
Female income and the divorce decision: evidence from micro data

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Escalating divorce rates during the 1960s and 1970s led to large numbers of academic investigations into the causes of divorce. Most of these studies concentrated on a significant increase in female income that resulted from rising female labour force participation rates. The difficulty with quantifying these arguments is that it is possible to observe the income of married females or it is possible to observe the income of divorced females, but it is not possible to observe both outcomes, simultaneously. This research attempts to resolve these difficulties by using sample selection techniques to correct for possible bias from simple observation of the income of married and divorced females.

I. Introduction

During the 1960s and 1970s divorce rates in the USA rose dramatically. This surprising increase led to rapid growth in the number of academic investigations seeking to quantify the causes and consequences of divorce. It soon became clear that the divorce phenomenon was not restricted to the geographic boundaries of the USA. Other industrialized countries, most specifically Great Britain, experienced similar if not identical tendencies to terminate marriages at previously unheard of rates. Even though divorce rates have stabilized in recent decades, the search for improved models of the divorce decision has persisted in a relatively unabated fashion. The reason for this is, undoubtedly, the fact that even though divorce rates stabilized they did so at a very high rate –50% (Kreider and Fields, 2002, p. 18).

This research specifically focuses on the economic causes of divorce. However, there can be little doubt that there are many other factors involved in the

decision to dissolve a marriage. For example, demographic factors like changes in the population's age structure contribute to changes in expected divorce rates. In developed countries where life expectancies have significantly increased, the opportunity for lengthier marriages has also increased. As a natural consequence of a lengthier marriage, the number of divorces would be expected to rise. Development of improved contraceptives and easier access to them has reduced the number of children, thus decreasing the transaction cost to obtaining a divorce. The costliness of children is well known and when a marriage dissolves, the children become an even larger economic burden. Offsetting this burden to a certain degree is the more extensive safety net provided by developed economies. In addition, regime changes like the emergence of no-fault divorce laws have reduced the transaction cost of litigation, and by doing so have increased the likelihood of divorce. Finally, one cannot ignore the personal aspect of the decision to end a marriage. Rapid and extensive societal changes can lead to marriage

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ending frictions that in other circumstances might well be ignored.

Although the factors mentioned above are clearly of importance, this research concentrates on three economic arguments that have persisted over the years. All three relate to the female's ability to generate income in the labour market. The first argues that as the female increases her ability to generate income, she becomes financially more independent thereby making divorce more likely. Inextricably tied to this argument is the relative cost of child bearing. As a female's connection to the labour force strengthens, it increases the transaction cost of child rearing. As a logical consequence, having fewer children reduces the transaction cost of divorce. So, by strengthening ties to the labour force, the female invariably weakens ties to the family. The second argument contends that, as female earnings become a larger share of family income, marital friction results and the likelihood of divorce increases. Finally, it has also been argued that the family unit places a high value on the ability of the married female to earn income and, therefore, strives harder to avoid divorce as the female's ability to earn income rises.

The remainder of the paper proceeds in five additional sections. The next section of the paper provides a short literature review. It examines both some of the theoretical and some of the previous empirical work dealing with the economic issues of divorce. Section III provides a brief explanation of the statistical model used to accomplish the estimations. Section IV describes the data used in the estimations. Section V discusses the empirical results and, finally, some conclusions and *caveats* are offered in Section VI.

II. Literature Review

Theoretical models

In their seminal work on marital instability, Becker *et al.* (1977) argue that the decision to divorce compares the value of being single to the joint value of being married. Following the modeling work of Weiss (1996), let $G(X_t^M, X_t^F, K_t, \theta_t)$ be the household production function that measures the joint value of staying married. This joint valuation is a function of the characteristics of both spouses, X_t^M for the male and X_t^F for the female. The characteristics X_t^M and X_t^F include the earnings of each respective spouse. The production function also includes K_t , which measures marriage-specific capital such as children. The final

argument in the production function, θ_t , is an unobservable measure of the quality of the relationship. All the arguments of the production function have a subscript 't' to denote a particular time period. The value of these arguments will vary over the duration of the marriage as will the likelihood of getting a divorce.

Let the post-divorce value of being single equal A_t^M for the male and A_t^F for the female. Among other things, these variables include each spouse's estimate of the option value of remarriage, a possibility that occurs only after the current marriage is dissolved. The transactions cost to obtaining a divorce, C_t , not only includes legal expenses, but it also captures the opportunity cost of the time lost in divorce negotiations and the emotional costs incurred during dissolution of the marriage.

Divorce occurs when the sum of the values of becoming single, minus the transaction cost of the divorce, is greater than the joint value of remaining married. Using the terms defined above, divorce is optimal when

$$A_t^M + A_t^F - C_t > G(X_t^M, X_t^F, K_t, \theta_t).$$

Of primary interest to this research are the theoretical inferences about income. For example, an increase in female labour force participation increases female income, which, in turn, increases A_t^F and makes divorce more likely. Higher female salaries increase the opportunity cost of children, reduce K_t , and increase the likelihood of marriage dissolution. Also, higher female salaries threaten male egos, leading to marital stress that reduces θ_t , the quality of the relationship, and increases the probability of divorce.

Empirical literature

Various empirical studies of divorce in the USA have used a wide assortment of techniques, variables and data to produce results that often appear contradictory and, sometimes even, counterintuitive. In explaining the decision to divorce, cross-sectional, micro-level econometric studies have used independent variables such as marriage tenure; working status of the female; the husband's earnings, age, and educational level; the wife's earnings, age, and educational level; the number and age of children; and the occurrence of a previous divorce. Time-series analyses of a country's divorce rate have used macroeconomic variables such as the unemployment rate, the inflation rate and the rate of growth in real GDP to explain changes in the divorce rate.

Micro, cross-sectional studies. Lombardo (1999) and Greene and Quester (1982) argue that wives facing a higher risk of divorce will hedge against that risk with higher levels of labour force participation, and that they will also respond by working longer hours. The basic argument made in these papers is that investment in nonmarket activities, such as child rearing, becomes relatively less attractive (it yields a lower expected return), and investment in human capital becomes relatively more attractive (it yields a higher expected return) as the probability of divorce increases. Studies by Shapiro and Shaw (1985) and Johnson and Skinner (1986) provide additional evidence for the above argument by finding that women increase their labour force participation prior to dissolution of a marriage. The above papers make a clear causality argument that an increase in the likelihood of divorce increases a female's willingness to enter the labour force.

Spitze and South in two separate studies (1985, 1986) argue a different line of causality. Their conclusion is that an increase in female labour force participation leads to an increase in familial conflict and, consequently, an increase in divorce. Substantiating evidence for this view is provided by Mincer (1985). In a survey of twelve industrialized nations he found that rising divorce rates lag rising female labour force participation rates.

Previous studies of the impact of income on divorce have provided mixed results. Becker *et al.* (1977) find that a rise in expected female earnings increases the probability of divorce, while a rise in expected male earnings reduces the probability of divorce. D'amico (1983) recognizes two distinctly different possible effects of income on divorce. One hypothesis is that as the female's wage relative to the male's rises, conflict based on competition for status within the marriage will occur and will increase the likelihood of divorce. The second, opposing hypothesis is the notion that the pursuit of higher socioeconomic status is a familial one and that a wife earning a relatively higher wage than that of the husband may contribute to the overall status goal and solidify the marriage. D'amico's results tend to confirm the latter hypothesis. Finally, Hoffman and Duncan (1995) find no support for the hypothesis that higher real female wages lead to increased divorce rates and a study by Sayer and Bianchi (2000) tends to confirm this finding.

However, Spitze and South raise another question that is closely related to the income issue. In a 1985 study, they produce evidence that the number of hours a wife works has a greater impact on the probability of divorce than do various measures of the wife's income.

Macro, time-series studies. In an empirical study of the growth of divorce rates in Great Britain, Smith (1997) finds no evidence that marriage dissolution increases because of the introduction of no-fault divorce laws. He argues that, rather than being the vehicle of change, these types of legal modifications merely codify, react to, and regulate ongoing social and economic transformations. Smith finds that procedural and legal changes do have a powerful, albeit temporary impact. One procedural change that did increase the number of divorces was revised court settlement rules that reduced transactions costs and improved the financial position of females post-divorce. Smith attributes the increased number of divorces in Great Britain to rising female labour force participation, higher female income and the subsequent reduction in the female's economic dependency on marriage. In addition, technological change giving females greater control over fertility has had a significant impact. With improved fertility control resulting in fewer children, a significant transaction cost of divorce has been effectively reduced.

South (1985) finds little evidence that the divorce rate rises during periods of recession and falls during periods of expansion. He does find a positive, albeit small, effect of unemployment on the divorce rate. His model indicates that changes in the age structure and the labour force participation rate of women have significantly stronger impacts on the divorce rate than other macroeconomic variables.

Using a simple vector autoregressive (VAR) approach with macro, time-series data, Bremmer and Kesselring (1999) show that the female labour force participation rate does not Granger-cause divorce rates. However, they do provide statistical evidence that divorce rates Granger-cause female participation in the labour force. They also show that past participation in the labour market influences women's earnings.

In another time-series study using macro data, Bremmer and Kesselring (2004) use cointegration techniques to investigate the relationship between divorce, female labour force participation, and median female income. Though these variables had unit roots, their first differences were stationary, and these variables were shown to be cointegrated. Impulse functions from this model reveal that an increase in divorce leads to a rise in female labour force participation; but positive innovations to female labour force participation imply a decline in the divorce rate. Impulse function analysis also shows that a positive innovation to median female income leads to increased divorce and increased labour force participation on the part of females.

III. The Statistical Model

The most pervasive thread tying the above literature together is the relationship between female earning capacity and its relationship to divorce. This argument takes several important forms. First is a line of reasoning that developed during the 1970s and 1980s when females experienced a substantial increase in their ability to successfully participate in the labour market. Unquestionably, female labour force participation increased during this time and, along with this increase came improved salaries and benefits. Consequently, academics argued that as females developed better access to income outside the marriage the likelihood of divorce increased. While this idea was written about in many ways it proved difficult to quantify. It also led to counter arguments that when a married female's value in the labour market increased it might well strengthen a marriage and reduce the probability of divorce. The difficulty with quantifying these arguments is the very nature of the observable outcomes. It is possible to observe the income of married females. It is also possible to observe the income of divorced females. Unfortunately, it is not possible to simultaneously observe both outcomes for an individual female. So, while the data may indicate that divorced females participate in the labour force at substantially higher rates than married females, it provides no valid evidence that ready access to the labour market is a causal factor in divorce. In other words, this is a classic sample selection problem.

Over the years, academics of various disciplines began to develop another income-related argument that they hoped would explain the increasing occurrence of divorce. As a married female's contribution to household income grows, it gives her more say in the conduct of the marriage. So, conflict within the marriage is given an opportunity to flourish. Disagreements about the way that money is spent and, for that matter, disagreements over the conduct of everyday household responsibilities become much more likely. However, the sample selection problem arises again. It is possible to observe the amount that married females contribute to the household but it is not possible to directly observe the amount that a divorced female would have contributed to the household had she remained married. Consequently, econometric techniques accounting for these difficulties are required.

A typical statistical approach to solving the above problems begins by specifying a selection equation.

For example, the selection equation for the divorce problem would be:

$$D_i^* = \gamma' \mathbf{w}_i + u_i$$

where \mathbf{w}_i represents a vector of variables that predict the likelihood of divorce. In this case (as in most cases) the selection variable (D_i^*) is not observed. Instead, only its sign is observed:

$$\begin{aligned} D_i &= 1 && \text{if } D_i^* > 0 \\ D_i &= 0 && \text{if } D_i^* \leq 0 \end{aligned}$$

In order to test the above hypotheses regarding divorce, three different income equations need to be estimated. So, there are three equations that will make similar (though not identical) use of the information from the selection equation. The three equations are:

$$\begin{aligned} E[PY|divorced] \\ E[PY|married] \\ E[FY|married] \end{aligned}$$

where PY stands for personal earnings and FY stands for family income.

The estimation technique used for all three is very similar. So, model development proceeds by using the first equation as an example. The usual equation that one is interested in estimating is:

$$PY_i = \beta' \mathbf{x}_i + \varepsilon_i$$

where \mathbf{x}_i is the vector of independent variables used to predict PY . Unfortunately, PY_i is only observed when $D_i = 1$. Also, for this derivation the standard assumptions are made about ε_i and u_i . In other words, they have a bivariate normal distribution with zero means and a correlation of ρ .

What one truly wishes to estimate is:

$$E[PY_i | PY_i \text{ is observed}] = E[PY_i | D_i^* > 0]$$

which is equivalent to

$$E[PY_i | PY_i \text{ is observed}] = E[PY_i | \mathbf{x}_i, D_i = 1]$$

Incorporation of the selection equation results in the above equation yields:

$$\begin{aligned} E[PY_i | PY_i \text{ is observed}] &= E[PY_i | D_i^* > 0] \\ &= E[PY_i | u_i > \gamma' \mathbf{w}_i] \\ E[PY_i | PY_i \text{ is observed}] &= \beta' \mathbf{x}_i + E[\varepsilon_i | u_i > -\gamma' \mathbf{w}_i] \\ &= \beta' \mathbf{x}_i + \rho \sigma_\varepsilon \lambda_i(\alpha_u) \\ &= \beta' \mathbf{x}_i + \beta_\lambda \lambda_i(\alpha_u) \end{aligned}$$

where: $\alpha_u = -\gamma' \mathbf{w}_i / \sigma_u$ and $\lambda(\alpha_u) = \phi(\gamma' \mathbf{w}_i / \sigma_u) / \Phi(\gamma' \mathbf{w}_i / \sigma_u)$. The equation in estimable form becomes:¹

$$E[PY_i | PY_i \text{ is observed}] = \beta' \mathbf{x}_i + \beta_\lambda \lambda_i(\alpha_u) + v_i$$

Consequently, application of OLS to the model results in two problems. First, omitting λ (commonly referred to as the inverse Mills ratio) creates a bias similar to that attributed to an omitted variable and, second, the disturbance term, v_i , is heteroscedastic. As a result, estimation proceeds in a two-step manner. First, following the methodology recommended by Heckman (1979), the selection equation is estimated and used to create a $\hat{\lambda}$ for each observation. Then, β is estimated by regressing PY on \mathbf{x} and $\hat{\lambda}$. Finally, the correction for heteroscedasticity recommended by Greene (1981) is applied to the estimates. By following similar logic and making minor adjustments, estimates for all three of the equations can be obtained.

In order to test the hypotheses specified earlier, an additional step must be taken. It is necessary to use the estimated coefficients obtained from the least squares regressions to produce expected values (observations) for every individual (both married and divorced) in the data set (Lee, 1978). Once these observations have been obtained, the necessary relationships can be calculated.

The created variable used to test the first hypothesis is:

$$\hat{\Delta}_1 = E[PY | married] - E[PY | divorced]$$

Smaller values for $\hat{\Delta}_1$ indicate that the female is better equipped to enter the labour force and, consequently, better prepared to live independently. If a female were the only participant in the marriage, it would make sense to argue that as $\hat{\Delta}_1$ declines the likelihood of divorce would definitely increase. However, the male is also a participant in the marriage and while his interaction in the process has not been written about as frequently as the female's, it should (might?) be just as important. If the male values the possible economic contribution of the female to the family's economic welfare, he would have an increasing preference to remain married as $\hat{\Delta}_1$ declines and should, therefore, seek to reduce the likelihood of divorce.

The other variable of interest is created in the following manner:

$$\hat{\Delta}_2 = E[FY | married] - E[PY | married]$$

As $\hat{\Delta}_2$ declines, the percentage of total family income accounted for by female earnings increases.

Some authors have argued that this increasing share of income on the part of the female can cause friction within the marriage and, consequently, lead to a greater likelihood of divorce. Others have argued that the female's contribution could be highly valued by the other family members and should, therefore, reduce the likelihood of divorce. So, the question of whether $\hat{\Delta}_2$ or $\hat{\Delta}_1$ has a positive or negative impact on divorce becomes an empirical issue.

The following two equations were formulated to provide a statistical test of these issues:

$$D = f(\hat{\Delta}_1, \hat{\Delta}_2, \text{state of residence}), \text{ and}$$

$$D = f(\hat{\Delta}_1, \hat{\Delta}_2).$$

where, as before, D , stands for divorce. The equations differ only by the inclusion of the entire series of state dummies in the first equation. The second equation only includes the variables hypothesized to affect the divorce decision. Equations of this type have been referred to in the literature as structural equations (see Lee, 1978) because they include the specific variables hypothesized to predict the binary outcome. In this particular case, the question of whether to include the series of dummy variables representing the fifty different states is assumed to be an empirical one. The reason is that information on the fifty states is being provided to the income equations, albeit indirectly, through their correlation with the choice equation. Consequently, direct inclusion of these variables may be redundant.

IV. The Data

Most of the variables were taken from the March Supplement (Annual Demographic File) of the Current Population Survey. The complete surveys for the years 1990, 1995 and 2000 were obtained from the web site maintained by the National Bureau of Economic Research. State per capita income was obtained from the Bureau of Economic Analysis web site under the heading of State and Local Personal Income. Finally, the Consumer Price Index for 1990, 1995 and 2000 came from the Bureau of Labour Statistics. The names and definitions of all of the variables are provided in Table 1.

The statistical procedures required observations for married females and for divorced females. Application of these restrictions to the data set resulted in 112740 usable observations. Of this

¹ For a very good explanation of this technique see Greene (2000).

Table 1. List of variables

Variable	Definition
<i>S</i> (two letter state code)	Binary: 1 for selected state, 0 otherwise (Washington, D.C. is included)
<i>ED_56</i>	Binary: 1 if highest grade attempted was fifth or sixth, 0 otherwise
<i>ED_78</i>	Binary: 1 if highest grade attempted was seventh or eighth, 0 otherwise
<i>ED_9</i>	Binary: 1 if highest grade attempted was ninth, 0 otherwise
<i>ED_10</i>	Binary: 1 if highest grade attempted was tenth, 0 otherwise
<i>ED_11</i>	Binary: 1 if highest grade attempted was eleventh, 0 otherwise
<i>ED_12</i>	Binary: 1 if highest grade attempted was twelfth, 0 otherwise
<i>ED_Hsgd</i>	Binary: 1 if high school graduate, 0 otherwise
<i>ED_Univ</i>	Binary: 1 if some college was attempted, 0 otherwise
<i>ED_BA</i>	Binary: 1 if college graduate, 0 otherwise
<i>ED_Grad</i>	Binary: 1 if some graduate school was attempted, 0 otherwise
<i>OC_Exec</i>	Binary: 1 if executive, 0 otherwise
<i>OC_Prof</i>	Binary: 1 if Professional, 0 otherwise
<i>OC_Tech</i>	Binary: 1 if Technician, 0 otherwise
<i>OC_Sales</i>	Binary: 1 if Sales, 0 otherwise
<i>OC_Clerical</i>	Binary: 1 if Clerical and administrative support, 0 otherwise
<i>OC_Household</i>	Binary: 1 if Household service worker, 0 otherwise
<i>OC_Guard</i>	Binary: 1 if Protective service worker, 0 otherwise
<i>OC_Oservice</i>	Binary: 1 if Other service worker, 0 otherwise
<i>OC_Craft</i>	Binary: 1 if Craft and repair worker, 0 otherwise
<i>OC_Machine</i>	Binary: 1 if Machine operator, 0 otherwise
<i>OC_Transport</i>	Binary: 1 if Transportation and material moving, 0 otherwise
<i>OC_Equipment</i>	Binary: 1 if Handler, equipment cleaners, etc., 0 otherwise
<i>OC_Farm</i>	Binary: 1 if Farming, forestry and fishing, 0 otherwise
<i>IN_Ag</i>	Binary: 1 if Agriculture, 0 otherwise
<i>IN_Mine</i>	Binary: 1 if Mining, 0 otherwise
<i>IN_Construction</i>	Binary: 1 if Construction manufacturing, 0 otherwise
<i>IN_DGS</i>	Binary: 1 if Durable goods manufacturing, 0 otherwise
<i>IN_NDGS</i>	Binary: 1 if Non Durable goods manufacturing, 0 otherwise
<i>IN_Trans</i>	Binary: 1 if Transportation, communication and public utilities, 0 otherwise
<i>IN_Whtr</i>	Binary: 1 if Wholesale trade, 0 otherwise
<i>IN_ReTr</i>	Binary: 1 if Retail trade, 0 otherwise
<i>IN_Fin</i>	Binary: 1 if Finance, Insurance or Real Estate, 0 otherwise
<i>IN_Bserv</i>	Binary: 1 if Business and repair services, 0 otherwise
<i>IN_Pserv</i>	Binary: 1 if Personal services, 0 otherwise
<i>IN_Ent</i>	Binary: 1 if Entertainment and recreation services, 0 otherwise
<i>IN_Profs</i>	Binary: 1 if Professional and related services, 0 otherwise
<i>IN_Padm</i>	Binary: 1 if Public administration, 0 otherwise
<i>MIG_MM</i>	Binary: 1 if Migrated from MSA to MSA in previous year, 0 otherwise
<i>MIG_MNON</i>	Binary: 1 if Migrated from MSA to non MSA in previous year, 0 otherwise
<i>MIG_NONM</i>	Binary: 1 if Migrated from non MSA to MSA in previous year, 0 otherwise
<i>MIG_NN</i>	Binary: 1 if Migrated from non MSA to non MSA in previous year, 0 otherwise
<i>MIG_ABM</i>	Binary: 1 if Migrated from abroad to MSA in previous year, 0 otherwise
<i>MIG_ABN</i>	Binary: 1 if Migrated from abroad to non MSA in previous year, 0 otherwise
<i>WC_Fed</i>	Binary: 1 if Worked for federal government, 0 otherwise
<i>WC_Local</i>	Binary: 1 if Worked for local government, 0 otherwise
<i>WC_State</i>	Binary: 1 if Worked for state government, 0 otherwise
<i>LF_Work</i>	Binary: 1 if Working, 0 otherwise
<i>LF_Unemp</i>	Binary: 1 if Unemployed but in the labour force, 0 otherwise
<i>Black</i>	Binary: 1 if African American, 0 otherwise
<i>Indian</i>	Binary: 1 if American Indian, 0 otherwise
<i>Asian</i>	Binary: 1 if Asian, 0 otherwise
<i>Hispanic</i>	Binary: 1 if Hispanic, 0 otherwise
<i>Age</i>	Age of the individual measured in years
<i>Under18</i>	Number of children under 18 years of age living with the family
<i>MSA</i>	Binary: 1 if living in an MSA, 0 otherwise
<i>Selfemploy</i>	Binary: 1 if Self employed, 0 otherwise
<i>Homebuy</i>	Binary: 1 if Purchasing the home, 0 otherwise
<i>Statepcy</i>	Per capita income of the state of residence
<i>Famsize</i>	Number of people in the family
<i>1995</i>	Binary: 1 if Observation is from 1995, 0 otherwise
<i>2000</i>	Binary: 1 if Observation is from 2000, 0 otherwise
<i>Divorce</i>	Binary: 1 if Divorced, 0 otherwise
<i>Fincome</i>	Family income measured in constant dollars
<i>Pincome</i>	Personal income measured in constant 1982–1984 dollars

total, 16,760 represented divorced females and 95,980 represented married females.

V. Statistical Estimations

Table 2 provides the results from the probit procedure that was applied to the divorce selection equation. All variables used in the various estimation procedures were included in this equation. This is the usual procedure for estimations of this type because any variable that affects income should also have an effect on the occurrence of divorce.

A well-known concern with models of this type is identification. If the model lacks sufficient identification, erratic slope estimates and exaggerated standard errors can occur in the second stage of estimation. One way that many researchers have approached identification is through the nonlinearity of the inverse Mills ratio. This nonlinearity, if of sufficient magnitude, eliminates the need for exclusion restrictions. But, this practice can be problematical because the inverse Mills ratio is effectively linear within specific ranges of estimation. As a consequence, researchers have closely examined the necessary behavior of the inverse Mills ratio to produce a sufficient level of identification. Leung and Yu (1996) find that Heckman's two-step estimator is sufficiently identified as long as one of the regressors has enough variation to produce 'tail behaviour' in the inverse Mills ratio.²

The current model relies on a large number of binary variables that, in all likelihood, would not produce the necessary tail behavior. However, there are also several other variables (state per capita income, age and family size) that provide considerable variation and, in all probability, produce the necessary effect. While this approach might be reasonable, an additional possibility arises. If variables can be reasonably excluded from the second stage equations, identification becomes more certain.

Fortunately, this formulation of the model provides an entire set of variables that can reasonably be excluded from the income equations – the series of state dummy variables. The state dummies are included in the selection equation to account for differences in state laws and socio-economic conditions that, theoretically, should affect the decision to obtain a divorce. They are excluded from the income equations in favor of state per-capita income. This variable is included in the income equations to

Table 2. Estimation results for the probit selection equation (dependent variable = Divorce)

Variable	Coefficient	t-score
Constant	0.1509	0.732
<i>ED_56</i>	-0.1522	-2.324**
<i>ED_78</i>	0.0642	1.117
<i>ED_9</i>	0.1505	2.494**
<i>ED_10</i>	0.1864	3.254*
<i>ED_11</i>	0.1403	2.432**
<i>ED_12</i>	0.1420	2.020**
<i>ED_Hsgd</i>	0.1072	2.104**
<i>ED_Univ</i>	0.1847	3.577*
<i>ED_BA</i>	-0.0445	-0.830
<i>ED_Grad</i>	0.0675	1.206
<i>MIG_MM</i>	0.0578	3.547*
<i>MIG_MNON</i>	0.0904	2.004**
<i>MIG_NONM</i>	-0.1364	-2.542**
<i>MIG_NN</i>	0.2473	8.365*
<i>MIG_ABM</i>	-0.4063	-5.572*
<i>MIG_ABN</i>	-0.5810	-2.192**
<i>WC_Fed</i>	0.0293	0.720
<i>WC_Local</i>	0.0138	0.576
<i>WC_State</i>	0.0801	2.531**
<i>LF_Work</i>	0.2836	6.397*
<i>LF_Unemp</i>	0.3325	6.267*
<i>Black</i>	0.4260	21.769*
<i>Indian</i>	0.3022	5.695*
<i>Asian</i>	-0.4105	-10.159*
<i>Hispanic</i>	0.0427	2.158**
<i>Age</i>	0.0134	27.633*
<i>Under18</i>	0.7474	92.804*
<i>MSA</i>	0.1631	10.171*
<i>Selfemploy</i>	-0.2555	-11.475*
<i>Homebuy</i>	-0.5600	-43.586*
<i>Statepcy</i>	-0.0000	-1.185
<i>Famsize</i>	-0.9525	-125.417*
<i>1995</i>	0.1055	7.305*
<i>2000</i>	0.1649	4.895*
<i>n</i>	112,740	
Chi squared	28,632.46*	
Estrella (Goodness of Fit)	0.26093	

* Significant at the 1% level.

** Significant at the 5% level.

account for variation in labour market conditions on a geographical basis.

Due to the rather large number of variables included in the estimation procedure, the coefficients for the state dummy variables (*S_*), the occupational dummy variables (*OC_*) and the industry dummy variables (*IN_*) are omitted.³ Of the 34 variables listed in Table 2, 28 are significant at the 1% or 5% level. Most of the variables behaved in predictable ways. For the most part, if the female in question had

²Vella (1998) provides an excellent discussion of these issues.

³ Full results will be supplied on request.

migrated within the USA during the previous year (*MIG_*), the probability of being divorced was significantly higher. On the other hand, if the migration was from abroad (*MIG_ABM*, *MIG_ABN*), the probability of divorce significantly decreased. While the results for the education dummies (*ED_*) provided some mixed evidence, generally, they indicated that having a lower level of education increases the likelihood of divorce. As family size increases the likelihood of divorce significantly declines and being of Asian descent also reduces the likelihood of divorce. Of course the primary purpose of this equation is not for statistical inference, but for use in estimating the earnings equations.

Table 3 provides the results for the selection corrected estimation of divorced female personal earnings. The coefficients and *t*-scores for the thirteen occupation dummies and the 14 industry dummies that were included in the estimation are not displayed.⁴ The education variables reveal no significance until the equivalent of a bachelor's degree is attained. Then the coefficients increase in size and significance as education rises. The estimated coefficients for the migration variables are negative (with one exception) and both of the coefficients that are significantly different from zero are negative. Not surprisingly, the coefficient on being a federal worker is significantly positive while the coefficients on being either a state or a local government worker are significantly negative.⁵ Being a member of the labour force significantly increases earnings whether the participant is employed or unemployed. Of the ethnic variables, only the coefficient on being Hispanic is significantly different from 0 (at the 10% level of significance) and it is negative. It is a little surprising that the coefficient for age is negative and significant. However, the rest of the variables behave in expected ways. As the number of children in the household increase (*Under18*), earnings significantly decline. There is also a significant negative relationship between self-employment and earnings. On the other hand, living in a metropolitan statistical area, purchasing a home, increasing levels of state per capita income, and increasing family size all significantly increase earnings. Finally, for this equation, the estimated coefficient for the selection variable (λ) is negative and significant. The adjusted R-squared for this equation is 0.47, which is a very

Table 3. Estimation results for the divorced personal income equation (dependent variable = Personal Earnings)

Variable	Coefficient	<i>t</i> -score
Constant	-5938.062	-3.961*
<i>ED_56</i>	414.453	0.363
<i>ED_78</i>	376.520	0.349
<i>ED_9</i>	-229.585	0.838
<i>ED_10</i>	-568.008	-0.467
<i>ED_11</i>	-481.276	-0.434
<i>ED_12</i>	-173.434	-0.144
<i>ED_Hsgd</i>	398.550	0.376
<i>ED_Univ</i>	846.582	0.785
<i>ED_BA</i>	3840.904	3.595*
<i>ED_Grad</i>	7318.364	6.680*
<i>MIG_MM</i>	-511.214	-2.705*
<i>MIG_MNON</i>	-880.202	-1.609
<i>MIG_NONM</i>	-1537.966	-2.486**
<i>MIG_NN</i>	-533.094	-1.470
<i>MIG_ABM</i>	651.284	0.631
<i>MIG_ABN</i>	-219.384	-0.051
<i>WC_Fed</i>	1994.064	4.281*
<i>WC_Local</i>	-1099.755	-3.716*
<i>WC_State</i>	-960.939	-2.600*
<i>LF_Work</i>	5402.567	8.594*
<i>LF_Unemp</i>	1444.790	2.105**
<i>Black</i>	-395.019	-1.534
<i>Indian</i>	-194.288	-0.331
<i>Asian</i>	611.861	1.140
<i>Hispanic</i>	-443.722	-1.865***
<i>Age</i>	-26.624	-2.883*
<i>Under18</i>	-1071.602	-3.753*
<i>MSA</i>	1358.628	6.372*
<i>Selfemploy</i>	-836.517	-2.624*
<i>Homebuy</i>	2068.368	8.241*
<i>Statepcy</i>	0.360	11.251*
<i>Famsize</i>	780.981	2.134**
<i>1995</i>	224.029	1.290
<i>2000</i>	27.884	0.149
Lambda (IMR)	-1423.519	-2.689*
Rho	-0.164	
<i>n</i>	16,760	
F	241.95*	
Adjusted R ²	0.471	

* Significant at the 1% level.

** Significant at the 5% level.

*** Significant at the 10% level.

respectable showing considering that most of the variables used in the equation are binary.

Table 4 presents the estimation results for the selection corrected equation predicting personal earnings for married females. Once again the coefficients and *t*-scores for the 13 occupation dummies

⁴ Full results will be supplied on request.

⁵ Stanley and Jarrell (1998, p. 963) in their meta-regression on gender wage discrimination point to the importance of job classification variables that specify governmental employment in the estimation of female earnings.

Table 4. Estimation results for the married personal income equation (dependent variable = Personal Earnings)

Variable	Coefficient	t-score
Constant	-6415.416	-17.545*
ED_56	-284.100	-0.991
ED_78	-1.920	-0.007
ED_9	-238.122	-0.827
ED_10	-374.250	-1.327
ED_11	-507.512	-1.832**
ED_12	-336.782	-0.979
ED_Hsgd	-345.321	-1.423
ED_Univ	82.323	0.334
ED_BA	2028.300	8.007*
ED_Grad	6270.188	23.618*
MIG_MM	-14.550	-0.175
MIG_MNON	-98.368	-0.440
MIG_NONM	-997.990	-3.654*
MIG_NN	-297.523	-1.966**
MIG_ABM	-1112.558	-3.962*
MIG_ABN	77.786	0.101
WC_Fed	2428.852	11.379*
WC_Local	-749.226	-6.593*
WC_State	84.579	0.525
LF_Work	5197.963	27.379*
LF_Unemp	1513.559	6.089*
Black	748.609	6.650*
Indian	134.426	0.482
Asian	793.503	5.587*
Hispanic	13.274	0.149
Age	-11.689	-4.758*
Under18	-529.507	-10.081*
MSA	915.309	13.491*
Selfemploy	-931.276	-9.990*
Homebuy	1277.754	16.798*
Statepcy	0.300	24.607*
Famsize	92.319	1.744**
1995	461.506	7.190*
2000	679.873	9.799*
Lamda (IMR)	-621.565	-3.027*
Rho	-0.795	
n	95980	
F	1450.42*	
Adjusted R ²	0.484	

* Significant at the 1% level.

** Significant at the 5% level.

and the 14 industry dummies that were included in the estimation are not reported.⁶ The results for this equation are very similar to those for the divorced earnings equation. Education doesn't have a significantly positive affect on earnings until a bachelor's degree is obtained at which point it has a large impact. Graduate education has an even greater positive effect. Of the six migration variables, only three have significant coefficients and they are all negative. Once again, working for the federal

government has a significant and positive impact on earnings, as does participation in the labour force whether employed or not. The estimated coefficients for the ethnic dummies vary considerably from the divorced equation. The coefficients for being African American and Asian are both positive and significantly different from zero at the 1% level. However, the coefficients on being Hispanic or Indian are not significantly different from zero. Once again, age has a significant and negative effect on earnings. The number of children in the household and self-employment both reduce income while living in an MSA, buying a home, having a larger family size, and living in a higher income state all significantly increase earnings. The estimated coefficient for lamda (the selection variable) is negative and significant. Finally, the adjusted R-squared is 0.48.

Table 5 presents the selection corrected results for the equation predicting family income. The coefficients and t-scores for the 13 occupation dummies and the 14 industry dummies that were included in the estimation are not reported.⁷ The education variables behave in the expected fashion (very similar to the personal earnings equations) with increasing levels of education producing higher levels of income once the high school graduate stage is reached. The migration variables also behave very similarly to the way they behave in the personal earnings equation with a recent migration (within the previous year) resulting in reduced income. The labour force participation variables behave quite differently. If the female is employed it has a positive and significant impact on family income, but if the female is unemployed there is a negative and significant impact on family income. The ethnic variables also behave very differently in this estimation. The estimated coefficients for Black, Indian, and Hispanic are all negative and significant. The coefficient for Asian is insignificant. Increasing numbers of children and age significantly decrease family income. Living in an MSA, being self-employed, buying a home, increasing family size, and living in a state with a higher per capita income all significantly increase family income. The estimated coefficient for the selection variable (lambda) is negative and significant. Finally, the adjusted R-squared is 0.38.

In all three of the income equations, the estimated coefficient for the selection variable (the inverse Mills ratio) is negative and significantly different from 0. The fact that these coefficients are significantly different from 0 provides important statistical

⁶ Full results will be supplied on request.

⁷ Full results will be supplied on request.

Table 5. Estimation results for the married family income equation (dependent variable = Family Income)

Variable	Coefficient	t-score
Constant	-21996.904	-10.538*
ED_56	305.502	0.218
ED_78	429.783	0.301
ED_9	157.097	0.107
ED_10	98.911	0.058
ED_11	487.994	0.333
ED_12	2023.786	1.305
ED_Hsgd	4495.666	3.138*
ED_Univ	7822.660	5.430*
ED_BA	15525.113	10.604*
ED_Grad	21973.639	14.962*
MIG_MM	-1156.044	-5.255*
MIG_MNON	384.954	0.659
MIG_NONM	-3809.466	-5.389*
MIG_NN	-1897.787	-4.740*
MIG_ABM	-4557.808	-6.199*
MIG_ABN	335.830	0.168
WC_Fed	512.926	0.935
WC_Local	-2357.779	-8.045*
WC_State	-1963.318	-4.740*
LF_Work	3099.166	6.306*
LF_Unemp	-1434.980	-2.240**
Black	-5554.957	-19.133*
Indian	-3469.821	-4.842*
Asian	298.584	0.802
Hispanic	-4286.220	-16.786*
Age	-320.324	-40.466*
Under18	-7449.363	-49.628*
MSA	4869.148	26.902*
Selfemploy	2363.281	9.798*
Homebuy	10163.315	49.171*
Statepcy	1.118	35.063*
Famsize	8795.796	49.702*
1995	-1372.387	-8.270*
2000	-325.845	-1.832**
Lamda (IMR)	-8807.076	-14.156*
Rho	-0.434	
n	95,980	
F	962.07*	
Adjusted R ²	0.383	

* Significant at the 1% level.

** Significant at the 5% level.

evidence for the existence of selection bias in the model (Melino, 1982). Interpreting the signs attached to these coefficients is much more problematical. Many condemnatory comments have been written about the perverse nature of these signs because to many researchers, they have seemed counterintuitive. However, attaching an expected sign to these coefficients based on economic theory is not, in all likelihood, a possibility (Dolton and Makepeace, 1987). There are too many feasible mathematical outcomes to allow specification of a particular sign.⁸ Consequently, the most important outcome is that the estimated coefficients are significantly different from 0.

Of course, the final probit provides the most intriguing results and one possible version of these results is provided in Table 6.⁹ Both of the created difference variables ($\hat{\Delta}_1$ and $\hat{\Delta}_2$) have negative and significant estimated coefficients. The result for $\hat{\Delta}_1$ indicates that as females become more successful at producing income in the divorced state, the more likely they are to become divorced. The result for $\hat{\Delta}_2$ indicates that as female earnings becomes a larger portion of total family income, the likelihood of divorce increases. Interestingly, the idea that the family attaches a positive value to the female's earnings and therefore, attempts to continue the state of marriage fails to overcome the previous two arguments. There may be some validity to this contention, but the positive effect (if present) is obviously not large enough to offset either of the other two effects.

In addition to the two difference variables, the entire series of state dummy variables was included in this estimation (they are excluded from the individual income equations) just as it was in the original selection probit (although the results do not appear in Table 6).¹⁰ The reason for including these variables is primarily that the various states have different legal systems and, as mentioned earlier, other studies have found that the legal situation does have an important impact on the willingness and ability to dissolve a marriage. Curiously enough, 39 of the 50 estimated

⁸ Additional insight on this issue is provided by Ermisch and Wright (1994).

⁹ An anonymous referee requested that in addition to the series of state dummies an additional series of variables be investigated – interaction variables between year and state. This created an unacceptably large number of variables for the estimation procedures. So, two alternatives were tried. First, a probit procedure with divorce as the dependent variable and just the year and state dummies was estimated. Then, a series of interaction variables between one year and the states was added. Neither probit was able to correctly predict even a single divorce (0.5 was used as the threshold for prediction). In addition, the Hosmer–Lemeshow statistic recommended against both specifications. The same results were produced for the final two series of interaction variables. Finally, a similar procedure was attempted for the structural probit that included the state dummies. The interaction variables (added separately, one year at a time) had no effect on the signs or the levels of significance for the difference variables. They also had almost no effect on the Estrella statistic and were recommended against by the Hosmer–Lemeshow statistic.

¹⁰ The coefficient estimates and t-scores for the state dummy variables are omitted from Table 6 because of concerns for space. Full results will be supplied on request.

Table 6. Estimation results for structural probit with state dummies (dependent variable = Divorce)

Variable	Coefficient	<i>t</i> -score
Constant	-0.10681	-0.913
$\hat{\Delta}_1$	-0.00014	-16.978*
$\hat{\Delta}_2$	-0.00016	-121.822*
<i>n</i>	112,740	
Chi squared	54,877.90*	
Hosmer–Lemeshow chi squared	20.93*	
Estrella (goodness of fit)	0.517	

*Significant at the 1% level.

coefficients were significantly different from zero at the 10% level of significance.¹¹ However, the issue of whether the state dummies should be included in the final estimation is clouded by examination of the Hosmer–Lemeshow statistic. It indicates that the estimation is not a very good ‘fit’. So, an additional estimation was run excluding the state dummies. Table 7 provides the results of this procedure. The two created variables retain their negative coefficients and their high degree of significance. There is little change to the Estrella statistic and the Hosmer–Lemeshow statistic is highly significant. In other words, eliminating the state dummies did not change the essential features of the estimation procedure. Finally, even though either of these structural probits makes use of many fewer variables than the selection probit, their goodness of fit scores based on Estrella’s (1998) methodology is essentially double that of the selection estimation –0.52 or 0.49 compared to 0.26.¹²

VI. Conclusions

The estimations reported in this paper tend to confirm arguments that have long been made about the causes of divorce. As females experience greater levels of success in the labour market, they also tend to experience higher levels of divorce. This occurs for two important reasons. First, greater financial independence clearly makes the decision to seek a divorce much simpler. In this respect, developing countries that have concentrated on guaranteeing equal economic status for females have reduced the burden of living with unhappy marriages strictly for economic reasons. However, it also appears that a female’s economic success may, indeed, cause friction

Table 7. Estimation results for structural probit without state dummies (dependent variable = Divorce)

Variable	Coefficient	<i>t</i> -score
Constant	-0.06604	-2.927*
$\hat{\Delta}_1$	-0.00012	-15.763*
$\hat{\Delta}_2$	-0.00015	-120.946*
<i>n</i>	112,740	
Chi squared	52,425.10*	
Hosmer–Lemeshow chi squared	9.77	
Estrella (goodness of fit)	0.492	

*Significant at the 1% level.

within the family. The results of the estimations in this paper clearly indicate that as the female’s earnings become a larger portion of total family income, the likelihood of divorce increases even while controlling for general success in the labour market ($\hat{\Delta}_1$). Of course, over time the causes of this effect (fragile male egos?) could well change.

Finally, there is little doubt that many other contributory factors affect the decision to seek a divorce. This is the reason that the series of state dummy variables was maintained in the final probit equation. As all statisticians know, resorting to the use of binary variables reveals a certain degree of ignorance. In this particular case, that degree of ignorance turned out to be relatively important, as thirty-nine of the estimated coefficients for the state dummy variables in the final probit were significantly different from zero. In other words, opportunities still exist in the search for a more perfect statistical model of marriage dissolution.

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¹¹ Washington, D.C. was included in the estimations as a state and Kansas was excluded. Thus, 50 coefficients were estimated.

¹² In addition, several other goodness of fit measures all indicate that either of the ‘‘structural’’ probits provides superior statistical results to the estimates produced by the reduced form equation.

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