnancy, but only the Hispanic effect is significant at $p=0.05$. Work during pregnancy has become more common over the NLS-Y sampled period. Finally, the factor loading is positive; women with higher tastes for work are more likely to work during pregnancy.

The results for the competing risk of quitting work during pregnancy are nearly the mirror image of any work during pregnancy. Older women and college graduates are less likely to quit/quit later in their pregnancy. High school drop-outs, those with other children at home, and those who have never married or are currently divorced are more likely to quit and to quit earlier in their pregnancies. Quitting has become less common over time. Finally, the factor loading is negative; women with higher tastes for work are less likely to quit/quit later.

The sign patterns for the competing risk of beginning unpaid leave during pregnancy and the competing risk of beginning paid leave during pregnancy are similar to the sign patterns for quitting a job during pregnancy. However, fewer of the parameter estimates are significant, as would be expected since there are considerably fewer "failures"--women who leave pregnancy job for unpaid leave or paid leave (compared to quitting their jobs; 2036 in Cases 3 and 4 those who quit their jobs, vs. 570 in Case 5 unpaid leave and 318 in Case 7 paid leave).

The signs of the probit coefficients for taking leave at pregnancy (rather than quitting) are similar to those for taking paid leave at delivery (rather than taking unpaid leave). However, many of the coefficients are not significantly different from zero at p=0.05. Among the significant results are that exits to both types of leave now occur later (though only the result for unpaid leave is significant), those with more education begin their leaves later (though only the some-college result in the paid leave equation is significant). The factor loadings in all three competing risks imply that women with higher tastes for work, work later into their pregnancies (with the quit and paid leave parameters significant at p=0.001, but the unpaid leave parameter insignificant even at p=0.05).

The results for speed of return to work after childbirth (presented in Table F.4) are more subtle. The estimates for returning to work after quitting the pregnancy job (or never having been employed during pregnancy) are consistent with the previous literature. High school drop-outs, those who have never been married, and those with more children return more slowly. Those with some college return more quickly. Return to work has become faster over the sampled period. Women with higher tastes for work (whether due to the work itself or the resulting earnings) return more quickly. The only anomalous result is that older women return more slowly. Perhaps they have more resources (assets) with which to finance a leave.

For return from unpaid leave and return from paid leave, again few of the parameter estimates are significantly different from zero at p=0.05. The year parameters imply that leaves are getting shorter over the period. Compared to younger women, older women take longer leaves (though only the result for unpaid leave is significant).

IV.B The Shape of the Hazard

Figures 2 and 3 plot the shape of the hazard. The hazard is the probability of leaving work/returning to work, conditional on not having left work/returned to work. By the proportional hazards assumption, the shape of the hazard is the same for all individuals in the sample; only its height shifts up and down with covariates (and the random effects). These shapes are thus scale independent (and we plot them without a scale on the y-axis). In all three plots there is clear evidence supporting the flexible cubic spline baseline hazard used here. Unlike standard parametric hazards, the hazards for leaving work during pregnancy rise sharply at the end of pregnancy; the hazards for returning to work from leave (paid or unpaid) are non-monotonic and there is strong evidence that they are multi-modal.

Figure 2 plots the hazard for leaving work during pregnancy. All three hazards are low through the first two tri-mesters after which they rise quickly at an accelerating rate. The rise for paid leave starts latest and is sharpest. Thus women who are still working become increasingly likely to leave work for all three statuses as their pregnancy progresses, with sharp increases in the probability of leaving work in the last few weeks of pregnancy.

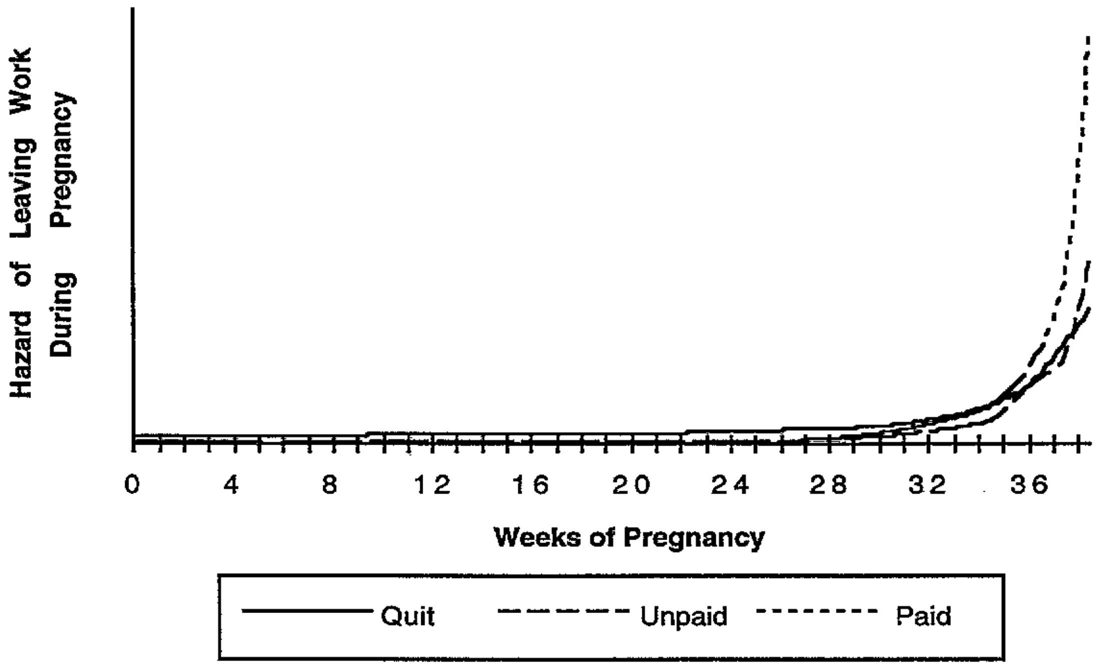

Figure 2—Hazard for Leaving Work During Pregnancy, by Type of Leave

Figure 3 plots the hazard for return to work after childbirth. The hazard for return to a new job (after quitting the pregnancy job, or after not having worked during pregnancy) is the lowest of the three hazards. It has a local maximum between about week 6 and week 10, after which it returns to a lower level.

The hazards for unpaid leave and paid leave show considerably more variation (Figure 3 plots the first six months after delivery; Figure G.1 in Appendix G plots the hazard through 24 months). The hazard for return from unpaid leave is low through about week 6 after which it stays high. We only plot the hazard through the 95th percentile of the survivor function. Towards the end of the plot, there is some evidence of a decline in the hazard.

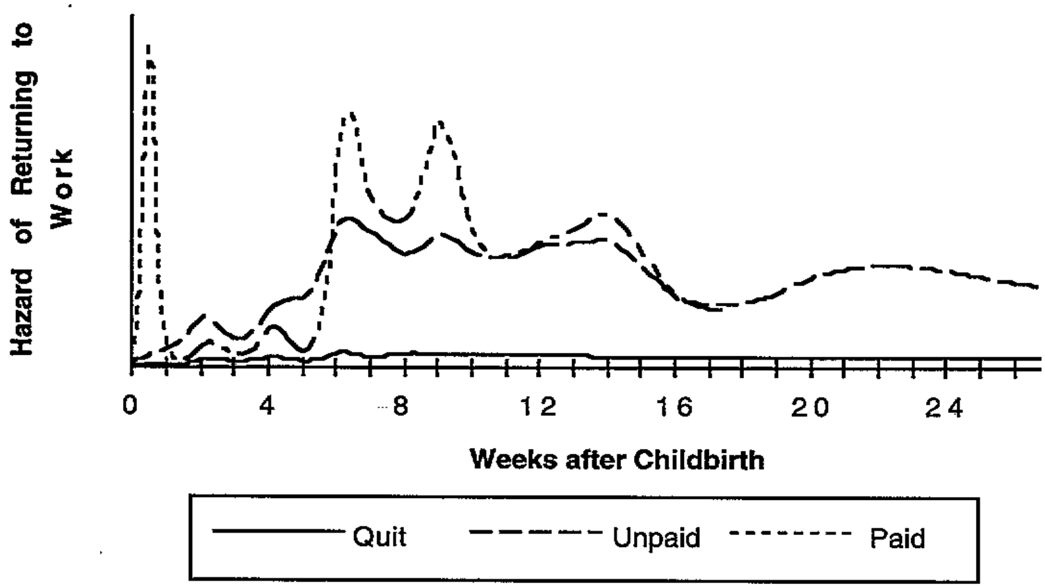

Figure 3—Hazard for Returning to Work after Childbirth, by Type of Leave (first six months, 26 weeks)

The hazard for return to work from paid leave is very high in the first week. This is an artifact of our coding of women who report continuous employment (consistent with the interviewer instructions,) as having had some paid leave of up to seven days. The hazard then exhibits twin modes at seven and 10 weeks (where there are less distinct peaks in the unpaid hazard as well). There is some evidence of another peak about 15 weeks. Again we plot the hazard through the 95th percentile of the survivor function (about 49 weeks). There is evidence of oscillations in the hazard at the tails. These oscillations were also found in an earlier version of the paper which approximated the log hazard with high order polynomials (see Klerman, 1991). We explain these oscillations as follows: There is simply not a lot of data (returns to work) at these durations. Thus, even in the flexible spline context, the optimizer tries to improve the fit to the (truly) rapidly changing hazard at earlier durations, at the cost of inducing oscillations where there is little data (at longer durations).

In summary, women have a very high probability of returning to work in the first week after childbirth (especially for women who are on paid leave). For those women who do not return within the first week the probability of returning in each week conditional on not having returned through that week remains low until about six weeks when it jumps up staying high until nearly all women have returned. There is some evidence of sharp increases in the probability of returning to work among those women not yet working at weeks six and nine. The evidence is more pronounced in the hazard for paid leave than in the hazard for unpaid leave.

IV.C Simulations: Type of Leave

These parameter estimates and hazard shapes are not particularly informative for our objects of interest, the type of leave (none, unpaid, paid) and the timing of leaving and returning to work among recent births. To compute these parameters of interest we simulate our model using the CPS sample of recent births. Table 3 showed that the CPS sample had more recent births, was older (27.6 years old in the CPS vs, 24.7 in the NLS-Y) , had more children (65.3% second or later vs. 35.7%; 30.3% third or later vs. 18.8%), had more education (16.2% high school dropouts vs. 24.8%; 42.6% at least some college vs. 29.7; 20.4% college graduates vs. 10.8%) and was less likely to have never been married (13.8% vs. 21.%).

Table 4

Comparing Simulations Based on NLS-Y sample with Simulations based on CPS sample (which is representative of all recent mothers)

	NLS-Y	CPS
When left during pregnancy		
Never worked	37%	33%
1-13	10%	7%
14-26	10%	8%
27-38	31%	30%
At delivery	12%	22%
Type of leave		
Never worked	37%	33%
Quit	31%	34%
Unpaid	14%	14%
Paid	17%	19%
Back by 6 weeks		
Quit	4%	6%
Unpaid	37%	39%
Paid	49%	58%

Note: NLS-Y data is unweighted

Consistent with these differences in covariates, Table 4 shows that it is important to not interpret estimates based on cohort samples such as the NLS-Y (or the NLS-YW) as population estimates, as has been done by some previous studies (at least in as much as they plot and interpret the empirical hazards; e.g. Mott and Shapiro, 1978; Shapiro and Mott, 1979; Wenk and Garrett, 1980; Desai and Waite, 1992). The NLS-Y simulations over-predict the share of women who never work and under predict the share of women who quit their jobs. Furthermore within a leave type, those simulations under-predict the share of women who will return to work within six weeks. The difference is particularly large for the paid leave group.

We turn now to the main task of the paper characterizing leave for maternity, using the simulations based on the CPS sample. Table 5 presents a broad picture of the patterns. The columns divide women by their immediate post-delivery status, never worked during pregnancy, quit pregnancy job (i.e. no job), unpaid leave, and paid leave. The rows divide women by the length of their leave. Women on short-leave returned within a week. Women on long leave return sometime between the second week and the end of the second year. Finally, some women do not return by the child's second birthday. The upper panel of the table presents estimates for the entire population (the cells in the entire panel sum to 100 percent). The lower panel tabulates leave length within leave type (the cells in a given column sum to 100 percent).

Table 5

General Characterization of Leave

Type of Leave	Never	Quit	Unpaid	Paid	Total
Short Leave	0%	0%	0%	8%	8%
Long Leave	17%	27%	14%	11%	69%
No Return	16%	7%	0%	0%	23%
Total	33%	34%	14%	19%	100%
w/in Type					
Short Leave	0%	0%	2%	41%	
Long Leave	51%	80%	98%	59%	
No Return	49%	19%	0%	0%	
Total	100%	100%	100%	100%	

Overall about a third of all women do not work at all during pregnancy; a third quit their jobs during pregnancy; and a third retain some connection with their employer through childbirth. Of those new mothers who retain some connection to their employer, a quarter have short leaves (8 percent of all women), a third take long (over a week) paid leaves (11 percent of all women), and the remaining approximately two-fifths take long unpaid leaves (14 percent of all women). Table G.1 (in Appendix G) shows that most of these "short-leaves" are the result of our coding of "continuous work.

IV.D Simulations: Timing

We now turn to the timing of last work during pregnancy and first work after childbirth. Figure 4 plots labor market status during pregnancy. The lowest band are the third of women who never worked during pregnancy. The second band are the women who quit their pregnancy jobs. The third band are the women who take unpaid leave. Finally, the fourth band are the women who take paid leave. The area above the fourth band represent women who are still "at work" as of this point in the pregnancy.

Although the hazard for quitting the pregnancy job appeared to be low in Figure 2 (especially in the first two-trimesters), the number of women who quit their jobs (which will eventually reach a third) rises nearly linearly until the last six weeks of pregnancy when the number of women who have quit their jobs accelerates above the linear trend. Note that a third of all mothers are still working three days before the birth of a child.

Neither unpaid leave nor paid leave become appreciable until the eight weeks prior to delivery. Through (but not including) delivery, paid leave is more common than unpaid leave. Note that none of these curves include the discontinuous jump in quits and leaves at delivery (within three days). Table G.2 presents numerical estimates of labor market status for selected weeks of pregnancy.

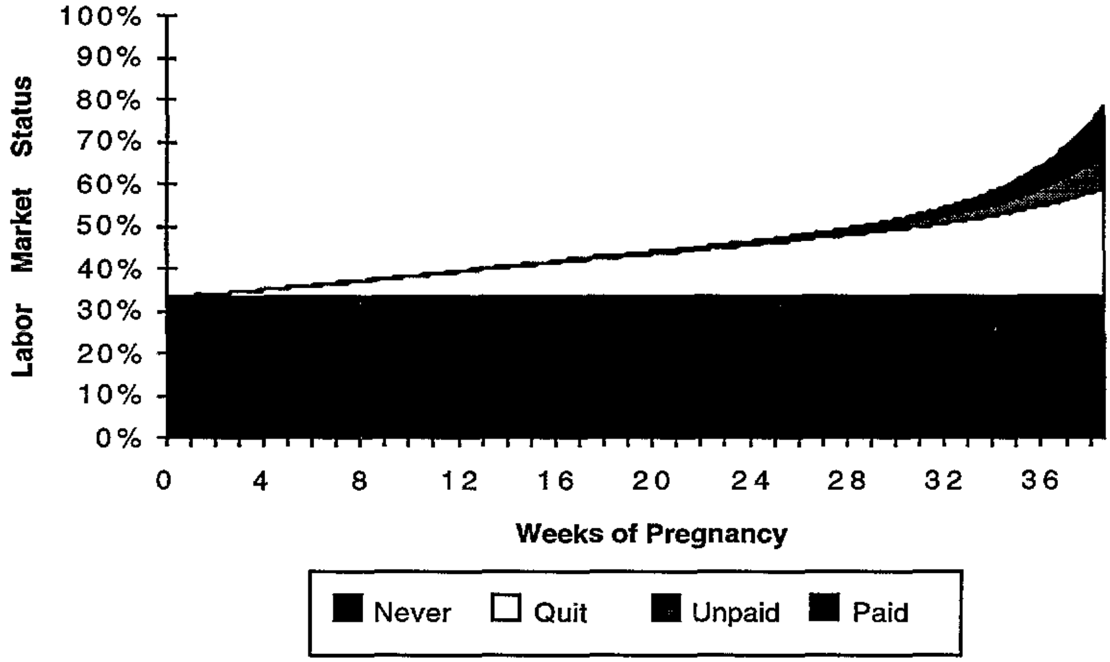

Figure 4—Probability of Not Working by Weeks of Pregnancy, stratified by Labor Market Status. Complement is women still working. Pregnancy assumed to last 39 weeks. Never-Never worked during pregnancy, Quit-Quit pregnancy job, Unpaid-On unpaid leave, Paid-On paid leave.

Figure 5 plots the distribution of women working in the first six months after birth by their status at birth. Table 6 presents the same information in tabular form (Figure G.3 presents the equivalent plot for the full two years after childbirth). The lowest band is women who were on paid leave. It shows a sharp jump in the first week corresponding to the short-leaves and another clear jump between week 6 and week 10. The number of women returning from unpaid leave rises smoothly from 2 to 6 weeks, with an acceleration from 6 to 10 weeks after which the return is nearly complete.

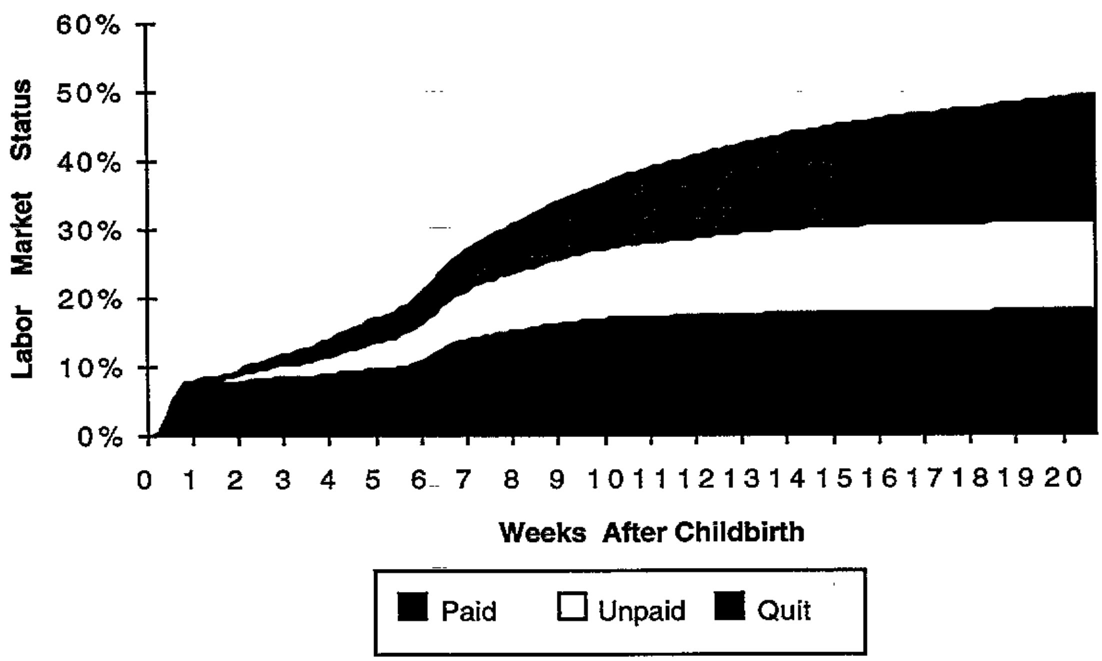

Figure 5—Probability of Not Working by Weeks After Childbirth, stratified by Labor Market Status (detail of first five months after childbirth). Complement is women who have returned to work Quit-Quit pregnancy job, Unpaid-On unpaid leave, Paid-On paid leave.

Women return after having quit a job (or not having had one during pregnancy) throughout the first 24 months. This result differs from that of Klerman and Leibowitz (1994) using CPS data. They find the total number of women at work barely rises after about six months. Part of the difference is definitional. These NLS-Y estimates are based on time of first return as a function of the age of the reference child. While subsequent births are not uncommon (about a third of the NLS-Y births, unweighted, are followed by another birth within twenty-four months), the bias due to using age with respect to the reference child rather than age of the youngest child works in the wrong direction.[13] However, the bias due to first return vs. currently working explains

---

[13]Assuming that women with more births are less likely to work (as is supported by the results reported here), then subsequent births select out the non-workers, causing the

some of the difference. First return is an absorbing state, so the curves must be monotonically non-decreasing. Leaving work after, returning is not uncommon. This would cause the NLS-Y results to be more positively sloped.

CPS work estimates to be higher than the NLS-Y work estimates. Since the number of births increases as the duration since the reference birth increases, this would induce amore positive slope in the CPS data (the opposite of the difference we are trying to explain).

Table 6

Leave Status in Selected Weeks after Childbirth

Weeks	Quit	Unpaid	Paid	Total
1	67%	14%	12%	93%
2	66%	13%	11%	90%
3	66%	12%	10%	88%
4	65%	11%	10%	86%
6	63%	9%	8%	80%
8	60%	5%	4%	69%
10	58%	4%	2%	64%
12	55%	3%	2%	60%
14	53%	2%	1%	56%
16	52%	1%	1%	54%
18	51%	1%	1%	53%
20	49%	1%	1%	51%
26	46%	0%	1%	47%
39	39%	0%	0%	39%
52	35%	0%	0%	35%
65	30%	0%	0%	30%
78	27%	0%	0%	27%
91	25%	0%	0%	25%
104	23%	0%	0%	23%

NOTE: Table cells are percentage of women in each leave status in each month. Complement (i.e. 100%-Total) is women who are working.

Another difference between the two studies is that the CPS results in Klerman and Leibowitz (1994) are based on the age of the youngest child. The results reported here are based on a sample of all births. Some of these women may have had a subsequent birth by the end of two years. This, however, appears to be rare. Relatively few women in the NLS-Y sample have a second birth within 24 months.

IV.E Characteristics of Leaves

We can also use the model estimates to describe the characteristics of leaves of different types. Figure 6 plots, by their eventual leave status, the percentage of all women in that status who have left work by a given point in pregnancy, overall and for those who quit their jobs, took unpaid leave, or took paid leave. The difference between the plot at 38 weeks and 100 percent are those who work until childbirth and then begin the corresponding status.

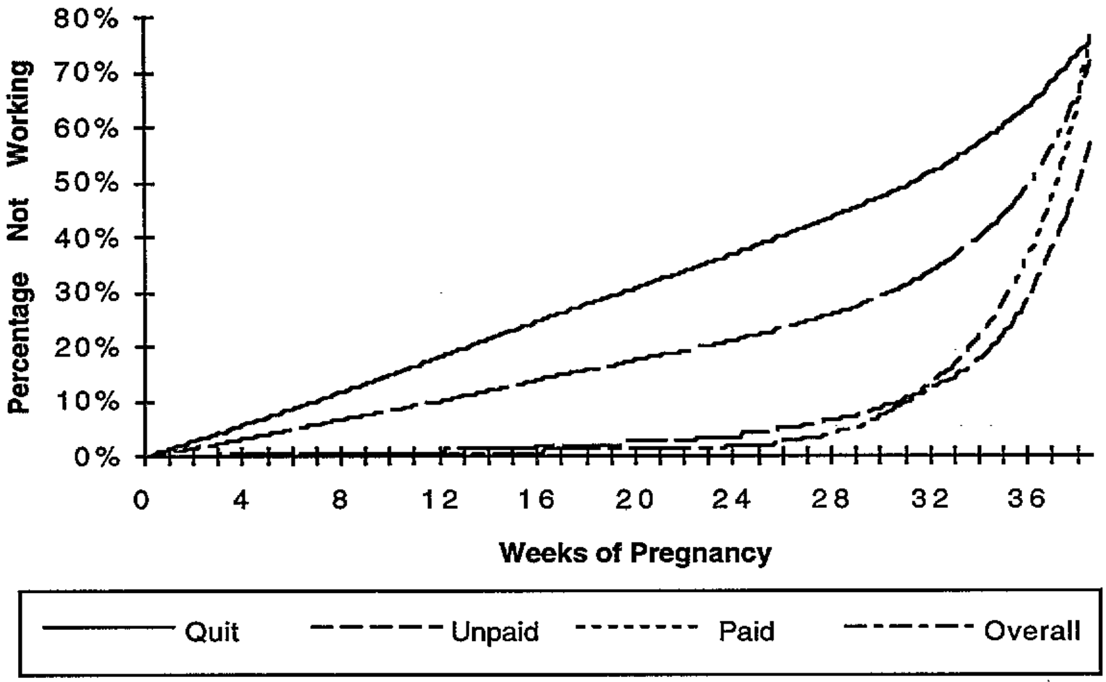

Figure 6—Percentage of Each Category of Leavers Who Have Left by Each Week of Pregnancy (excluding women who never worked during childbirth).
Difference between curves at 39 weeks and 100 percent is quits/unpaid leaves/paid leaves at birth.

Quitters leave earliest. The rates of leave for unpaid leave and paid leave are relatively similar. Unpaid leaves are slightly more likely to begin before 31 weeks, when they are overtaken by paid leaves. However, unpaid leaves are more likely to start at childbirth (within three days).

Figure 7 plots the percentage of women who have returned to work within a leave type (excluding the short leaves; Table G.3 presents the same information in tabular form with and without the short leaves). It shows that rates of return from unpaid and paid leave are quite similar. Return from paid leave is slightly less common through about 7 weeks and again after 15 weeks. Through about 7 weeks, the fraction of those taking paid leave who had returned is slightly smaller than the analogous fraction of those on unpaid leave. The same is true after 15 weeks.

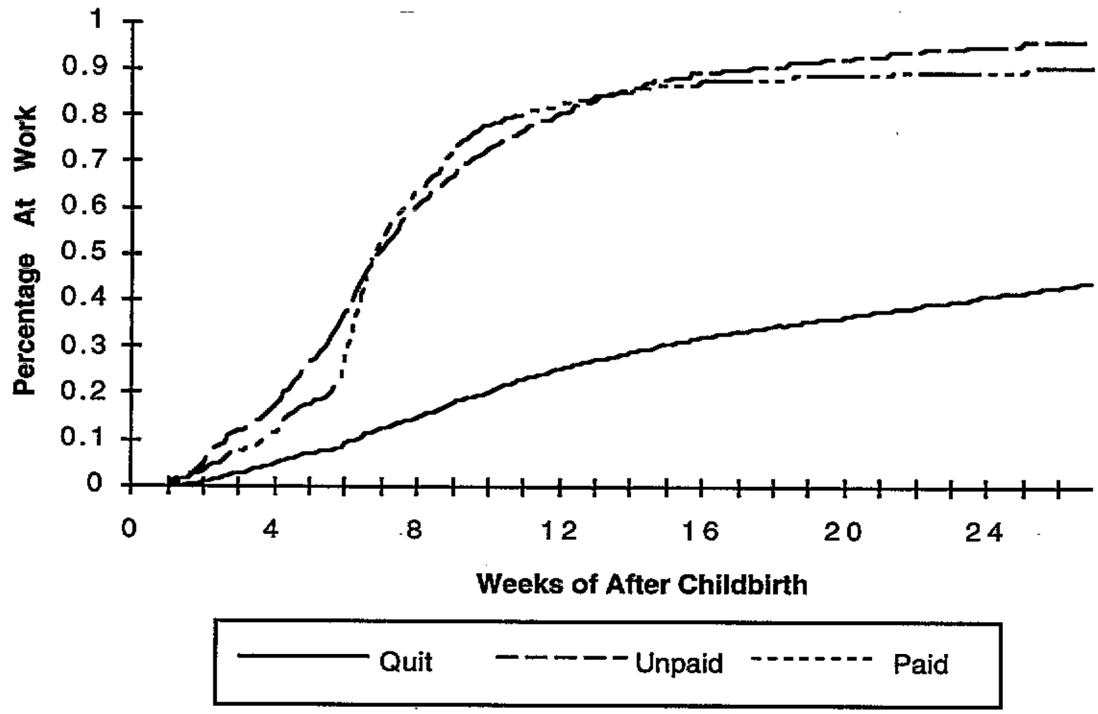

Figure 7—Percentage of Women Who Have Returned to Work at Each Week after Childbirth, by Ultimate Leave Status (excluding short leaves)

A different way of comparing leave patterns, is to consider the distribution of leave patterns by the week in which the leave began/ended. Figure 8 perform those comparisons for the beginning of leave during pregnancy (see Table G.4 for a tabular presentation). Through the beginning of the third trimester, almost all women who leave work quit their jobs. From week 26 through week 38, quitters shrink from over 78 percent of those leaving work to 28 percent. By week 30 new leaves are more likely to be paid than unpaid. As of three days before delivery, nearly half of all leaving work are going to paid leave.

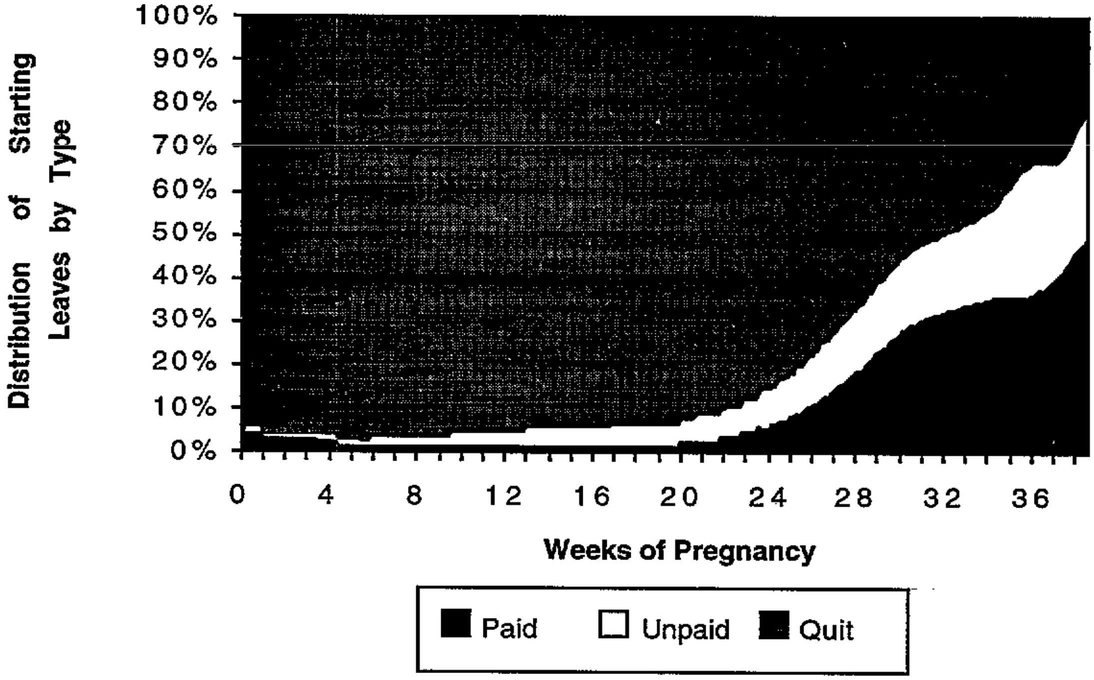

Figure 8—Distribution of Leave Type, by Week Leave Began in Pregnancy

Figure 9 contains the equivalent results for return to work after childbirth (see Table G.4 for a tabular presentation). Again, the results in the first week are dominated by the short paid leaves. Thereafter through about 10 weeks women returning to work are approx' ately equally divided between paid leave, unpaid leave, and women who quit their job (where this group excludes women with no work during pregnancy). Women returning after 10 weeks are very unlikely to be returning from paid leave (leave which began as paid; unpaid leaves immediately following paid leaves are coded as extensions of the paid leave). Women returning after 16 weeks are very unlikely to be returning from unpaid leave.

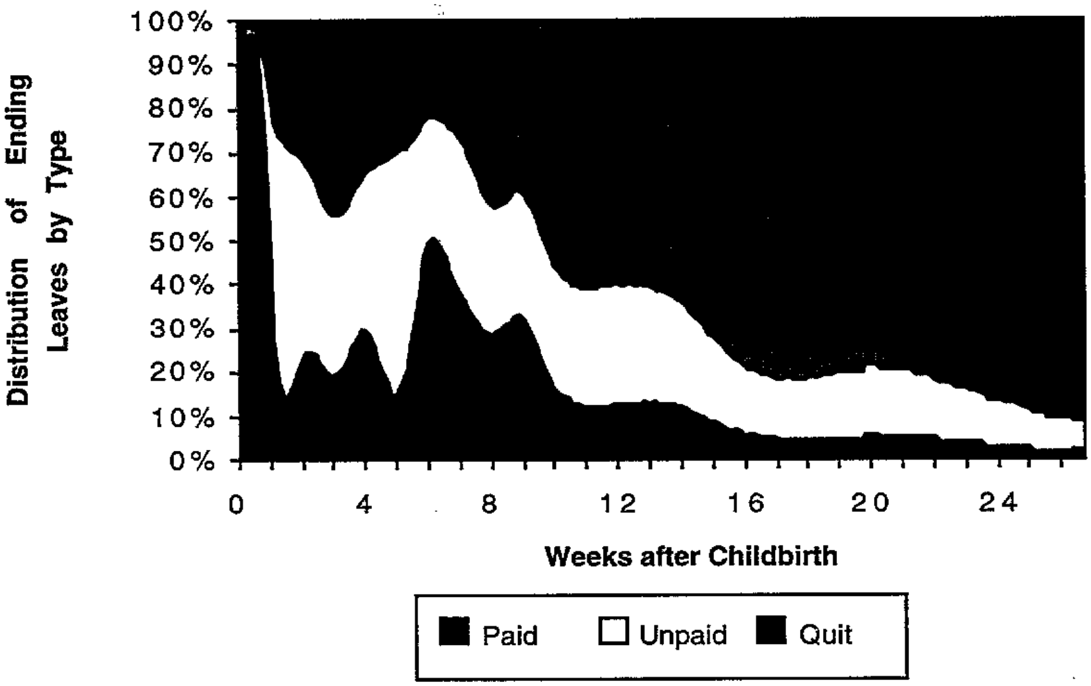

Figure 9—Distribution of Leave Type, by Week Leave Ended After Childbirth

IV.F Leave-Return Correlation

In the introduction to the paper, we noted that a consistent result in the literature is that work during pregnancy is strongly correlated with return to work after childbirth. Table 7 tabulates return to work by when women left work during pregnancy. As expected, women who never work during pregnancy, return to work the most slowly. Women who work until delivery return to work most quickly after delivery. Women who leave work during pregnancy fall between the two extremes. Note that leaving work during the first two trimesters of pregnancy is relatively rare (15 percent of all women; see Table 7).

Table 7

Percentage of Women who Have Returned to Work, by When Left work in Pregnancy

Weeks	Overall	Never Worked	W1-W13	W14-W26	W27-W38	To Delivery
1	8%	0%	1%	1%	13%	18%
2	10%	0%	2%	2%	15%	21%
3	12%	1%	3%	4%	18%	25%
4	14%	2%	4%	6%	21%	29%
6	21%	3%	8%	10%	32%	40%
8	31%	5%	13%	16%	48%	56%
10	37%	7%	17%	22%	58%	65%
12	41%	10%	21%	26%	62%	70%
14	44%	11%	24%	29%	66%	74%
16	46%	13%	26%	32%	69%	76%
18	48%	14%	29%	34%	70%	78%
20	49%	15%	30%	36%	72%	79%
26	53%	19%	36%	41%	75%	83%
39	60%	27%	47%	52%	81%	88%
52	65%	33%	54%	59%	85%	91%
65	69%	39%	61%	66%	88%	93%
78	72%	44%	66%	70%	90%	95%
91	75%	48%	70%	74%	91%	96%
104	77%	51%	73%	77%	93%	97%
Quit	67%	100%	96%	90%	39%	38%
Unpaid	14%	0%	2%	6%	24%	28%
Paid	19%	0%	2%	3%	36%	34%
In State	100%	33%	7%	8%	30%	22%

V. CONCLUSION

This paper has specified and estimated a model of leave for maternity appropriate for and estimated on the National Longitudinal Survey-Youth data. Unlike other datasets, the NLS-Y dates most events to the day. It can, therefore, be used to examine timing of return to work to the week (or day). Since most return to work which will occur over the first two years of the newborn's life occurs in the first two months after childbirth, understanding timing within this period immediately after childbirth is of considerable importance.

To model leave and return to work, the paper specified a model of the timing of leaving work during pregnancy and returning to work after childbirth which was disaggregated into quitting work, taking unpaid leave, and taking paid leave. The baseline hazards were specified as exponentiated cubic splines. The different decisions were linked by a random effect. The resulting parameter estimates strongly support the use of a flexible baseline hazard (as provided by the cubic splines) and correlation across the decisions within a given birth and across births to a given mother as provided by the random effects). Furthermore, with multiple decisions (hazards and probits), the data clearly identify a (complicated) baseline hazard, in a model which allows for unobserved heterogeneity.

The model was specifically constructed to include a class of "can't tell" women. Due to the nature of the NLS-Y questionnaire, for some women it is not possible to tell if they took an extended (i.e. several weeks) paid leave or worked through childbirth (taking leave of under a week). This ambiguity has been a significant stumbling block for researchers wishing to investigate the relation between earlier maternal presence (i.e. not at work) and subsequent child development. The estimates presented here exploit all of the information on work in the NLS-Y data. Appendix E of the paper shows how to use the parameter estimates to impute the probability that a given "can't tell" woman actually followed a given labor market behavior.

On a substantive level, the paper's estimates refine our understanding of the speed of return to work following childbirth. The data used here cover behavior through 1990. This is before the passage of the Federal Family Leave Act in January 1993 and before the implementation of most state maternity leave legislation. In the absence of such government restrictions, leave for maternity was quite common. About half of all women who worked at any time during childbirth and almost all women who were still working within three days of delivery retained their connection with their pregnancy employer, taking unpaid leave or paid leave rather than quitting their pre-childbirth job.

However, the leaves were quite short. Proponents of maternity leave legislation and the Federal Family Leave Act have argued for the importance of maternal presence in the period immediately after the birth of a child for the child's emotional and intellectual development. During that debate, developmental psychologists argued for leaves of two to six months (see the papers in Zigler and Merrill, 1988; for example

Brazelton, 1988, argues for leaves of 12 weeks). The results presented here suggest that in the absence of maternity leave legislation the vast majority of women, even among those who had worked during pregnancy (and would return to work before the child's second birthday) take some leave after delivery. However, among women who would return to work before the child was two years old, the modal leave was only about six weeks and few women took as much as 12 weeks of leave. The Federal Family Leave Act, (which went into effect August 1, 1993), was intended to make longer leaves (up to twelve weeks) more common. Future research should evaluate the future trends in leave for maternity and the effects of that legislation.