Marital Dissolution among Young Americans: The Role of Income Variables and Past Family Formation Behaviour

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Abstract

This paper presents an econometric model of marital dissolution using data on young American women. A distinguishing feature of this paper is that the initial conditions (the family formation process leading up to divorce) are modelled explicitly, and thus included as covariates in the divorce transitions. A considerable advantage of this approach is that marriage (and divorce) and fertility are modelled in a joint econometric framework. The paper examines how economic variables affect marital dissolution. In addition to the respondent's predicted wages, welfare benefits, and family income, we introduce a new income variable which represents the respondent's earnings capacity (or quality) which is unlikely to be fully anticipated by the partner at the time of marriage. The model is estimated using data on young American women from the NLSY. The results indicate that the respondent's earnings quality tend to be positively associated with divorce, whereas positive values of the spouse's earnings quality is negatively associated with divorce. Quality has relatively little explanatory power when there is no marital specific capital present in the household. The other income variables are also found to be important determinants of divorce. Furthermore, the results indicate that past family formation transitions are crucial in determining marital dissolution[1].

JEL classification: J0, J1

1. Introduction

The rise in marital dissolution is one of the most striking features of the changing patterns of family formation in Western societies. As a result, a considerable amount of research into the determinants of divorce has taken place over the last two decades. The first rigorous economic analysis of marital dissolution was undertaken by Becker et al (1977 [2]). They expressed an individual's divorce behaviour in terms of marital strategies of which marriage and fertility decisions are crucial components. A distinguishing feature of the econometric framework presented here is that the family formation process leading up marital dissolution is modelled explicitly. This means that individuals' marital strategies, including divorce, are incorprated in one unified econometric model - a feature that makes it possible to analyse the impact of past family formation transitions on divorce directly.

Becker et al emphasise, however, that most divorce decisions are unlikely to be part of individuals' utility maximising behaviour. More important, they argued, is the stochastic nature of the outcomes that affect marital traits over time. If realised outcomes deviates sufficiently from what is expected, then the gain to marriage may have fallen to an extent where the individual will reconsider their original decision to marry. They consider therefore not only the probability of divorce as a function of the expected gain to marriage, but also the distribution of a random variable describing unexpected outcomes. The probability of divorce is smaller the greater the expected gain from marriage, and the smaller the variance of the distribution of unanticipated gains from marriage. In this analysis we capture this aspect of marital dissolution by constructing a variable that measures the earnings quality of the wife (the respondent) and of the husband. This variable is defined as the difference between the actual and predicted wage rate and captures how well (or how bad) an individual is performing in the labour market compared to the average level of his or her kind.

Another feature of the analysis by Becker et al, is the importance children as marital specific capital, and its effect on marital dissolution. Our econometric framework allows divorce before and after childbearing to be different processes. This means that we are able to avoid the bias caused by endogeneity of children with respect to divorce. The results suggest that divorce behaviour is significantly different when children are not present in the household.

We find that the respondent's earnings quality tend to be positively associated with divorce, whereas positive values of the spouse's earnings quality is negatively associated with divorce. Quality has relatively little explanatory power when there is no marital specific capital present in the household. The other income variables are also found to have an important effect on divorce. Goodness-of-fit tests show that the econometric model performs quite well.

The paper is outlined as follows. Section 2 gives an overview of important contributions to the literature. Section 3 outlines the econometric specification and the NLSY sample. Section 4 discusses important empirical issues as well as construction of the covariates. Section 5 presents the results. Section 6 provides a simulation analysis, whereas section 7 concludes.

2. Previous research

Becker et al.(1977[2]) analysed divorce with respect to age at marriage, education, and different measures of the respondent's earnings. They found husband's earnings to be negatively related to divorce, increase the probability of remarriage, but reduce the likelihood of divorce in subsequent marriages. An increase in the wife's earnings was found to increase the probability of divorce. Different variables were constructed to measure unexpected changes in earnings and their general finding was that these variables had an important impact on marital dissolution. They also found some evidence to support that search and match quality affect marital stability. Individuals who married at a relatively young age, presumably after a relatively short search period, were more prone to marital dissolution, whereas no strong and conclusive effects of educational attainment were found[2].

Weiss & Willis (1997[18]) use the National Longitudinal Survey of High School Class of 1972 to analyse the impact of unexpected deviations in earnings capacity on marital dissolution. The earnings surprises are constructed by taking the difference between Predicted earnings[3] at the time of marriage and at time t which is based on new information accumulated after the marriage took place.

[2] A drawback of the empirical analysis by Becker et al was that they had no longitudinal information on earnings, which made it hard to distinguish between divorces caused by initial bad matches and divorces triggered by surprises in traits that would influence the gain to marriage over time. This problem is to a large extent resolved in Weiss & Willis (1997).

[3] Predicted earnings are constructed from the individuals' work history, time spent in school, highest degree attained, plus a set of variables capturing personal characteristics and family background.

Their findings suggest that an unexpected increase in husbands earnings capacity reduces the likelihood of divorce whereas an unexpected increase in the wife's earnings makes divorce more likely. They also find that at higher levels of the wife's earnings capacity, any increase in husbands earnings capacity will be less effective in reducing the probability of divorce. Simulations show that the most disruptive event is when the husband suffers a negative surprise at the same time as the wife experiences a positive surprise. In contrast to the earnings surprise measure they find that predicted earnings at the time of marriage have only weak effects on marital dissolution.

In terms of search effort and match quality they find that couples with similar level of schooling are less likely to experience a divorce. Similarly, partners of same ethnicity or religion are less likely to divorce. They also find that cost of divorce has a significant impact on dissolution. For instance, presence of marital specific capital, most noticeable children, tend to reduce the risk of dissolution. The results show that presence of young children has the strongest effect, whereas the effect of older children is smaller. A large amount of property reduce the likelihood of divorce. Dissolution also depends on the legal regime. States that put less weight on fault considerations tend to have a higher incidence of divorce. Individuals who marry at a young age are much more likely to experience a divorce and it is more likely at the earlier stages of the marriage.

Duncan & Hoffman (1993[13]) use PSID data from 1968 to 1987 to estimate the effects of the wife's wage rate, husband's income level, AFDC receipts, and child support on marital dissolution[4]. They use a three alternative competing risk model in which they distinguish between two different divorce states, one where the woman receives AFDC and one where she does not[5].

They find husband's income to have a strong stabilising effect on marriage, whereas the wife's wage rate has a destabilising effect. AFDC receipts are found to have a positive and significant effect on divorce, whereas AFDC-UP eligibility has no effect[6]. The level of child support received from the husband has no significant effect on the likelihood of divorce. A range of other background variables, as well as age and duration effects, are also included, all of which conform to previous

[4] Child support payments are not observed for non-eligible individuals. Likewise, wages are not observed for non-working respondents. As a result these variables are instrumented by separate equations. The predicted values from these equations were used in the divorce equation.

[5] This model was estimated by a nested logit procedure.

[6] AFDC-UP is a welfare benefit available to couples with dependent children with low income. It is hypothesised that this should have a negative effect on divorce as it increases the income within marriage.

Table 3.1: Family states

State 1:	[Not Married , No Children (NM,K0)]
State 2:	[Married , No Children(M,K0)]
State 3:	[Not Married , One Child (NM,K1)]
State 4:	[Married , One Child(M,K1)]
State 5:	[Not Married, Two Children (NM,K2)]
State 6:	[Married, Two Children (M , K2)]

findings in the literature.

Bőheim and Ermisch (1999[5]) provide further evidence on the effect of financial surprises on partnership dissolution by using the British Household Panel Survey (BHPS). They estimate a discrete time transition model of the divorce event, including a range of background variables. The surprise variable is constructed by using information on individuals' one-year-ahead expectations and the actual outcome of their financial situation. They find that favourable surprises tend to stabilise marriage, whereas no significant effect is found from negative surprises[7].

3. Econometric specification

In this econometric model the family formation process is modelled by six mutually exclusive discrete family states (table 3.1), where these are defined by the fertility and marital status of each individual. All individuals start the family formation process in State 1 (single and without children) and it is assumed that individuals start this process at age thirteen. Over time individuals will move between the different states listed in table 3.1. The transitions between states are recorded by their exact dates which implies that a transition from state 1 to state 4 is not possible[2], nor is a transition from state 4 to state 5 possible. Child births are treated as irreversible events implying that a transition from state 4 to state 2 or a transition from state 3 to state 1 is not possible. Child mortality in this sample is small and consequently ignored. It is assumed that the child always stays with the mother in case of a divorce.

[7] Marital dissolution has been a frequent research topic among sociologists and demographers. Although this literature tend to put less emphasis on the association between economic variables and marital stability, they do provide useful insights to the role played by other background variables. See Aassve (2000[1]) for a detailed survey of this literature.

[2] The remote possibility that child birth and marriage takes place at the same day is ignored.

Table 3.2: Family formation transitions

Transition 1:	State 1 → State 2 (f)
Transition 2:	State 1 → State 3
Transition 3:	State 1 → State 2 (s)
Transition 4:	State 2 → State 1
Transition 5:	State 2 → State 4
Transition 6:	State 3 → State 4
Transition 7:	State 3 → State 5
Transition 8:	State 4 → State 3
Transition 9:	State 4 → State 6

There are two types of marriage transitions from state 1; transition to marriage first time, and any subsequent transitions to marriage after divorce (return to state 1) has taken place. This structure generates nine distinct family formation transitions (table 3.2). The table shows that marriage can be reached through transitions 1, 3, and 6, first birth reached through transitions 2 or 5, second birth is reached through transitions 7 and 9, and finally and crucial for this analysis, divorce through transitions 4 and 8. This means that divorce can take place before child bearing or after, each being a specific transition. The family formation process is analysed up until second birth implying that states 5 and 6 are absorbing. Individuals become right censored at the state they occupy at the end of the survey period if none of the absorbing states have been reached.

We define continuously distributed latent variates T_{ij}^r associated with the risk at the rth transition of moving from state i to state j, with $i,\, j \in \mathcal{S} = \{1, 2, 3, 4, 5, 6\}$, $r \in \{1, 2, 3, \ldots\}$. In order to keep the model tolerably simple, and in view of the limits on the information contained in the data, the conditional distributions (given covariates to be introduced shortly) of the variates T_{ij}^r are restricted to have distribution functions $F_{ij}^r(\cdot|\cdot)$ satisfying $F_{ij}^r(\cdot|\cdot) = F_{ij}^s(\cdot|\cdot)$ for $r, s > 1$ and all $i,\, j \in \mathcal{S}$.

The hazard functions associated with these variates are denoted by

$$h_{ij}^r(s|x(s), v^r) \qquad i,\, j \in \{1, 2, 3, 4, 5, 6\}, r \in \{1, 2, 3, ...\}$$

where $x(s)$ is a vector of covariates, some of which may be time varying, and v^r is a realisation of a transition number specific time invariant random variable, V^r, included to capture the influence of unmeasured covariates varying across individuals and assumed to be distributed independently of the observed covariates.

The corresponding conditional integrated hazard functions are denoted by

$$I_{ij}^r(t|x(t), v^r) = \int_0^t h_{ij}^r(s|x(s), v^r)ds.$$

In this competing risks model transition r from state i to state k is regarded as occurring if $T_{ik}^r = \min_{j\neq i, j\in\mathcal{S}}(T_{ij}^r)$. Accordingly the probability of exit from state i to state k at transition r in the age interval $(t, t+dt)$ conditional on observed and unobserved covariates is (see e.g. Lancaster [14]):

$$h_{ik}^r(t|x(t), v^r)\exp\left(-\sum_{j=1}^{k} I_{ij}^r(t|x(t), v^r)\right)dt.$$

The effect of unobserved heterogeneity in duration analysis is well documented and here we find unobserved heterogeneity to have important effects on the estimated parameters. Earlier findings suggest that estimation results may be sensitive to the distribution function is used for v (see Heckman and Singer (1984[12])). We use a non-parametric approach which does not require an explicit distribution function of the unobserved heterogeneity term v. The distribution of V is modelled as a univariate discrete distribution where two or three points of support v are allowed with associated probability masses p. The expected value of V is required to be zero implying and entails introduction of a constant “covariate” in $x(t)$. This is similar to the non-parametric mass point specification employed by Heckman and Singer (1984) but note that in this specification there is no search for a likelihood maximising number of mass points. The masspoints will capture any unobserved heterogeneity which may arise from a range of different sources. Individuals with low values of V can be regarded as “stayers” whereas high values of V reflect ”mover” behaviour. It was not possible to estimate a distribution with more than three points of support for each set of transitions. In total 14 masspoints were estimated[3].

[3] The univariate specification implies that unobserved heterogeneity is assumed uncorrelated across spells. However, it is likely that being a ”stayer” or a ”mover” may be a personal characteristic that persists through time. In order to allow for correlation across spells we experimented with two random variables V^1 and V^2, where these were specified as a multivariate discrete distribution with two potential values for each variate. A bivariate specification was implemented and evidence of correlation across spells were found. But there is a problem in allowing for across-spell correlation in the unobserved heterogeneity terms. This arises from the fact that the unobserved heterogeneity may itself be correlated with the duration variables used as covariates. Earlier results showed that the coefficients associated with the duration variables

3.1. The NLSY sample

The data used in this analysis comes from the National Longitudinal Survey of youth (NLSY). This is a panel data set 12686 persons aged between 14 and 22 years of age when first interviewed in 1979. In this work we have used data from 1979 to 1992 on a sample of 3737 women. Missing values are reduced by implementing the data cleaning procedures as suggested in Cole & Curry (1994[9]). The sample consist of three race groups: Hispanics, blacks and whites, where the former is used as reference group in the estimation. Out of the final sample about 75 percent lived with both biological parents at age 14. About 30 percent of the individuals have mothers who had at least one teenage birth and 47 percent have mothers with less than 12 years of education. 43 percent of the sample had completed college at the end of the survey period, whereas 45 percent had only completed high school. 13 percent of the sample are classified as high school drop-outs. Some of the income variables have been re-scaled in order to make the estimation easier[4].

The data reveal quite different patterns of the family formation process with respect to the different race groups. Black women marry later than both Hispanics and whites and Hispanics marry at an earlier age than whites. Blacks have first premarital birth at a younger age than the other race groups. For second premarital birth there is no great difference between Hispanics and Blacks. Child bearing within marriage takes place on average three years later than child bearing outside wedlock and second child within marriage takes place 1.7 years after first birth. There is little difference in timing of the two divorce transitions, but it is interesting that mean age of divorce after child bearing is lower than divorces among couples who have no children.

Every individual in the sample is recorded with a "transition history". For instance the transition sequence "married - first child - second child" will produce transition history 1·2·4·6. Table 3.4 provides the frequency distribution of these sample transition types. The most common form of family formation is to become married followed by a first and a second child (transition type 1·2·4·6). 27.9 percent belong to this group. 13.8 percent of the sample do not make any transitions.

were significantly altered when correlation is allowed for in the unobserved heterogeneity terms. The specification with univariate masspoints avoids this problem and was therefore chosen as the preferred specifiaction.

[4] The estimation procedure is extremely sensitive to the set of starting values for the first iteration. It was felt easier to choose a good set of starting values when the continuous variables where rescaled in line with the dummy variables.

Table 3.3: Mean age for transitions

Age at:	**All**	**Whites**	**Hispanics**	**Blacks**
first transition	22.68	22.98	22.23	22.29
first marriage (prior to birth)	21.85	21.93	21.29	22.15
first marriage (after 1st birth)	22.29	22.08	21.49	22.89
first premarital birth	20.11	20.22	20.33	19.99
second premarital birth	22.96	23.71	22.68	22.75
first birth (married)	23.22	23.48	22.43	23.03
second birth (married)	24.92	25.05	24.64	24.76
divorce (no children)	24.87	24.94	24.14	25.25
divorce (one child)	24.42	24.16	24.56	25.21

A large proportion of the sample are right censored as only 50.8 percent of the sample reach the absorbing states (state 5 or state 6). 10.8 percent of the sample get married but have no children (history type 1·2) and 10.1 percent of the sample make transitions 1·2·4. Having children out of wedlock is a common event in this sample: 5.2 percent are recorded as having transition history 1·3 whereas 11.8 percent are recorded as transition type 1·3·5. Divorce takes place through any of the transition histories where there is either a movement from state 2 to 1 (before child bearing) or from state 4 to 3 (after child bearing). Out of this sample 12.5 percent experiences at least one divorce.

The transition type frequencies vary substantially between the three race groups. 11.4 percent of blacks have transition history 1· 3 whereas only 2.2 percent of whites belong to this group. The percentages show that black women are less likely to marry before first child birth. The most dramatic differences are for transition types 1·3·5 and 1·2·4·6. 31.1 percent of blacks are having both first and second child birth outside wedlock, whereas only 3.6 percent of white women follow this route. Only 11 percent of black women undertake the most common route of 1·2·4·6 compared to 33.2 and 36.1 percent for whites and Hispanics respectively.

4. Empirical issues

4.1. Earnings and predicted wages

We use predicted wages for two purposes in this analysis. First, since actual earnings are likely to be endogenous to marital status and fertility choice, we use the predicted wage as an exogenous measure of the individual's earnings ca-

Table 3.4: Sample transition histories. Simulated transition histories given in brackets.

	All	Whites		Hispanics		Blacks	
Transition type	Sample	Sample	Simul.	Sample	Simul.	Sample	Simul.
1	13.8	13.7	(11.6)	12.3	(10.4)	15.0	(12.3)
1·2	10.8	13.6	(13.0)	7.7	(8.8)	6.6	(4.7)
1·3	5.2	2.2	(1.1)	5.8	(2.2)	11.4	(7.4)
1·2·1	2.1	2.4	(3.5)	1.6	(2.1)	1.7	(1.6)
1·2·4	10.1	12.8	(12.8)	8.6	(10.9)	5.0	(5.4)
1·3·4	1.6	1.4	(1.3)	1.0	(1.5)	2.3	(2.7)
1·3·5	11.8	3.6	(4.2)	9.6	(12.3)	31.1	(33.1)
1·2·1·2	1.4	2.1	(1.6)	0.8	(1.0)	0.3	(0.3)
1·2·1·3	0.3	0.5	(0.2)	0.2	(0.2)	0.0	(0.3)
1·2·4·3	1.6	1.5	(1.2)	2.1	(0.7)	1.2	(0.9)
1·2·4·6	27.9	33.2	(34.8)	36.1	(32.3)	11.0	(13.0)
1·3·4·3	0.2	0.2	(1.3)	0.3	(1.8)	0.2	(3.4)
1·3·4·6	6.8	4.7	(3.0)	7.7	(4.7)	10.8	(4.5)
1·2·1·2·1	0.2	0.2	(0.1)	0.2	(0.0)	0.1	(0.1)
1·2·1·2·4	0.9	1.3	(1.3)	0.6	(0.7)	0.2	(0.2)
1·2·1·3·4	0.1	0.0	(0.0)	0.3	(0.1)	0.0	(0.0)
1·2·1·3·5	0.2	0.3	(0.1)	0.2	(0.1)	0.2	(0.3)
1·2·4·3·4	0.7	0.8	(0.7)	0.6	(0.6)	0.4	(0.2)
1·2·4·3·5	1.1	1.2	(0.7)	1.0	(1.1)	0.9	(0.6)
1·3·4·3·4	0.1	0.1	(0.7)	0.2	(1.0)	0.0	(0.8)
1·3·4·3·5	0.4	0.4	(1.2)	0.3	(2.8)	0.4	(4.8)
Other	2.9	3.7	(3.4)	3.1	(3.0)	1.0	(1.4)

pacity. These predicted wages are used as covariates in their own right in the family formation transitions leading up to divorce. In this case marital status and the number of children are excluded from the wage equation. Husband's actual earnings must be considered equally endogenous so we use predicted wages for husbands as well.

The other purpose is to use the predicted wage rate to construct our measure of the individuals' earnings performance. This measure is defined as the difference between an individual's actual wage rate and his/hers predicted wage rate and is referred to as the individual's earning quality. Note that in constructing this measure, marital status and children are included as covariates in the wage equation. The implication is that non-zero values of earnings quality are less likely to caused by changes in marital and fertility status. For instance, when the actual wage rate falls due to a birth, say, the predicted wage will also fall.

Although the NLSY sample used here contains 3737 individuals, we might still have groups with relatively small number of observations in which the predicted wages might be unreliable. Another problem associated with using the sample to predict wages is the possible bias generated by early exit of respondents into state 5 and 6 (the absorbing states). This means that the observed wage rates of the remaining sample (those who make transitions later) may not be representative for their age-group. Because of this we use data from the Current Population Survey (CPS) to generate predicted wages. The CPS, which contains around 60000 respondents, is likely to overcome both of these problems. We use a standard Mincerian earnings equation (Mincer (1974[15])) from which we map the predicted wages into the NLSY sample. For the respondents we apply a two step procedure in order to control for self-selection into the labour force. Individuals are defined to participate in the labour force if they report the usual hours worked in a week to be positive. The following covariates are included: age, age squared, years of schooling, race, urban/rural dummy, year and state dummies. For the predicted wages used to construct the earnings quality variable we also include marital status and children. The results conform well to the existing literature. Wages are positively associated with age but at a declining rate, whereas the coefficient on education is within the standard range reported in the literature. Living in an urban area increases the wage. Marital status has a positive effect on the spouse's earnings, whereas the presence of children tend to reduce female wages[5].

[5] The results from the estimated wage equations are available from the author on request.

4.2. Earnings quality

The individuals' earnings quality measure is defined as the difference between the realised wage and the predicted wage level at time t, where the latter is derived from the Current Population Survey. This measure of quality will reflect how much more or less the individual is earning compared to the average level and is unlikely to be fully anticipated by the partners at the time of marriage.

An important issue is to what extent individuals tend to interpret this measure as permanent shifts in earnings capacity, as opposed to being random and temporary deviations fluctuating around the predicted wage profile. If the latter is most frequent, and provided the deviations are not too large in magnitude, then we expect the earnings quality to have little impact on divorce. If, on the other hand, earnings quality is either above or below the predicted wage profile for several periods in sequence, then this becomes more likely to be perceived as a permanent shift, and thus we expect a stronger effect on the stability of the marriage. Another issue is to what extent individuals can anticipate their partner's earnings quality at the time of marriage. For instance if a woman knows or expect at the time of marriage that her spouse will be earning a wage that is higher than the average level of his kind, then positive values of the earnings quality will not imply a shift in her expectations, and consequently the effect on divorce should be small.

In order to explore whether the deviations between actual and predicted wages tend to be permanently above or below the predicted wage profiles we count the number of shifts between negative and positive values of these differences for each individual. A high number of shifts indicates "stationarity" (shocks are temporary and fluctuates around the predicted wage path), whereas a low number indicates "non-stationarity" (the sign associated with the deviations stays fixed for several periods in sequence). If we let the number of periods the individuals are married be denoted by N, then the maximum number of possible shifts is given by $N - 1$[6]. Denote the number of actual shifts taking place by S and dividing by $N - 1$ gives us an indicator for the number of shifts which is bounded between zero and one. A value close to zero indicates few shifts and will suggest that differences between actual earnings and predicted earnings are likely be interpreted as permanent. Table 4.1 and table 4.2 present a list of the percentiles of this measure for respondents and spouses, respectively.

[6] For an individual to experience the maximum obtainable number of shifts, the sign of the earnings quality must switch for every time period throughout the marriage.

Table 4.1: Distribution of shifts, respondents

Percentiles	**S/(N-1)**
5%	0.08
10%	0.10
25%	0.15
50%	0.23
75%	0.33
90%	0.50
95%	0.67

Table 4.2: Distribution of shifts, spouses

Percentiles	**S/(N-1)**
5%	0.09
10%	0.11
25%	0.16
50%	0.25
75%	0.36
90%	0.50
95%	0.75

The tables give a good indication of the distribution of this variable. For instance if the distributions were symmetric, we would expect the median to be close to 0.5. Here it is clear that the distributions for both the respondents and their spouses are skewed indicating that most individuals experience relatively few shifts. A comparison between the two tables show that the male spouses tend to experiences slightly more shifts than the respondents[7].

[7] There is a potential problem in calculating this measure. Suppose a respondent is married for only two time periods with a negative value in first period and positive value in second period. This person will then be recorded as having one shift. But also note that the maximum number of shifts possible for this person is one. This means that these individuals will have either be recorded as having no shifts (0) or one shift (1). As a result one might have too many observations at the tails of the distribution. Another drawback of this procedure is that it does not capture the magnitude of the shocks. This means that the absolute value of the deviations might be quite large at the same time as the expected value is close to zero. This means that the number of shifts computed here reflects only one dimension of the earnings quality measure.

4.3. Welfare Benefits

A range of different welfare schemes were available to the respondents during the survey period. The schemes are generally available to low income families, although most of them are only applicable if the family unit is headed by a single person with dependent children[8]. The main source of welfare income is Aid to Families with Dependent Children (AFDC). The AFDC levels have remained fairly stable over the survey period, although the levels vary quite substantially across the states. We therefore implement our measure of welfare generosity by using the cross state variation as a non-time varying variable. The actual values are based on the typical payment for a two-person family as recorded by AFDC Program Fiscal Year 1992.

4.4. Match Quality and Search

Match quality is here based on the partner's level of education. The dummy variable ('SCHMATCH') takes the value 1 if the couple have the same level of schooling, zero otherwise. A negative coefficient on this variable will indicate that similar level of schooling increases the quality of the marriage. The NLSY does not provide unambiguous information on the spouse's religious affiliation nor their ethnicity so match quality based on these characteristics are not included.

An important covariate in divorce transition $4 \rightarrow 3$ is whether the respondent experienced an out-of-wedlock birth ('PREM BIRTH'). The variable is constructed from the individual's transition path and included as a covariate in the divorce transitions. One would generally expect this variable to have a destabilising effect on the marriage. Search effort is primarily captured by lagged duration variables (duration until first marriage and first birth). These variables are also included as dynamic interaction terms in the divorce transitions. Long duration until first marriage generally implies more search effort and should lower the likelihood of divorce. We also include an indicator for whether the couple were in a cohabiting union prior to marriage.

[8] AFDC-UP is the exeption as this can be granted to two parent families provided their income is sufficiently low. However, AFDC-UP was first introduced in 1992 and is not relevant for this analysis.

4.5. Divorce Rates

The NLSY does not include detailed information about the marriage market which might be important for both partnership formation and marital dissolution. It also contains little information on the legal regimes concerning divorce. The legal environment is likely to affect the cost of divorce settlements and hence the likelihood of marital dissolution. This applies particularly to the grounds for divorce, division of property, assignment of custody and child support. In an attempt to control for these effects we include the local divorce rate as a covariate in the divorce transitions. The local divorce rate is constructed to be non-time varying. It is given as the average of the reported divorce rate over the time periods where the respondents are observed. This has the advantage of reducing the number of time varying variables to be included in the analysis.

4.6. Family Background Variables and Intergenerational Effects

We operate with three dichotomous background variables to capture possible intergenerational effects. The first takes the value 1 if the respondent was from a two parent family at age 14, zero otherwise ('FAM BACKGR'). This can be seen as a proxy for the expected relative benefits of family life. The second dummy takes the value 1 if the respondent's mother had a birth as a teenager ('M.TEEN.BIRTH'), and provides a measure of intergenerational effects in terms of fertility behaviour. The third variable takes the value 1 if the mother had less than 12 years of schooling ('M.HSCH.DROPOUT'). This dummy is a measure of parents' educational choice and possibly an indication of their attachment to the labour force.. It will also be positively correlated with the parents' wealth as higher education is likely to generate higher incomes. The latter variable is complemented by the family income variable ('FAMINC') which is the real total income in 1978 of the respondents' household, excluding that of the respondent. When the individual lives in the parental home, which is the majority in 1978, this income refers to the whole household excluding the respondent. These variables are non-time varying.

4.7. Goodness of fit

Simulations were undertaken to evaluate the goodness of fit of the preferred specification. For each individual in the original sample, we created five replications, each with the same covariate values as the individuals in the original sample. Informal comparisons can be made from table 3.4 where the simulated transitions histories are reported next to the sample transitions. The table reveal a good overall accuracy of the model. The fit is particularly good for 'common' transition histories such as 1·3·5, 1·2·4 and 1·2·4·6. The simulated transition histories are less accurate for infrequent transitions types. The largest discrepancy is found for transition type 1·3·4·6 where the sample proportion is 6.8 percent but where the simulated proportion is only 3.7 percent. In this case the model over-predicts the number of individuals with transition type 1·3·4·3. This means that the model predicts slightly more divorces from state 4 compared to the original sample. The model performs quite well in predicting the race specific transition histories as well. It clearly captures the large race differences as reflected by transition histories 1·3·5 and 1·2·4·6. Within the race groups the largest difference between the replicated and actual samples is for Hispanics and blacks. The worst discrepancy is found among black women for transition type 1·3·4·6. In the original sample 10.8 percent of blacks has this transition path, whereas the estimated model predicts a percentage of 4.5. This under prediction is "compensated" by the over-prediction of transition type 1·3·4·3.

5. Results

Contrary to earlier findings (e.g. Greenstein (1995[10])) we find no strong differences between the three race groups, a result that holds independent of whether the couple has a child or not. Only when unobserved heterogeneity is not controlled for (table 5.2) do we find black women to be significantly more likely to divorce. Earlier work (Burgess et al (1996[8])) show that the effect of the black race dummy is generally significant. Note however that neither Burgess at al, nor Greenstein (1995) control for unobserved heterogeneity in their methodology, which might explain this disparity[9].

Coming from a single parent family does not appear to have any strong effect on the offspring's decision to divorce, which again runs counter to Greenstein (1995). None of the other family background variables showed any strong effects on the divorce transition after child birth and were eventually dropped from the final round of estimation.

Women with high educational levels appear to be less likely to divorce, although the negative coefficient associated with the High School dummy is never

[9] Note that Burgess et al (1996) and Greenstein (1995) define separation to be equivalent to a divorce event, which is in contrast to our work.

significant[10]. This relatively weak effect of educational attainment is supported by the literature. Greenstein (1995) finds that education is only weakly correlated with divorce, whereas Heaton (1991[11]) finds that educational attainment has mixed effects[11].

The results indicate that individuals who cohabit prior to marriage are more likely to divorce, although the coefficient is only significant when the couple has one child[12]. It is a well established empirical result that cohabitation prior to marriage accelerates divorce. More recent work (Brien et al (1997[6]) and Brüderl et al (1999[7])) show that the positive relationship between cohabitation and divorce might be caused by self-selection. That is, individuals who cohabit are intrinsically more likely to form and disolve partnerships. They show that when self selection is controlled for the parameter becomes generally insignificant[13]. This self-selection mechanism might be driving the positive and significant coefficent we find here.

The variable capturing match quality ('SCHOOL MATCH') has a negative and significant effect on divorce[14]. This indicates that couples with similar level of education tend to have more stable partnerships, and thus less likely to divorce, a result that holds independent of whether the couple has a child or not. The result supports the strong effects of match quality variables found by Weiss & Willis (1997[18]).

The coefficient associated with the divorce rate is always positive and significanr in most of the specifications, meaning that women living in areas with high divorce rates are themselves more likely to divorce. The divorce rate might reflect the legal environment, which will affect the cost of divorce. Weiss & Willis (1997[18]) found that couples who live in areas with strong emphasis on fault considerations are less likely to divorce and the positive coefficient that we find here might be a reflection of this. The positive sign found here might be a reflection

[10] The educational dummies were not included in the divorce transition after childbirth as it had no explanatory power.

[11] South and Spitze (1986[17]) find that the effect of educational attainment on divorce tend to change over the life-course.

[12] Becker et al (1977[2]) argue that cohabitation might work as a screening process prior to marriage and should therefore have stabilising effect on marriage.

[13] Böheim and Ermisch (1999[5]) on the other hand find no evidence to support that premarital cohabitation is endogenous with respect to marital dissolution.

[14] Becker et al (1977[2]) constructed several measures for match quality, including a dummy variable taking the value 1 if the couple has similar level of schooling, 0 otherwise. This is the definition we have used here as well.

of this[15]. The positive effect of the divorce rate variable is independent of the presence of children.

There are important duration and age effects. Consistent with both theory and empirical findings we find that duration until marriage ('DURMAR') has a strong negative effect on divorce prior to child bearing, implying that individuals who marry at a later age are significantly less likely to divorce. The coefficient associated duration until first birth is strongly negative which indicates that couples who delay childbearing are at lower risk of divorce. This is consistent with results found by Becker et al (1977 [2]) and Weiss & Willis (1997[18]). Duration until first marriage has a smaller effect on divorce when childbearing has started. Table 5.2 shows that these coefficients change substantially when unobserved heterogeneity is not controled for - in particular we note that duration until first birth is close to zero and insignificant when the heterogeneity terms are omitted.

The shape parameters of the log hazard (A1, A2, and A3) show that the divorce hazard has the strongest increase at the early years of the marriage. This is consistent with earlier empirical findings (Becker et al. (1977 [2]), Weiss & Willis (1997[18]), and Heaton (1991[11])) and supports the view that new partner revelations are more frequent at the early stage of the marriage. Comparing tables 5.1 and 5.2 demonstrate the "classic" effect of neglecting unobserved heterogeneity. In the latter, where unobserved heterogeneity is not controlled for, the shape parameters form an inverted u-shape, which becomes monotonically increasing (table 5.1) when the masspoints are included.

The strong and positive coefficient associated with the pre-marital child bearing dummy is consistent in all specifications. The fact that a premarital birth will destabilise the relationship is consistent with theory (Becker et al (1977[2]) and supported by empirical research (e.g. South & Spitze (1986[17])). A pre-marital birth should increase the gain to marriage since specialisation within the household becomes more beneficial. A single mother may therefore lower her reservation quality and accept a marriage offer of poorer quality. As a result partners might have less information about each other at the time of marriage, thus making the marriage more prone to dissolution through new revelations.

A potential problem here is that we are not able to distinguish between women

[15] The positive sign might also be a reflection of the marriage market. If married women face an abundance in outside partnership options, they might re-evaluate the value of their current match, and might as a result initiate a divorce. Another possibility is that the county divorce rates is a reflection of differences in divorce rates between rural and metropolitan areas (Heaton (1991[11])).

who had a pre-marital birth for then to marry the father of the child, from women who remain single mothers and search for a new marriage partner. It is likely that the former group will marry sooner than single mothers that have to find a new partner. This difference in behaviour is captured by the unobserved heterogeneity terms. Appendix A shows that the three masspoints associated with marriage after an out-of-wedlock birth (i.e. transition 3→4) take values 2.48 (the 'movers' and thus women marrying the father of the child), 0.34, and -2.02 (the 'stayers' women who have to search for a new partner), where 36.1 of the sample belongs to the 'mover' group and 47.1 percent belongs to the 'stayer' group.

We find income variables to have important effects on divorce. Out of the earnings quality variables we find that the wife's quality after childbearing has the strongest effect. The coefficient is positive (0.758) which suggests that couples having a child are more likely to divorce if the wife earns a wage higher than the predicted level. This is in line with Weiss & Willis (1997[18]) and indicates that high performing women derives a lower gain from marriage than what they first anticipated.

We find the wife's earnings quality to have a negative association with divorce when there are no children present in the household.The coefficient is smaller in magnitude (-0.369) but significant in all specifications, implying that the sign of the wife's earnings quality parameter depends on whether there is marital specific capital present in the household. Becker (1973[3] and 1974[4]) argue that couples with dis-similar wage levels derive higher gain from marriage, and thus facing a lower probability of divorce, since they face larger scope for specialisation between household production and market activities. However, this argument rests on there being marital specific capital present in the household. The negative coefficient on the wife's earnings quality prior to childbearing might suggest that wages are less likely to be substitutes when there are no children in the household.

However, the interpetation of the negative coefficient is in this case not necessarily straight forward. Note thet the coefficient associated with the first birth transition is also negative, but more important here is that the magnitude of the coefficient is larger than the coefficient accociated with the divorce transition. This implies that an increase in the wage will make women delay divorce, but they will delay childbearing even more, making the woman being at risk of divorce for a longer time. The net effect is therefore not so obvious. Simulations (section 6.1) shows that increases in the wage rate decreases the proportion of divorced couples prior to childbearing, although the impact is relativley small.

An alternative explanation of the negative coefficient can be brought forward if the earnings quality is somehow anticipated prior to marriage. High performing women will be considered more attractive in the marriage market and therefore more likely to obtain a high quality match. This might have a positive effect on her bargaining power within marriage, and thus enable her to obtain a larger share of the marriage output. As a result high performing women will derive higher gain from marriage all else equal. This effect is reversed when childbearing has started. High performing women might realise that their gain to marriage is not as high as first expected, possibly due to a small scope for specialisation between the partners. Given their higher degree of economic freedom they might consider living as a single mother a more viable option compared to low performing women.

Husband's earnings quality show a different pattern. We find no significant association between husband's earnings quality and marital dissolution prior to childbearing, a result that again might be a reflection of a relative low importance of specialisation between the partners there is no marital specific capital present in the household. When the couple has started the childbearing process we find that the coefficient becomes positive and significant, a result that is in line with the results reported by Weiss & Willis (1997)[16].

The AFDC generosity level is not included as a covariate in the divorce transition prior to childbearing since the woman is only eligible to AFDC when she has at least one dependent child. The generosity level has a weak positive effect on divorce when there are children present in the household, although the coefficient is not generally significant. The positive sign is in line with our priors since a high welfare should increase the utility associated with being single. However, this weak effect is in line with previous empirical evidence (e.g.. Duncan & Hoffman (1997[13])). The indirect effect of AFDC, on the other hand is far stronger. Appendix A shows AFDC generosity levels are positively associated with out-of-wedlock childbearing and negatively associated with marriage, both of which will affect the duration until marriage, and the proprtion of out-of-wedlock births, which in turn have strong effects on the likelihood of divorce. These effects are explored in detail by the help of simulations (see section 6).

[16] We also estimate a model where we substitute the earnings quality measure by predicted wages. We find that the coefficient associated with wives' predicted wages are insignificant, whereas the husband's predicted wage are found to have a significant effect. The latter being independent of whether children are present or not. Becker et al. (1977) and Weiss & Willis (1997) also find that predicted wage levels have only weak effects on marital dissolution. These results are available from the author on request.

Table 5.1: Full specification, including time varying income variables and control for unobserved heterogeneity (Predicted wages used to construct earnings quality are taken from NLSY).

MARRIED AND NO CHILDREN				
	DIVORCE (2→1)		**FERTILITY (2→4)**	
VARIABLE	**COEFF.**	**S.E.**	**COEFF.**	**S.E.**
INTERCEPT	-1.749	(0.532)	2.205	(0.215)
WHITE	-0.165	(0.230)	-0.389	(0.096)
BLACK	0.231	(0.313)	0.002	(0.132)
FAM. BACKGR	0.048	(0.204)	0.124	(0.096)
HIGH SCHOOL	-0.144	(0.299)	-0.128	(0.125)
COLLEGE	-0.620	(0.323)	-0.600	(0.135)
FAMILY INC.	-0.299	(0.437)	-0.315	(0.195)
DURMAR	-1.898	(0.318)	-1.276	(0.125)
DIVORCE RATE	10.44	(4.783)	-3.310	(2.085)
SCHOOL MATCH	-0.526	(0.160)	-0.194	(0.074)
COHABITATION	1.015	(0.194)	0.197	(0.093)
QUALITY RESP.	-0.369	(0.194)	-0.748	(0.059)
QUALITY SPOUSE	-0.042	(0.133)	0.012	(0.053)
A1	11.42	(1.214)	3.437	(0.440)
A2	4.546	(1.372)	3.191	(0.946)
A3	1.169	(1.061)	0.368	(0.842)
MASSPT 1 [PROB 1]		0.944	[0.678]	
MASSPT 2 [PROB 2]		-1.208	[0.259]	
MASSPT 3 [PROB 3]		-5.217	[0.063]	
MARRIED AND ONE CHILD				
	DIVORCE (4→3)		**FERTILITY (4→6)**	
VARIABLE	**COEFF.**	**S.E.**	**COEFF.**	**S.E.**
INTERCEPT	-3.545	(0.507)	-1.720	(0.309)
WHITE	0.041	(0.208)	-0.044	(0.108)
BLACK	0.202	(0.284)	-0.185	(0.139)
DIVORCE RATE	10.73	(4.732)	8.010	(2.656)
SCHOOL MATCH	-0.347	(0.169)	0.095	(0.086)
COHABITATION	0.191	(0.252)	-0.969	(0.119)
PREM. BIRTH	2.885	(0.331)	-1.217	(0.358)
AFDC	0.341	(0.675)	0.478	(0.369)
DURMAR	-0.373	(0.649)	2.292	(0.238)
DURBIRTH	-1.359	(0.518)	-2.655	(0.203)
QUALITY RESP.	0.758	(0.142)	-0.270	(0.062)
QUALITY SPOUSE	-0.370	(0.147)	0.015	(0.054)
A1	13.53	(1.179)	12.248	(0.688)
A2	4.678	(1.459)	2.235	(0.908)
A3	2.612	(1.219)	0.900	(0.869)
MASSPT 1 [PROB 1]		1.684	[0.491]	
MASSPT 2 [PROB 2]		-0.925	[0.405]	
MASSPT 3 [PROB 3]		-4.375	[0.103]	
N = 3737, Log Lik = -5066.98				

Table 5.2: Specification without control for unobserved heterogeneity.

MARRIED AND NO CHILDREN				
	DIVORCE (2→1)		**FERTILITY (2→4)**	
VARIABLE	**COEFF.**	**S.E.**	**COEFF.**	**S.E.**
INTERCEPT	-2.027	(0.474)	2.399	(0.146)
WHITE	-0.051	(0.207)	-0.325	(0.063)
BLACK	-0.102	(0.265)	-0.245	(0.088)
FAM. BACKGR	0.005	(0.174)	0.108	(0.065)
HIGH SCHOOL	0.138	(0.249)	-0.046	(0.074)
COLLEGE	0.109	(0.270)	-0.255	(0.084)
FAMILY INC.	0.009	(0.386)	-0.143	(0.151)
DURMAR	-1.192	(0.280)	-0.897	(0.094)
DIVORCE RATE	1.023	(0.423)	-0.339	(0.147)
SCHOOL MATCH	-0.238	(0.140)	-0.030	(0.050)
COHABITATION	0.673	(0.163)	-0.034	(0.066)
QUALITY RESP.	-0.029	(0.187)	-0.494	(0.055)
QUALITY SPOUSE	-0.079	(0.122)	-0.007	(0.050)
A1	7.087	(1.139)	-0.106	(0.328)
A2	-0.191	(1.163)	-1.554	(0.619)
A3	-1.944	(0.784)	-2.990	(0.587)
MARRIED AND ONE CHILD				
	DIVORCE (4→3)		**FERTILITY (4→6)**	
VARIABLES	**COEFF.**	**S.E.**	**COEFF.**	**S.E.**
INTERCEPT	-1.985	(0.466)	0.007	(0.185)
WHITE	0.187	(0.169)	-0.002	(0.072)
BLACK	0.522	(0.244)	-0.107	(0.096)
DIVORCE RATE	0.726	(0.416)	0.291	(0.166)
SCHOOL MATCH	-0.422	(0.145)	0.086	(0.055)
COHABITATION	0.254	(0.196)	-0.109	(0.078)
PREM. BIRTH	2.274	(0.220)	-1.247	(0.363)
AFDC	0.525	(0.599)	0.273	(0.238)
DURMAR	-1.616	(0.482)	0.509	(0.131)
DURBIRTH	0.071	(0.415)	-0.880	(0.107)
QUALITY RESP.	0.536	(0.145)	-0.374	(0.062)
QUALITY SPOUSE	-0.258	(0.147)	0.066	(0.051)
A1	6.051	(1.100)	5.436	(0.421)
A2	-0.647	(1.342)	-3.797	(0.562)
A3	-0.682	(0.860)	-2.117	(0.502)
N = 3737, LogLik = -5412.69				

Table 5.3: specification with control for unobserved heterogeneity, but without time varying income variables.

MARRIED AND NO CHILDREN				
	DIVORCE (2→1)		**FERTILITY (2→4)**	
VARIABLE	**COEFF.**	**S.E.**	**COEFF.**	**S.E.**
INTERCEPT	-1.686	(0.522)	2.389	(0.217)
WHITE	-0.164	(0.225)	-0.381	(0.096)
BLACK	0.255	(0.312)	0.017	(0.133)
FAM. BACKGR	0.052	(0.206)	0.115	(0.097)
HIGH SCHOOL	-0.102	(0.291)	-0.150	(0.126)
COLLEGE	-0.570	(0.311)	-0.624	(0.136)
FAMILY INC.	-0.404	(0.432)	-0.469	(0.195)
DURMAR	-2.025	(0.315)	-1.355	(0.128)
DIVORCE RATE	8.891	(4.689)	-4.127	(2.100)
SCHOOL MATCH	-0.556	(0.162)	-0.216	(0.074)
COHABITATION	1.019	(0.202)	0.186	(0.094)
A1	12.140	(1.288)	3.464	(0.466)
A2	3.893	(1.383)	2.983	(0.983)
A3	0.918	(1.085)	0.104	(0.827)
MASSPT 1 [PROB 1]		0.959	[0.662]	
MASSPT 2 [PROB 2]		-1.179	[0.276]	
MASSPT 3 [PROB 3]		-4.985	[0.062]	
MARRIED AND ONE CHILD				
	DIVORCE (4→3)		**FERTILITY (4→6)**	
VARIABLES	**COEFF.**	**S.E.**	**COEFF.**	**S.E.**
INTERCEPT	-3.767	(0.522)	-1.685	(0.305)
WHITE	0.087	(0.213)	-0.042	(0.107)
BLACK	0.300	(0.281)	-0.214	(0.138)
DIVORCE RATE	12.630	(4.891)	8.357	(2.617)
SCHOOL MATCH	-0.395	(0.169)	0.088	(0.862)
COHABITATION	0.215	(0.250)	-0.103	(0.119)
PREM. BIRTH	2.754	(0.329)	-1.341	(0.359)
AFDC	0.507	(0.674)	0.420	(0.368)
DURMAR	-0.404	(0.649)	2.270	(0.238)
DURBIRTH	-1.317	(0.525)	-2.660	(0.202)
A1	13.961	(1.220)	12.239	(0.681)
A2	5.046	(1.486)	2.292	(0.918)
A3	2.536	(1.243)	0.937	(0.887)
MASSPT 1 [PROB 1]		1.679	[0.497]	
MASSPT 2 [PROB 2]		-0.950	[0.399]	
MASSPT 3 [PROB 3]		-4.358	[0.104]	
N = 3737, Log Lik = -5207.98				

6. Simulation analysis

Given the complexity of the model prediction of the net impact of a parameter becomes near impossible without using the tool of simulations. The main aim of the simulations is therefore to explore the sensitivity of divorce behaviour with respect to changes in the income variables. Simulations are undertaken for different levels of husband's and wife's earnings quality, their predicted wage rates, and for different AFDC levels. We operate with a range of descriptive statistics to analyse the impact of these income variables. 'Age at first transition' is the median age for first transition, independent of whether this to marriage or to out-of-wedlock child bearing[17]. 'Age at divorce, no children' refers to the median age of first divorce prior to child bearing. 'Percent divorce, no children' is the proportion of women who becomes divorced prior to child bearing[18]. 'Percent divorce, one child' refers to the proportion who experiences a divorce after child bearing (first child). This is computed by dividing the number of women who experienced a transition 4→3 by the total number of women who at some stage in their life reached state 4 (i.e. married and one child). 'Age at divorce, one child' refers to the median age at divorce after child bearing. 'Duration of marriage' refers to the median spell length of first marriages and is recorded as the duration from the date of marriage, until the date of first divorce[19].

6.1. Earnings quality

Different values of earnings quality are imposed by adding or subtracting one standard deviation to the original levels. The results are reported in tables 6.1 - 6.2. The minus sign means that the standard deviation is subtracted, the plus sign implies adding the standard deviation, whereas 'zero' indicates that the original levels are retained.

Table 6.1 shows that the effect of changing the husband's earnings quality values has little impact on both the median age at divorce, and the proportions of

[17] Note that in calculating median age, we have included individuals who are censored at state 1 at the end of the survey period. These individuals have been assigned the age at the censoring date.

[18] This proportion is computed by dividing the number of women who undertake transition 2→1 by the total number of women who at some stage in their lives were at risk of exiting to state 1 from state 2 (i.e. all women who ever experienced being in state 2). This will therefore include individuals who have transition histories such as 1·2·4·6.

[19] This statistic includes censored women as well. For these women the marriage durations are computed by using the difference between date of marriage and the censoring date.

divorcees. The largest effects are for black women when the respondent's earnings quality is either low (-) or high (+). In this case the proportions of divorcees ranges from 45.53 to 41.85 and 53.69 to 47.43 respectively. For white women the different levels of husband's earnings quality have almost no effect.

Respondent's earnings quality have a stronger effect on divorce, although the effect is only prevalent in terms of percentages of divorcees. The median age of divorce remains fairly constant for the different values of respondent's earnings quality, both before and after child bearing. In fact table 6.1 shows that the median age of divorce prior to childbearing varies from 25.31 to 25.28 for white women and 26.14 to 26,21 for black women, whereas the variation in median age of divorce after child bearing is only marginally larger. The percentages of divorcees, however, ranges from 9.78 to 13.32 for white women and 7.78 to 11.23 for black women, before child bearing. After child bearing the proportions are 18.34 to 23.33 for white women and 43.64 to 48.30 for black women.

The highest divorce percentage is obtained at high levels of the respondents earnings quality and low levels of husbands earnings quality, a result that is in line with Weiss & Willis (1997). This is also the case for proportion of divorcees prior child bearing even though the estimated coefficient is negative (-0.369). This of course is explained by the fact that the magnitude of the negative coefficient on fertility, transition 2→4 (which is the alternative destination state to divorce), is larger than the negative coefficient on divorce transition 2→1. This means that as earnings quality is increased, less women will undertake the fertility transition, and as a result, more women will be at risk of experiencing a divorce. So although the negative coefficient suggest a negative association between earnings quality and divorce, the simulations show that higher earnings quality values will in fact increase the proportion of divorcees.

The small impact respondent's earnings quality on median age of divorce after childbearing is a result of a similar effect. Note that the coefficient on respondent's earnings quality is quite large (0.758) so we would high levels to accelerate divorce. But a high level of earnings quality will delay the fertility transitions (transition 2→4), which means that the durations from the time the process starts until child bearing takes place will be longer. Since the coefficient associated with the duration variable ('DURBIRTH') is strongly negative, women will as a consequence delay any divorce transition. The result is that the net effect from increasing the earnings quality levels is fairly small.

6.2. AFDC generosity

We also simulate transition histories for different levels of AFDC generosity (tables 6.3 - 6.4). The five different levels of AFDC have been generated by multiplying the levels by factors (MF) of 0.5, 0.75, 1.00, 1.25, and 1.50. In section 5 we concluded that the effect of AFDC generosity on divorce was weak and generally insignificant. However, appendix A shows that AFDC generosity levels are important in the transitions leading up to divorce. In particular we find AFDC generosity to be positively associated with marriage and negatively associated with premarital childbearing. This will affect the duration until first marriage, duration until first birth, and the likelihood of having an out-of-wedlock birth, all of which are included as covariates in the divorce transitions. The effect of different AFDC levels are therefore likely to be complex. High levels will make women less likely to marry. Delayed marriage implies a higher value of duration until first marriage (DURMAR) which will consequently delay the divorce transitions. It will accelerate the out-of-wedlock birth transition and produce a positive effect on divorce when child bearing has taken place, and it will delay the marriage transition after a pre-marital birth has taken place (transition 3→4). The latter will increase the duration until marriage and consequently reduce the likelihood of divorce. The net effect is therefore unclear.

The percentage of divorced women prior to child bearing does not change much with the different AFDC levels. This is also the case for the median age of divorce post child bearing. The change in the proportion of divorced women after child bearing, on the other hand, is more substantial, although still modest compared to the effects from changing the wage levels. The median duration of marriage falls as a result of increased AFDC levels.

We find strong differences among the race groups. White women are fairly sensitive with respect to age at first divorce prior to child bearing. As the table shows, the median age increases from 24.76 years when MF is 0.5, to 25.47 years when MF is 1.50. The change in median ages among black women is in strong contrast to this. Table 6.4 shows that the median ages ranges from 25.81 to 26.07. The percentages of divorced women does not change by much within the race groups, nor between the race groups. However, the percentage of black women becoming divorced react in a non-monotonic fashion to the different AFDC levels. The largest change is again found with respect to median age at divorce after child bearing, and again we see that there are substantial difference between the race groups in terms of the levels of these statistics.

6.3. Predicted wage rates

Predicted wage rates are not included as covariates in the divorce transitions implying that the effects from varying the predicted wages are generated solely from the family formation transitions prior to divorce. As was the case with the AFDC levels in previous section the effects are fed through the dynamic interaction terms (duration until marriage, duration until first birth, and the out-of-wedlock child bearing indicator). Appendix A shows that predicted wages are positively associated with marriage, negatively associated with pre-marital child bearing, and positively associated with marriage after a pre-marital child bearing has taken place[20].

Tables 6.5 - 6.6 show that these indirect effects on divorce are quite substantial. The tables show that age at first transition is reduced as predicted wage rates are increased whereas age at divorce (without children) is lower, the latter being a result of the negative association between duration until first marriage and consequent divorce. The net effect on the percentage of divorcees before child bearing is relatively small: on one hand high earnings tend to accelerate divorce through the duration effect; on the other hand, high earnings increases the proportion of married women, as opposed to exiting into state 3 (out-of-wedlock child bearing), which in turn reduces the proportion of divorcees.

The effect of predicted wages on divorce after childbearing is substantially larger. Again high wages will tend to accelerate marriage, and given the negative coefficients associated with the duration variables, accelerate divorce. However, as the predicted wage rates are increased, more women will marry and fewer will experience out-of-wedlock child bearing, reducing the likelihood of divorce. The latter dominates the effect of the duration variable so the overall effect on divorce is negative.

We find only modest differences between the two race groups in terms of the age at divorce. For white women we find that median age of divorce *prior* to childbearing varies in a monotonic fashion from 25.94 years when the wage is low to 24.68 when the wage is high. The range for black women is 26.57 to 25.78. The variation in median age at divorce *after* childbearing shows a non-linear relationship between the median age and the wage levels. For instance we see that for white women the median age is highest when the wage level is retained at the original level but falls if the wages are either reduced or increased. A more complex pattern is evident for black women.

[20] The predicted wage levels are multplied by factors of (MF) of 0.5, 0.75, 1.00, 1.25.

Table 6.1: Simulated values by respondent's and spouse's earnings quality, white women

	Whites								
'QUALITY RESP':	-			0			+		
'QUALITY SPSE.':	-	0	+	-	0	+	-	0	+
Age at first transition	22.79	22.81	22.81	22.90	22.79	22.81	22.87	22.90	22.80
Age at divorce (2→1)	25.19	25.31	25.18	25.40	25.14	25.22	25.31	25.28	25.30
% divorced (2→1)	9.93	9.78	9.26	12.27	11.27	11.92	14.11	13.32	14.04
Age at divorce (4→3)	24.35	24.42	24.78	24.53	24.58	24.56	24.81	24.81	24.67
% divorced (4→3)	18.31	18.34	17.4	21.26	20.69	19.87	24.56	23.33	23.22
Duration of marriage	3.86	3.88	3.86	4.00	3.99	4.02	4.14	4.17	4.18

Table 6.2: Simulated values by respondent's and spouse's earnings qualit, black women

	Blacks								
'QUALITY RESP':	-			0			+		
'QUALITY SPSE.':	-	0	+	-	0	+	-	0	+
Age at first transition	21.99	22.00	22.06	22.09	21.99	22.00	21.82	22.04	22.02
Age at divorce (2→1)	26.12	26.14	25.35	26.45	26.20	25.96	25.76	26.21	26.37
% divorced (2→1)	7.35	7.78	8.70	9.88	9.92	9.29	12.76	11.23	11.1
Age at divorce (4→3)	23.65	23.81	23.67	23.75	23.62	23.82	23.67	23.75	23.73
% divorced (4→3)	45.53	43.64	41.85	46.87	46.38	46.54	53.69	48.30	47.43
Duration of marriage	3.00	3.13	3.24	3.10	3.15	3.24	3.15	3.22	3.30

The strongest effect from varying the wage levels are on the proportions of divorced women after child bearing. This applies to both within and between the two race groups. For white women there is a fall from 29.5 percent when MF is 0.5, to 15.5 percent when MF is 1.5. For black women the within difference is substantially larger: 57.6 percent when MF is 0.5, and 35.1 percent when MF is 1.5. The high divorce proportions among black women is caused by the premarital birth dummy, which has a strong positive effect on divorce. Since black women are much more likely to experience out-of-wedlock childbearing, they also become more sensitive to variations in the wage levels.

Table 6.3: Simulated values by AFDC generosity level * 0.5,0.75,1.0,1.25,1.50, white women

	Whites				
AFDC multiplied by:	0.50	0.75	1.00	1.25	1.50
Age at first transition	22.31	22.57	22.80	23.12	23.27
Age at divorce, no child	24.76	25.01	25.14	25.33	25.47
Percent divorce, no child	11.95	11.82	11.28	11.58	11.06
Age at divorce, one child	24.42	24.68	24.58	24.50	24.47
Percent divorce , one child	17.14	18.50	20.70	22.29	23.24
Duration of marriage (yrs)	4.08	4.13	4.00	3.91	3.83

Table 6.4: Simulated values by AFDC levels * 0.5,0.75,1.0,1.25,1.50, black women

	Blacks				
AFDC multiplied by:	0.50	0.75	1.00	1.25	1.50
Age at first transition	22.03	21.95	21.99	21.85	21.87
Age at divorce, no child	25.81	26.04	26.00	25.94	26.07
Percent divorce , no child	10.03	9.68	9.92	8.43	10.60
Age at divorce, one child	23.71	23.53	23.62	23.76	23.70
Percent divorce , one child	43.50	44.27	46.38	49.31	50.78
Duration of marriage (years)	3.32	3.26	3.15	3.07	3.08

Table 6.5: Simulated values by predicted wages * 0.5,0.75,1.0,1.25,1.50, white women

	Whites				
Predicted wage multiplied by:	0.50	0.75	1.00	1.25	1.50
Age at first transition	23.76	23.39	22.79	22.29	21.70
Age at divorce, no child	25.94	25.66	25.14	24.98	24.68
Percent divorce , no child	11.27	11.25	11.28	11.31	11.99
Age at divorce, one child	24.46	24.38	24.58	24.54	24.46
Percent divorce , one child	29.52	24.14	20.69	15.54	15.52
Duration of marriage (yrs)	3.69	3.87	3.99	4.17	4.23

Table 6.6: Simulated values by predicted wages * 0.5,0.75,1.0,1.25,1.50, black women

	Blacks				
Predicted wage multiplied by:	0.50	0.75	1.00	1.25	1.50
Age at first transition	21.55	21.78	21.99	21.95	21.75
Age at divorce, no child	26.57	26.05	26.20	25.67	25.78
Percent divorce , no child	9.62	9.76	9.92	10.30	9.74
Age at divorce, one child	23.21	23.54	23.62	23.88	23.71
Percent divorce , one child	57.61	53.16	46.38	40.56	35.09
Duration of marriage (yrs)	2.78	2.99	3.15	3.43	3.54

7. Concluding remarks

This paper has examined marital dissolution among young American women. A distinguishing feature is that the initial conditions (the family formation process leading up to divorce) are modelled explicitly, and thus included as covariates in the divorce transitions. The emphasis is on how economic variables affect family formation and marital dissolution, both indirectly and directly. In addition to the respondent's predicted wages, welfare benefits, and family income, we introduce a new income variable which represents the respondent's earnings capacity (or quality).

The results show that divorce behaviour is quite different depending on whether there is marital specific capital present in the household. In particular we find that the earnings quality variables have different effects in the two cases: when children are present we find that respondent's earnings quality is positively associated with divorce and positive values of the spouse's earnings quality is negatively associated with divorce, whereas quality has relatively little explanatory power when no marital specific capital is present. The other income variables are also found to be important determinants of divorce. The direct effect of welfare benefits is found to be relatively weak, whereas the indirect effects are substantially stronger.

The results also indicate that past family formation transitions are crucial in determining marital dissolution. This is particularly the case with pre-marital childbearing, which is found to have a strong positive association with marital dissolution. The timing of first marriage and birth are also found to be important and the parameter estimates give a clear indication that marriages that take place at a young age are relatively more prone to dissolution. Cohabitation prior to marriage is found to have different effects depending on whether children are present in the household. However, it is argued that this parameter estimate should be treated with caution given the possible endogeneity of this variable. We also include a match quality variable which is based on educational attainment. The parameter estimate suggests that couples who have similar level of education are less likely to divorce. Demographic variables, such as the regional divorce rate has a strong effect, implying that couples who live in areas with a high divorce rate, possible determined by the legal environment, are considerable more likely to divorce.

Given the complexity of the econometric model we use simulations as a tool to assess the effect of the various income variables. This confirms the important role played by income variables in explaining divorce through the initial family formation transitions taking place prior to divorce. It also shows that the respondents' divorce behaviour changes in a way that is not easily predictable from the parameter estimates.

A. Parameter estimates of family formation transitions prior to divorce

SINGLE AND NO CHILDREN						
	Marriage: (1→2)		**Fertility: (1→3)**		**Marriage: (1→2s)**	
VARIABLE	**COEFF.**	**S.E.**	**COEFF.**	**S.E.**	**COEFF.**	**S.E.**
INTERCEPT	-4.818	(0.336)	-3.515	(0.385)	-0.525	(1.036)
WHITE	0.119	(0.089)	-0.358	(0.127)	0.008	(0.404)
BLACK	-0.868	(0.115)	1.056	(0.127)	-0.918	(0.520)
FAM. BACKGR.	0.081	(0.082)	-0.248	(0.090)	0.561	(0.247)
M. PREM. BIRTH	0.281	(0.075)	0.455	(0.087)	-0.193	(0.330)
M. HSCH. DROPOUT	0.195	(0.075)	0.397	(0.094)	0.179	(0.326)
HIGH SCHOOL	-0.922	(0.109)	-0.913	(0.120)	-0.385	(0.451)
COLLEGE	-2.685	(0.137)	-2.167	(0.154)	-0.157	(0.556)
FAMILY INCOME	-0.854	(0.188)	-2.397	(0.285)	-1.496	(0.699)
MARRIAGE RATE	1.976	(1.620)	4.258	(1.916)	-9.553	(5.517)
AFDC GENEROSITY	-2.773	(0.326)	1.810	(0.420)	-2.026	(0.995)
PRED. EARNINGS	3.328	(0.283)	-2.314	(0.499)	-1.238	(1.236)
A1	8.391	(0.408)	7.012	(0.384)	1.643	(1.256)
A2	2.481	(0.226)	1.827	(0.273)	2.942	(2.260)
A3	-0.128	(0.336)	0.696	(0.519)	19.399	(1.649
MASSPT 1 [PR 1]		1.156	[0.499]		3.763	[0.614]
MASSPT 2 [PR 2]		-0.376	[0.343]		-5.974	[0.386]
MASSPT 3 [PR 3]		-2.859	[0.157]			

SINGLE AND ONE CHILD				
	Marriage: (3→4)		**Fertility: (3→5)**	
	COEFF.	**S.E.**	**COEFF.**	**S.E.**
INTERCEPT	-1.785	(0.564)	-2.583	(0.629)
WHITE	0.172	(0.169)	-0.319	(0.205)
BLACK	-1.092	(0.183)	0.075	(0.199)
HIGH SCHOOL	0.431	(0.178)	-0.092	(0.175)
COLLEGE	-0.103	(0.244)	-0.709	(0.259)
FAMILY INCOME	0.183	(0.430)	-1.065	(0.501)
DURBIRTH	-1.218	(0.255)	-0.869	(0.265)
AFDC GENEROSITY	-2.991	(0.618)	0.138	(0.682)
MARRIAGE RATE	-1.195	(2.999)	2.410	(3.231)
PRED. EARNINGS	4.071	(0.728)	0.999	(0.881)
A1	8.341	(1.242)	15.101	(1.481)
A2	5.351	(2.477)	2.132	(2.456)
A3	-1.640	(0.588)	-1.292	(0.492)
MASSPT 1 [PR 1]		2.479	[0.361]	
MASSPT 2 [PR 2]		0.344	[0.168]	
MASSPT 3 [PR 3]		-2.021	[0.471]	

B. The likelihood function

Individuals are observed from age t^0 until first entry into state 5 and 6, or until age c after which the event history is censored. Let $R \geq 0$ be the number of transitions made by an individual. Let t^r be age at transition r. Let $z^r = \min(t^r, c) - t^{r-1}$, $1 < r \leq R$, and let $1_{[\mathcal{C}]} = 1$ if $\mathcal{C}$ is true and 0 otherwise.

The log likelihood contribution for an individual making R transitions with state occupancy history $(i_1, i_2, i_3, \ldots, i_{R+1})$ and transitions at ages

$(t^1, t^2, t^3, \ldots, t^R)$, time z^r being the time spent in state i_r, conditional on observed and unobserved covariates is

$$\begin{aligned} L &= 1_{[t^1<c]} \log h^1_{i_1 i_2}(z^1|x(z^1), v^1) - \sum_{j=1}^{k} I^1_{i_1 j}(z^1|x(z^1), v^1) \\ &\quad +1_{[R>1]} \sum_{r=2}^{R} \left(1_{[t^r<c]} \log h^2_{i_r i_{r+1}}(z^r|x(z^r), v^2) - \sum_{j=1}^{k} I^2_{i_r j}(z^r|x(z^r), v^2) \right) \end{aligned}$$

Note that the final term is only present when there is more than one transition, that all individuals start in state $i_1 = 1$ and that all event histories are either right censored or end with $i_{R+1} = [5, 6]$.

The likelihood contribution conditional on observed covariates *alone* is the expectation of the likelihood contribution, given by exponentiating the previous expression, with respect to the joint distribution of V^1 and V^2.

C. The conditional hazard functions

A variety of patterns of duration dependence in the hazard function is accommodated by using a continuous piecewise linear functional form for the log hazard functions with two knots, as employed by Newman and McCulloch [16]. For $b > a$ let

$$A(t, a, b) = \max(0, \min(t, b) - a)$$

then the hazard function associated with passage from state i to state j at transition r is

$$h^r_{ij}(t) = \exp(x(t)'\beta^r_{ij} + \alpha^r_{1ij}A(t, 0, w_1) + \alpha^r_{2ij}A(t, w_1, w_2) + \alpha^r_{3ij}A(t, w_2, \infty) + \gamma^r v^r)$$

in which $\gamma^r = 1$ or 0, $r \in \{1, 2\}$, depending on whether allowance is made for across individual heterogeneity and if so whether a univariate or bivariate specification is employed. For example for $t > w_2$ the hazard function is

$$h_{ij}^r(t) = \exp(x(t)'\beta_{ij}^r + \alpha_{1ij}^r w_1 + \alpha_{2ij}^r (w_2 - w_1) + \alpha_{3ij}^r t + \gamma^r v^r).$$

The knot locations, w_2 and $w_{1,}$ are fixed *a priori.* For $r = 1$, $w_2 = 15$ and $w_1 = 6$ (corresponding to ages 28 and 19). For $r = 2$, $w_2 = 5$ and $w_1 = 3$. The three segment hazard functions can be everywhere increasing or decreasing, or bathtub or inverted bathtub shaped. If $\alpha_{3ij}^r < 0$ then the associated duration distribution is defective with a non-zero probability of no transition from state i to state j at transition r.

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