Does it Pay for Women to Volunteer?*

Robert M. Sauer†

Royal Holloway, University of London

Abstract

This paper estimates the economic and non-economic returns to volunteering for prime-aged women. Estimates of a DCDP model indicate that an extra year of volunteer experience increases wage offers by 8.5% in future part-time work and by 2.6% in future full-time work. On average, working for free increases lifetime earnings by 16.7%. The economic returns to volunteering are more important than the non-economic returns in increasing lifetime utility. The model also reveals an adverse selection mechanism into volunteering that helps explain why reduced-form regressions of the returns to working for free will likely be downward biased.

Keywords: Volunteering, Female Labor Supply, Marriage, Fertility, Negative Selection, Dynamic Programming, Simulated Maximum Likelihood

JEL Codes: C35, C53, C61, D91, J12, J13, J22, J24, J31, J64

*Manuscript submitted on December 17, 2012. Revision completed on June 30, 2014.

†I would like to thank Holger Sieg, two anonymous referees, and numerous conference and seminar participants for providing valuable feedback. I am also extremely grateful to the Earhart Foundation for their vision and generosity in financially supporting this research.

1 Introduction

Working for free is a widespread economic activity. Data from the 2005 Panel Study of Income Dynamics (PSID) reveal that 32.7% of the prime-aged US population engaged in unpaid work for non-profit organizations in the preceding year. This surprisingly high incidence of volunteering is not unique to the US. It is found in many other advanced economies as well. Despite the worldwide prevalence of volunteer work, the reason people choose to donate their time is not yet well understood. Identifying the main motivations underlying the decision to work for free is important. It can help make sense of charitable responses to changes in economic conditions. It can also aid in designing incentive schemes aimed at influencing the supply of volunteer labor.

Previous research by economists has focussed on two main motivations for donating labor. The first is referred to as the consumption motive. It is an intrinsic motivation associated with a direct increase in current utility. The price of consuming (or cost of supplying) volunteer hours is the opportunity cost of time which could have been devoted to paid work or leisure. The second is referred to as the investment motive. It is associated with an indirect increase in future utility. Supplying volunteer hours today may expand networks, signal productive characteristics or raise human capital levels which enhance future earnings potential.

In an early empirical study on donated labor, Menchik and Weisbrod (1987) analyze each of these two volunteering motives in isolation. In one model, only the consumption motive is operative. In the other, the investment motive drives volunteering. The estimation results suggest that both motivations are important and the opportunity cost of volunteer time is substantial. In contrast, Freeman (1997) fails to confirm the importance of the consumption motive, and does not find a strong relationship between the propensity to volunteer and alternative paid work opportunities.

The conclusions reached in these two leading studies, and in essentially the entire literature on volunteer labor supply, should be considered highly tentative for at least three reasons.[1] First, the expected future monetary payoff to volunteer experience is not incorporated into the decision problem. This is mainly due to data limitations. The data sources rarely contain sufficient information on an individual's post-volunteer employment status or earnings. Second, foregone earnings in paid employment options are treated as exogenous. This yields biased estimates of the opportunity cost of time. Third, marital status and the presence of children, both key determinants of the propensity to volunteer, are not recognized

[1] While there is a vast number of studies on the charitable giving of money, the economics literature on volunteering is extremely limited. See Andreoni (2006) for a short review.

as endogenous.

In this study, all three of these major problems in the literature are explicitly addressed. The focus is on a woman's decision to work for free, using comprehensive longitudinal data from the PSID. Between the years 2001 and 2005, the PSID collected information on volunteering for non-profit organizations. These data are well suited for identifying the two volunteering motives and the opportunity cost of time. Crucial for identification, the data contain individual-level transitions between unpaid and paid employment states as well as pre- and post-volunteering earnings.

The theoretical framework used to interpret the data assumes that each woman, between the ages of 25 and 55, maximizes the discounted present value of expected lifetime utility by making joint and sequential decisions on unpaid and paid employment status. It is particularly appropriate in this context to formulate the decision problem as a dynamic program since the investment motive is naturally forward-looking. Because wage offer functions in paid employment options are estimated simultaneously with the decision to work for free, the model also produces selection-corrected estimates of volunteer experience and the opportunity cost of time. In the spirit of Keane and Wolpin (2010), the endogeneity of non-labor income and family composition are accounted for by modeling marriage and conception choices jointly with labor supply decisions.

The dynamic decision model nests the consumption and investment motives for volunteering into one unified framework, providing an empirical strategy for estimating their relative importance. This is the first study to offer relative importance estimates. It is accomplished by separating the contemporaneous utility flow into two main components. The first component is CRRA in household consumption, representing the investment motive or the economic returns to volunteering. The second component is additively separable and captures the consumption motive or the non-economic returns to working for free.

This study also employs a novel approximate solution technique for discrete choice dynamic programming (DCDP) models. The approximate solution technique combines approaches proposed by Keane and Wolpin (1994) and Geweke and Keane (1995). The simulated maximum likelihood (SML) procedure used to estimate the parameters of the model, originally developed by Keane and Wolpin (2001) and made more general by Keane and Sauer (2009,2010), is further extended in this study by including probabilities of survey non-response in the likelihood. Thus, the estimation procedure accounts for the initial conditions problem, incorporates measurement error in discrete and continuous outcomes, and corrects for potential biases due to non-random missingness/attrition.

The SML estimates of the model indicate that the economic returns to working for free are substantial. An additional year of volunteer experience raises wage offers by 8.5% in future part-time work and by 2.6% in future full-time work. On average, working for free increases lifetime earnings by 16.7%. These estimates are more plausible than the negative wage returns generally produced by reduced-form regressions. In fact, the decision model reveals a negative selection mechanism that helps explain why reduced-form estimates of the wage returns to volunteering will likely be downward biased.

The model conceptualizes volunteer work as the optimal choice whenever the non-economic returns and expected future economic returns sufficiently outweigh the disutility of unpaid work effort and volunteering-related childcare costs. According to the estimates, this occurs most often amongst highly educated women who also have low unobserved market-productivity. Highly educated women place greater value on the non-economic returns, and conditional on education, lower market-productivity implies greater benefits from future wage returns. This is because low market-productivity leads to low wage offers, low consumption levels, and a high marginal utility of consumption. Heterogeneity in the marginal utility of consumption emerges as a result of the estimated curvature of the consumption component of utility. Once this negative selection based on unobserved market-productivity differences and differential marginal utilities is accounted for, the wage returns to volunteering become positive and substantial in magnitude.

The estimation results also reveal that the economic returns to working for free are relatively more important than the non-economic returns in increasing lifetime utility. In other words, the investment motive outweighs the consumption motive. The economic returns account for 73.5% of the overall increase in lifetime utility due to volunteer experience. Using the model estimates in a policy experiment, interpreted as the introduction of a tax credit for volunteering-related childcare costs, shows that a full tax credit generates a 23% increase in volunteer labor supply and a 1.9% increase in mean lifetime earnings. The increase in mean lifetime earnings amongst volunteers covers approximately 25% of the mean cost of providing tax relief.

The rest of the paper is organized as follows. The next section describes the PSID data used in estimation. Section 3 presents the model and solution method. Section 4 outlines the estimation procedure and discusses identification. Section 5 highlights key parameter estimates. Section 6 explains the negative selection mechanism, measures the relative importance of the investment and consumption motives, and evaluates the introduction of a tax credit for volunteering-related childcare expenses. Section 7 summarizes and enumerates several extensions of the model that could be incorporated in future research.

2 Data

The data are drawn from the Panel Study of Income Dynamics (PSID), including both the core random sample and the nonrandom Survey of Economic Opportunity. PSID families were interviewed annually between 1968 and 1997, and biennially thereafter. Between 2001 and 2005, the PSID introduced questions on volunteer work for charitable organizations. After the 2005 wave, the volunteering questions were dropped, due to a lack of funding (charitable donations).

The three PSID waves between 2001 and 2005 contain a total of 7,778 female household heads or spouses. Restricting the sample to those aged 25 to 55 reduces the number of women to 4,254. The age restriction is imposed to avoid explicitly modeling education and retirement decisions. Women aged 25 to 55 who are students, retired, disabled, or in jail at any time during the three waves are dropped, as are those for whom it is impossible to infer education level or marital status. These latter restrictions reduce the number of women to 3,664. For computational tractability, black women are excluded from the analysis. This yields a sample of 2,479 women who responded to at least one survey wave between 2001 and 2005.[2]

The meaning of volunteering for a charitable organization is made explicit in the PSID. The questionnaire states that charitable organizations "include religious or non-profit organizations that help those in need or that serve and support the public interest. They range in size from national organizations like the United Way and the American Red Cross down to local community organizations. They serve a variety of purposes such as religious activity, helping people in need, health care and medical research, education, arts, environment, and international aid."

Volunteering is defined for respondents as "spending time doing unpaid work and not just belonging to an organization. Volunteers are involved in many activities such as coaching, helping at school, serving on committees, building and repairing, providing health care or emotional support, delivering food, doing office work, organizing activities, fund-raising, and other kinds of work done for no pay."

In the 2001 wave, respondents are asked to provide the total number of hours volunteered in the previous year, as well as the subset of hours donated to charitable organizations that help the needy. In the 2003 and 2005 waves, the volunteering questions changed. Respondents are requested to provide the number of hours in the previous year donated to

[2]Approximately 90 percent of the excluded cases follow from the age and race restrictions, implying that any induced sample selection biases are likely to be small. It is worth noting that women report volunteering more often than men across all age and education groups and other major demographic characteristics (35% vs. 30%). Future work can analyze the importance of gender and race differences.

each of seven different types of charitable organizations.

Summary statistics on volunteer hours per week, computed from the annual totals, are presented in Table 1. The top panel shows that the distribution of non-zero volunteer hours in 2000 is markedly different from the distributions in 2002 and 2004. In particular, the mean, median and standard deviation in 2000 are all considerably lower than in subsequent years. The bottom panel displays the percentage of non-zero volunteer hours donated to charitable organizations in different categories. In 2000, 12.4% of total volunteer hours went to help the needy, with the rest going to all other unspecified types of organizations. Pooling over 2002 and 2004, only 4.2% of total volunteer hours went to help the needy. The rest were mainly donated to religious organizations (41%) and organizations that aid children or youth (35.2%).

Because of the change in the volunteering questions and its influence on the distribution of annual hours and organization type, as well as other documented problems with the hours data (see Wilhelm (2008)), only the extensive margin of volunteering is considered. Specifically, categories of charitable organizations are pooled and a woman is classified as volunteering for the year if annual volunteer hours are greater than zero. This crude classification is consistent with the volunteering question re-introduced into the 2011 wave of the PSID, which simply asks whether the respondent volunteered in the previous year.

Women are also classified into paid work categories in each year depending on reported annual work hours and labor earnings. Part-time employment is assigned if annual paid work hours are greater than zero and less than or equal to 1750, and labor earnings are either greater than zero or missing. If annual paid work hours are greater than 1750 and labor earnings are greater than zero or missing, full-time employment is assigned. A woman is classified as non-employed for the year if she did not work for free or engage in paid work.

According to these assignment rules, a woman can be classified as both employed in a paid job and working for free in the same year. In fact, the overwhelming majority of volunteering is in conjunction with paid work. However, it is possible that some of these women are volunteering and engaging in paid work at distinct times *within* a year. For this reason, and other possible assignment errors related to mis-reported paid work hours, it is important to incorporate classification error into the estimation procedure.

Sample means and standard deviations for key variables in the analysis are displayed in column (1) of Table 2. Columns (2) and (3) split the sample by frequency of survey response. Several substantial differences between women who respond in every wave and those who do not can be clearly discerned. Women who do not respond in every wave, constituting 14% of the sample, are much less likely to volunteer. They also work full-time more often, are more likely to be single, have fewer children, and have lower-earning husbands. These sharp differences highlight the importance of accounting for endogenous missingness/attrition in estimation.

The employment choice distribution by age range, over six mutually exclusive employment states, is shown in Table 3. The bottom row displays row percentages for the age range 25-55. It indicates that volunteering is rarely an exclusive activity. Only 5.1% volunteer without holding a paid job, while 12% work part-time and volunteer, and 16.8% work full-time and volunteer. The choice distribution does not shift substantially with age. However, the proportion in the part-time and volunteer state does exhibit a slight inverse u-shaped pattern.

Table 4 reports the two-year (one-wave) transition matrix for the six employment states. The diagonal elements of the matrix range from 42.4% to 61.7%, implying a high incidence of transitions. From the non-employed state, 23.5% transit to volunteer jobs, and from the volunteer only state, 40.2% transit to paid employment. From the part-time and volunteer category, the largest combined transition rate is into full-time work. From the full-time and volunteer state, the largest transition rate is into full-time work only. Persistence is strongest in the full-time only category.

Table 5 reports the results of several reduced-form regressions. The dependent variables in columns (1) - (3) are indicators for having volunteered in the previous year, marital status, and birth outcome, respectively. Estimates of linear probability models with random effects show that the incidence of working for free, being married and giving birth all increase with education. The propensity to volunteer and to be married increases with age at a decreasing rate, while the propensity to give birth decreases with age. The proportion volunteering and the proportion giving birth are higher when married and increase with the stock of children at a decreasing rate.

Note that the fraction of variance due to the random effect is largest in column (2), as there is greater persistence in marital status than in working for free or giving birth. The relatively low persistence in the volunteer state is consistent with the high incidence of transitions displayed in the employment transition matrix. Giving birth has virtually no persistence after controlling for the number of children already born. Column (4) displays the results of a regression with the log of husband wage as the dependent variable. The estimated coefficients on the *woman's* education level are quite similar to those in Column (8) using the log of female wage as the dependent variable. The fraction of variance due to the random effect is also similar. This is highly suggestive of positive assortative mating.

The OLS estimates in column (5) show that mean accepted female wages rise with education level, while age has a negligible effect. Column (6) adds an indicator for working for free in the previous wave as a proxy for accumulated volunteer experience. Surprisingly, the coefficient on the volunteering dummy is -.143. Column (7) adds indicators for having worked part-time and full-time in the previous wave, as proxies for accumulated paid work experience. It is possible that the negative coefficient on the volunteering dummy reflects less time spent in the paid labor market rather than a negative return to volunteer work per se. However, the coefficient on lagged volunteering remains negative, -.069, and precisely estimated. Note that the coefficients on the part-time and full-time dummies are positive and have expected relative magnitudes.

Column (8) adds random effects to the specification with volunteer, part-time and full-time experience proxies included. The coefficient on the volunteering dummy weakens and is less precisely estimated. However, the magnitude is still substantially negative, -.038. Negative returns to volunteer experience are robust to a variety of alternative specifications, including fixed effects and reduced-form selection-correction techniques. In sharp contrast, structural estimates of the behavioral model outlined below yield substantially positive returns to volunteer experience. The estimated decision model also uncovers a mechanism for negative selection which may underly the negative returns to volunteer experience often found in reduced-form wage regressions.[3]

3 Model

A woman is assumed to maximize the expected present discounted value of remaining lifetime utility in each period by choosing an employment state, a marital status and whether to conceive a child. The length of a period is a year and decisions are made between the ages of 21 and 55. Women differ at age 21 according to completed education level and unobserved type. Education and unobserved type are allowed to be correlated and remain constant throughout the decision-making horizon.

3.1 Basic Structure

The employment choice set a woman faces at each age a, denoted as K, contains six mutually exclusive elements: non-employed ($k = 1$), volunteer only ($k = 2$), part-time only ($k = 3$), full-time only ($k = 4$), part-time and volunteer ($k = 5$), and full-time and volunteer ($k = 6$).

[3] In reduced form regressions, Day and Devlin (1998) find that the wage returns to volunteering for a religious organization in Canada are a precisely estimated -17.8%. As noted earlier, 41% of volunteer hours in the PSID, during the years 2002 and 2004, are donated to religious organizations. Non-profits that aid children and youth (35.2% of donated hours) may also be partially affiliated with religious organizations.

The employment choice variable, d_a^k, $k \in K$, is defined such that $d_a^k = 1$ if a woman chooses employment state k at age a and $d_a^k = 0$ otherwise.

Part-time and full-time wage offers, denoted by w_a^p and w_a^f, are drawn at the start of each period from known distributions $F^j(w_a^j)$, $j = p, f$. Accumulated volunteer, part-time and full-time experience shift the means of the wage offer distributions. Transitions between employment states may occur depending on both wage draws and preference shocks.

Marital status at age a is denoted by m_a, where $m_a = 1$ if a woman is married (or cohabiting) and $m_a = 0$ if single (or divorced). The decision to marry is constrained by receipt of a marriage offer. The probability of receiving a marriage offer at the start of the period, when single, is denoted by π^m. Receipt of a marriage offer is accompanied by a random draw μ, from a known distribution $F^\mu(\mu)$, which partially determines the husband's earnings w_a^h. Husband wages constitute a woman's non-labor income. If the marriage offer is accepted, μ remains fixed for the duration of the marriage.

Conditional on μ, w_a^h is drawn each year from a known distribution $F^h(w_a^h)$. Marital separation may occur depending on the yearly spousal wage draw. After one period of separation, new marriage offers and μ draws can once again be received. The restriction of no "on-the-marriage" search helps generate a lower option value to marriage relative to being single.

The fertility choice variable is denoted by b_a, where $b_a = 1$ if a child is conceived at age a and $b_a = 0$ otherwise. The fecundity of a woman is taken into account by constraining b_a to zero for $a \geq 46$. Additional fecundity constraints are not incorporated (e.g., probability of miscarriage). If a woman chooses to conceive at age a, live births occur with certainty before the beginning of period $a + 1$. A woman can choose to conceive a child in any employment and marital state.

Let $U_{a,j}$ denote the utility flow at age a from a feasible choice combination $j \in (\{d_a^k\}_{k \in K}, m_a, b_a)$. $U_{a,j}$ is specified as CRRA in consumption $C_{a,j}$ with several additively separable components,

$$U_{a,j} = \frac{\mu_k C_{a,j}^{1-\lambda}}{1-\lambda} + \sum_{k \in K^v} g_a d_a^k + \sum_{k \in K} s_k d_a^k d_{a-1}^k + \psi_a^m + \psi_a^n + \varepsilon_a^u d_a^1. \quad (1)$$

The CRRA component of utility corresponds to the investment motive because the wage returns to having worked for free affect $C_{a,j}$. $1 - \lambda$ is the parameter of constant relative risk aversion. λ determines the curvature of the consumption component of utility as well as the willingness to substitute consumption inter-temporally. μ_k shifts the marginal utility of consumption depending on employment state k, incorporating leisure into the utility flow. Work effort, or forgone leisure, is equivalent to a decrease in the marginal utility of consumption. The disutility of work effort is restricted such that $\mu_k = 1$ when $k = 1$ (non-employed) and $0 < \mu_k \leq 1$ for $k = 2, ..., 6$. Adding volunteer work on top of a paid job can result in a lower value of μ_k.

The first additively separable component in (1), g_a, captures the consumption motive or the non-economic returns to volunteering. It is referred to as the warm-glow function. K^v is the subset of K that contains the volunteering options ($k = 2, 5, 6$). Note that not only is g_a of direct interest, omitting it from the utility flow might lead to an upward bias in the wage returns to volunteering.

The second additive component in (1) captures switching costs or habit persistence. Remaining in the same employment state as in the previous period may increase utility. In order to separate warm glow from switching costs, switching costs from volunteer jobs are normalized to zero. The remaining terms are the utility of being married, ψ_a^m, the utility of children, ψ_a^n, and a non-employment preference shock, ε_a^u.

The utility flow specification allows the consumption of goods, warm glow, marriage and children to be partial substitutes, highlighting the endogeneity of marriage and fertility in the paid/unpaid labor supply decision. In particular, low potential earnings, which lead to decreased labor market attachment and lower consumption, can be offset by working for free, getting married (obtaining non-labor income) and having children.

Consumption at age a, or the budget constraint, is specified as

$$C_{a,j} = \tau^{m_a}\{b(d_a^1 + d_a^2) + w_a^p(d_a^3 + d_a^5) + w_a^f(d_a^4 + d_a^6) + w_a^h m_a - c_k\} \quad (2)$$

where τ^{m_a} is the sharing parameter. $\tau^{m_a} = 1$ if $m_a = 0$ and $0 \leq \tau^{m_a} \leq 1$ if $m_a = 1$. τ^1 must be sufficiently high to induce high wage women to marry low wage men. The lower is τ^1, the higher w_a^h must be to compensate, encouraging positive assortative mating.

Unobserved income when non-employed or in the volunteer only state is represented by b. b may be partially determined by unemployment insurance benefits, unobserved assets and job search costs while non-employed or volunteering. Note that there is no additional income when adding a volunteer job on top of paid work. Consumption could in fact be higher in this latter state if one received in-kind benefits from volunteering such as tickets to events or dinners, or one volunteers to help protect neighborhood property. This is not incorporated due to lack of relevant data.

The costs of children c_k in (2) are shared when married and depend on employment state k. In particular, childcare costs can be higher when one volunteers. Childcare costs that increase with the amount of time devoted to the labor market may be an additional factor that discourages women with low potential earnings and children to accept full-time employment or engage in volunteer work.[4]

3.2 Additional Parameterizations

Additional parameterizations of the model involve more fully characterizing the part-time, full-time and husband wage offer functions, the warm-glow function, the utilities of marriage and children, childcare costs, permanent unobserved heterogeneity, and the joint distribution of productivity and preference shocks. The particular specifications adopted are motivated by interpretability, parsimony, identification and model fit. Justifications for specific modeling choices and robustness to various alternative parameterizations are mentioned throughout. The final structure of the model is flexible enough to produce either positive or negative selection into volunteering.

Wage offers in part-time and full-time work are Mincer-style functions of general and specific skills, i.e., education, accumulated work experience, and unobserved (to the econometrician) productivity,

$$\begin{aligned} ln(w_a^p) &= \beta_{0p} + \beta_{1p}E_1 + \beta_{2p}E_2 + \beta_{3p}A_1 + \beta_{4p}A_2 + \beta_{5p}A_3 \\ &\quad + \beta_{6p}x_a^v + \beta_{7p}x_a^p + \beta_{8p}(x_a^p)^2 + \beta_{9p}x_a^f + \varepsilon_a^p \\ ln(w_a^f) &= \beta_{0f} + \beta_{1f}E_1 + \beta_{2f}E_2 + \beta_{3f}A_1 + \beta_{4f}A_2 + \beta_{5f}A_3 \\ &\quad + \beta_{6f}x_a^v + \beta_{7f}x_a^p + \beta_{8f}x_a^f + \beta_{9f}(x_a^f)^2 + \varepsilon_a^f \end{aligned} \tag{3}$$

where E_1 and E_2 are completed education dummies (see Table 5), A_1 and A_2 are unobserved time-invariant productivity effects, x_a^v is accumulated volunteer experience, x_a^p is accumulated part-time experience, x_a^f is accumulated full-time experience, and ε_a^p and ε_a^f are transitory productivity shocks. The wage returns to working for free (β_{6p} and β_{6f}) depend only on type of job (part-time or full-time), not on observed or unobserved individual characteristics. Additional quadratic terms and interactions are difficult to identify due to lack of sufficient variation in the data.

[4] A time constraint is not included because the μ_k's partially capture this notion, and the number of volunteering hours observed in the data are limited. Estimates of job offer, job termination and marriage "layoff" probabilities did not deviate substantially from either one or zero in previous versions. For computational reasons, asset accumulation is not incorporated.

The laws of motion for the experience variables are

$$\begin{aligned} x_{a+1}^v &= x_a^v + d_a^2 + d_a^5 + d_a^6 \\ x_{a+1}^p &= x_a^p + d_a^3 + d_a^5 \\ x_{a+1}^f &= x_a^f + d_a^4 + d_a^6 \end{aligned} \tag{4}$$

where volunteer experience is augmented by one each year an individual works for free. Accumulated volunteer experience does not vary by paid work status in order to limit the size of the state space. Part-time (full-time) experience is also augmented by one each year an individual engages in paid part-time (full-time) work. The initial conditions are $x_{21}^v = x_{21}^p = x_{21}^f = 0$.

The warm glow function is

$$g_a = \beta_{0g} + \beta_{1g}E_1 + \beta_{2g}E_2 + \beta_{3g}a + \beta_{4g}n_a^{1,6} + \beta_{5g}n_a^{7,18} + \varepsilon_a^g \tag{5}$$

where $n_a^{1,6}$ is the number of children between the ages of 1 and 6, $n_a^{7,18}$ is the number of children between the ages of 7 and 18, and ε_a^g is a transitory preference shock. There is no well-established theory of what determines preferences in this context. However, non-economic returns are likely to vary with education, age and the presence of children. In particular, education and age may proxy for peer and informational effects (see Freeman (1997)). Children of different ages can shift the utility of volunteering for organizations that aid children or youth, including the educational institutions of one's own children.[5]

The laws of motion for $n_a^{1,6}$ and $n_a^{7,18}$ are

$$\begin{aligned} n_{a+1}^{1,6} &= n_a^{1,6} + b_a - n_a^6 \\ n_{a+1}^{7,18} &= n_a^{7,18} + n_a^6 - n_a^{18} \end{aligned} \tag{6}$$

with initial conditions $n_{21}^{1,6} = n_{21}^{7,18} = 0$. For purposes of normalization, children are born at the beginning of period $a+1$ at age 1.

The potential husband's wage offer is also a Mincer-style function,

$$ln(w_a^h) = \beta_{0h} + \beta_{1h}E_1 + \beta_{2h}E_2 + \beta_{3h}a + \beta_{4h}a^2 + \mu + \varepsilon_a^h \tag{7}$$

where E_1, E_2 and a are the *woman's* education and age. This is justified when there is a

[5]Unobserved type could enter the warm glow function, capturing unobserved heterogeneity in pro-social preferences or altruistic inclinations. However, preliminary versions indicated type effects are different from zero only in the wage offer functions. Crude measures of religiosity are also omitted from the warm glow function due to lack of sufficient variation.

high degree of assortative mating, as indicated by the raw data. Excluding observed male characteristics also economizes on the state space (see Keane and Wolpin (2010)). μ is the unobserved husband individual effect described earlier and ν_a is a transitory productivity shock. Inclusion of μ helps compensate for the absence of observed male characteristics in the model.

In addition to the husband productivity shock, the utility of marriage affects couple formation and separation decisions. The utility of marriage is

$$\psi_a^m = \beta_{1m} x_a^m \tag{8}$$

where x_a^m is marriage duration. This simple specification is sufficient to capture persistence in marital status and the timing of divorce.

The law of motion in the duration of marriage is

$$x_{a+1}^m = x_a^m + m_a \tag{9}$$

with initial condition $x_{21}^m = 0$.

The utility of children is

$$\psi_a^n = \beta_{1b} n_a + \beta_{2b} (n_a)^2 + \beta_{3b} m_a n_a + \beta_{4b} m_a (n_a)^2 \tag{10}$$

where n_a is the existing stock of children. The quadratic in n_a aids in reproducing the sharp drop-off in the distribution of the number of children observed in the data. The interaction with m_a helps generate the observed difference in the stock of children by marital status. The quadratic in n_a is interpretable as diminishing marginal utility in the number of kids. The interaction with marital status allows for a possibly lower incidence of divorce when married with children.

The law of motion in the stock of children is

$$n_{a+1} = n_a + b_a \tag{11}$$

with initial condition $n_{21} = 0$. Note that if a woman chooses to conceive at age a, the number and utility of children increase at $a + 1$, while pregnancy and other child "start-up" costs are incurred in period a. Thus, conceiving a child is viewed as a dynamic investment decision.

The childcare cost function depends on conception choice at age a, employment state, and the stock of children at different ages,

$$c_k = \begin{cases} \beta_{0c} b_a & if\, n_a = 0 \\ \beta_{0c} b_a + \sum_{k \notin K^v} \beta_{kc} d_a^k \left(n_a^{1,6} + \alpha_c n_a^{7,18}\right) + \beta_{vc} \sum_{k \in K^v} d_a^k & otherwise \end{cases} \tag{12}$$

where β_{0c} captures pregnancy and other child start-up costs, and $\beta_{kc,}\, k \notin K^v$ are the per-child costs of younger children when non-employed, working part-time and working full-time, respectively. α_c is the percentage change in costs for older children. β_{vc} is the extra cost per child when working for free. The restriction that child start-up costs and volunteering-related childcare expenses do not vary by paid work status aids in separate identification of the childcare cost function from other utility and budget constraint parameters.

The joint distribution of the transitory preference and productivity shocks is $\left(\varepsilon_a^u, \varepsilon_a^g, \varepsilon_a^p, \varepsilon_a^f, \varepsilon_a^h\right) \sim N(0, \Sigma)$. $\Sigma = LL'$ where L is the Cholesky factor. L is restricted for identification reasons and specified as

$$L = \begin{bmatrix} l_{11} & 0 & 0 & 0 & 0 \\ l_{21} & l_{22} & 0 & 0 & 0 \\ 0 & 0 & l_{33} & 0 & 0 \\ 0 & 0 & l_{43} & l_{44} & 0 \\ 0 & 0 & 0 & l_{54} & l_{55} \end{bmatrix} \tag{13}$$

allowing for heteroskedasticity and several non-zero covariances. The distribution of the permanent component of husband productivity is $\mu \sim N\left(0, \sigma_\mu^2\right)$ and orthogonal to $\left(\varepsilon_a^u, \varepsilon_a^g, \varepsilon_a^p, \varepsilon_a^f, \varepsilon_a^h\right)$.

3.3 Solution Method

At each age a, from the first decision period $\underline{a} = 21$ until the terminal period $\overline{a} = 55$, a woman chooses an optimal choice combination $j \in \left(\left\{d_a^k\right\}_{k \in K}, m_a, b_a\right)$ that corresponds to the maximum over alternative-specific value functions

$$V_{a,d_a}\left(\Omega_a\right) = U_{a,d_a}\left(\Omega_a\right) + \delta E\left(V_{a+1}\left(\Omega_{a+1}\right) | \Omega_a, d_a\right), \tag{14}$$

where $d_a = j$, Ω_a is the state space, δ is the subjective discount factor and $V_{a+1}\left(\Omega_{a+1}\right) = \max_{d_{a+1}}\left[V_{a+1,d_{a+1}}\left(\Omega_{a+1}\right)\right]$. The expectation is taken over transitory shocks. A full numerical solution to the DCDP model requires calculating $E\left(V_{a+1}\left(\Omega_{a+1}\right) | \Omega_a, d_a\right)$ by backward recursion for all $\left(\Omega_a, d_a\right)$. However, since the state space is extremely large, a full numerical solution is not computationally practical. Thus, an approximate solution technique is employed.

The novel approximate solution technique introduced in this study, referred to as the "hybrid" method, uses simulation to calculate expected future payoffs, as in Keane and Wolpin (1994), and incorporates polynomial approximation of expected future payoffs, as in Geweke and Keane (1995). In the hybrid method, the alternative-specific value functions in (14) are re-written as

$$V_{a,d_a}(\Omega_a) \quad = \quad U_{a,d_a}\left(\Omega_a|\theta^S\right) + F_{a+1}(\Omega_a, d_a|\theta^S, \pi^F), \tag{15}$$

where θ^S is a vector of structural parameters and π^F is a vector of coefficients in a polynomial function of state variables at $a+2$. $F_{a+1}\left(\Omega_a, d_a|\theta^S, \pi^F\right)$ replaces $\delta E\left(V_{a+1}\left(\Omega_{a+1}\right)|\Omega_a, d_a\right)$ in (14). $F_{a+1}\left(\Omega_a, d_a|\theta^S, \pi^F\right)$ is approximated by

$$\hat{F}_{a+1}(\Omega_a, d_a|\theta^S, \pi^F) \quad = \quad \delta\hat{E}\left[\max_{d_{a+1}}\left\{U_{a+1,d_{a+1}}(\Omega_{a+1}|\theta^S) + \bar{F}_{a+2}\left(\Omega_{a+1}, d_{a+1}|\pi^F\right)\right\}|\Omega_a, d_a\right], \tag{16}$$

where the expectation is simulated by Monte Carlo integration for every for every (Ω_a, d_a). In the backward recursion, $\bar{F}_{a+2}\left(\Omega_{a+1}, d_{a+1}|\pi^F\right)$ is a known constant because it is a polynomial function of state space values in $a+2$. The state space elements at $a+2$ are determined by the laws of motion.[6]

The approximating function in (16) is specified as

$$\begin{aligned}\bar{F}_{a+2}\left(\Omega_{a+1}, d_{a+1}|\pi^F\right) \quad &= \quad \pi_1^F x_{a+2}^v + \pi_2^F x_{a+2}^p + \pi_3^F x_{a+2}^f + \pi_4^F x_{a+2}^m \\ &+ \quad \pi_5^F n_{a+2} + \pi_6^F (a+2) + \pi_7^F (a+2)^2 .\end{aligned} \tag{17}$$

Accumulated paid and volunteer work experience, marriage duration and the number of children enter linearly as quadratic and higher order terms do not have an effect. Time-invariant elements of the state space, such as education and unobserved type, are excluded for similar reasons. Note that age appears quadratically, allowing the future to have decreasing influence as the finite-horizon is approached.

In contrast to approximation techniques that deal with the curse of dimensionality by reducing the number of state space points for which $E\left(V_{a+1}\left(\Omega_{a+1}\right)|\Omega_a, d_a\right)$ is evaluated (see, e.g., Keane and Wolpin (1994) and Rust (1997)), the Geweke and Keane (1995) and hybrid approaches ease the computational burden in the time dimension. The Geweke and Keane (1995) technique approximates alternative-specific value functions at a by imbedding a polynomial function of state space elements at $a+1$, using the laws of motion to capture the forward-looking aspect of the model. The hybrid method incorporates more of the model's

[6] In a full solution method, $F_{a+2}\left(\Omega_{a+1}, d_{a+1}\right)$ is a known constant because it is calculated in a previous step of the backward recursion.

structure by integrating over alternative-specific value functions at $a+1$ and imbedding a polynomial function of state space elements at $a+2$. Thus, the hybrid method more closely mimics the Bellman principle.

In contrast to Wolpin (1992), which also employs an approximate solution technique centered on the time dimension, decision-making periods do not become successively longer as the finite-horizon is approached. The length of the period remains constant throughout. Since the hybrid method can be thought of as imposing a terminal value function at $a+2$ in each period a, it also differs from solution techniques that use a terminal value function at a reduced $\overline{a}$ (see, e.g., Keane and Wolpin (2001) and Blau and Gilleskie (2006,2008)).[7]

3.4 Performance of the Hybrid Method

The performance of the hybrid method is examined via Monte Carlo experiments. To facilitate the assessment, the data generating process (DGP) is the same four-alternative occupational choice model Keane and Wolpin (1994) use to test their approximation method. The model is estimated using a version of the SML algorithm described below.

In the DGP, agents decide between four mutually exclusive options at the beginning of each time period t. The options are work in occupation one ($j=1$), work in occupation two ($j=2$), attend school ($j=3$) or remain at home ($j=4$). The utility flows are

$$\begin{aligned} U_{t,1} &= \exp\left(\alpha_{10}+\alpha_{11}S_t+\alpha_{12}X_{1t}-\alpha_{13}X_{1t}^2+\alpha_{14}X_{2t}-\alpha_{15}X_{2t}^2+\varepsilon_{1t}\right) \\ U_{t,2} &= \exp\left(\alpha_{20}+\alpha_{21}S_t+\alpha_{22}X_{1t}-\alpha_{23}X_{1t}^2+\alpha_{24}X_{2t}-\alpha_{25}X_{2t}^2+\varepsilon_{2t}\right) \\ U_{t,3} &= \beta_0-\beta_1 I\left(S_t\geq 12\right)-\beta_2 I\left(d_t\neq 3\right)+\varepsilon_{3t} \\ U_{t,4} &= \gamma_0+\varepsilon_{4t}, \end{aligned} \tag{18}$$

where X_{jt}, $j=1,2$, is the number of periods of work experience in occupation j at the beginning of period t, S_t is the number of periods of completed schooling at the beginning of period t, and the ε_{jt}, $j=1,..,4$, are serially uncorrelated productivity and preference shocks. $\varepsilon_{jt} \backsim N\left(0,\Sigma_1\right)$ where $\Sigma_1=\left(\sigma_{ij}\right)$ is the covariance matrix. The initial conditions are $S_1=10$ and $X_{11}=X_{21}=0$.

The α parameters in the occupation one and two wage offer functions capture the returns to schooling and experience. β_0 is the consumption value of schooling. β_1 is a constant tuition rate for each year of post-secondary schooling. β_2 is an additional cost incurred when

[7]The Keane and Wolpin (1994) technique was employed to solve earlier versions of the model. However, the number of points for which $E\left(V_{a+1}\left(\Omega_{a+1}\right)|\Omega_a,d_a\right)$ could be solved exactly, within a reasonable time frame, was too small to produce reliable interpolations.

returning to school from occupation one or two, or from home in the previous period. γ_0 is the value of the home alternative. The true parameter values are displayed in column (1) of Table (6). This is Data Set One in Keane and Wolpin (1994). Column (2) reports the absolute value of the mean bias in each parameter when the data are repeatedly generated by a full solution of the model, but the model is estimated using the hybrid solution method. Column (3) shows that the biases are negligible in magnitude for every parameter. The t-stats of the bias are also never significant at the 5% level.

The bottom panel of Table (6) assesses the predictive accuracy of the hybrid method by comparing the mean of the state variables after period 40 for both a full solution and the hybrid method. The means are calculated at the true parameter values. After 40 decision periods, the hybrid method over-predicts accumulated schooling by .86 years, under-predicts accumulated experience in occupation one by 1.4 years and over-predicts accumulated experience in occupation two by .83 years. The deviation between the out-of-sample means are negligible in magnitude for all three accumulated experience state variables. The results in Table (6) suggest that the hybrid method can be reliably used for estimating structural parameters and conducting certain types of policy simulations.[8]

4 Estimation

The parameters of the model are estimated by SML. For each trial vector of parameters, the dynamic program is solved using the hybrid solution method, event histories are simulated, and the likelihood function is constructed. The estimation procedure, originally developed by Keane and Wolpin (2001) and made more general by Keane and Sauer (2009,2010), accounts for the initial conditions problem and incorporates measurement error in discrete and continuous outcomes. The algorithm is further extended in this study to account for possible biases due to non-random missingness/attrition.

[8]One potential drawback of the hybrid method, as in the Geweke and Keane (1995) technique, is that tweaks of structural parameters θ^S may not map clearly into corresponding tweaks of reduced-form parameters π^F. A referee also found preliminary evidence that the performance of the hybrid method may deteriorate with the extent of permanent unobserved heterogeneity and/or age dependence. This was not the case in the occupational choice model examined here.

4.1 SML Procedure

Simulated choices are input into the likelihood function via classification rates. Classification rates are joint probabilities of reported choices conditional on simulated choices. These conditional choice probabilities take a logistic form, derived from an underlying classification error model with a type 1 generalized extreme value distribution. By assuming independent classification errors in the three dimensions of choice (employment, marriage, conception), classification rates can be constructed for each choice in isolation.

Denote the reported employment choice of woman i at age a by $d_{ia}^{*} = k$ and let $d_a^r = j$, $r \in R$, be the rth simulated employment choice. Conditional on d_a^r, there are six classification rates, $\pi_{jk}^{e} = \Pr\left(d_{ia}^{*} = k \mid d_a^r = j\right)$, that obey the adding up constraint $\sum_{k=1}^{6} \pi_{jk}^{e} = 1$. Identification of these classification rates is heavily based on deviations between actual and predicted employment transitions. To further aid in identification, the 6×6 matrix of employment classification rates is partially restricted (see Table 9).

The classification rates for reported marital status m_{ia}^{*} and reported conception outcome b_{ia}^{*} are denoted by $\pi_{jk}^{m} = \Pr\left(m_{ia}^{*} = j \mid m_a^r = k\right)$ and $\pi_{jk}^{b} = \Pr\left(b_{ia}^{*} = j \mid b_a^r = k\right)$, respectively. m_a^r and b_a^r are the simulated counterparts to the reported outcomes. π_{11}^{m} and π_{11}^{b} are set close to one in estimation, implying approximately no classification error in marriage and conception choices. Transition rates in these choice dimensions are fit well without incorporating classification error.

The reported accepted wage w_{ia}^{*} is also allowed to be measured with error and is assumed to be distributed lognormal with density

$$f^{w}\left(w_{ia}^{*}\right) = \frac{1}{w_{ia}^{*}\sigma_v^k\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left[\frac{\ln\left(w_{ia}^{*}\right) - \bar{w}_a^k}{\sigma_v^k}\right]^2\right) \tag{19}$$

where $\bar{w}_a^k$, $k = p, f$, are the deterministic components of the part-time and full-time wage offer functions. $\sigma_v^k = \sqrt{l_{33}^2 + \sigma_{\eta,p}^2}$ for $k = p$, and $\sigma_v^k = \sqrt{l_{43}^2 + l_{44}^2 + \sigma_{\eta,f}^2}$ for $k = f$. The density of reported husband wages, $f^{h}\left(h_{ia}^{*}\right)$, takes the same form after substituting in the reported husband wage h_{ia}^{*}, $\bar{w}_a^h$ and $\sigma_v^h = \sqrt{\sigma_\mu^2 + l_{54}^2 + l_{55}^2 + \sigma_{\eta,h}^2}$.

The new aspect of the SML procedure is the incorporation of non-response probabilities which helps correct for biases due to non-random missingness/attrition. The non-response probability is specified as

$$\pi^{nr} = \pi^{nr}(d_a^{k,r}, m_a^r, n_a^{1,6r}, n_a^{7,18r}, l_{i,2003}), \tag{20}$$

where $d_a^{k,r}$ is a set of employment choice dummies corresponding to simulated choice $d_a^r = k$.

m_a^r, $n_a^{1,6r}$ and $n_a^{7,18r}$ are simulated marriage and fertility outcomes. $l_{i,2003}$ is the *reported* length of the interview (in minutes) in the 2003 wave. π^{nr} is logistic in form, implying that the stochastic element in the non-response process is distributed type I generalized extreme value.

Missingness/attrition is endogenous because preference and productivity shocks, and unobserved type, affect the probability of non-response via simulated outcomes. The length of the interview $l_{i,2003}$ is included as a covariate because it provides a plausible source of exogenous variation that helps identify π^{nr}. $l_{i,2003}$ is assumed to be randomly assigned after controlling for endogenous employment, marriage and conception choices. It is non-zero for individuals that answered the 2003 wave but did not respond in the 2005 wave. Length of interview information is not available for the 2001 wave.

Note that the specification for π^{nr} would not be computationally practical in a non-simulation based estimation procedure. The paths to the non-reported choices at age a would have to be integrated out. Integrating out is circumvented because π^{nr} is conditional on simulated outcomes, rather than reported outcomes. Adjusting for non-random missingness is empirically important. In particular, it produces more conservative estimates of the economic returns to volunteering.

The simulator for the likelihood contribution of woman i, conditional on unobserved type A_l and observed education level E_i, can be written as

$$\begin{aligned}
\hat{\ell}_i\left(D_i^* \mid A_l, E_i, \theta\right) = & \frac{1}{R}\sum_{r=1}^{R}\prod_{a=\tilde{a}_i}^{\tilde{a}_i+5}\left\{\sum_{j=1}^{6}\sum_{k=1}^{6}\pi_{jk}^{e} I\left[d_a^r = j, d_{ia}^* = k\right]\right\}^{I\left(d_{ia}^* \in D_i^*\right)} \\
& \times\left\{f^w\left(w_{ia}^*\right)\right\}^{I\left(w_{ia}^* \in D_i^*\right)} \\
& \times\left\{\sum_{j=0}^{1}\sum_{k=0}^{1}\pi_{jk}^{m} I\left[m_a^r = j, m_{ia}^* = k\right]\right\}^{I\left(m_{ia}^* \in D_i^*\right)} \\
& \times\left\{\pi^m\right\}^{I\left(m_{a-1}^r = 0, m_a^r = 1\right)} \times\left\{f^h\left(h_{ia}^*\right)\right\}^{I\left(h_{ia}^* \in D_i^*\right)} \\
& \times\left\{\sum_{j=0}^{1}\sum_{k=0}^{1}\pi_{jk}^{b} I\left[b_a^r = j, b_{ia}^* = k\right]\right\}^{I\left(b_{ia}^* \in D_i^*\right)} \\
& \times\left\{\pi^{nr}\right\}^{I\left(NR_{ia}^* = 1\right)}\left\{1-\pi^{nr}\right\}^{1-I\left(NR_{ia}^* = 1\right)}
\end{aligned} \tag{21}$$

where θ is the vector of parameters to be estimated and $D_i^* = \{d_{ia}^*, m_{ia}^*, b_{ia}^*, w_{ia}^*, h_{ia}^*\}_{a=\tilde{a}_i}^{\tilde{a}_i+5}$ is woman i's history of reported employment states, marital states, birth outcomes, accepted employment wage offers, and accepted husband wage offers. $\tilde{a}_i \geq 25$ is the age woman i enters the sample. Note that $\tilde{a}_i$ is always greater than $\underline{a} = 21$, the age at which simulation of choices begins. This constitutes the solution to the initial conditions problem.[9]

The indicator functions $I\left[d_a^r = j, d_{ia}^* = k\right]$, $I\left[m_a^r = j, m_{ia}^* = k\right]$, and $I\left[b_a^r = j, b_{ia}^* = k\right]$ "pick out" the appropriate classification rates depending on the reported and simulated choice combination at age a. The indicator functions $I\left(d_{ia}^* \in D_i^*\right)$, $I\left(m_{ia}^* \in D_i^*\right)$, $I\left(b_{ia}^* \in D_i^*\right)$, $I\left(w_{ia}^* \in D_i^*\right)$ and $I\left(h_{ia}^* \in D_i^*\right)$ are equal to one if the corresponding choices/wages at age a are available in the data, and zero otherwise. If it is a survey year and woman i does not respond, the indicator function $I(NR_{ia}^* = 1)$ is equal to one, and zero otherwise.

The conditional likelihood contributions in (21) are weighted by the joint probability of unobserved type and observed education level. Conditional on birth cohort C_i, the joint probability is

$$\pi^{AE}\left(A_l, E_i \mid C_i\right) = \pi^A\left(A_l \mid E_i, C_i\right)\pi^E\left(E_i \mid C_i\right),\ l = 0, 1, 2, 3, \tag{22}$$

where the $\pi^A(\cdot)$'s are mass point probabilities corresponding to the four unobserved types in the model. The $\pi^E(\cdot)$'s are the probabilities of the three observed education levels. C_i provides a plausible source of exogenous variation that helps identify the mixing distribution. The identifying assumption is birth cohort determines unobserved type and education level, but conditional on type and education, birth cohort does not influence preferences, productivity or constraints in the behavioral model.[10]

Weighting the conditional likelihood contributions yields

$$\hat{\ell}_i\left(D_i^*, E_i \mid C_i, \widetilde{\theta}\right) = \left[\sum_{l=0}^{3} \hat{\ell}_i\left(D_i^* \mid A_l, E_i, \theta\right)\pi^A\left(A_l \mid E_i, C_i, \theta^A\right)\right]\pi^E\left(E_i \mid C_i, \theta^E\right) \tag{23}$$

where $\widetilde{\theta} = \left\{\theta, \theta^A, \theta^E\right\}$. π^A and π^E take logistic forms ensuring that probabilities lie in the unit interval and sum to one. θ^A and θ^E are the mixing distribution parameters. The simulated likelihood function is $\prod_{i=1}^{N}\hat{\ell}_i\left(D_i^*, E_i \mid C_i, \widetilde{\theta}\right)$, where N is the number of women in the sample. Standard errors are obtained by calculating numerical derivatives and the outer product approximation to the Hessian.

[9]There are three education levels and four unobserved productivity types so the total number of event histories simulated is $12 * R$. R is set to 40. Analysis of the raw data suggests three education levels is sufficient and more than four unobserved productivity types does not improve model fit. $S = 20$ is the number of draws used to simulate expected future payoffs. Further increasing R and S does not lead to important differences in point estimates or simulated outcomes.

[10]The cohort effect C_i is defined as $C_i = \tilde{a}_i - 22$ and then discretized into three categories; i) $C_i \leq 15$, ii) $15 < C_i \leq 25$ and iii) $C_i > 25$. The first category contains women who are younger than the mean age in the sample. Analysis of the raw data suggests that birth year is strongly correlated only with education level, as captured in (22).

4.2 Identification

In static selection models, identification of selection-corrected returns to education or experience relies heavily on variables that enter the choice equation but not the outcome equation (Heckman (1979)). In the DCDP model, the alternative-specific value functions are analogous to the choice equation, and the wage offer functions correspond to the outcome equation. Exclusion restrictions are present because the alternative-specific value functions contain all the elements of the state space, while wage offers are determined by a subset of state variables.

Wage offers are viewed as arising from a human capital production function (see Keane and Wolpin (1997)). General and specific skills, such as education and work experience (both paid and unpaid), naturally enter the production function. It is less obvious that a woman's marital status, duration of marriage, husband's productivity and the stock of children at different ages should be considered inputs. After controlling for the relationship between chosen type of employment and marriage and fertility via preferences, any direct influence of marriage and fertility outcomes on skill production is likely to be of second-order importance. Hence, these latter variables are excluded from the wage offer functions.

Identification of the non-economic returns to volunteering also relies on exclusion restrictions. Identification requires that the warm-glow function be excluded from the current period returns of at least one of the alternative-specific value functions. This condition is satisfied as warm glow enters the utility flows of the volunteering options only. Similarly, unobserved consumption appears only in the budget constraint of the non-employed and volunteer only options. Both unobserved consumption and warm glow are excluded from the part-time only and full-time only utility flows.

The CRRA parameter is identified by transitions between part-time and full-time work (accepted wage variation), marital status changes (non-labor income variation) and the birth of children. These outcomes generate shifts in consumption levels that may be smoothed over time. In particular, birth spacing plays an important role because it can be optimal from a life cycle consumption perspective to have children in different age groups. The implications of marriage, birth frequency and spacing for identification of the CRRA parameter, and hence unpaid and paid employment choices, highlights an additional reason marriage and fertility decisions are profitably included in a labor supply model.

Identification can also be understood via a simple analogy to the method of moments. The parameters of the female wage offer functions are tightly tied to the observed wage data and the employment choice distribution. The parameters of the husband wage offer function, also selection-corrected, are similarly tied to the observed husband wage data and marriage choices. Unobserved consumption (b), warm glow (g), childcare costs (c_k), the utility function parameters (μ_k, λ, ψ^m, and ψ^n), the marriage offer probability (π^m), expected future payoffs (π^F), and the extent of income sharing (τ^m) are free parameters that are related to observed moments through cross-equation restrictions. There is a very large number of observed moments that are implicitly taken into account in estimation. These include the employment choice distribution and transition rates, marriage rates and durations, birth rates and timing, and the distributions of accepted part-time, full-time and husband wages.[11]

5 Estimation Results

Because there are 106 estimated parameters, only key point estimates are discussed. Parameter estimates and asymptotic standard errors are reported in Tables 7 through 9. To assess model fit, simulated outcomes at the SML estimates are compared to corresponding outcomes in the raw data. Simulated outcomes are adjusted to take into account measurement error and non-response.

5.1 Parameter Estimates

Part-time and full-time wage offers increase sharply with education level and differ substantially by unobserved type. Type 1 women, constituting 9.1% of the population, are the least productive in both part-time and full-time jobs. Type 2 and 3 women are the most productive in both types of paid work (48.3% and 20.0% of the population, respectively). The probability of being Type 3, the highest productivity woman, increases with education level and is higher in more recent birth cohorts.

In contrast to the negative returns to volunteer experience generally found in reduced-form wage regressions, the estimated wage offer functions reveal significantly positive returns. Each year of volunteer experience increases wage offers in part-time work by 8.5% and by 2.6% in full-time work. These returns are especially substantial considering the relatively limited number of hours per week devoted to volunteering. This suggests that signaling

[11]Functional form assumptions and parametric distributions for wage offers also help identify non-wage parameters (see Flinn and Heckman (1982)). Parameters associated with unobserved types are identified by observed persistence in wages and choices. Although the discount factor is theoretically identified (Wolpin (1987)), it is fixed at 0.95. Several other identification considerations were mentioned earlier, e.g., exogenous variation in non-response probabilities and the mixing distribution. See also Geweke and Keane (2001) for an identification analysis related to π^F.

may be an important component of the wage returns. There are no other estimates in the literature to which these volunteer wage offer returns can be directly compared.

The returns to working for free suggest substantial investment value. However, volunteering has costs in terms of the disutility of work effort. The $\hat{\mu}_k$ estimates show that full-time work is more costly than part-time work, and volunteering adds disutility when it is combined with either of these paid work options. An additional factor affecting the investment motive, discussed in detail below, is the curvature of the consumption component of utility. The estimate of the CRRA parameter ($\hat{\lambda} = .273$), is close to previous estimates produced by DCDP labor supply models which explicitly incorporate data on assets. Imai and Keane (2004), Van der Klaauw and Wolpin (2008) and Keane and Wolpin (2001) obtain $\hat{\lambda}$'s of .26, .40 and .48, respectively. Point estimates in this range imply a higher willingness to substitute consumption inter-temporally than what is often found in the life cycle consumption literature with non-separable labor supply (see Keane, Todd and Wolpin (2010)).

Regarding the consumption motive, the non-economic returns to volunteering increase with education but do not vary much with age. Compared to women with no children, women with young children dislike volunteering, while women with older children experience considerably more warm glow. This pattern is suggestive of a substitutability between informal volunteering to raise one's own young children and formal volunteering for charitable organizations.

Estimates directly related to the marriage decision indicate that husband wage offers increase with a woman's education level and are quadratic in her age. Idiosyncratic variance constitutes 5.4% of total variance, with the remainder due to the husband individual effect. The income sharing parameter is 43.5%, meaning that a woman consumes 43.5 cents of every dollar of net household income. Keane and Wolpin (2010) find a somewhat higher sharing parameter (54.6%). The estimated probability of receiving a marriage offer during the year is 9.1%. Perhaps surprisingly, the utility of marriage increases significantly with its duration.

The estimated childcare cost function shows that annual costs increase with the amount of time devoted to the labor market. The per-child costs of children younger than 7 are $19,789, $22,466, and $25,994 when non-employed, working part-time and working full-time, respectively. Children between the ages of 7 and 18 cost 40.2% *more* than younger children in each labor market state. Child start-up costs are estimated to be $30,049. This is comparable to the monetary equivalent of the disutility of pregnancy estimated in Keane and Wolpin (2010). Additional childcare costs when volunteering are estimated to be $5,025 per-child.

Ignoring start-up costs and discounting, the estimates imply that the total costs of raising a child through age 18 are $481,713 (in 2010 dollars). This is a lower bound estimate because it assumes a woman is always non-employed. Assuming a woman always works full-time and volunteers produces an upper bound estimate of \$623,336. The lower bound is 49% higher than the upper bound of \$322,560 estimated by the U.S. Department of Agriculture (USDA), using the Consumer Expenditure Survey. This confirms the suspicion that the USDA cost estimates are downward biased (see Lind (2010)).[12]

5.2 Model Fit

A comparison of the actual and simulated employment choice distribution, over the age range 25-55, is shown in the top panel of Table 10. The estimated model fits the choice distribution very well. There is only a small under-prediction in the part-time only state and an over-prediction of similarly small magnitude in the full-time and volunteer state. The slight changes by age in the choice distribution are also generally reproduced by the model.

Table 11 displays the actual and predicted two-period (one-wave) employment transition matrices. The transition rates are fit very well. In the raw data, 23.5% transit to volunteer jobs from the non-employment state, and 40.2% transit to paid employment from the volunteer only state. The corresponding figures produced by the estimated model are 25% and 39.2%, respectively. From the part-time and volunteer option, most transitions in the raw data are into full-time work, and from the full-time and volunteer option, the largest transition rate is into full-time work only. Both of these important patterns are accurately reproduced by the model. The only relatively large deviation between actual and predicted transition rates is the proportion that remains in the volunteer only state. However, this is the category with the smallest overall frequency in the choice distribution.

The middle and bottom panels of Table 10 illustrate the ability of the model to fit mean accepted wage outcomes and the distribution of accumulated volunteer experience. The differences between actual and predicted mean accepted wages are negligible in magnitude. The standard deviations of accepted wages are accurately reproduced as well, although there is an under-estimate for husband wages. The actual and predicted proportions of volunteer experience between 0 and 3 years are also within the same range. The proportion with 1 and 2 years of experience is slightly over-predicted and the proportion with 3 years of experience is correspondingly under-predicted. However, the sharp drop off between 1 and 3 years of accumulated volunteer experience is accurately reproduced. The model's explanation for why the tail of the distribution falls off sharply will be discussed below.

[12] The point estimate of annual unobserved income is $\hat{b} = 4,658$. This seems somewhat low. However, fixing b at various higher levels, rather than estimating it, hurts model fit. Other estimates not discussed for the sake of brevity include the utility of children, the Cholesky elements, the approximation of expected future payoffs, classification rates, measurement error variances and the probability of non-response.

The fit to marriage and birth outcomes is shown in Table 12. The actual and predicted proportions in the married state and the actual and predicted transition rates between marriage and divorce are all very close. The same is true for the actual and predicted proportions giving birth and the actual and predicted proportions giving birth by marital status.[13]

6 Discussion

6.1 Negative Selection into Volunteering

Volunteering is an optimal choice in the model when the non-economic returns and the expected future economic returns sufficiently outweigh the disutility of unpaid work effort and volunteering-related childcare costs. According to the structural estimates, this outcome occurs most often amongst highly educated, low market-productivity women. Thus, the behavioral model reveals a negative selection mechanism capable of explaining why reduced form estimates of the wage returns to working for free are downward biased.

Highly educated women tend to volunteer more often because the non-economic returns increase with education level. However, conditional on observed education, the lower is a woman's unobserved market-productivity, the higher are the benefits from future wage returns. Low market-productivity implies low wage offers and consumption levels, and hence higher marginal utilities of consumption. Heterogeneity in the marginal utility of consumption arises from the estimated curvature of the consumption component of utility, i.e., the CRRA parameter. Once this negative selection based on unobserved market-productivity and differential marginal utilities is accounted for, the future wage returns to working for free become positive.

It is worth emphasizing that both differential unobserved market-productivity and sufficient curvature of the utility function are necessary to generate negative selection. Had the estimated model produced a substantially higher CRRA parameter, negative selection would not have arisen. For example, with a linear utility flow, the marginal utilities of future consumption would be uniform for all productivity types and selection into volunteering would be driven solely by the positive relationship between education and unobserved non-economic returns. That is, positive selection based on warm-glow would have resulted.

Note that negative selection could have been generated even in a linear utility context if low market-productivity women had differentially higher wage offer returns to volunteering. However, differential wage returns by productivity type (random coefficients) were not

[13]More powerful approaches to model validation, such as those pursued by Arcidiacono, Sieg and Sloan (2007), are difficult to implement in the current context.

empirically identified. The CRRA parameter is easier to identify because it is a direct function of more moments in the data, e.g., accepted wages, employment and marriage choice frequencies, and birth spacing.

The negative selection mechanism revealed by the model also helps explain the inverse u-shaped age pattern in the part-time and volunteer state, and the sharp drop off in the distribution of volunteer experience. Low market-productivity is an initial condition (an endowment) and does not change over time. However, other dimensions of productivity can adjust and lead to higher wage offers. In particular, low market-productivity types that choose the part-time and volunteer state gain both part-time and volunteer experience. The effect is that wage offers in part-time and full-time work permanently increase, consumption levels rise, and the marginal utility of consumption falls. As the marginal utility of consumption falls, volunteering tapers off. Low market-productivity types who increase their productivity through the accumulation of paid work and volunteer experience begin to make decisions more in line with women who have a high market-productivity endowment. Volunteering then becomes less frequent and driven mostly by warm glow.

To further illustrate the ability of the estimated model to correct wage returns for negative selection, Table 13 presents the results of reduced-form wage regressions using simulated data. The specifications are analogous to those run on the actual data, and reported in columns (7) and (8) of Table 5. The regressions on simulated data produce *positive* wage returns both without and with controls for unobserved type (4.4% and 4.9%, respectively).

The regressions in Table 13 also facilitate a comparison of the returns to education, volunteer and paid work experience implied by the model. Column (8) shows that the 4.9% increase in mean accepted wages from having volunteered two years earlier is slightly less than half the increase in mean accepted wages from having worked part-time (11.9%). The corresponding magnitude for having worked full-time is much higher (72.1%). The returns to education are similarly large in magnitude. Having acquired between 12 and 16 years of education increases mean accepted wages by 55.8% compared to the base group with less than 12 years of education. The corresponding return to acquiring more than 16 years of education is 115.2%. The large coefficients for unobserved types clearly illustrate the importance of unobserved market-productivity.[14]

[14]The simulated data are not adjusted for classification error, measurement error or non-response. The simulated data are based only on parameters that represent the "true" economy, not on what may or may not be reported in data.

6.2 Relative Importance of Economic and Non-economic Returns

The estimation results imply that both the consumption and investment motives play important roles in the volunteering decision. But which motive is relatively more important in the decision to offer labor services for free? The previous literature has yet to provide relative importance estimates. In order to address this question, the model is simulated shutting down the non-economic and economic returns to volunteering. The non-economic and economic returns are then re-introduced into the model sequentially.

Columns (1)-(3) of Table 14 report the results of the simulation exercise. As expected, there is no volunteering when there are zero benefits and positive costs. Opening up the non-economic returns (warm glow) increases the incidence of volunteering from zero to 28.3%. The total proportion further increases to 30.0% when economic returns (wage offer effects of volunteer experience) are added. Although the total proportion only slightly increases with the addition of economic returns, the frequencies across the three volunteering options change substantially.

With warm glow only, 13.9% of all volunteering is in the part-time and volunteering state, and 66.4% is in the full-time and volunteer state. Adding economic returns, the proportion in the part-time and volunteer state increases sharply from 13.9% to 24.0%. It is mainly low market-productivity women (type 1) who volunteer in this latter state. High market-productivity women (types 2 and 3) tend to volunteer in the full-time and volunteer state. The implication is that the economic returns are relatively more important for low market-productivity types and the non-economic returns are relatively more important for high market-productivity women.

By examining changes in lifetime utility, it is possible to make a more general claim, i.e., the importance of economic returns far outweighs the importance of non-economic returns in the population as a whole. With the introduction of non-economic returns, lifetime utility increases from 5997.75 to 6009.42. Adding economic returns, lifetime utility further increases to 6041.79. Thus, working for free increases mean lifetime utility by 7.34% and the economic returns account for 73.5% of this total increase. The economic benefit to low market-productivity women drives the sharp rise in mean lifetime utility. Overall, volunteering increases mean lifetime earnings by a substantial 16.7%.[15]

[15] In the context of charitable monetary donations, Sieg and Zhang (2011) measure the relative importance of private benefits (e.g., invitations to dinner parties) and warm glow. They also find that private benefits are relatively more important than warm glow in determining donations in the majority of organizations that offer such benefits.

6.3 Tax Policy

Charitable time and money donations are not treated symmetrically in the US tax code. For itemizers, monetary donations are generally tax-deductible at the highest marginal tax rate. The tax-deductibility of monetary donations reduces the cost of giving money and encourages philanthropic activity of this type (see Auten, Sieg and Clotfelter (2002)). Volunteering is not directly encouraged in a similar way. For example, the US Internal Revenue Service (IRS) permits a tax credit to be received for childcare expenses if the purpose of the expense is to allow one to work. However, the IRS will not offer the tax credit for volunteer work.

Column (1) of Table 15 reports the results of a simulation exercise which sets the additional cost of childcare to zero when one volunteers. This corresponds to a childcare tax credit for volunteer work. The tax credit increases the total proportion volunteering from 30.0% to 36.9%, implying a 23.1% rise in volunteer labor supply. In percentage terms, the bulk of the increase is in the volunteer only and part-time and volunteer states. The higher incidence of unpaid work leads to an increase in mean accepted wages of 1.04% and an increase in mean lifetime earnings of 1.92%.

The increase in mean lifetime earnings of 1.92% corresponds to a benefit of $6,338 per woman. However, the "social" cost of providing tax relief is $25,487 per woman. Social cost is defined as a subsidy equivalent, in which 100% of volunteering-related childcare costs ($5,024 per-child) enter a discounted sum each period a woman volunteers. Thus, the increase in mean lifetime earnings covers only 24.9% of the mean lifetime social cost of providing tax-relief. Note that this is probably an upper bound on the shortfall in social welfare. The policy simulation does not take into account a possible increase in the husband's volunteering and lifetime earnings. In addition, there are likely to be many other net social benefits from more volunteer work in society, including poverty reduction, less crime, increased human capital of children and youth, and more charitable giving of money.

7 Conclusion

Volunteering is both a non-economic and economic activity that has not been extensively analyzed by economists. In this study, the returns to volunteering are estimated using data on female respondents in the PSID. The behavioral model assumes that a woman maximizes the discounted present value of expected lifetime utility by making joint and sequential decisions on unpaid and paid work, marital status and the conception of children.

The contemporaneous utility flow in the model is specified as CRRA in consumption with an additively separable component that captures the non-economic returns to volunteering.

This specification nests the investment and consumption motives for volunteering into one unified model, providing a new empirical strategy for directly estimating their relative importance.

The DCDP model is solved using a novel approximate solution technique, and the structural parameters are estimated by an SML procedure that is extended to adjust for biases due to non-random missingness/attrition. The SML estimates indicate that both the non-economic and economic returns to volunteering are substantial. In particular, an additional year of volunteer experience raises future wage offers in part-time work by 8.5% and by 2.6% in full-time work. Working for free increases mean lifetime earnings by 16.7%.

The behavioral model also reveals an adverse selection mechanism that helps explain why reduced-form wage regressions are likely to yield downward biased returns to volunteering. According to the structural estimates, highly-educated, low market-productivity women volunteer most often. This is because non-economic returns increase with education, and conditional on education, lower market-productivity implies greater benefits from future wage returns. Women with low initial market-productivity levels benefit more from the economic returns because they have higher marginal utilities of consumption. Differential marginal utilities of consumption arise from the estimated curvature of the consumption component of the utility flow.

A simulation exercise that sequentially introduces non-economic and economic returns into the model provides the first estimates of the relative importance of the investment and consumption motives in the context of volunteering. The results indicate that the economic returns account for 73.5% of the increase in lifetime utility from volunteer experience. Thus, the investment motive far outweighs the consumption motive.

The policy implications of the model are highlighted by simulating the introduction of a tax credit for volunteering-related childcare expenses. The tax credit produces a 23.1% increase in volunteer labor supply and a 1.92% increase in mean lifetime earnings. However, the increase in lifetime earnings covers only 24.9% of the costs of providing tax relief. This is probably an upper bound on the shortfall in social welfare since there are likely to be many other net social benefits from more volunteer work in society.

Future research could expand the model in several ways. First, heterogeneity in the returns to volunteering depending on type of organization could be analyzed with better data. Second, charitable monetary donations could be introduced into the decision problem. Money and time donations may be either substitutes or complements, implying that tax relief on time donations could affect monetary donations as well. Third, a more explicit household decision making model could be formulated, incorporating richer interactions between spouses in the dimension of volunteer work.

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Table 1: Weekly Volunteer Hours

Year	% Volunteer (Hours >0)	Mean	Standard Deviation	Percentile 10	25	50	75	90
2000	29.5	2.17	3.75	.29	.48	.96	1.92	4.81
2002	30.4	4.04	8.63	.19	.58	1.58	4.23	8.06
2004	34.7	3.49	7.41	.23	.58	1.73	3.69	7.31
Year	Helping the Needy	Religious	Children or Youth	Poor Health	Senior Citizens	Social Change	Other	Total
2000	.124	-	-	-	-	-	.876	1.00
2002-2004	.042	.410	.352	.044	.037	.032	.083	1.00

Note: The distributions in the top panel are for non-zero weekly volunteer hours, computed from annual totals. The bottom panel contains row percentages for non-zero hours.

Table 2: Sample Means by Frequency of Survey Response

	Full Sample (1)	Respond 3 Waves (2)	Respond < 3 Waves (3)
Volunteer	.338	.350	.200
	(.473)	(.477)	(.401)
Non-employed	.101	.099	.122
	(.301)	(.298)	(.328)
Part-time	.318	.321	.273
	(.466)	(.467)	(.446)
Full-time	.531	.526	.586
	(.499)	(.499)	(.493)
Married	.748	.796	.459
	(.434)	(.403)	(.498)
Children	1.82	1.86	1.57
	(1.31)	(1.27)	(1.49)
Female Wage	29.43	29.50	28.69
	(25.78)	(26.09)	(21.75)
Husband Wage	56.25	56.67	50.05
	(64.93)	(66.06)	(45.12)
Age	37.73	38.17	35.05
	(7.68)	(7.63)	(7.43)
Education	13.66	13.69	13.46
	(2.43)	(2.44)	(2.34)
N	2,479	2,129	350

Note: Wages are in 2005 constant dollars (thousands). N is the number of women. Standard deviations are in parentheses.

Table 3: Employment Choice Distribution

Age	Non-Employed (1)	Volunteer Only (2)	Part-time Only (3)	Full-time Only (4)	Part-time & Volunteer (5)	Full-time & Volunteer (6)	Woman-Years (7)
25-29	.117	.027	.229	.409	.090	.128	743
30-34	.129	.058	.213	.348	.109	.142	1,252
35-39	.088	.063	.210	.347	.112	.180	1,264
40-44	.091	.054	.195	.346	.155	.160	1,396
45-49	.092	.049	.175	.376	.123	.185	1,338
50-55	.093	.041	.174	.376	.110	.206	933
25-55	.101	.051	.198	.363	.120	.168	6,926

Note: Figures are row percentages. Percentages are computed conditional on non-missing employment choices.

Table 4: Two-Year Employment Transition Matrix

	Age+2					
Age	Non-Employed (1)	Volunteer Only (2)	Part-time Only (3)	Full-time Only (4)	Part-time & Volunteer (5)	Full-time & Volunteer (6)
Non-Employed	.496	.157	.186	.082	.056	.022
Volunteer Only	.159	.439	.070	.037	.229	.065
Part-time Only	.097	.024	.431	.266	.120	.063
Full-time Only	.054	.009	.146	.617	.034	.140
Part-time & Volunteer	.042	.066	.198	.106	.424	.164
Full-time & Volunteer	.022	.015	.075	.273	.122	.492

Note: Figures are row percentages. Percentages are computed conditional on non-missing employment choices.

Table 5: Reduced-Form Regressions

	Volunteer	Marriage	Birth	Log Husband Wage		Log Accepted Wage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	-.701	-1.035	.337	7.881	8.990	8.988	7.646	8.029
	(.168)	(.142)	(.113)	(.328)	(.331)	(.443)	(.419)	(.493)
I(12≤Edu<16)	.237	.097	.023	.518	.664	.678	.484	.563
	(.021)	(.028)	(.009)	(.059)	(.056)	(.068)	(.063)	(.086)
I(Edu≥16)	.418	.151	.066	.866	1.117	1.139	.935	1.007
	(.024)	(.029)	(.010)	(.063)	(.059)	(.073)	(.068)	(.091)
Age	.030	.076	-.013	.092	-.009	-.003	.023	.008
	(.009)	(.007)	(.006)	(.017)	(.017)	(.022)	(.020)	(.024)
Age-squared	-.0004	-.0008	.00004	-.0009	.0003	.0002	-.0001	.0001
	(.0001)	(.0001)	(.0001)	(.0002)	(.0002)	(.0003)	(.0002)	(.0003)
Married	.040		.045					
	(.015)		(.004)					
#kids	.077		.044					
	(.012)		(.005)					
#kids-squared	-.0095		-.0032					
	(.0025)		(.0013)					
Volunteer(t-2)						-.143	-.069	-.038
						(.034)	(.031)	(.028)
Part-time(t-2)							.681	.633
							(.093)	(.082)
Full-time(t-2)							1.365	.959
							(.090)	(.080)
ρ	.371	.805	.000	.666				.669
N	2,479	2,479	1,988	1,890	2,305	2,032	2,032	2,032
NT	6,926	12,395	8,953	4,798	5,877	3,707	3,707	3,707
R^2	.073	.024	.073	.101	.098	.100	.271	.245

Note: ρ is the fraction of variance due to the random effect. N is the number of women. NT is the number of woman-year observations. Column (3) includes only women less than 46 years old. The employment status dummies (Volunteer(t-2), Part-time(t-2), and Full-time(t-2)) refer to the prior wave (2 years earlier). Robust standard errors are in parentheses.

Table 6: Monte Carlo Estimation Results and Predictive Accuracy

Parameter	True Value (1)	Bias (2)	t-stat of Bias (3)
α_{10}	9.21	.0064	.35
α_{11}	.038	.0015	1.42
α_{12}	.033	.00002	.94
α_{13}	.0005	.000001	.26
α_{14}	0	.000001	.28
α_{15}	0	.0004	.31
α_{20}	8.48	.0183	.83
α_{21}	.070	.0032	1.71
α_{22}	.067	.0000008	.09
α_{23}	.001	0.0105	.97
α_{24}	.022	0.0006	.27
α_{25}	.0005	0.0019	1.11
β_0	0	.00003	.07
β_1	0	.00005	.26
β_2	4,000	47.78	.35
γ_0	17,750	1,599.1	.75
$(\sigma_{11})^{\frac{1}{2}}$	.20	.0019	.20
$(\sigma_{22})^{\frac{1}{2}}$	.25	.0038	.89
$(\sigma_{33})^{\frac{1}{2}}$	1,500	38.06	.29
$(\sigma_{44})^{\frac{1}{2}}$	1,500	7.85	.07

Mean of State Variables After Period 40

	Schooling (1)	Occ. 1 (2)	Occ. 2 (3)
Full Solution	12.84	11.79	24.80
Hybrid Solution	13.70	10.40	25.63

Note: Based on 25 sets of 100 individuals. The bias is the absolute value of $\hat{\theta} - \theta$, where θ denotes the true value in column (1) and $\hat{\theta} = \frac{1}{25}\sum_{j=1}^{25}\hat{\theta}_j$. The t-stat is the absolute value of $\left(\frac{\hat{\theta}-\theta}{\sigma_{\hat{\theta}}}\right)\sqrt{25}$ where $\sigma_{\hat{\theta}} = \left[\frac{1}{24}\sum_{j=1}^{25}\left(\hat{\theta} - \theta_j\right)^2\right]$. In the calculation of state variables after period 40, true values are used.

Table 7: SML Estimates

	Part-time Wage $ln\left(w_a^p\right)$ (1)	Full-time Wage $ln\left(w_a^f\right)$ (2)	Husband Wage $ln\left(w_a^h\right)$ (3)	Unobserved Income b (4)	Warm Glow g (5)	Approx Emax $\bar{F}_{a+2}(\cdot)$ (6)
Constant	7.521	8.451	8.447	4,658	-1.609	
	(.005)	(.007)	(.007)	(16.21)	(.006)	
E_1	.083	.432	.531		3.362	
	(.001)	(.002)	(.002)		(.011)	
E_2	.644	.958	.916		3.766	
	(.004)	(.004)	(.004)		(.017)	
A_1	-1.127	-.917				
	(.013)	(.009)				
A_2	1.059	.551				
	(.004)	(.003)				
A_3	1.939	1.166				
	(.006)	(.005)				
x_a^v	.085	.026				.048
	(.0003)	(.0002)				(.002)
x_a^p	.034	.030				.191
	(.0003)	(.0003)				(.004)
$(x_a^p)^2$	-.004					
	(.00004)					
x_a^f	.003	.035				.719
	(.00004)	(.0002)				(.007)
$\left(x_a^f\right)^2$		-.0004				
		(.000004)				
x_a^m						4.384
						(.083)
n_a						1.413
						(.012)
$n_a^{1,6}$					-1.516	
					(.014)	
$n_a^{7,18}$					3.794	
					(.019)	
a			.078		.0020	13.580
			(.0001)		(.0001)	(.206)
a^2			-.0009			-.242
			(.000002)			(.002)
σ_μ			.587			
			(.002)			
σ_{ε_a}	.018	.135	.118	4.363	4.266	
	(.001)	(.002)	(.001)	(.022)	(.014)	

Note: Asymptotic standard errors are in parentheses.

Table 8: SML Estimates (cont'd)

	Marriage Utility ψ^m (1)	Children Utility ψ^n (2)	(3)	Type Probs π_2^A (4)	(5)	Education Probs (6)	(7)	Attrition Prob π^{nr} (8)
			π_1^A		π_3^A	π_1^E	π_2^E	
Constant			-.385	1.088	.5697	2.014	1.476	-.622
			(.467)	(.288)	(.316)	(.114)	(.120)	(.166)
E_1			-.498	-.1526	.3646			
			(.487)	(.298)	(.323)			
E_2			-.199	-.5566	.1460			
			(.491)	(.305)	(.331)			
C_1			-.146	-.0032	-1.137	.027	-.195	
			(.230)	(.152)	(.164)	(.171)	(.180)	
C_2			-.719	-.2290	-1.831	.566	.507	
			(.379)	(.204)	(.262)	(.311)	(.322)	
x_a^m	5.061							
	(.137)							
n_a		14.280						
		(.085)						
n_a^2		-4.054						
		(.021)						
$m_a n_a$		15.750						
		(.091)						
$m_a n_a^2$		-1.719						
		(.012)						
Vol								.269
								(.176)
PT								-.129
								(.274)
FT								.571
								(.163)
m_a								-1.967
								(.152)
$n_a^{1,6}$								.394
								(.151)
$n_a^{7,18}$								-1.159
								(.301)
l_{2003}								-.042
								(.004)

Note: Asymptotic standard errors are in parentheses.

Table 9: SML Estimates (cont'd)

CRRA	Disutility of Work Effort						Income Sharing	Marriage Offer Prob
$1-\lambda$	μ_1	μ_2	μ_3	μ_4	μ_5	μ_6	τ^1	π^m
.273	1.0000	.9982	.9980	.9162	.9551	.8720	.435	.091
(.0010)		(.0009)	(.0007)	(.0005)	(.0008)	(.0006)	(.002)	(.0003)
		Child Care Costs						
		Birth	Nonemp	Vol	PT	FT	α_c	
		30,049	19,789	5,024	22,446	25,993	1.402	
		(101.2)	(41.9)	(29.6)	(49.2)	(66.1)	(.006)	
Switching Costs			Cholesky Elements			Measurement Error		
s_1	s_3	s_4	l_{21}	l_{43}	l_{54}	$\sigma_{\eta,p}$	$\sigma_{\eta,f}$	$\sigma_{\eta,h}$
3.009	4.440	4.547	2.028	-.014	-.077	.284	.387	.444
(.015)	(.014)	(.014)	(.010)	(.0006)	(.0008)	(.0009)	(.003)	(.007)
Classification Error								
Employment							Marriage	
π^e_{jk}							π^m_{jk}	
.9955	.0009	.0009	.0009	.0009	.0009		.9820	.0180
.0009	.9955	.0009	.0009	.0009	.0009		.0180	.9820
.0009	.0009	.9955	.0009	.0009	.0009		Birth	
.0008	.0008	.1429	.8540	.0008	.0008		π^b_{jk}	
.0008	.0008	.1632	.0008	.8337	.0008		.9820	.0180
.0007	.0007	.0007	.1224	.1288	.7468		.0180	.9820

Note: The employment classification error matrix is generated from four parameters with estimated values 5.212 (.044), 5.369 (.084), 5.191 (.081) and 5.243 (.067). Asymptotic standard errors are in parentheses.

Table 10: Actual and Predicted Employment Outcomes

Non-Employed	Volunteer Only	Part-time Only	Full-time Only	Part-time & Volunteer	Full-time & Volunteer
.101	.051	.198	.363	.120	.168
(.988)	(.051)	(.183)	(.369)	(.117)	(.181)
	Mean Accepted Wage	Mean Accepted Part-time Wage	Mean Accepted Full-time Wage	Mean Accepted Husband Wage	
	29,451	17,825	36,271	55,440	
	(31,811)	(18,434)	(39,126)	(58,797)	
Distribution Volunteer Work Experience					
0	1	2	3	4	5
.487	.221	.152	.140	0	0
(.421)	(.275)	(.191)	(.114)	(0)	(0)

Note: Predicted values are in parentheses.

Table 11: Actual and Predicted Two-Year Employment Transition Matrix

	$a+2$					
a	Non-Employed (1)	Volunteer Only (2)	Part-time Only (3)	Full-time Only (4)	Part-time & Volunteer (5)	Full-time & Volunteer (6)
Non-Employed	.496 (.541)	.157 (.178)	.186 (.157)	.082 (.052)	.056 (.056)	.022 (.016)
Volunteer Only	.159 (.247)	.439 (.360)	.070 (.116)	.037 (.034)	.229 (.196)	.065 (.046)
Part-time Only	.097 (.083)	.024 (.048)	.431 (.400)	.266 (.268)	.120 (.116)	.063 (.085)
Full-time Only	.054 (.025)	.009 (.008)	.146 (.126)	.617 (.656)	.034 (.033)	.140 (.153)
Part-time & Volunteer	.042 (.038)	.066 (.027)	.198 (.190)	.106 (.119)	.424 (.458)	.164 (.167)
Full-time & Volunteer	.022 (.011)	.015 (.006)	.075 (.121)	.273 (.259)	.122 (.106)	.492 (.497)

Note: Figures are row percentages. Predicted values are in parentheses.

Table 12: Actual and Predicted Marriage and Birth Outcomes

Married	Birth	Single Mother Birth	Married Mother Birth
.748 (.751)	.060 (.063)	.023 (.023)	.074 (.081)

Marital Status

	a+2	
a	Single	Married
Single	.799 (.805)	.201 (.195)
Married	.029 (.023)	.971 (.977)

Note: Birth percentages are for $a \leq 45$. Predicted values are in parentheses.

Table 13: Reduced-Form Wage Regressions (Simulated Data)

	Log Accepted Wage	
	(1)	(2)
Constant	7.093	7.251
	(.023)	(.012)
I(12≤Edu<16)	.523	.558
	(.003)	(.001)
I(Edu≥16)	.939	1.152
	(.003)	(.002)
Age	.027	.010
	(.001)	(.0006)
Age-squared	.00002	.0002
	(.00002)	(.00001)
Type 1		-1.189
		(.006)
Type 2		.720
		(.002)
Type 3		1.450
		(.002)
Volunteer(t-2)	.044	.049
	(.003)	(.001)
Part-time(t-2)	.804	.119
	(.007)	(.004)
Full-time(t-2)	1.480	.721
	(.006)	(.004)
$\bar{R}^2$	.5005	.8708
N	480	
NT	16,320	

Note: N is the number of simulated women. NT is the number of simulated woman-year observations. Robust standard errors are in parentheses.

Table 14: Relative Importance

	No Non-Economic or Economic Returns (1)	Only Non-economic Returns (2)	Economic and Non-economic Returns (3)
Volunteer (Total)	.0000	.2828	.3001
Non-employed	.2337	.1678	.1439
Volunteer Only	.0000	.0557	.0364
Part-time Only	.1350	.1034	.1334
Full-time Only	.6313	.4461	.4226
Part-time & Volunteer	.0000	.0394	.0719
Full-time & Volunteer	.0000	.1877	.1918
Married	.6995	.6995	.6990
Total Fertility	.5156	.5115	.5260
Husband Wage	47,332	47,332	47,394
Accepted Wage	25,671	25,503	29,838
Lifetime Earnings	282,233	284,020	329,445
		(0.63)	(16.73)
Lifetime Utility	5997.75	6009.42	6041.79
		(1.95)	(7.34)

Note: Lifetime figures are discounted between the ages of 22 and 55. Lifetime earnings includes zeros. Percentage increase from column (1) figures in parentheses.

Table 15: Child Care Tax Credit for Volunteering

	Baseline (1)	Tax Credit (2)
Volunteer (Total)	.3001	.3695
		(23.1)
Non-employed	.1439	.1189
Volunteer Only	.0364	.0432
Part-time Only	.1334	.1356
Full-time Only	.4226	.3759
Part-time & Volunteer	.0719	.1092
Full-time & Volunteer	.1918	.2172
Married	.6990	.6990
Total Fertility	.5260	.5298
Husband Wage	47,394	47,394
Accepted Wage	29,838	30,153
		(1.04)
Lifetime Earnings	329,445	335,783
		(1.92)
Lifetime Utility	6041.79	6056.51
		(0.24)
Program Evaluation		
Lifetime Subsidy		25,487
Lifetime Earnings Benefit		6,338
Net Cost Per Volunteer		19,149

Note: Lifetime figures are discounted between the ages of 22 and 55. Lifetime earnings includes zeros. Percentage increase from column (1) figures in parentheses.