A Bivariate Duration Model of the Joint Retirement Decisions of Married Couples

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Abstract:

We analyze the retirement behavior of married couples using a new bivariate proportional hazard model. This model generalizes the traditional univariate duration analysis to include a family-wide joint retirement process that induces both spouses to retire at the same time. The model is flexible and allows three unknown baseline hazard functions to be nonparametrically estimated. Fitting this model to data from the Retirement History Longitudinal Survey (RHS) we quantify the importance of the incidence of joint retirement and test the existence and the symmetry of the effects of one spouse's characteristics on the other spouse's retirement propensity. Our main empirical findings reveal strong associations between the retirement probabilities of the spouses. The effects of wages are significant and asymmetric by gender. The reported asymmetry by gender in the effect of spouse's health status on own retirement hazard is likely spurious due to specification error.

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Keywords: Household decision-making, Joint retirement, Bivariate durations, Proportional hazards, Grouped duration data.

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1 Introduction

Recent studies of retirement recognize the importance of explicit modelling of the joint labor force behavior of older married couples. Most older workers are married, and dual-career couples are becoming increasingly predominant in the cohorts approaching retirement age. Spouses are likely to coordinate their exit from the labor market if complementarities in leisure times are present. Additional sources of joint retirement behavior include assortative mating and correlation in unobserved tastes. It is important for policy purposes to understand the relation between the retirement decisions of spouses, since aggregate responses to labor market policy measures depend on this. Empirical evidence of the importance of joint retirement behavior is presented by Anderson et al. (1980), Clark et al. (1980), Henretta and O′Rand (1983), Hurd (1990), Christensen and Datta Gupta (1994), Gustman and Steinmeier (1994), Blau (1997) and Blau and Riphahn (1998).

In this paper, we estimate a bivariate proportional hazard model of the durations until husband′s and wife′s retirement. This model generalizes the traditional univariate duration analysis to include a family-wide joint retirement process that induces both spouses to retire at the same time. The model is quite flexible and includes nonparametric baseline hazards for both the husband and the wife, as well as a third nonparametric baseline hazard governing the incidence of joint retirement. In addition, all three hazard rates are allowed to depend on the observed individual characteristics of both spouses. The novel feature of designating a separate hazard rate to the incidence of joint retirement is useful for capturing the coordination of labor supply decisions of spouses empirically, and this additional hazard rate is found to be statistically significant.

Multivariate duration models are becoming increasingly important in empirical economics. In a recent overview, van den Berg (2000) considers multivariate mixed proportional hazard models, where the correlation between durations is driven by common unobserved heterogeneity. In our model, the correlation between durations until retirement is instead driven by the additional hazard governing the incidence of joint retirement, thus allowing easy economic interpretation.

Our model is simpler than the stochastic dynamic programming model estimated by Christensen and Datta Gupta (1994), in that it does not explicitly calculate the optimal retirement decision, taking into account the value of future, state-dependent optimal behavior. Similarly, it is simpler than the discrete choice model estimated by Blau (1997), which allows reentry into the labor market. As it is focussed on the duration until the first arrival at a suitably defined retirement state, our approach delivers a parsimonious descriptive tool that may be related directly to the duration literature. The simplicity relative to richer, structural models allows easier estimation, calculation of standard errors (often missing in more complicated models), and interpretation. In addition, we are able to include flexible, nonparametric baseline hazards that may capture empirically whatever effects a more complicated model might have generated. Finally, by designating a separate hazard specifically to joint retirement, we have a direct measure of this phenomenon, which is a useful alternative to indirect measures such as the dependence on spouse's labor force status of the effects of explanatory variables on individual retirement hazards.

We apply our model to data from the Retirement History Longitudinal Survey (RHS). Our results confirm the importance of joint retirement, consistent with previous studies. In particular, the specific hazard function for the incidence of joint retirement depends significantly on both spouses′ observed characateristics. The alternative specification corresponding to two separate univariate models for the husband and the wife is rejected statistically. Similarly, the nonparametric baseline hazards are statistically important. Thus, our results indicate duration dependence in all three hazards, including the hazard for joint retirement, and Weibull specifications are rejected in favor of our general model.

The paper is laid out as follows: Section 2 introduces the model and likelihood function. Section 3 presents the data and descriptive statistics. Section 4 discusses the estimation results and hypothesis tests. Section 5 concludes.

2 A Bivariate Duration Model of Joint Retirement

For a sample of married couples, we consider the durations until retirement of both the husband and the wife. In the empirical work in the following section, we measure both durations from the year where the husband turns

60, and we focus on couples where neither husband nor wife is retired in that year. Let $\left(T_n^m, T_n^f\right)$denote the husband′s respectively the wife′s duration for the n'th couple. As in An (1999), we model this pair of durations using three latent variables. Thus, let $\left(Y_n^m, Y_n^f\right)$ be latent variables associated with the husband respectively the wife, and let Y_n^c be an additional latent variable associated with the couple and capturing the incidence of joint retirement. That is, each spouse either retires individually, with duration given by $Y_n^k, k = m, f$ or together with the other spouse, with duration Y_n^c. Specifically, let $T_n^m = \min \{Y_n^m, Y_n^c\}, T_n^f = \min \left\{Y_n^f, Y_n^c\right\}$.Thus, joint retirement in the sense of coordination of retirement times occurs when the couple specific latent variable is the minimum among the three. This approach allows explicit modelling of the coordination of retirement times as stemming from assortative mating on both observables and unobservables, or from correlation across spouses in tastes. In particular, our analysis allows identification of the determimants of joint retirement, including investigation of the importance of financial variables in the common shock Y_n^c. In our model, the correlation between observed durations until retirement is precisely induced by the incidence of joint retirement.

As illustrated in Figure 1, the model allows that a married couple where initially both are employed (state (E, E) in the figure) may reach the ultimate state (R, R) where both are retired through either of three routes: Thus, the wife may retire before the husband, and the couple experiences a spell in state (E, R), until also the husband retires. Alternatively, the husband may retire first, and the couple visits state (R, E). Finally, the model explicitly accounts for the possibility of joint retirement, i.e. the husband and wife both retire at the same time. This type of transition is illustrated by the middle arrow in the figure.

The econometric model relates the duration variables with the observable covariates,

$$\left\{\mathbf{x}_n^m, \mathbf{x}_n^f\right\}, n = 1, 2, ..., N, \tag{1}$$

where $\mathbf{x}_n^k$ measures the observed characteristics of each spouse $k = m, f$ in couple n. Denote $\mathbf{w}_n = (\mathbf{x}_n^m, \mathbf{x}_n^f)$. In the empirical work below, the regressors include health, income, benefit eligibility and age variables.

It is conventional to characterize each of the three latent variables by a conditional intensity rate or hazard rate. The key model structure of the bivariate duration model is stated in the next two assumptions.

Assumption 1 (Conditional Independence) *Conditionally on w_n, the three latent duration times Y_n^m, Y_n^f, Y_n^c are mutually independent.*
Assumption 2 (Proportional Hazards) *For k=m, f, c, the marginal distribution of Y_n^k is represented by a conditional hazard function of the following proportional hazard form,*

$$h^k(t|\mathbf{w}_n) = \lambda^k(t)e^{\mathbf{w}_n\beta_k}, k = m, f, c. \tag{2}$$

In Equation 2, the baseline hazards $\lambda^k(t)$ are left unspecified to achieve flexibility. The primary parameters of interest, therefore, are the regression coefficients, $\beta = (\beta'_m, \beta'_k, \beta'_c)'$ which characterize the marginal effects of the covariates on the logarithm of the hazard rates. We are interested also in testing different hypotheses via restrictions on the β's.

Assumptions 1 and 2 lead to the joint distribution of (T_n^m, T_n^f), conditional on $w_n = \mathbf{w}$. The joint survivor function for the observed durations (T_n^m, T_n^f) is

$$\begin{aligned} S(t_1, t_2|\mathbf{w}) &\equiv P(T_n^m > t_1, T_n^f > t_2|\mathbf{w}) \\ &= P\left(Y_n^m > t_1, Y_n^f > t_2, Y_n^c > \max\{t_1, t_2\}|w\right) \\ &= \exp\left\{-H^m(t_1|\mathbf{w}) - H^f(t_2|\mathbf{w}) - H^c(\max\{t_1, t_2\}|\mathbf{w})\right\}, \end{aligned} \tag{3}$$

where for $k = m, f, c$,

$$H^k(t|\mathbf{w}) \equiv \int_0^t h^k(s|\mathbf{w})ds = e^{\mathbf{w}_n\beta_k}\Lambda^k(t) \tag{4}$$

is the integrated hazard function associated with the k-th latent variable, and $\Lambda^k(t) = \int_0^t \lambda^k(s)ds$ is the integrated baseline hazard which is differentiable, monotonically increasing, and satisfies $\Lambda^k(0) = 0$.

The bivariate proportional hazards model has the following properties:

(i) For $k = m, f$, the marginal distribution of T_n^k has hazard function $h^k(t|\mathbf{w}) + h^c(t|\mathbf{w})$, which is of the proportional hazard type if and only if $\lambda^k(t)$ is proportional to $\lambda^c(t)$.

(ii) The probability $P(T_n^m = T_n^f|\mathbf{w}) > 0$, unless $h^c(t|\mathbf{w}) = 0$ for all t. Hence, generically, the distribution is not absolutely continuous.

(iii) The joint density of the observed duration times (T_n^m, T_n^f) is

$$f(t_1,t_2|\mathbf{w}) = \begin{cases} h^m(t_1|\mathbf{w})[h^f(t_2|\mathbf{w}) + h^c(t_2|\mathbf{w})] \\ \cdot \exp\left\{-H^m(t_1|\mathbf{w}) - H^f(t_2|\mathbf{w}) - H^c(t_2|\mathbf{w})\right\}, & t_1 < t_2 \\ \\ h^f(t_2|\mathbf{w})[h^m(t_1|\mathbf{w}) + h^c(t_1|\mathbf{w})] \\ \cdot \exp\left\{-H^m(t_1|\mathbf{w}) - H^f(t_2|\mathbf{w}) - H^c(t_1|\mathbf{w})\right\}, & t_1 > t_2 \\ \\ h^c(t_1|\mathbf{w}) \cdot \exp\left\{-H^m(t_1|\mathbf{w}) - H^f(t_1|\mathbf{w}) - H^c(t_1|\mathbf{w})\right\}, & t_1 = t_2. \end{cases} \tag{5}$$

The joint density (5) contains three unknown baseline hazard functions. This means that direct maximum likelihood estimation is infeasible. As in the case of univariate proportional hazard models (see Kiefer (1988)), consistent estimation of the regression coefficients β from (2) is possible, however, using grouped duration data. Since β is the object of economic interest, while the baseline hazards may be thought of as nuisance parameters, and since our data are available only in grouped form (yearly intervals), anyway, this is no restriction.

Two main complications arise when deriving the likelihood function: Right censoring and time-varying covariates. We treat both death and survey end as right-censoring. For each couple we use two integer-valued duration measures (D_n^m, D_n^f) and two censoring indicators (Δ_n^m, Δ_n^f) with the convention that if $\Delta_n^m = 1$ then T_n^m falls into the interval between $D_n^m - 1$ and D_n^m, and if $\Delta_n^m = 0$ then T_n^m falls into the interval between $D_n^m - 1$ and ∞.

We allow for time-varying covariates, and due to the survey design in the empirical application we follow the conventional treatment of assuming that the time-varying covariates are constant within each yearly interval. With this assumption, the time-invariant covariates are special cases of the time varying covariates, so in the following discussion we do not distinguish the two kinds. We denote the covariate matrix as

$$\mathbf{w}_n = (\mathbf{w}_{n1}, \mathbf{w}_{n2}, ...). \tag{6}$$

Collecting the terms introduced so far, for each couple we have data in the form

$$(D_n^m, D_n^f, \Delta_n^m, \Delta_n^f, \mathbf{w}_n) = (i, j, \delta_m, \delta_f, \mathbf{w}) \tag{7}$$

The contribution to likelihood of an observation $(i, j, \delta_m, \delta_f, \mathbf{w})$ can be specified in the four relevant cases as follows, using S from (3):

- Case 1 ($\kappa_n = 1$): Neither duration is censored, that is, $(\delta_m, \delta_f) = (1, 1)$:

$$L_1(i, j, \mathbf{w}) = S(i, j|\mathbf{w}) + S(i-1, j-1|\mathbf{w}) - S(i-1, j|\mathbf{w}) - S(i, j-1|\mathbf{w}).$$

- Case 2 ($\kappa_n = 2$): Husband only censored, $(\delta_m, \delta_f) = (0, 1)$:

$$L_2(i, j, \mathbf{w}) = S(i, j-1|\mathbf{w}) - S(i, j|\mathbf{w}).$$

- Case 3 ($\kappa_n = 3$): Wife only censored, $(\delta_m, \delta_f) = (1, 0)$:

$$L_3(i, j, \mathbf{w}) = S(i-1, j|\mathbf{w}) - S(i, j|\mathbf{w}).$$

- Case 4 ($\kappa_n = 4$): Both censored, $(\delta_m, \delta_f) = (0, 0)$:

$$L_4(i, j, \mathbf{w}) = S(i, j|\mathbf{w}).$$

Define $\gamma_j^k = \log\left(\int_{j-1}^{j} \lambda^k(s)ds\right)$ as the logarithm of the increase in the k-th integrated baseline hazard over the interval $(j-1, j)$. Denote the extended parameter vector

$$\theta = (\beta_m, \gamma_1^m, ..., \gamma_J^m; \beta_f, \gamma_1^f, ..., \gamma_J^f; \beta_c, \gamma_1^c, ..., \gamma_J^c), \tag{8}$$

when grouping each duration into J intervals. With this notation, a generic term $S(i, j|\mathbf{w})$ required in the likelihood function is simply

$$S(i, j|\mathbf{w}) = \exp\left\{-H^m(i|\mathbf{w}) - H^f(j|\mathbf{w}) - H^c(\max\{i, j\}|\mathbf{w})\right\}, \tag{9}$$

where for $k = m, f, c$ and any integer l,

$$\begin{aligned} H^k(l|\mathbf{w}) &= \int_0^l h^k(s|\mathbf{w}(s))ds \\ &= \int_0^l \lambda^k(s)e^{\mathbf{w}(s)\beta_k}ds \\ &= \sum_{j=1}^{l} \exp\{\mathbf{w}_j\beta_k + \gamma_j^k\}. \end{aligned} \tag{10}$$

The sample log likelihood function is then

$$l(\theta) = \sum_{n=1}^{N} \sum_{j=1}^{4} 1_{\kappa_n = j} \log L_j \left(D_n^m, D_n^f, \mathbf{w}_n \right). \tag{11}$$

Numerical maximization of the log likelihood function produces the maximum likelihood estimate (mle) $\hat{\theta}$ of the extended vector of parameters θ. It follows from conventional asymptotic theory that $\hat{\theta}$ is consistent and asymptotically normal under correct model specification. The variance-covariance matrix of $\widehat{\theta}$ is estimated consistently by the negative of the inverse second derivative matrix of (11), evaluated at $\widehat{\theta}$. Using the asymptotic distribution, statistical inference may be conducted. The model is semiparametric in nature, with β the parameter of main economic interest, and the baseline hazards λ, summarized by γ, playing the role of nuisance parameters.

3 Data and Descriptive Statistics

We now consider an application of the bivariate duration model of the previous section to the joint retirement decision of married couples. We use the Retirement History Longitudinal Survey (RHS) data collected by the U.S. Social Security Administration. This is a survey of men and unmarried women who were between the ages of 58 and 63 in 1969, and who were resurveyed biannually up to and including 1979. Spousal information is present for the husbands in the sample in each of the survey years. This allows the creation of a couples data base.

The RHS contains detailed work-history, income and expenditure information. We condition on labor-force participation (employed or unemployed) of both husband and wife in the first year of the survey, 1969. We focus on couples who are married and remain married to each other throughout the sample period, if both remain alive in this interval. If one of the individuals dies, we require for simplicity that the spouse does not remarry within the sample period. Thus, surviving spouses are retained in the analysis. We consider the durations until the wife respectively the husband retires, starting from the year where the husband turns 60. For simplicity, we only consider those couples where the husband is older than the wife. Our final sample consists of 978 couples.

From the survey data we know whether a person is retired, in the sense of receiving Social Security or private benefits, or working less than 5 hours per week over the year. All other persons are considered to be working. We consider only those couples where both are working in the year where the husband turns 60, and we consider only the time until the first year of retirement, for each person. In years where there was no survey (the even-numbered years 1970, 1972, ..., 1978), all variables are assigned the value from the previous year. With durations measured from the year where the husband turns 60, this allows construction of our grouped (into yearly intervals) duration data.

Table 1 reports the observed bivariate duration data. Due to right-censoring (death or survey end), we only observe the completed durations for both the husband and the wife for 311 of the 978 couples in our sample. For 183 of the couples the wife's duration is right-censored. For 52 of them the husband's duration is right-censored. For 432 of the couples both the husband's and the wife's durations are right-censored. Using only the first group of 311 couples, the distribution of the bivariate durations is reported in the second part of the table. Wives tend to have shorter durations until retirement than husbands in the sample. In addition, both panels clearly show concentration of the observations along the diagonal. This indicates a propensity to joint retirement.

In addition to labor force participation, we have data on wife's and husband's age and labor market earnings, as well as a dichotomous variable indicating either good or bad health for each individual, based on a self-reported survey measure. Table 2 reports descriptive statistics for the additional survey data used to construct regressors. The first two columns report statistics for the initial year, where the husband is 60 years of age. It is noted that their wives are almost four years younger, on average. The last two columns report summary statistics across all sampled person-years. Health (1 if good, 0 if poor) is considerably better among wives than among husbands initially, then drops faster among wives than among husbands, although on average, wives remain of best health. The relative drop in wives' health might help explain their shorter durations until retirement (see Table 1). Income (labor market earnings) is considerably higher among husbands than among wives, but goes down more over time among husbands than among wives, although husbands continue to earn the most throughout.

Figure 2 exhibits the grouped bivariate duration data. Figure 2.a shows the distribution also reporterd in the first panel of Table 1. Again, the concentration along the diagonal is evident. Figure 2.b shows the similar picture for the completed durations (see Table 1.b).

Figures 2.c and 2.d are the estimated bivariate survivor function and hazard function, respectively, using Kaplan-Meier nonparametric methods. These plots are generated using maximization of the nonparametric likelihood. The parameter of the nonparametric likelihood is a vector of 10*10 = 100 cell probabilities

$$q_{ij} = \Pr\left(T^m \in [i-1, i), T^f \in [j-1, j)\right), \quad i, j = 1, 2, ..., 10, \tag{12}$$

with restrictions that they are all nonnegative and sum to unity. These restrictions are naturally accomodated by introducing 99 unrestricted parameters τ_{ij} with $\tau_{10,10} = 1$ and

$$q_{ij} = \frac{\exp\{\tau_{ij}\}}{\sum_l \sum_k \exp\{\tau_{lk}\}}. \tag{13}$$

These define a multinomial random variable on the two-dimensional grid. With this nonparametric specification, each observed pair of durations is then just a simple grouped multinomial random variable. Each pair of durations contributes to likelihood with a sum of such cell probabilities.

The estimated survivor function and hazard function are derived from the estimated cell probabilities,

$$\widehat{s}_{ij} = \sum_{l=i+1}^{10} \sum_{k=j+1}^{10} \widehat{q}_{lk}, \quad i, j = 0, 1, ..., 9 \tag{14}$$

and

$$\widehat{h}_{ij} = \frac{\widehat{q}_{ij}}{s_{i-1,j-1}} \quad i, j = 1, 2, ..., 10. \tag{15}$$

Again, the nonparametric bivariate hazard places considerable mass on the diagonal, hence showing the need for explicit joint retirement modelling.

4 Estimation Results

4.1 Model Choice and Goodness of Fit

We now apply the joint retirement model of Section 2 to the bivariate duration data presented in Section 3. Thus, the log likelihood function is (12), where the durations D_n^m and D_n^f for the husband and wife in the n'th couple are those presented in summary form in Table 1 and Figure 2, and $w_n = \left(x_n^m, x_n^f\right)$ contains regressors constructed from the data summarized in Table 2. Our specifications use health and log income of husband and wife, along with three age-dependent variables for the wife. In particular, we use the difference between the wife's and the husband's ages, along with a dummy variable indicating whether the wife is in the age interval 62-64, making her eligible for Social Security early retirement benefits, and another dummy variable indicating whether the wife is in the age interval 65 and above, making her eligble for Social Security normal (old age) retirement benefits. With our nonparametric specification of the baseline hazards, and since the durations are measured from the year the husband turns 60, there is no need for similar age variables for the husband.

The results of estimation of the bivariate duration model under different model specifications appear in Table 3. We first focus on the first column, where all explanatory variables are included in all three hazards. Figure 3 shows the estimated baseline hazards for the husband, the wife, and the couple for the model in the first column. In each graph, the middle line is the estimated hazard, and the two other lines give the 10% and 90% quantiles. It is noted that the husband's baseline hazard peaks at age 64. Both wife's and couple's hazards peak in the eight and last interval in the figure, corresponding to husband's age 68. Given the four year difference in husband's and wife's age (see Table 2), this implies that wives (and couples) also exhibit a peak around wife's age 64 point. Our definition of retirement, which in addition to receipt of Social Security benefits also includes a drop in work hours to below 5 per week or receipt of private benefits, may put the peak in retirement hazards slightly off the expected point of 65, corresponding to the date of Social Security normal benefits eligibility. Rust (1990) compares various alternative definitions of retirement empirically. Of course, we have regressor effecs that are not captured in the baseline hazard plots.

To assess the model fit, we attempted to test down from the nonparametric baseline hazard specification to a standard Weibull hazard for each of the husband, wife, and couple. The Weibull specification is the most common parametric assumption in duration analysis. The Weibull baseline hazard with shape parameter α^k is $\lambda^k(t) = \alpha^k t^{\alpha^k - 1}$. Testing for this amounts to putting $3 * (J-1)$ nonlinear restrictions on the γ_j^k's. The restrictions take the form

$$\gamma_j^k = \log[(j)^{\alpha^k} - (j-1)^{\alpha^k}], \quad j = 2, ..., J \tag{16}$$

This test rejected, indicating that the nonparametric baseline hazard is required in order to fit the bivariate duration data.

We may in addition inspect the validity of the Weibull baseline specification graphically. Thus, the Weibull integrated hazard function is $\Lambda^k(t) = t^{\alpha^k}$. That is, $\log(\Lambda^k(t)) = \alpha^k \log(t)$, so if we plot the estimated $\log(\Lambda^k(t))$ against $\log(t)$, a departure from a linear relationship is visual evidence against a Weibull baseline hazard. This is done in Figure 4. Each graph (husband, wife, couple) should show a linear shape under the Weibull restriction. Given the nonlinear shapes in the pictures, and our relatively large sample size, the result of this informal graphical test is in agreement with the formal hypothesis test.

In sum, we reject the Weibull baseline specification, and work with the nonparametric specification for the remainder of this paper.

Returning to the results in Column 1 of Table 3, which are based on the nonparametric baseline hazard specification, we find that the parameter estimates are as expected, for the most part. Husband's own good health lowers his retirement hazard, and the effect is significant (t statistic of -3.8). Wife's poor health induces the husband to continue working (reduces his retirement hazard), possibly to be able to afford purchased care. The higher the husband's labor market earnings, the lower is his retirement hazard. Thus, the substitution effect dominates the income effect. Wife's earnings have a positive sign (an income effect), but is insignificant. The husband is more likely to retire if the wife is closer to him in age, perhaps indicating complementarity in leisure time (the wife cannot as easily retire if she is much younger than the husband). On the other hand, the husband's retirement hazard is actually significantly lower when the wife is eligible for Social Security benefits, so the evidence in favor of complementarity in leisure time is weakened.

Turning to the wife, her own good health naturally decreases her retirement hazard, but the husband's health has no significant effect. Own income increases her retirement hazard, i.e. the income effect dominates the substitution effect, and this result is opposite of that for the husband. The husband's income significantly reduces the wife's retirement hazard. Clearly, a pooled family income measure would be insufficient to capture these cross-income effects. Regarding the age-related effects, the wife is more likely to retire when eligible for Social Security benefits and when closer to the husband in age.

Turning to the couple hazard, there is a reduced tendency to joint retirement when either party is in good health, and when husband's earnings are high. Wife's earnings have the opposite effect. The greater the age difference, the less likely is joint retirement. This helps explain the effect of wife's eligibility on the husband's hazard, which was negative. Thus, when the wife is eligible, the husband is not likely to retire alone, but joint retirement is likely. Clearly, the bivariate model is required for picking up this type of effect.

4.2 Evidence of Joint Retirement

It is a key feature of our bivariate duration model that it includes a couple-wide hazard rate governing the incidence of joint retirement, in the sense of husband and wife retiring at the same time. It is therefore of interest to test for the significance of this third hazard rate. This may be done by testing for whether $(\exp(\gamma_1^c), ..., \exp(\gamma_J^c))$ are jointly 0. We did this, and the test rejected. This indicates the importance of joint retirement effects in this sample.

We may in addition test the less severe restriction that the couple hazard does not depend on the regressors, i.e. that joint retirement is purely driven by the (non-Weibull) couple baseline hazard. Results from estimation of a model imposing this restriction are exhibited in the second column of Table 3. Apart from the effect of husband's health in the wife's hazard, which is imprecisely estimated, anyway, the coefficient estimates do not change much under this restriction, relative to the unrestricted model in the first column of the table. From the last two rows, the drop in log likelihood is very large, from -2368.8 to -2481.5, given that only seven parameters have been dropped, and the restriction is rejected at all conventional significance levels. This reinforces the notion that the couple hazard is important for modelling joint retirement in this sample.

4.3 Inter-Dependence in Retirement Hazards

We now turn to a test of the hypothesis that the husband's hazard does not depend on the explanatory variables pertaining to the wife. This may be related to Killingsworth's (1983) discussion of the variant of the family labor supply model in which the husband's decision-making is independent of the wife, or the "male-chauvinist" model. Column 3 of Table 3 reports estimates of the model. It is rejected in a LR test against the original model in column 1. We also test the corresponding symmetric hypothesis that the wife's hazard does not depend on the husband's variables (health and earnings). This model is presented in the fourth column, and is rejected, too. Thus, both husband's and wife's retirement behavior take the other spouse into account. This result is quite robust. Thus, in the fifth column, we show results of estimating the model, combining both sets of restrictions, i.e. neither party's hazard depends on the spouse's variables, and this specification is rejected, too.

It could be argued that for each party's behavior not to be affected by the spouse, the couple hazard should be unaffected by the spouse's variables, too. Thus, in the sixth column, we estimate the model where each party's own hazard only depends on own variables and the couple's hazard does not depend on either party's variables (but only on the baseline hazard). This model is rejected, too. Thus, retirement behavior is fully interdependent across wife and husband. The best model so far is still the unrestricted model in the first column.

4.4 Cross-Effects of Health

Finally, we turn to the issue of symmetry in the own and cross health effects. As already noted, the cross wage effects are clearly asymmetric across wife and husband. Considering the health effects, own good health reduces the retirement hazard for both wife and husband. Spouse's good health increases the retirement hazard in both cases, although the effect is only significant for husbands. The coefficients for the significant own effects are of the same order of magnitude, about -0.5. To see whether the own and cross health effects are symmetric between wives and husbands, we consider in the last column of Table 3 the same model as in the first column, but with the restriction that the own and cross health effects are identical for wives and husbands. This restriction is not rejected. Furthermore, both own and cross effects are significant in the restricted model. The result indicates that individuals in good health tend to continue to work longer, as do individuals whose spouses are in poor health, and these effects are identical in magnitude across gender.

Note also that the other coefficients in the model hardly change relative to the model in the first column.

These results are somewhat at odds with some of the findings in the literature, e.g. those in Anderson et al. (1980), Clark et al. (1980), and Henretta and O'Rand (1980), who all use RHS data and find that while husbands tend to substitute own care by purchased care, wives do the opposite and actually withdraw earlier from the labor market when their husbands are in poor health. Our results, which indicate symmetry by gender in the cross-effects of health, are more in line with the findings in the later studies by Pozzebon and Mitchell (1989) and Blau (1997), who also use RHS data. To investigate the reason for this difference, we next estimate conventional univariate duration models for the wives and the husbands, separately. The results appear in Table 4. In this case, our results actually agree with the earlier literature, in particular with respect to the asymmetry in the health effects. However, in a LR test, the univariate models are rejected against the bivariate. Thus, the retirement decisions of husbands and wives are dependent and must be modeled as such, in particular allowing for joint retirement through inclusion of the couple's hazard. When doing so, the health effects are symmetric by gender.

Why does application of univariate models indicate an asymmetry in health effects by gender? Consider the specific new element introduced in the bivariate model, viz. the couple's hazard. From the first column of Table 3, both husband's and wife's good health reduce joint retirement. These negative effects on retirement tendency must in the univariate specification be captured in wife's and husband's own hazards. From Table 3, in the wife's own hazard, the effect of husband's good health is to increase retirement. By the symmetry test, this positive effect is actually not significantly different from the corresponding positive effect of wife's good health on the husband's hazard. However, the effect in itself is not very strong (t-statistic of 0.4) and when combined with the much stronger negative effect (t-statistic of -2.8) of husband's good health through the couple's hazard, it is actually a negative effect that the univariate model must explain. This shows up as the significantly negative effect (t-statistics of -2.0) of husband's good health on wife's retirement hazard in the univariate model in Table 4.

5 Conclusions

In this paper, we have introduced a flexible, semiparametric bivariate proportional hazard model of the joint distribution of the durations until wife's and husband's retirement. The key feature of the model is the use of a separate family-wide hazard rate governing the incidence of joint retirement. This gives the correlation between durations an easy economic interpretation and empirically captures the effects of assortative mating, correlation between unobserved preferences, and complementarities in leisure. This additional hazard rate represents a natural extension of the conventional use of separate univariate duration analyses for each spouse, and proves statistically significant, consistent with married couples' coordination of retirement dates. Using this framework, we confirm earlier findings of asymmetry between the effects of husband's and wife's incomes on their retirement hazards. As regards the cross-effects of health, the results of our analysis differ from those obtained using a traditional univariate analysis. The univariate analysis suggests that the husband tends to stay longer at work if the wife is in poor health, possibly to be better able to afford purchased care, whereas the wife tends to retire earlier if the husband is in poor health, possibly in order to substitute own for purchased care. On the other hand, results from the new bivariate joint retirement model (which nests the univariate models) indicate symmetry across gender: Both wife's and husband's retirement hazard is lowered when the spouse is in poor health.

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Table 1
Observed Bivariate Durations

1.a All Observations:

		Husband's duration:								
		1	2	3	4	5	6	7	8	9
Wife's duration	1	47	0	8	0	9	0	7	0	3
	2	0	30	0	9	0	21	0	4	3
	3	7	0	135	0	25	0	20	0	39
	4	0	5	0	42	0	37	0	22	9
	5	4	0	48	0	52	0	30	0	34
	6	0	4	0	4	0	41	0	6	1
	7	1	0	17	0	11	0	62	0	12
	8	0	4	0	4	0	2	0	21	2
	9	5	3	19	3	9	1	14	2	80

1.b Non-Right-Censored Observations Only:

		Husband's duration:								
		1	2	3	4	5	6	7	8	9
Wife's duration:	1	3	0	6	0	8	0	2	0	0
	2	0	2	0	7	0	10	0	3	0
	3	0	0	20	0	20	0	12	0	19
	4	0	1	0	24	0	20	0	11	0
	5	1	0	11	0	23	0	19	0	12
	6	0	2	0	3	0	12	0	4	0
	7	0	0	4	0	5	0	20	0	4
	8	0	1	0	1	0	1	0	4	0
	9	0	0	2	0	3	0	2	0	9

Table 2
Descriptive Statistics

Variable	First Year		All Person-Years	
	Mean	Std. Dev.	Mean	Std. Dev.
Health-Husband	.7812	.4134	.7331	.4423
Health-Wife	.9387	.2400	.7957	.4032
Logincome-Husband	8.3773	2.6910	7.9754	2.5974
Logincome-Wife	6.4134	3.0140	6.3229	2.8765
Age-Husband	60.0000	.0000	64.9767	2.3187
Age-Wife	56.3241	3.4169	61.0250	4.0167

Table 3
Estimated Coefficients under Different Parameter Restrictions
(Semiparametric Bivariate Proportional Hazard Model)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Husband's Hazard:							
Health-Husband	-.439	-.449	-.379	-.438	-.382	-.408	-.465
	(-3.787)	(-3.664)	(-3.329)	(-3.670)	(-3.375)	(-3.770)	(-4.785)
Health-Wife	.316	.261	——	.305	——	——	.229
	(2.218)	(1.757)	——	(2.083)	——	– —	(2.137)
Logincome-Husband	-.046	-.047	-.034	-.046	-.033	-.029	-.041
	(-2.381)	(-2.274)	(-2.306)	(-2.520)	(-2.274)	(-2.070)	(-2.421)
Logincome-Wife	.030	.040	——	.030	——	——	.033
	(1.584)	(1.993)	——	(1.554)	——	– —	(2.522)
Agediff	-.087	-.093	——	-.087	——	——	-.085
	(-3.718)	(-3.732)	——	(-3.651)	——	– —	(-4.018)
Dum6264	-.983	-.791	——	-.980	——	——	-.970
	(-5.857)	(-4.491)	——	(-5.691)	——	– —	(-6.136)
Dum65up	-1.626	-1.453	——	-1.629	——	——	-1.604
	(-5.876)	(-5.111)	——	(-5.809)	——	– —	(-5.909)
Wife's Hazard:							
Health-Husband	.086	-.162	.093	——	——	——	-.465
	(.426)	(-.971)	(.471)	——	——	– —	(-4.785)
Health-Wife	-.594	-.575	-.646	-.992	-1.025	-.930	.229
	(-2.479)	(-3.031)	(-2.984)	(-5.795)	(-5.540)	(-6.218)	(2.137)
Logincome-Husband	-.121	-.097	-.119	——	——	——	-.137
	(-4.515)	(-3.602)	(-4.274)	——	——	– —	(-6.824)
Logincome-Wife	.090	.099	.093	.039	.043	.046	.080
	(3.117)	(3.484)	(3.420)	(1.661)	(1.834)	(1.891)	(3.087)
Agediff	-.167	-.168	-.160	-.174	-.167	-.174	-.173
	(-5.106)	(-5.130)	(-4.663)	(-5.341)	(-5.134)	(-6.673)	(-5.413)
Dum6264	1.191	1.390	1.218	1.086	1.115	1.272	1.149
	(5.597)	(7.051)	(5.722)	(5.281)	(5.577)	(7.693)	(6.314)
Dum65up	.558	.424	.688	.383	.508	.292	.481
	(1.507)	(1.242)	(1.889)	(1.069)	(1.354)	(1.022)	(1.487)
Couple's Hazard:							
Health-Husband	-.401	——	-.461	-.402	-.456	——	-.421
	(-2.753)	——	(-3.088)	(-3.062)	(-3.060)	– —	(-3.145)
Health-Wife	-.293	——	-.198	-.191	-.091	——	-.315
	(-1.658)	——	(-1.049)	(-1.139)	(-.491)	– —	(-2.202)
Logincome-Husband	-.127	——	-.124	-.132	-.131	——	-.124
	(-5.516)	——	(-6.382)	(-6.027)	(-5.466)	– —	(-6.658)
Logincome-Wife	.115	——	.113	.109	.107	——	.117
	(4.486)	——	(4.504)	(4.421)	(3.819)	– —	(9.424)
Agediff	-.142	——	-.160	-.141	-.158	——	-.142
	(-5.025)	——	(-5.114)	(-4.709)	(-8.243)	– —	(-4.811)
Dum6264	1.451	——	1.376	1.445	1.370	——	1.455
	(7.876)	——	(7.267)	(7.973)	(7.669)	– —	(8.225)
Dum65up	.522	——	.265	.536	.289	——	.528
	(1.665)	——	(.764)	(1.692)	(1.091)	– —	(1.710)
log likelihood	-2368.805	-2481.533	-2394.925	-2376.630	-2402.648	-2511.208	-2369.607
# of parameters	45	38	40	43	38	31	43

Table 4.
Estimated Coefficients under Different Parameter Restrictions
(Semiparametric Univariate Proportional Hazard Model)

Husband's Hazard:					
Health-Husband	-.400	-.380	-.352	-.400	-.352
	(-4.313)	(-5.445)	(-3.829)	(-4.271)	(-3.795)
Health-Wife	.215	-.008	——	.215	——
	(1.893)	(-.110)	——	(1.889)	——
Logincome-Husband	-.059	-.049	-.016	-.059	-.016
	(-3.610)	(-3.988)	(-1.251)	(-3.420)	(-1.274)
Logincome-Wife	.075	.085	——	.075	——
	(4.411)	(6.046)	——	(4.369)	——
Agediff	-.083	-.079	——	-.083	——
	(-4.207)	(-4.249)	——	(-4.219)	——
Dum6264	-.315	-.293	——	-.315	——
	(-2.474)	(-2.357)	——	(-2.478)	——
Dum65up	-.832	-.794	——	-.832	——
	(-4.041)	(-3.978)	——	(-4.077)	——
Wife's Hazard:					
Health-Husband	-.195	——	-.195	——	——
	(-1.957)	——	(-1.913)	——	——
Health-Wife	-.371	——	-.371	-.634	-.634
	(-3.048)	——	(-3.004)	(-6.156)	(-5.746)
Logincome-Husband	-.092	-.103	-.092	——	——
	(-4.978)	(-6.518)	(-4.649)	——	——
Logincome-Wife	.110	.107	.110	.053	.053
	(5.489)	(6.583)	(5.373)	(3.415)	(3.073)
Agediff	-.139	-.140	-.139	-.146	-.146
	(-6.033)	(-6.207)	(-5.864)	(-6.741)	(-6.396)
Dum6264	1.586	1.566	1.586	1.432	1.432
	(11.086)	(10.927)	(11.150)	(10.404)	(9.942)
Dum65up	.827	.790	.827	.598	.598
	(3.709)	(3.502)	(3.563)	(2.826)	(2.570)
loglikelihood	-2462.289	-2465.515	-2482.847	-2477.803	-2498.361
# of parameters	30	28	25	28	23

Figure 1. Dynamic Decision Tree and Transition of States

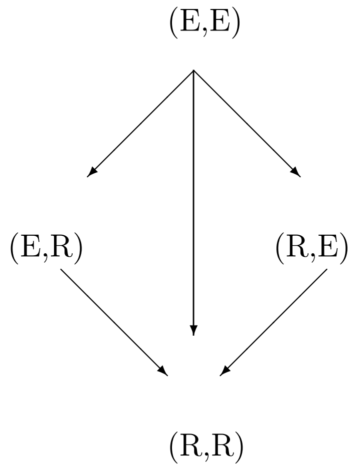


Figure 2.a Grouped Bivariate Durations (All Couples)

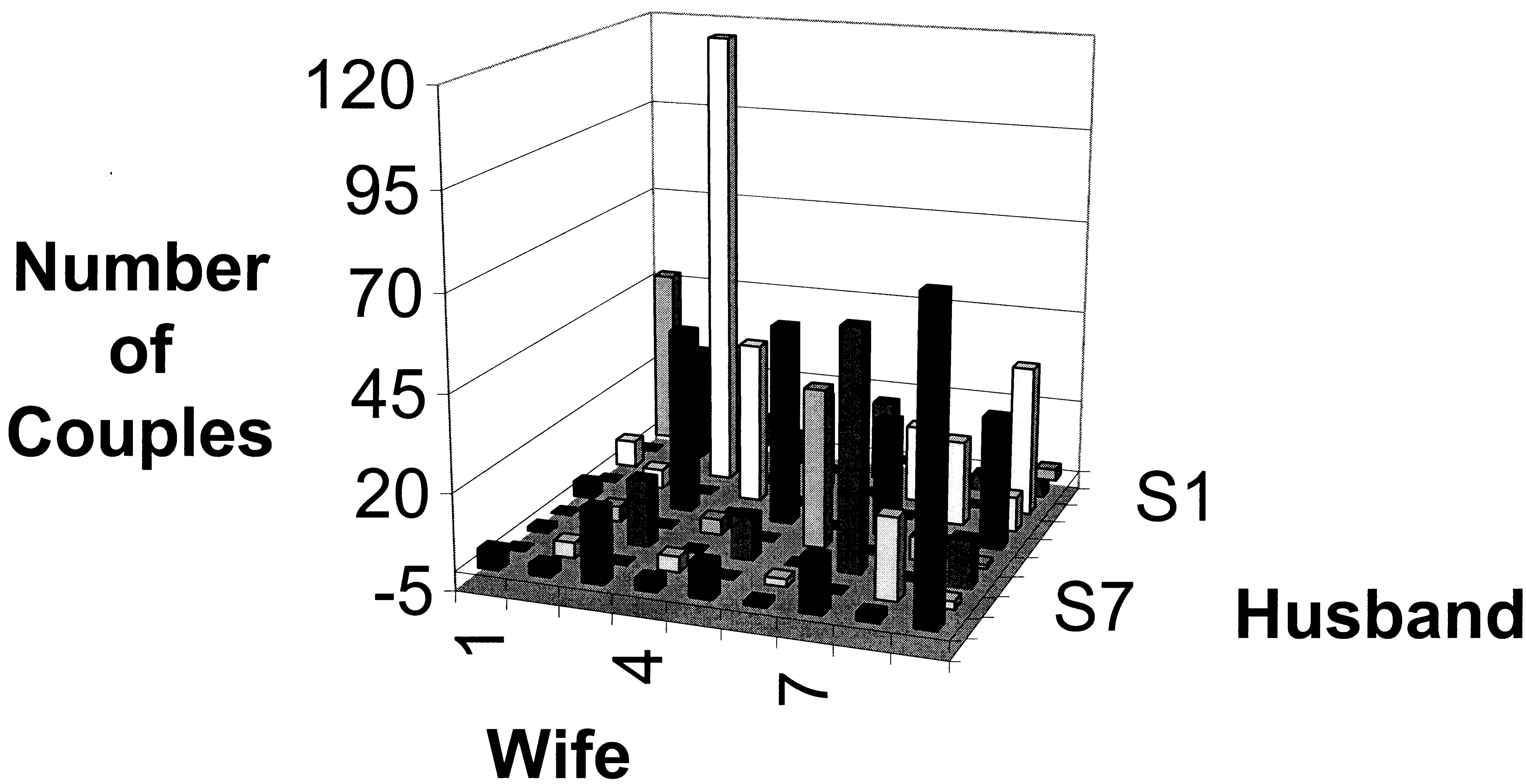


Figure 2.b Grouped Bivariate Durations (Completed Spells Only)

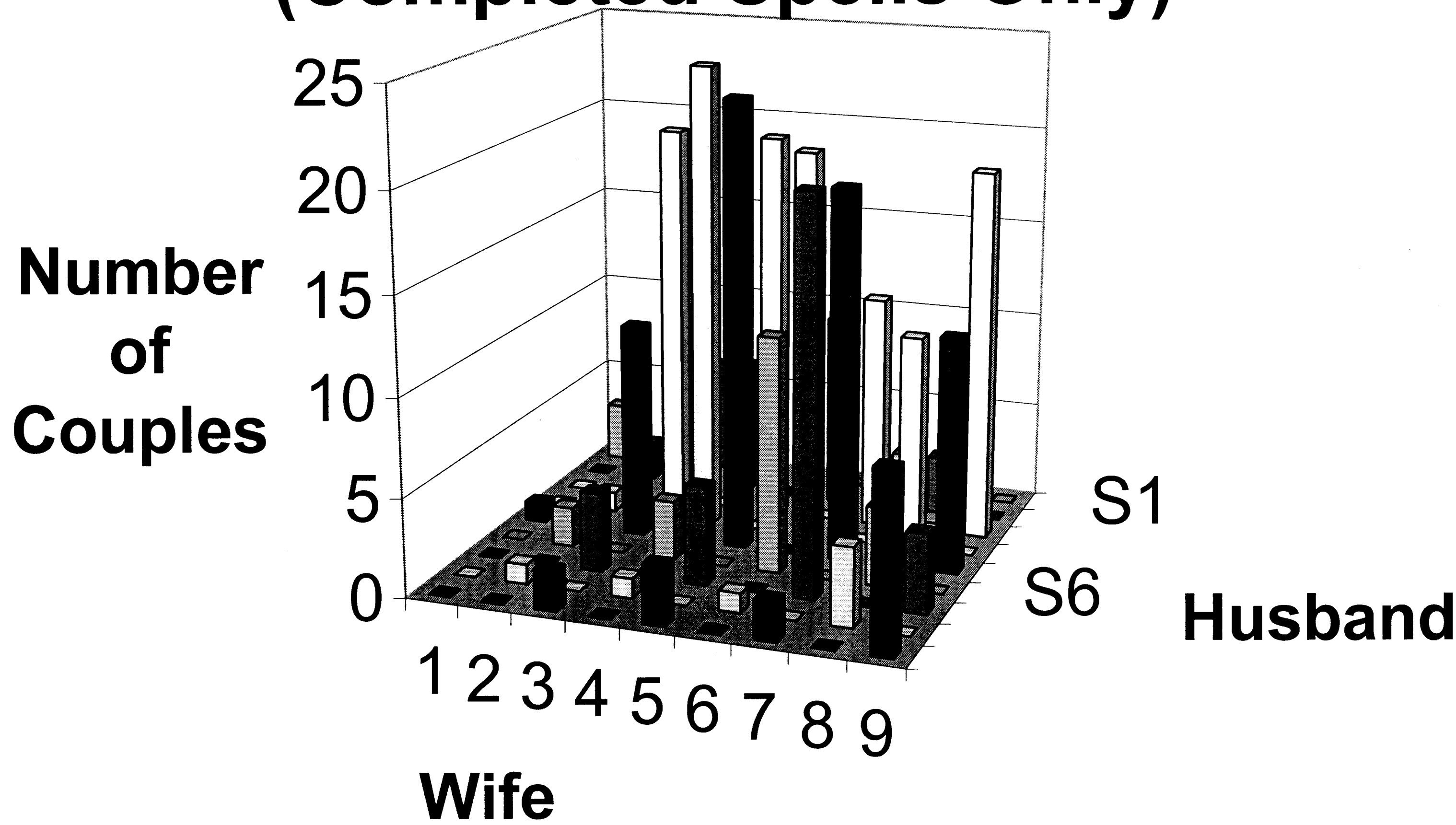


Figure 2.c Kaplan-Meier Estimates of Bivariate Survivor Function

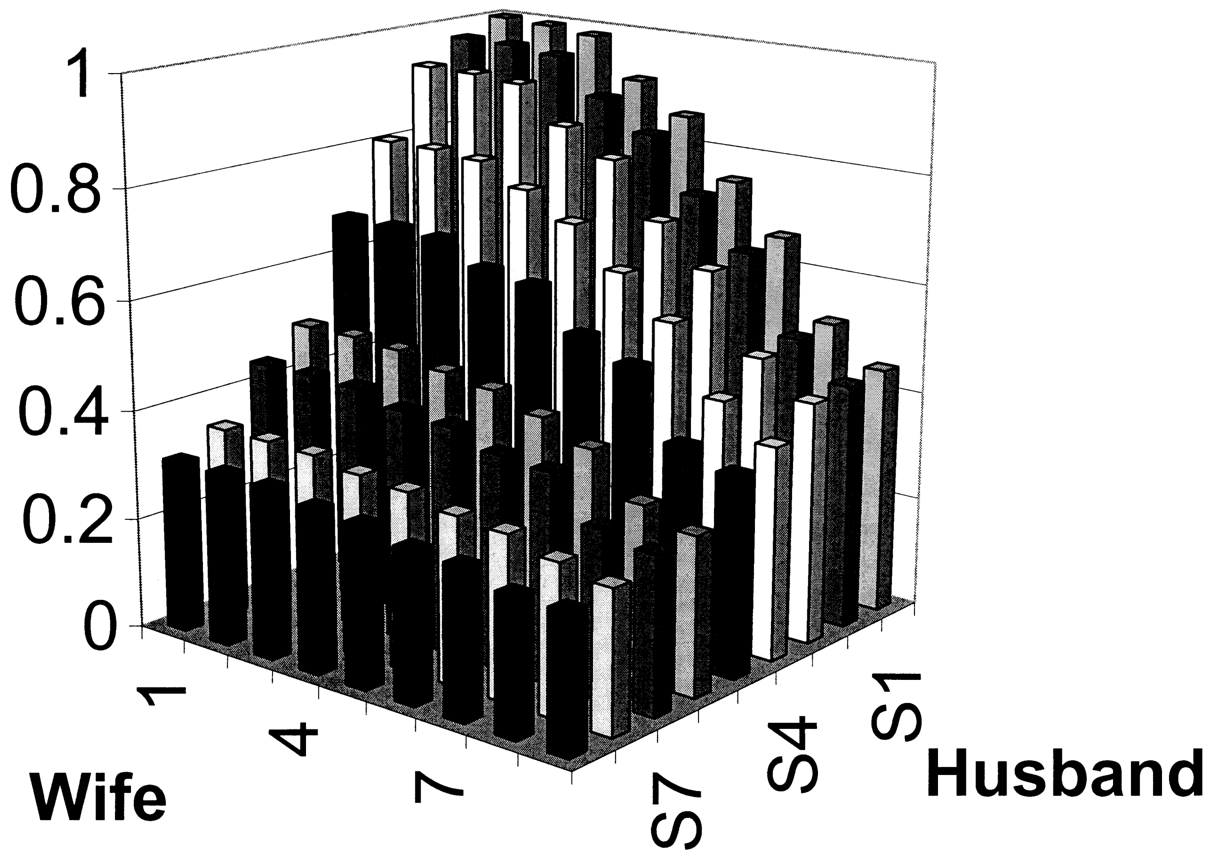


Figure 2.d Kaplan-Meier Estimates of Bivariate Hazard Function

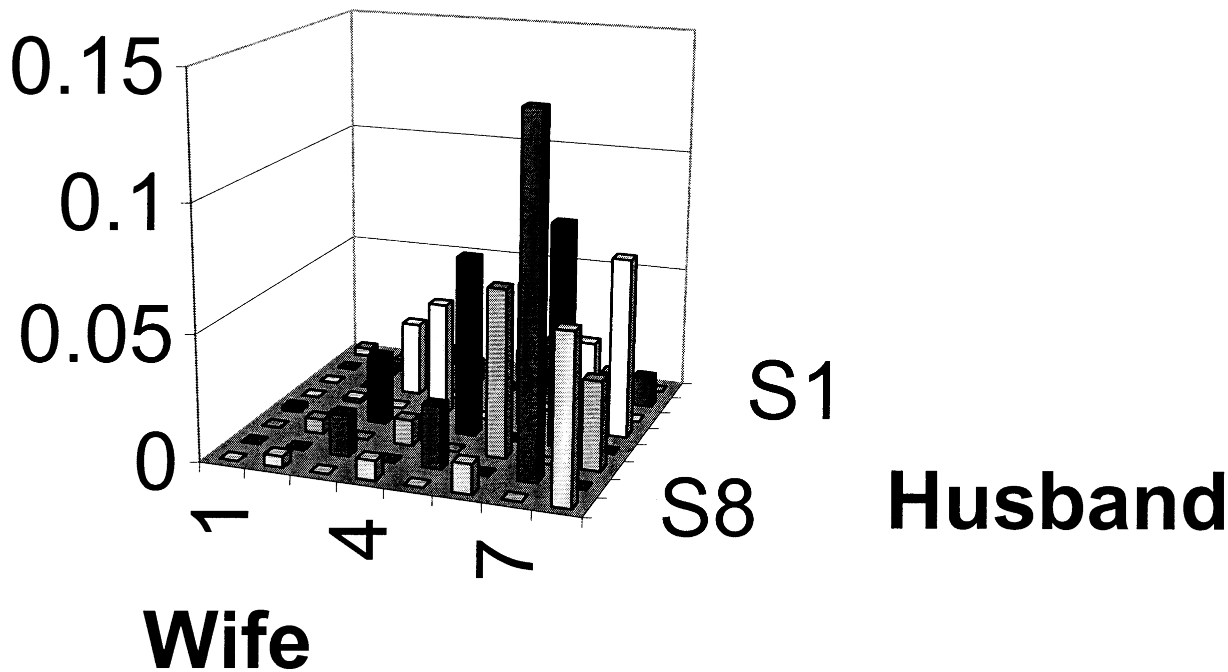
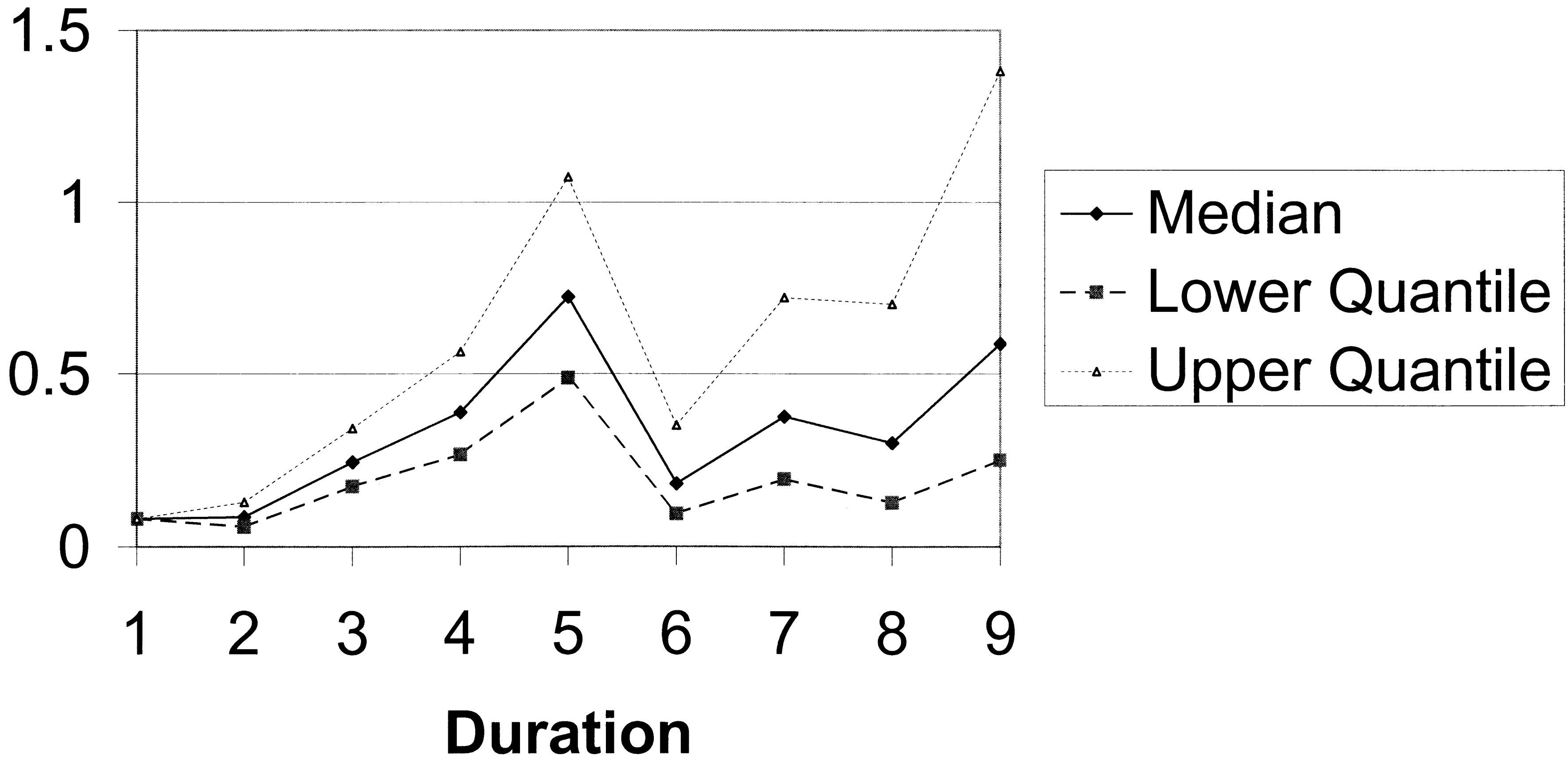


Figure 3.a Baseline Hazard (Husband)



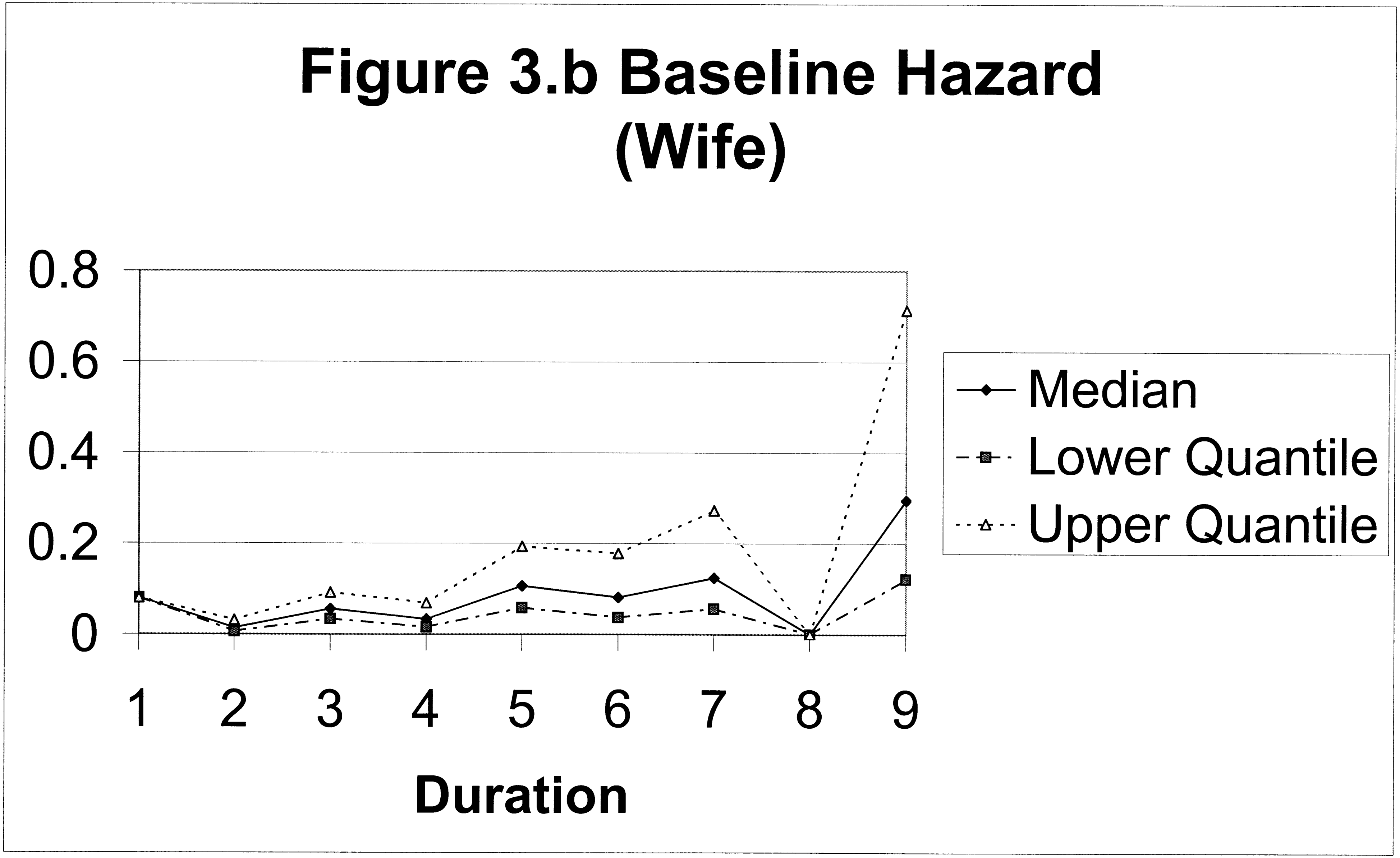
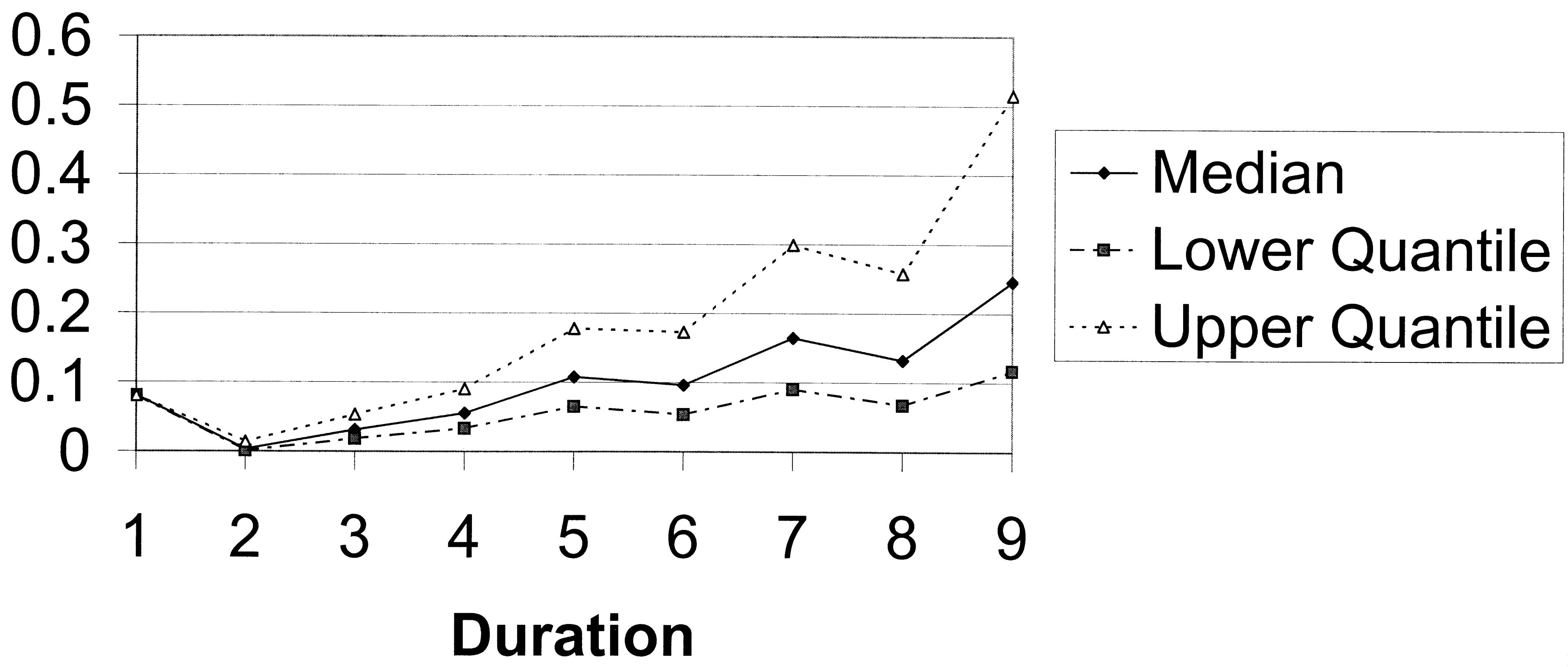


Figure 3.b Baseline Hazard
(Wife)
0.8
0.6
0.4
0.2
0
Median
Lower Quantile
Upper Quantile
1
2
3
4
5
6
7
8
9
Duration

Figure 3.c Baseline Hazard (Couple)



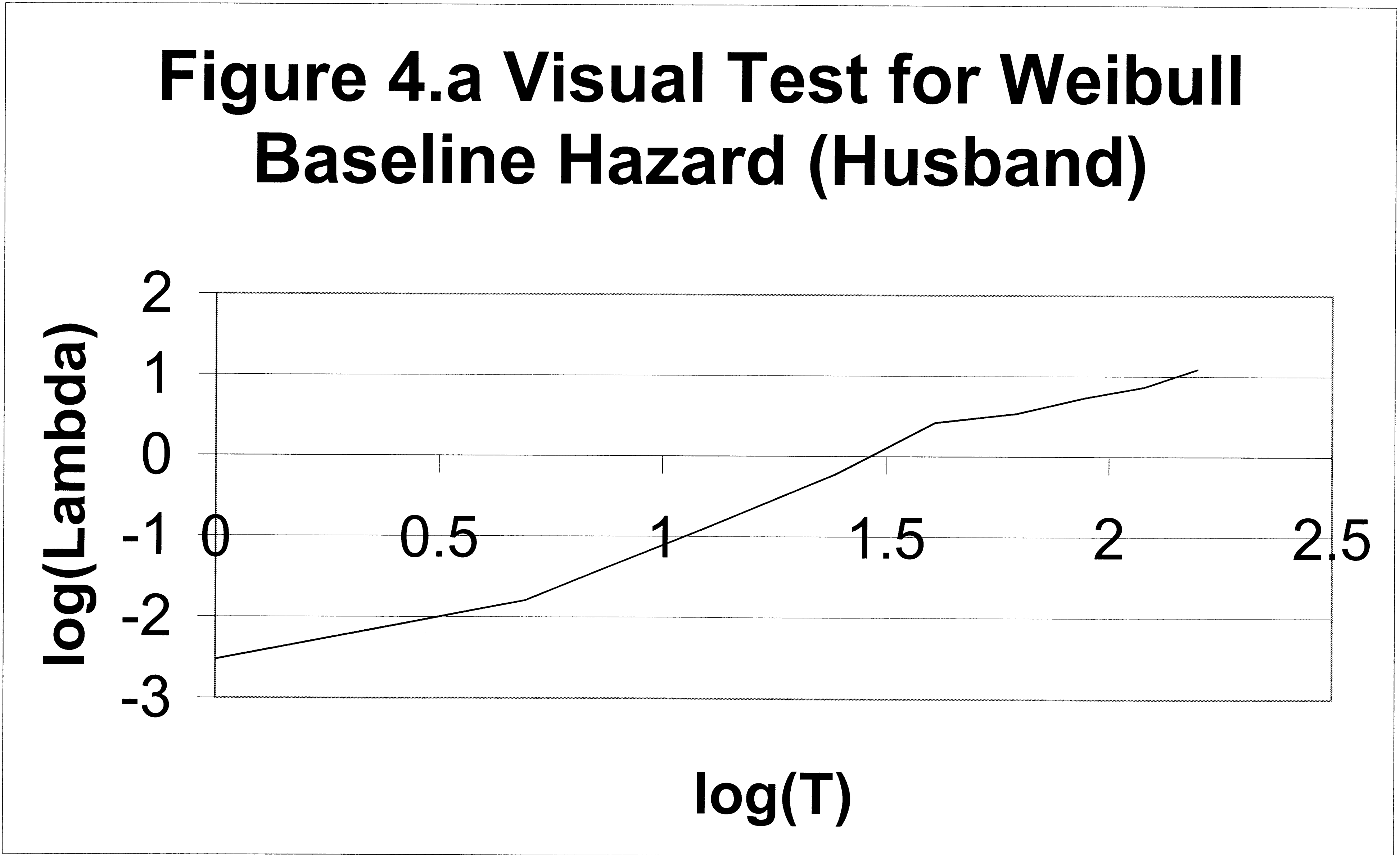


Figure 4.a Visual Test for Weibull Baseline Hazard (Husband)
log(Lambda)
2
1
0
-1
-2
-3
0
0.5
1
1.5
2
2.5
log(T)

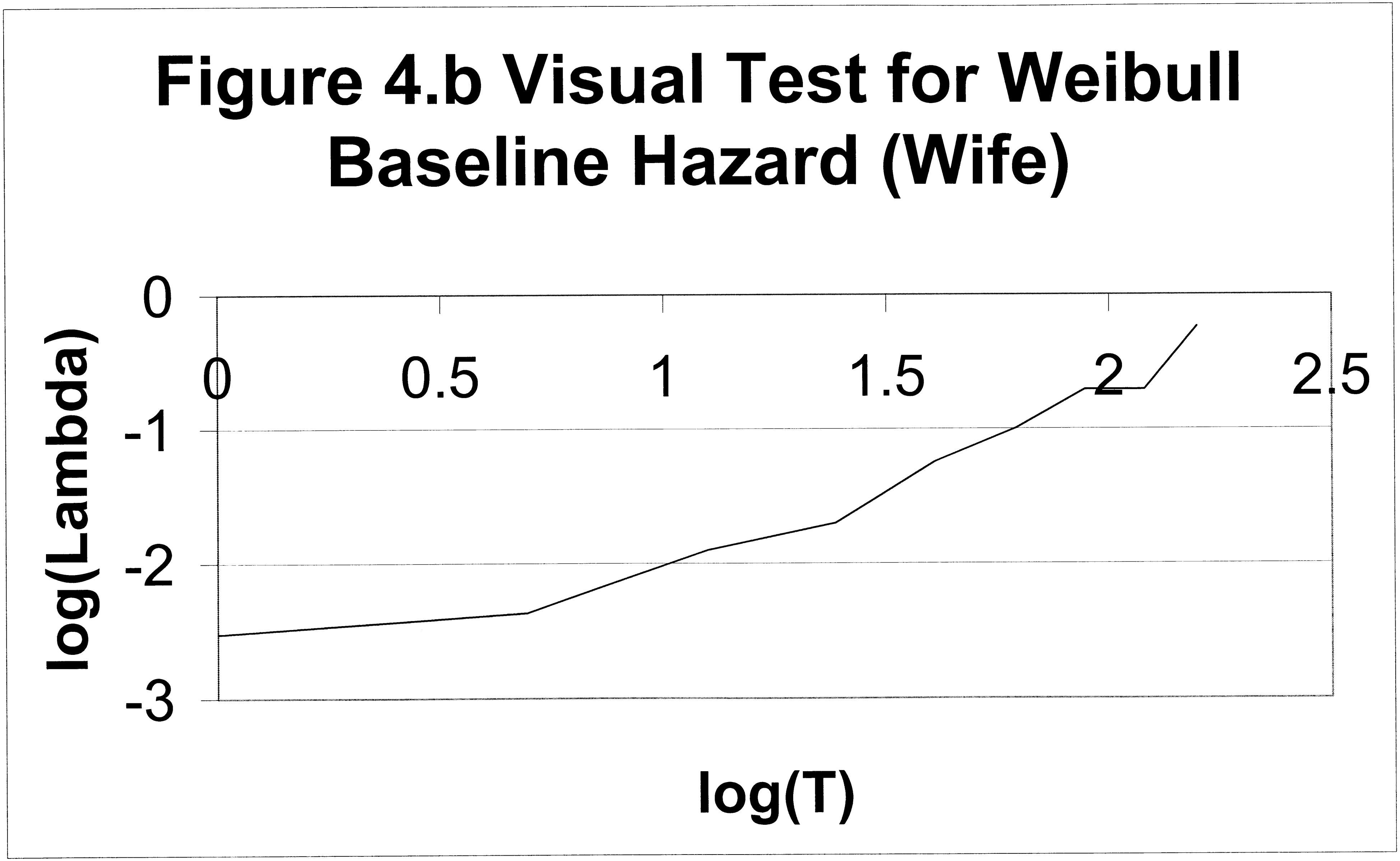


Figure 4.b Visual Test for Weibull Baseline Hazard (Wife)
0
-1
-2
-3
log(Lambda)
0
0.5
1
1.5
2
2.5
log(T)

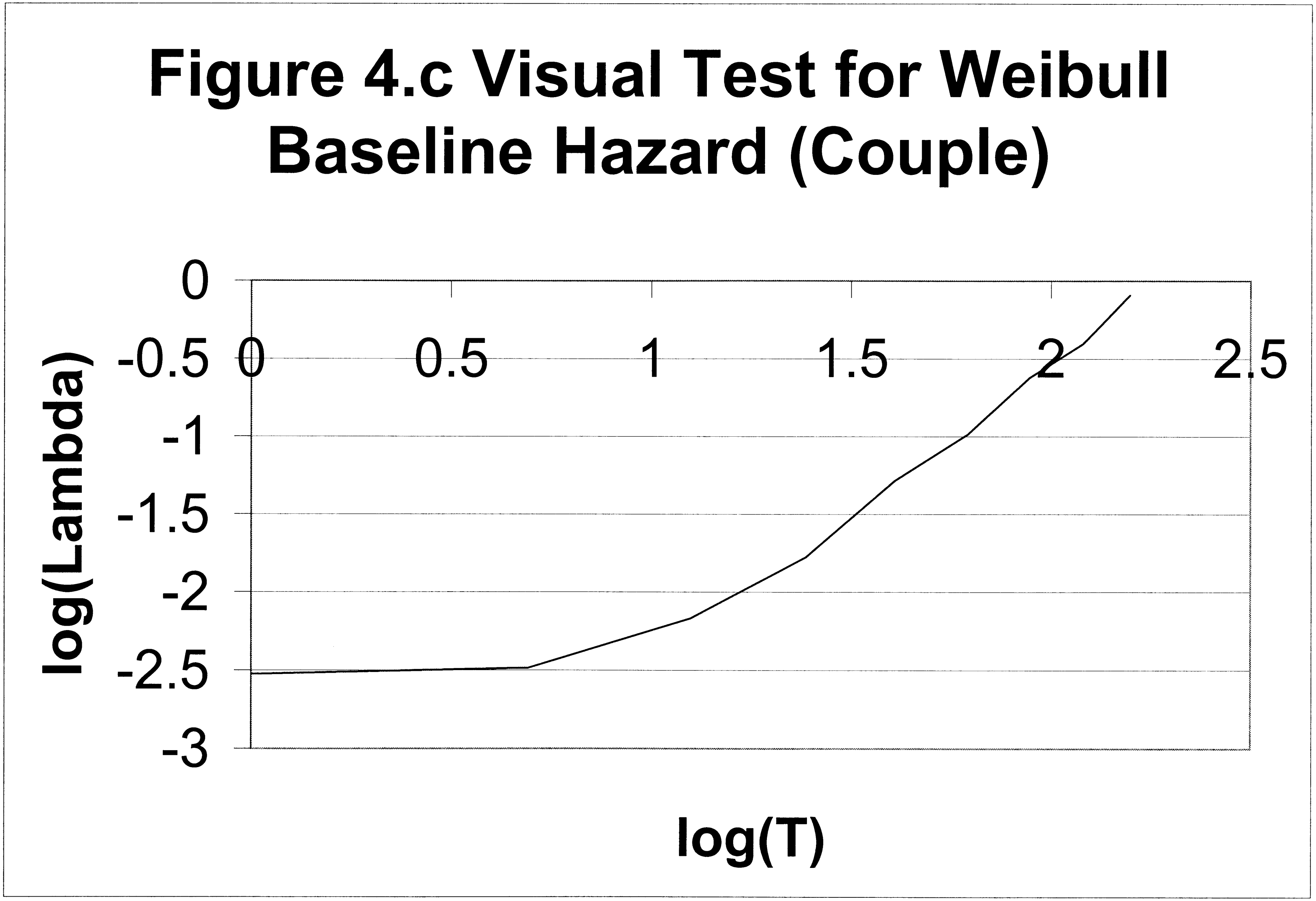


Figure 4.c Visual Test for Weibull Baseline Hazard (Couple)
0
-0.5
-1
-1.5
-2
-2.5
-3
0
0.5
1
1.5
2
2.5
log(Lambda)
log(T)