Appendix C: The IWPR/LRC Paid Family and Medical Leave Simulation Model

Introduction

In developing a simulation model to estimate the cost of paid family and medical leave programs in a given state, we rely on data documenting actual known leave-taking behavior. Where this is not possible, we provide a set of reasonable assumptions about unknown aspects of behavior in the presence of a paid leave program. To obtain the best estimates possible about known leave-taking behavior, we use the Department of Labor's *Family and Medical Leave 2000 Survey of Employees* (hereinafter referred to as the DOL survey) to estimate behavioral models of leave-taking conditional on the demographic characteristics of individuals, combined with the Census Bureau's March Annual Demographic sample of the Current Population Survey (hereinafter referred to as the CPS) to predict for data on the demographic characteristics of individuals in individual states.

Data

The DOL survey is the best available source of information on leave-taking behavior. It is a representative national sample of leave takers, leave needers (those persons who said they needed but did not take a leave), and other workers who did not take a leave.[1] The survey, which covers the 19-month period January 1999 through July 2000, includes extensive information on the number and types of leaves taken, how long they were, whether and to what extent the employer provided pay during the leave, and whether or not some or additional pay during the leave would result in a decision to take a leave or to take a longer leave. The DOL survey includes several demographic characteristics related to leave-taking behavior, including sex, race and ethnicity, age, martial status, the presence of children, education, family income, and whether or not the respondent was paid on an hourly basis. We use the DOL survey to estimate several aspects of leave-taking behavior, conditional on demographic characteristics and leave type. These include the probability of needing a leave, taking a leave, getting paid for a leave, and extending a leave if some or more pay were received.

The CPS is a nationally representative sample of households, families, and persons. It is of sufficient size at the state level to obtain reliable estimates of total paid leave program costs and of the distribution of program benefits using multiple years of survey data. The CPS also provides a rich array of demographic characteristics that closely match those in the DOL survey, which means that the behavioral models estimated on the DOL survey can be used to predict the leave-taking behavior of the population as represented by the CPS. We draw from data on employed persons who are not self-employed – the entire universe of potential paid program users.

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[1] The DOL 2000 Survey was conducted by Westat for the Department of Labor, between July and October of 2000. People were asked about any leaves from employment taken since January 1, 1999. The data file is available on-line at http://www.dol.gov/asp/fmla/database.htm. There were three distinct types of respondents in the survey. The first were employees who reporting taking a FMLA–defined leave in the prior 19 months (N=1,229). The second category was employees indicating they needed but did not take a FMLA-defined leave over the period (N=203). The third group was comprised of employees who neither took nor needed a FMLA-defined leave during the prior 19 months (N=1,126).

The CPS surveys people in households. Therefore, for our Massachusetts cost estimate, the data include workers who live in Massachusetts, regardless of which state they are employed. There may be workers eligible for a paid leave program who work in Massachusetts but do not live in the state. Our simulation data does not capture them. Conversely, there may be people who live in Massachusetts but work in another state and would not be eligible for a Massachusetts paid leave program. Our simulation data do include them. We assume that the net difference is negligible.

Concatenating and "Cloning" CPS data
Aside from errors in estimates of the behavioral equation parameters and errors in assumptions (discussed in depth later in this appendix), there are two sources of statistical error that are important to consider. One is sampling error in the CPS. The magnitude of this sampling error is approximately inversely proportional to the square root of sampling size and can be reduced by concatenating successive years of the CPS together. We have done that with our Massachusetts estimates by using data from the March 1999, 2000, 2001, and 2002 surveys.[2]

The second source of statistical error is caused by the simulation methodology itself when the dependent variable is binary (or categorical). Even if the coefficients of a behavioral equation are "correct," individual predictions are not. For example, suppose a logit equation predicts that the probability of taking a leave is 30 percent for a person with a certain set of demographic characteristics. For any *single* person, the simulation onto the CPS data results in either the person taking the leave (a leave-taking "probability" of 100 percent, or an error of 70 percent) or the person not taking the leave (an error of 30 percent). The law of large numbers assures that the error percentages approach zero on average as the number of persons "run" through this equation approaches infinity. The magnitude of this type of error is inversely proportional to the square root of the number of "runs" through the equation. The incidence of some types of leave is small enough that this source of error is not negligible. Concatenating CPS data files reduces this type of error, but we have devised another way to reduce errors of this sort. We "clone" each sample CPS person (i.e., create several duplicates of the same person) and then run each duplicate person through the simulation (correspondingly reducing their sample weight). The reason for cloning is to make the simulated results conform, on average, with the estimated models.

A simple example helps illustrate how this technique works. Suppose we estimate a model that explains what percent of coin tosses comes up heads, and suppose, just for simplicity sake, that the estimate is 50 percent. It is not important whether or not 50 percent is the true probability or not. This simple model is analogous to a behavioral equation in used in our model, which is designed to estimate the probability of something happening, such as taking a particular kind of leave.

Next, we apply the coin-tossing model to a sample of persons to simulate their coin tosses. The sample of persons corresponds to the CPS in our model. A desirable outcome for this simulation exercise would be to find that the simulation yields an estimate of 50 percent of the coin tosses coming up heads. That is, the idea is get a simulated result that conforms to the estimated model.

In the most extreme example, suppose there was only one flip of the coin (or one person in our sample) with which to perform the simulation (a very small CPS indeed!). The simulation either ends in a head, or not, with an estimated probability of 100 percent or zero percent. The expected result is 50 percent, but the simulation is doomed to be very misleading. Furthermore, if the simulation were performed again, it could result in a quite different result.
Now suppose the flipping is repeated – or in our case a person is "cloned," creating a second, identical person, so that there are now two persons on whom to perform the simulation. Then, the simulation could end in one of three ways: a 25 percent chance of simulating heads being thrown zero percent of the

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[2] The unweighted sample size for the four concatenated years is 6,405.

time, a 50 percent chance of simulating heads being thrown half the time, and a 25 percent change of simulating heads being thrown 100 percent of the time. If the cloning factor were set to 20, binomial tables indicate that there would be nearly a 75 percent chance of the simulator resulting in estimates that fell between 40 and 60 percent, and different "runs" of the simulator initialized at different random numbers would more likely be closer to one another than with a smaller cloning factor. Any degree of reliability could be achieved by an appropriate choice for the cloning factor.

There are two results of note. One is that cloning has nothing to do with the behavioral-model estimate (as opposed to the simulated result) of the probability of a coin toss coming up heads. The second result is that the reliability of the simulator increases with the size of the cloning factor (and, of course, with the size of the CPS). Reliability means the ability of the simulator to produce results that are insensitive to the seed of the random number generator, that is, to produce the same or close to the same results again and again given the same input parameters.

For this report we used a cloning factor of 32. Cloning factors larger than 32 did not appreciably increase the model's reliability.

Simulation model

The simulation model we employ is a software application that "runs" each "cloned" sample person from the CPS through the estimated behavioral models and sets of assumptions about leave-taking behavior. The flow of the person through the software mimics the sequence of decisions and events that a person makes and experiences in the leave process. At several points during the simulation, such as when a person decides to take a leave of a particular type or not, a decision is made based on a logit behavioral equation (derived form the DOL survey responses). The logit equation estimates the probability of deciding "yes" (to taking a leave, taking multiple leaves, seeing a doctor, etc.). [3]   This probability, which is a function of the person's demographic characteristics, is compared to a random "draw" from a standard uniform distribution (any point on the number line between zero and one is equally likely to be chosen). If the random draw is less than or equal to the probability given by the logit equation, the decision "yes" is simulated; otherwise, the decision "no" is simulated.

A note on assigning probabilities
Whenever we use logit regressions to estimate the probability of deciding "yes" (needing a leave, taking a leave, getting pay from employer), we use the following formula to calculate the probability.

Probability $= \quad e^{x\beta} / (1+ e^{x\beta})$

where x is a vector of independent variables used, β is the vector coefficients estimated in the logit regressions and simulations described in this appendix, and e is the natural log.

Behavior Estimations

To estimate the cost of paid leave using individual wage and salary workers on the CPS we generate a range of data: the likelihood and actuality of taking a leave, the number of leaves, and the length of leave in the absence of a paid program. We estimate if any particular worker who takes a leave has some form of employer benefits and how much.

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[3] A logit equation estimation is a statistical method similar to linear regression estimations, but with logit analysis, the dependent variable is binary (0 or 1) rather than continuous.

We derived probabilities of leave-taking behavior based on findings from several logit regressions based on the following three models.

1. Universe of Leavers

We theorize that whether an employee will take or want to take a leave depends on a variety of factors that include:

a. If the employee is eligible and needs a leave (paid or unpaid) measured by the worker's own health status; the health status of family members; a new child in the household; and eligibility requirements (hospital stay, doctor's visit, employer size);

b. The conditions of employment measured by whether the employee has a job-protected leave and the kind of employment (salary or wage worker); and

c. An employee's tastes, preferences, and constraints (work and income) measured by the employere's demographic characteristics
(marital status, family income level, age, gender, education level, and race/ethnicity).

We run logit regressions separately for the six types of leave (own health, maternity disability, new child, ill health of spouse, ill health of child, ill health of parent), with varying results on the importance of explanatory variables.[4]

The March CPS has values for most of the variables used in the logit regression performed on the DOL survey but there are several we needed to generate. The first is if a worker is covered by and eligible for FMLA. We use CPS data on hours worked over the past year and employer size to estimate that eligibility. Employer size is estimated from the CPS categorical employer size variable by randomly interpolating within the CPS category (25-75 employees) using an exponential distribution. The CPS only contains information about worker type (hourly or salaried) for a portion of the sample, from which we estimate the probability of being an hourly earner for the entire sample. Whether one is salaried or waged is a function of education level; earnings; race, ethnicity, full-time (vs. part-time) work; number of weeks worked in the previous year; health insurance and pension plan participation; occupation; industry; and gender. The CPS does not include information about FMLA health condition eligibility criteria (hospital stays or doctor visits); we estimated those probabilities (for each kind of leave) from the DOL using the equation above and generated that information for individual workers in the CPS.

We also determine if a person meets the work requirements for a proposed paid leave program   While the CPS does not indicate how long any worker works with the same employer, it does ask how many employers the worker had in the previous year and the number of weeks worked over the last year, allowing us to generate the average weeks worked per employee.

2. Length Of Leave

We theorize that the number of weeks of paid or unpaid leave a person takes depends on:

a. The presence of a family or medical leave condition (this affects the type and severity of leave);

b. Conditions of employment(number of weeks with paid leave, how employer leave is paid, difficulty in taking leave, if leave is job-protected); and

c. The employee's tastes, preferences, and constraints, measured through demographic characteristics (marital status, family income level, age, gender, education level, race/ethnicity).

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[4] Detailed results are available from the authors.

Logit regression reveals that outside of severity of health condition (for own health only) and gender for all but own health, none of the variables help predict length of leave. One would suspect that whether or not a leave is paid would determine the length of leave. DOL survey data clearly reveal that shorter leaves are more likely to be fully paid than longer leaves. And in fact, length of leave turns out to be a significant way to determine if all or part of the leave was paid (see next section). Of those with employer benefits, longer leaves are partially paid. A closer examination of the specific own health ailments indicated that leave lengths are related to the severity of illness.

Aside from the gender of the leave-taker (for all but own-health) and severity of illness, there are no other significant predictors of leave length. Importantly, whether or not the leave-taker receives pay from her employer does not seem to be associated with the length of the leave. Since the CPS does not have information on individuals' illnesses, we simulate leave length by randomly drawing from the distribution that corresponds to the type of leave and gender of the leave-taker.

3. Employer benefits
We hypothesize that the amount of employer pay a leave-taker receives (if any) is related to:

a. length of leave.

b. conditions of employment (whether the worker is covered by and eligible for FMLA).

c. the employee's tastes, preferences, and constraints measured through demographic characteristics (marital status, family income level, age, gender, education level, and race/ethnicity).

The DOL survey asks if people taking a leave receive employer pay and if so, how much. The DOL survey provides the following breakdowns: fully paid, more than half pay, less than half pay or about half pay.

We use logit regression to estimate if a worker on leave receives any employer benefits separately for each of the six types of leave. We then use ordered logit regressions to estimate the probability of which proportion of employer benefits one receives.

A Note on Methodology
The basic strategy in specifying the behavioral models described above was to use a full set of demographic variables (based on our hypotheses) that might be related to the behavior in question, and then "test down" by eliminating variables that had very high p-values.[5] Because the significance of one independent variable often depends on what other independent variables are included in the model, various combinations of independent variables were tried, until the remaining independent variables had low p-values (generally below .05) or moderately low p-values, had coefficients of the expected sign, and seemed to be theoretically appropriate. That is, we "tested-down" incrementally, one variable at a time, and followed alternative paths that allowed for detecting the potential problem of any one independent variable being dependent on another independent variable. For example, if both the income and the education dummy variables were "insignificant," we would follow one path in which we eliminated education variables first, then following an alternative path that eliminated income first. Furthermore, after reaching a proposed "tested-down" model, we would trace alternative paths backward and add in variables. The order in which variables are dropped can affect which specification is ultimately chosen, so we compared alternative specifications on fit, statistical significance of individual variables or sets of variables, plausibility, and agreement with expectations.

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[5] A p-value is an indication of how well the variable helps explain the likelihood that the event being explained happens. It is equivalent to t-statistics or z-statistics in linear regressions.

An alternative way to proceed would have been to conduct a forecasting exercise including a large number of regressors, and choose the model that minimizes forecasting error. Given that we had several dozen models to estimate, we chose the more feasible route described above, and we are confident that the "testing-down" and other criteria that we use yields model specifications that are both plausible and close, in terms of simulation estimates, to those that could have been achieved with other specifications.

Our choice, or any particular choice, of a critical p-value to employ in the testing-down process, is arbitrary. We generally used .05 as a cutoff, but that was not our only criterion. Reasonableness of the model and the conformity of the coefficients with our preconceptions of the relationships between the independent factors and the dependent variable also played an important role. Thus we sometimes included variables whose p-values were above .05, and excluded some variables whose p-values were below .05, especially if they had the "wrong" sign given our preconceptions.

To test our model, we compared estimates drawn from our original fully specified model with estimates based on our "tested-down" model for one leave type (new child), to see whether or not they gave similar program estimates.[6] We took the original "full" specifications for the "new child" leave type and recoded all the behavioral equations in the simulator for that leave type with the full set of variables and coefficients, ignoring p-values, signs, and sizes of coefficients.[7] We found that these "full" specifications estimated 22 percent more leaves of this type and 13 percent higher program benefit costs than our tested-down models. Most of this difference, however, was accounted for by one variable in one equation. The dummy variable that indicated eligibility under the FMLA work and employer size requirements entered the full model for the "needing or taking leave" equation with the "wrong" (i.e., negative) sign and was of marginal statistical significance, with a p-value of .07. When just this single variable in this single equation was dropped, the resulting model produced estimates that were reasonably close. We found that this one change from the "full" specifications estimated 3.2 percent more leaves of this type and 5.7 percent fewer program benefit costs than our tested-down models. These are reasonably close, especially considering that for the remaining leave types, the combined differences were 0.5 percent in the number of leaves and 2.3 percent in program benefit costs. (These latter differences are due to the simulating variation that can be mitigated by "cloning." In this test, we set the cloning factor to 16.)

Simulating Unknown Behavior

Some information about leave-taking behavior needed for our simulation procedure cannot be estimated from the DOL survey, although some information collected there is useful in making some reasonable assumptions. The three main pieces of unknown information – whether a worker will use a paid program or employer benefits; program take-up rates; and whether a worker will extend a leave in the presence of a program -- are discussed in the body of the report. We elaborate here on two of those: how employer benefits affect paid program participation and whether to extend a leave in presence of a paid program.

1. How employer benefits affect participation in paid program.
The decision to participate in the paid leave program, given that a person is eligible, will in large part be based on the level of program benefits the worker would receive compared to the next best alternative. These alternatives consist of employer pay (if the person receives it) or nothing (if the leave is unpaid in the absence of the program). In order to compensate for the time and effort of applying to the program, program benefits would have to exceed the next best alternative by some amount. This amount may differ

[6] Thanks to Professor Michele Naples for making this suggestion.
[7] We selected parental leave type for this test since there is more policy interest in that type of leave, and we chose "new child" rather than "maternity/disability" because it was larger in terms of estimated program costs.

systematically by income and by other factors. It may also vary randomly across different individuals, and even for the same individual, at different times.

In our model, this participation decision is implemented by an arbitrary logit equation with two independent variables: the difference between weekly paid program benefits and weekly pay received while on leave, and family income. The participation probabilities it yields are given in Table C.1 below for several combinations of benefit/pay differentials and family income.

Table C.1
Probability of Participating in a Paid Leave Program for Selected Values of the Benefit/Wage Differential and Family Income

	Difference Between Weekly Program Benefit Amount and Next Best Alternative		
	$ 25	$ 50	$ 125
$ 10,000	0.12	0.59	1.00
$ 20,000	0.08	0.48	1.00
$ 30,000	0.05	0.38	1.00
$ 40,000	0.04	0.28	1.00
$ 50,000	0.02	0.21	1.00
$ 60,000	0.02	0.15	1.00
$ 70,000	0.01	0.10	0.99
$ 80,000	0.01	0.07	0.99
$ 90,000	0.00	0.05	0.98
$100,000	0.00	0.03	0.98

(Row labels are under the axis label "Family Income")

These probabilities are based on a logit equation where the independent variables are the difference between the weekly program benefit and the next best alternative, and family income. The "next best alternative" is either the weekly pay received from the employer while on leave, or zero if the leaver receives no pay while on leave.

2. Extending a leave in the presence of a program
In the presence of a paid leave program, leaves would not be shorter than in the absence of the program, but they may be longer. Lacking empirical evidence about the effect of program benefits on extending leave lengths, we estimate the probability of extending a leave. Because this decision is complex and affected by length of leave before the decision to extend, availability of employer pay, and whether the leave is job-protected, we use different extension rules in the simulation. For workers with short leaves (leaves that end before the waiting period of the program is over), we estimate the probability of taking a longer leave using logit regression estimations relying on the response to the DOL survey question, "Would you take a longer leave if you received some/additional pay?" If the model simulates an extension, we arbitrarily extend the leave for 1 week. We assign a different decision to those employees who reach the end of their original leave length (the length they would take if there was not program) and are receiving either program or employer benefits (but not both). We assume the probability of extending these leaves using program benefits are 25 percent and for those who do extend, that the extension is equal to 25 percent of their original length, not to exceed the maximum length of the program. The last decision applies only to those who have exhausted the paid program and still have some employer benefits available to them (based on the simulation). In this case the simulator assigns them a 50 percent

probability of taking an extended leave for as long as they still have employer benefits. In all cases, if the original length of leave is less than the FMLA job-protection length of 12 weeks, then the leave is not extended beyond 12 weeks.

The Simulator Flow

The following describes the way the simulator processes the CPS data (including the generated or estimated information) on individuals. Points where logit probabilities are used are starred (*). This flow is illustrated in Figures 1-5.

First, the simulator person either needs a leave of each type or not*. If the person needs the leave, their eligibility is then determined. The work and employer eligibility conditions have already been determined by this point, so here it is determined whether or not they saw a doctor or went to a hospital (or whether the person they took a leave to care for saw a doctor or went to the hospital)*. If the person needs the leave, it is then determined whether or not the person takes the leave*.

The leave-taking decision just simulated assumes that there is no paid leave program available, other than the benefits the person's employer provides. For those persons who needed but did not take a leave, it is then determined whether or not they would take a leave if a paid leave program were available*. If the person does not take a leave even in the presence of a paid leave program, they are classified as a leave-needer.

If the person takes a leave, we simulate if they took more than one leave*. Then, for each leave, we assign the length of leave. Leave lengths are counted in days, ignoring weekends, so a leave of two weeks, for example, is ten days. At this point in the program flow, the leave lengths represent those in the absence of a paid leave program, except for those persons who would not have taken a leave in the absence of such a program. Later in the flow, in the presence of the paid leave program, we simulate the person's "choice" about extending their leave.

Leaves are then distributed across a calendar of 19 months beginning in January 1999, the same period of time covered by the DOL Survey. In that survey, 12 percent of leavers had a leave that was still underway and not completed by the end of July 2000. Leave lengths for these truncated leaves are thus shortened, with consequent effects on the observed distribution of leave lengths. In an attempt to distribute leaves over the 19-month period realistically, a simple probability model was developed which determines the probability that a leave is truncated, given its observed length. Truncated leaves are positioned so that the end of their observed length coincides with the end of the 19-month period. Leaves that are not truncated are positioned randomly over the calendar, subject to the condition that they lie entirely within the 19-month period. We found that the most accurate estimates of annual program payments and other estimates derived from the simulator are obtained by using the full 19-month period and converting to annual amounts as appropriate. For example, annual program payments (or employer benefits) are best estimated by multiplying the totals from the full 19-month period by 12/19.

The simulator next determines which leaves are employer-paid*, and, for those that are, whether they are partially or fully paid*, as illustrated in Figure 2. In order to simulate a paid leave program, it is necessary to build a weekly schedule of employer payments. This is done using the estimate of weekly wages from the CPS and the information from the DOL survey on how much pay was received by leavers. For leavers who received full pay, the calculation is straightforward: the person is assigned pay at their full weekly rate throughout the leave. For those who were partially paid, the DOL survey asked if the respondent received some pay for each pay period that they were on leave; and if not, in the pay periods for which they *did* receive pay, was it for their full salary? The survey was used to estimate these

conditional probability distributions for each leave type and payment group (less than half pay, about half pay, more than half pay). If a person's leave was partially paid, their payment schedule was randomly selected from the corresponding conditional probability distribution for their leave type.

At this point, the application has determined if a person received some pay each week; and if not, if that person received full pay for some weeks; and if, over the course of their leave, a person received less than half of full pay, about half of full pay, or more than half of full pay. The weekly pay schedule is then filled out using arbitrary rules subject to these payment schedule and amounts constraints. For example, those persons who received some pay for each week of their leave, but who received less than half of their full pay in total, were assigned 30 percent of their weekly pay in each week of their leave. Those persons who received some (but not full) pay for each week of their leave, but more than half pay in total, were assigned 75 percent of their weekly pay in each week of their leave.

The next step in the application is to simulate employer pay, program benefits, and possible extensions of leave length in the presence of a paid leave program and is illustrated in Figures 3 through 5. The application simulates the sequence of events and choices that a leaver would reasonably experience, given their weekly leave history and weekly schedule of employer payments simulated up to this point, in the absence of a paid leave program. The software models the process as a sequence of "states" (i.e., points on the decision making path—they can be beginning, intermediate, or ending points), represented as circles in the diagrams. The transition from state to state, represented by arrows, is the result of events or decisions, such as the end of receipt of employer pay, the original length of leave being reached, the decision to participate or extend a leave, etc. Diamonds represent predetermined conditions or conditions over which the person has no control, such as whether the person is eligible or receives employer pay. The paths taken are determined by the probabilities and assumptions built into the program.

Reliability of Estimates

We are able to check the accuracy of estimating DOL data onto the CPS by comparing our CPS-generated data for the entire U.S. workforce against the DOL sample. Table C.2 presents the distribution of leavers by longest leave in the two samples. As the table indicates, the simulation model is reasonably accurate in reproducing the actual distribution of longest leave.

Percent of Leave-Takers by Longest Leave in DOL Survey and IWPR/LRC Model, United States

Type of longest leave	DOL 2000 Leavers	IWPR/LRC model CPS, March 2001 Leavers	Difference
Own health	47.2%	51.8%	4.6%
Maternity-disability	7.8%	7.8%	0.0%
New child	17.9%	20.6%	2.7%
Care for ill child	9.8%	5.3%	-4.5%
Care for ill spouse	5.9%	4.7%	-1.2%
Care for ill parent	11.4%	9.7%	-1.7%
Three types of leave			
Own health	47.2%	51.8%	4.6%
Parental	25.7%	28.4%	2.7%
Ill relative	27.1%	19.7%	-7.4%

Source: For DOL data, Cantor et al. 2000, Table 2.5.

Since there are few, if any, data sets that contain useful information about family and medical leaves, it is difficult to check the reliability of our estimates from independent sources. We are able to compare the number of leaves women took for new child and maternity disability to the actual number of newborns in Massachusetts in 2000. There were just under 81,600 babies born in Massachusetts in 2000 (data from *Statistical Abstract 2002*, Table 70). Our estimate of the number of women who took parental leave was just under 64,000 (about 27,000 for maternity disability and about 37,000 for a new child).[8] With a 77 percent employment rate of mothers in Massachusetts in 2000, it is likely that just over 62,800 women who work gave birth in 2000 and would almost certainly take a leave.[9] We would expect our estimates of those who took a pregnancy/birth-related leave to be higher than the percentage of working mothers who gave birth since all those who take maternity disability do not necessarily carry a child to term, and there are women who adopt or bring a foster child into their home and take parental leave.

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[8] An additional 3,100 women reported needing a parental leave but not taking one.

[9] This is the percent of women with children under the age of 18 who were earners in 2000, calculated by authors using the CPS.

Figure C.1
Paid leave simulation flow

Information on individuals estimated or computed from CPS

Weekly wage
Salaried or hourly worker
Employer size
FMLA eligibility (work and employer requirements)
Paid leave program eligibility (work and employer requirements)

Need a family or medical leave?

Do for each leave type

See a doctor or stay in hospital?

Take leave?

no

Would take a leave if a paid leave program existed?

yes

no

Number of leaves

Leave needer

Length of leave

Do for each leave of this type

Weekly employer payments in absence of paid leave program. *see figure 2 for path*

Weekly employer pay and leave program benefits in presence of paid leave program (*see figure 3 for path)*
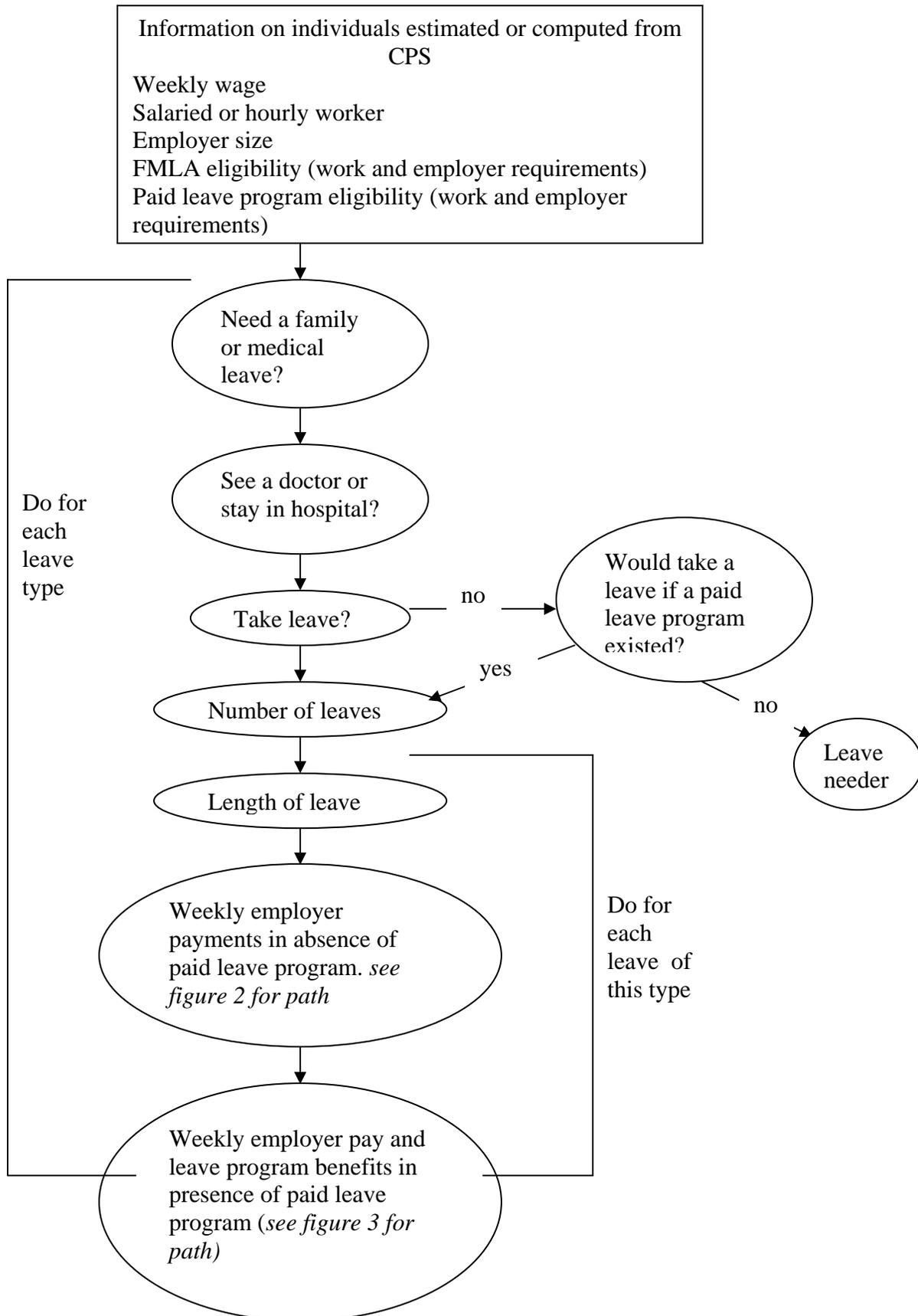
Figure C.2
Weekly employer payments for leave in absence of a paid leave program
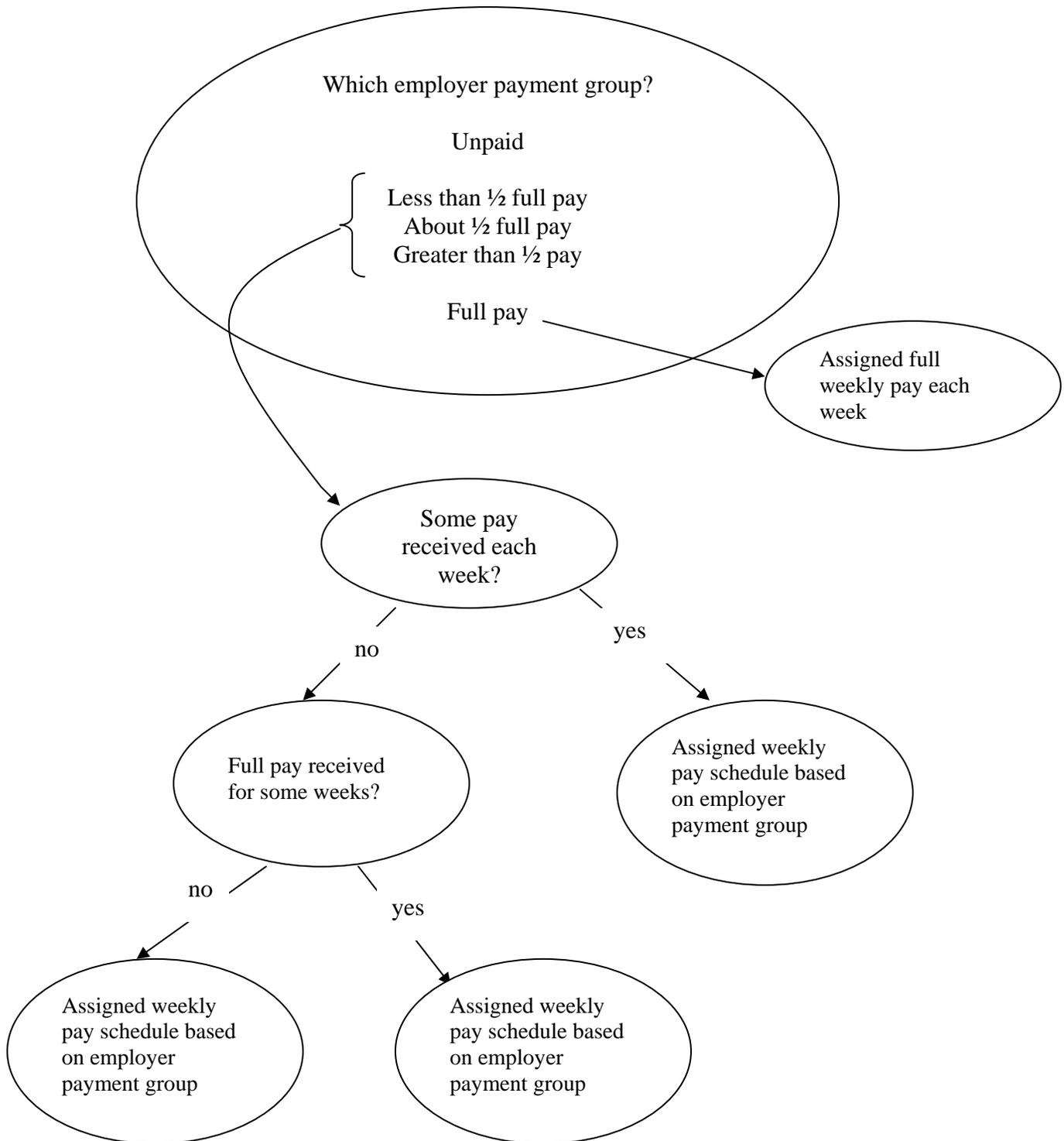
Figure C.3
Simulating Weekly employer pay and leave program benefits in presence of paid leave program
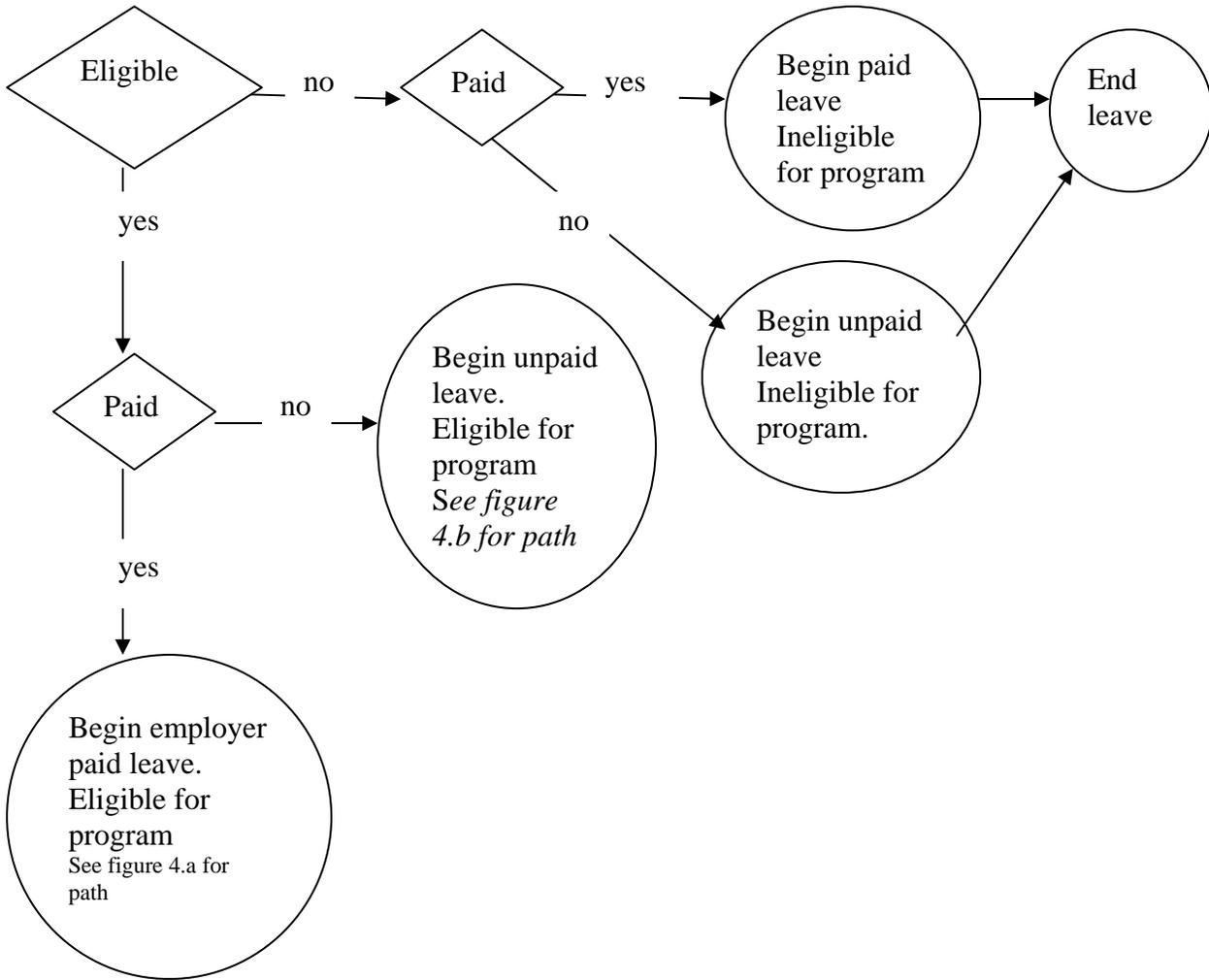
Eligible — no → Paid — yes → Begin paid leave Ineligible for program → End leave

Eligible — yes ↓
Paid — no → Begin unpaid leave. Eligible for program *See figure 4.b for path*

Paid (first) — no → Begin unpaid leave Ineligible for program.

Paid — yes ↓
Begin employer paid leave. Eligible for program See figure 4.a for path

Begin unpaid leave Ineligible for program. → End leave

Figure C.4a
Simulating Use of Paid Leave Program and Employer Benefits for Employees with
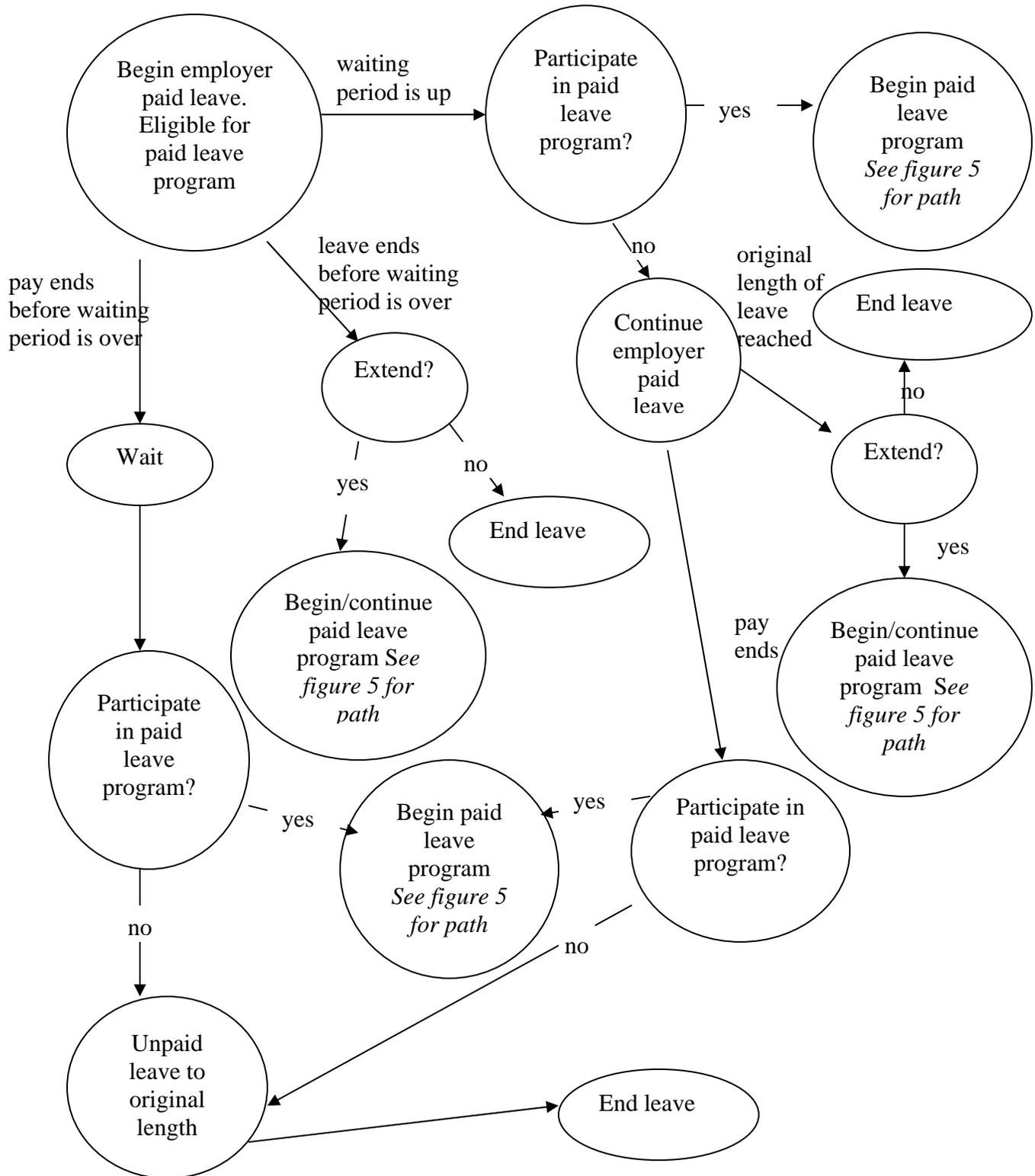Some Employer Paid Leave

Figure C.4b
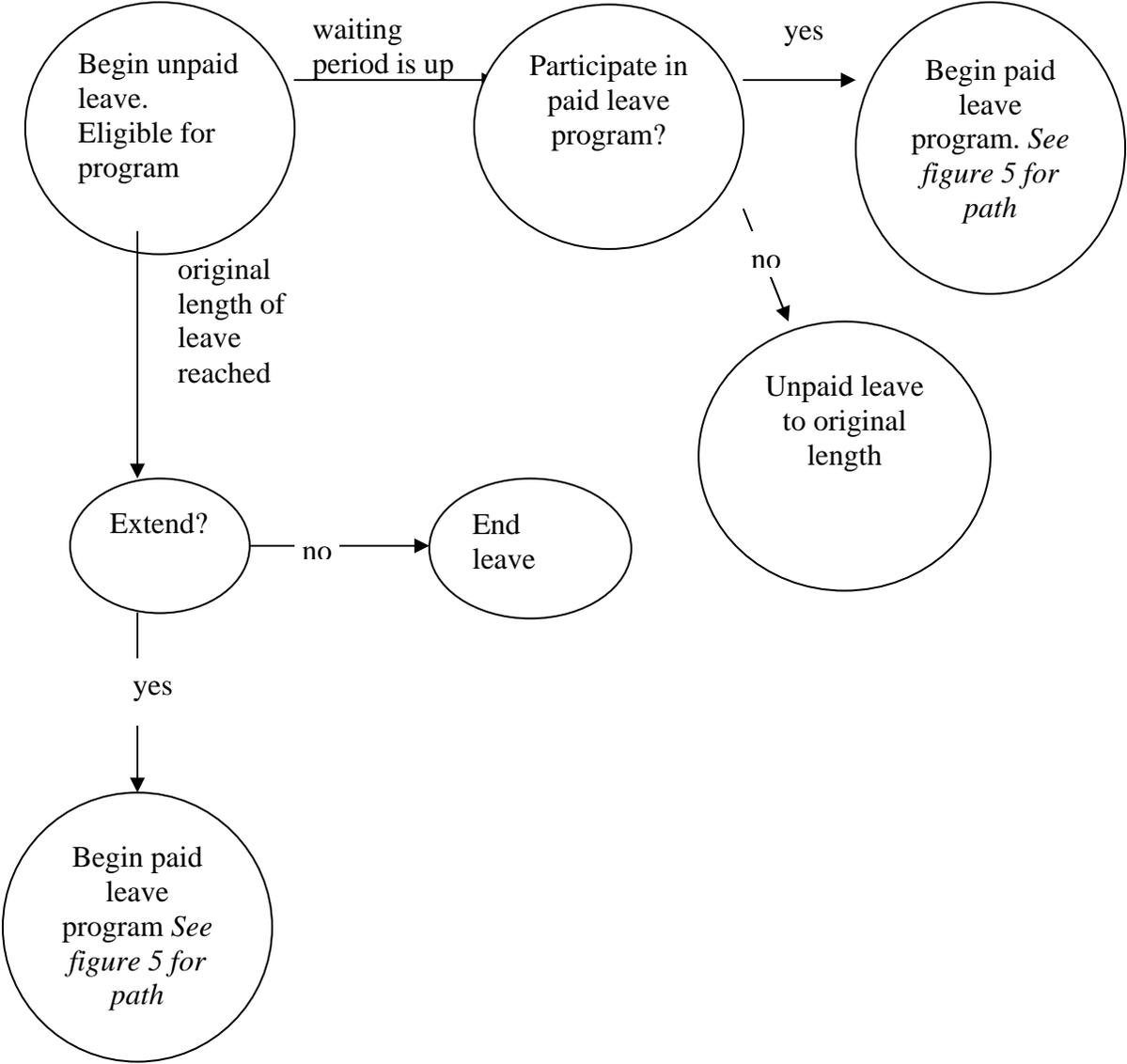Simulating Use of Paid Leave Program for Employees with no employer paid leave

Figure C.5
Simulating Use of Paid Leave Program Once it Begins