Women's Labor Force Participation and Probability of Getting Divorced

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Abstract

By using individual level panel data from 1995 to 1997, and running models with individual fixed effect and year fixed effect, the author concludes that there is no valid evidence that increase in women labor force participation can lead to rise of probability of getting divorced. Furthermore, this effect is heterogeneous among different education levels. Empirical results also find out that having high school degree has positive effect on the probability of getting divorced, while having college degree, income and number of children inthe family all have negative effect. Based on these results, measures which can increase women's college education rate can help lower divorce rate.

Section 1: Introduction

Does increased women's labor force participation result in increased divorces or does an increased probability of divorce cause more women to diversify their risk and invest more time and skills in the labor market (Kesselring and Bremmer, 2008)? This is an interesting topic that has drawn much attention but has not been fully solved yet.

Many economists have made great efforts in shedding light on one direction of the question, namely the effect of potential divorce on women's labor force participation. However, few works have been focused on the influence of the opposite direction. It is reasonable to argue that increased women's labor force participation results in less time allocated to family, a rise of women's status inside the family and potentially more disputes with husbands. As a result, it is important to test whether a rise in women's labor force participation increases the likelihood of divorce.

In this paper, the author will test the hypothesis that participating in the labor force increases the probability of getting divorced for women. Section 2 presents previous literature on this topic; section 3 describes the data used, and displays summary statistics in tables and graphs; section 4 presents the econometric models to be estimated; section 5 conducts empirical analysis; and section 6 summarizes the whole paper.

Section 2: Literature Review

Many previous literatures tried to explain the change in women's labor participation from the perspective of divorce risk and divorce law. Using human capital as an explanation, Parkman (1992) found that introduction of unilateral divorce (no-fault based divorce) has increased the LFPR of married women. South (1985) found a small but direct relationship between unemployment rates (i.e. business cycle) and divorce rate. Shapiro and Shaw (1983) found out that women increase their labor force participation prior to dissolution of a marriage.

Some previous literatures focused on the same topic and yielded illuminating results. Smith (1997) found that a higher divorce rate was caused by increasing women's labor force participation and rising female income. He also found that having fewer children resulted from fertility control had an impact on the divorce rate increase.

Similarly, Bremmer and Kesselring (1999, 2004) have investigated in this issue in three papers in 1999 and 2004. They used macro data, Granger causality test and cointegration techniques and concluded that women's labor force participation led to an increase in the divorce rate. Many papers compare the impact for different subgroups of women, such as women with and without children, black women and women as a whole group. This is also worth trying.

Section 3: Data

I use the data from PSIDbetween 1995 and 1997, which is individual level panel data. I drop the observations which do not have a family indicator since I cannot get the variables in family dataset for these individuals. The variable definitions can be found in table 1.

The dependent variable in this model is change in marital status, and the whole definition of it can be found in table 2. Since the model is focused on estimating the effect of being employed on the probability of getting divorced, so the interested sample only consists of those who are married in previous year (i.e. those who are unmarried in previous year should be excluded from the sample). It is also clear that the gender of individuals in the sample can only be female. Based on the two restrictions above, the number of observations is 17,584. What is also worth mentioning is that we are having an unbalanced panel dataset.

The summary statistics for the variables (table 3) can be found below. There are 575 out of 17584 observations which have marital status changed from married to divorced, and the percentage of this part is 3.27%. 41% of the sample have been employed, which a fairly large proportion. The average yearly family taxable income is $54,580, with a large standard deviation implying that the distribution is spread out. The average number of children in the family is 1.57, and we can find that the majority of the families in the sample have less than 3 children. In terms of education status, 42% of the sample has high school degree as their highest education earned, while 15% of the sample has college or higher degree.

Table 4 displays the correlation matrix for all the variables in the model.The signs for the correlation of *div* with *employ*, *income*, *hs* and *col* are negative, which gives interesting intuition. The sign for the correlation of *div* with *children* is positive, which is contrary to common sense. There does not exist multicollinearity because all the correlation coefficients are below 0.5.

Another interesting way to get more information about the data is to draw graphs based on comparison. Figure 1 contains three graphs, comparing many characteristics between those who get divorced and those who do not. We can see that on average, divorced female have lower employment rate, lower degree earned and considerably lower family income. The number of children inside the family is almost the same for the two groups.

Section 4: Model

The dependent variable in the model is a dummy variable, div_{it}, which equals one if individual i is married in year t-1 but is divorced in year t. This reflects the change in the marital status. The main independent variable we are interested in is $employ_{it}$, which refers to whether individual i is employed in year t. Control variables include *hs, col* (refers to highest degree earned), *income* (husband and wife yearly taxable income) and *children* (number of children in family), which is also what is included in vector X_{it}in the model. Two dummies variables, *hs* and *col*, are introduced in order to test the heterogeneous effect of being employed on probability of getting divorced.

My model is:

$$\text{model 1}: div_{it} = \beta_0 + \beta_1 * employ_{it} + \beta_2 * hs_{it} + \beta_3 * col_{it} + X_{it} * \beta + u_i + v_t + \varepsilon_{it}$$

$$\text{model 2}: div_{it} = \beta_0 + \beta_1 * employ_{it} + \beta_2 * hs_{it} + \beta_3 * col_{it} + \beta_4 * employ_{it} * hs_{it} \\ + \beta_5 * employ_{it} * col_{it} + X_{it} * \beta + u_i + v_t + \varepsilon_{it}$$

$$\text{model 3}: div_{it} = \beta_0 + \beta_1 * hours_{it} + X_{it} * \beta + u_i + v_t + \varepsilon_{it} \ \text{(tentative)}$$

It is worth mentioning that model 1 is estimated on samples that are married in previous year, because the labor market behavior of those who are married and those who are not differs significantly in many aspects. Another reason to rule out unmarried people is that div_{it} for them is always 0.

The author hypothesizes that being employed has a positive effect on the probability of getting divorced, this is because employment reduces the time spent with family, increases the status of women in the family and is likely to increase disputes between couples. The effect of education level on the probability of getting divorced is hard to predict since there are a lot of factors working on both directions. But testing the existence and direction of this effect is important in that it reveals great insight of divorce decisions.

What's more, the sign of coefficient for *income* is also hard to predict, because in one direction, lower income and regular changes of marriage are often seen happening together, but in the other direction, higher income could raise economic dependency of female and leads to more divorce in turn. Number of children is predicted to have a negative relationship with probability of getting divorced, as responsibilities coming with raising children could make the cost of divorce higher.

Model 2 incorporates two interaction terms, namely *employ*hs*and*employ*col*. The coefficients have the following interpretations: on average and ceteris paribus, the difference of the effect of being employed on the probability of getting divorced, between married female with highest degree earned as high school (college) and those who have not finished high school. The sign for these two interaction terms is undetermined.

From model 1, we will get the sign of estimated coefficient of employ and test whether it is statistically different from 0. From model 2, we can test whether this impact is heterogeneous among different education level, namely high school degree and college degree.

This model cannot be used to estimate the causal impact because increased risk of getting divorced also increases women labor force participation, which has already been proved by previous research. Thereverse causality problem is not solved in this model. But this paper will shed light on the correlation problem.

Section 5: Empirical Analysis

1. Employment

Regression results and economic significance level are listed in table 5 and 6. The main hypothesis is that being employed increases the probability of getting divorced. However, the estimated coefficient for *employ* in model 1 is negative, implying that being employed has a lower 0.0009 probability of getting divorced on average and holding other variables fixed. It is neither statistically nor economically significant. In model 2, being employed has a higher 0.0033 probability of getting divorced on average and holding other things equal. However, this is also not economically significant.

When taking into account the two interaction terms, *employ_hs* is estimated to be 0.0035, meaning that employed female with high school degree has a higher 0.0035 probability of getting divorced than their counterpart without high school degree. This is neither statistically nor economically significant. As to *employ_col*, it is estimated to be -0.0362, meaning that employed female with college degree has a lower 0.0362 probability of getting divorced than those without high school degree. It is worth mentioning that it is significant at 5% significance level. We can conclude that the influence of being employed on the probability of getting divorced is heterogeneous among different education levels.

The insignificance of the coefficient may be due to omitted variable bias, because employment status is correlated with race, and race has non-trivial effect on probability of getting divorced. So omitted race in the model could be the reason why *employ* is not significant. However, the author thinks multicollinearity is not the potential reason for insignificance.

2. Education levels

From previous analysis, the effect of employment on the probability of getting divorced is heterogeneous among different education levels. Next we want to look at the direct effect of education levels on the probability of getting divorced.

The effect is hard to estimate theoretically in that higher education level can not only lead to factors that increases the probability of getting divorced (such as rise of women's status inside the family, pursuit of better partner, financial independence etc.), but can lead to factors that decreases the probability of getting divorced as well (such as stability of family financial conditions, better living standards, increased identity recognition between couples, similar interests and hobbies, potentially fewer working hours in general etc.). The contradictory forces make it difficult to estimate the effect. In the following analysis, we use "pro-force" and "con-force" to refer to these two forces.

Model 1 and model 2 reveals interesting and consistent results about this relationship. Both models report having high school degree increases the probability of getting divorced compared with those without high school degree, and the semi-elasticity ranges from 0.54 to 0.66. What's more, both models report having college degree decreases the probability of getting divorced compared with the same base group, and the semi-elasticity ranges from -1.48 to -0.87. In all, we can conclude that "pro-force" outweigh "con-force" as to high school, but "con-force" outweigh "pro-force" when female has college or even higher degree.

3. Income

In section 3, multiple reasons are listed as to why the sign of coefficient for *income* is undetermined. From both models, the estimated coefficient for *income* is -0.0006, and it is significant at 1% significance level. A $1,000 increase of yearly family taxable income will lower the probability of getting divorced by 0.6%, on average and ceteris paribus. The elasticity for *income* is -1.09, which is very high.

4. Number of children in the family

In the hypothesis, we estimate the coefficient for number of children in the family to be negative, because it raises the potential cost of divorce. Both models correspond with this prediction by getting the estimated coefficient to be -0.0289, which is significant at 1% significance level. The elasticity is -0.96, and it is also very high.

Section 6: Conclusion

Using panel data from PSID and running models with individual fixed effect and year fixed effect, we can draw the following conclusions:

(1) There is no valid evidence that increase in women labor force participation can lead to the rise of probability of getting divorced. Further test of interaction terms confirms that the effect of being employed on the probability of getting divorced is heterogeneous among different education levels, namely high school and college.

(2) Education levels have significant effect on the probability of getting divorced: having high school degree increases the probability of getting divorced compared with those without high school degree, while having college degree decreases the probability.

(3) Income has significant negative effect on the probability of getting divorced: a $1,000 increase of yearly family taxable income will lower the probability of getting divorced by 0.6%, on average and ceteris paribus.

(4) Number of children in the family also has significant negative effect on the probability of getting divorced: having 1 more children decreases the probability of getting divorced by 0.0289, on average and holding other variables fixed.

From these results, we can find that college degree has negative effect on the probability of getting divorced, both directly and indirectly through employment. So increasing the amount of females who receive college education could be an effective way to lower divorce rate. The measures such as more gender equality in recruitment, higher financial aid to students from low income families could thus be promoted.

References

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2. South, Scott. "Economic Conditions and the Divorce Rate: A Time-Series Analysis of Postwar United States," *Journal of Marriage and the Family*, February 1985, vol. 47, no. 1: 31-41.

3. Shapiro, David and Lois Shaw. "Growth in Supply Force Attachment of Married Women: Accounting for Changes in the 1970's," *Southern Economic Journal*, vol. 6, no. 3, September 1985: 307-329.

4. Smith, Ian. "Explaining the Growth of Divorce in Great Britain," *Scottish Journal of Political Economy*, vol. 44, no. 5, November 1997: 519-544.

5. Bremmer, Dale and Randy Kesslering. "The Relationship between Female Labor Force Participation and Divorce: A Test Using Aggregate Data," unpublished mimeo, 1999.

6. Bremmer, Dale and Randy Kesselring. "Divorce and Female Labor Force Participation: Evidence from Times-Series Data and Cointegration," *Atlantic Economic Journal*, September 2004, vol. 32, no. 3: 174-189.

Appendix 1: Tables and graphs

Table 1: Description of Variables

Variable	Description
div	1 if changing from married to divorced, 0 otherwise
employ	1 if being employed, 0 otherwise
income	Husband and wife taxable income, in $1,000s
children	Number of children in family
hs	1 if the highest degree earned is high school, 0 otherwise
col	1 if the highest degree earned is college, 0 otherwise

Table 2: Definition of Change in Marital Status

Code	Description
1	head and Wife/"Wife" or head and husband of head remained married to each other
2	head remained unmarried (single, separated, widowed, divorced)
3	head and Wife/"Wife" or head and husband of head were married in previous year, head is one of these two individuals and divorced or separated in this year
4	head and Wife/"Wife" or head and husband of head were married in previous year, head is one of these two individuals and is widowed in this year
5	head was unmarried (i.e. no spouse present) in previous year but was married in this year and has either stayed head or become Wife/"Wife" or husband of head
6	head and Wife/"Wife" or head and husband of head were married in previous year, became divorced and married someone in this year
7	head and Wife/"Wife" or head and husband of head were married in previous year, became widowed and remarried in this year
8	Other, including all splitoffs except those who were either Head or Wife/"Wife" in previous year; recontact family

Table 3: Summary Statistics

variable	mean	p50	sd	min	max
div	0.03	0	0.18	0	1
employ	0.41	0	0.49	0	1
income	54.58	44.5	57.25	-128.56	1034.93
children	1.57	2	1.37	0	9
hs	0.42	0	0.49	0	1
col	0.15	0	0.35	0	1
Count: 17,584					

Table 4: Correlation Matrix

	div	employ	income	children	hs	col
div	1					
employ	-0.0146	1				
income	-0.1177	0.1019	1			
children	0.0007	-0.2165	0.008	1		
hs	-0.0131	0.4161	-0.0955	-0.2562	1	
col	-0.0229	0.265	0.2042	-0.1193	-0.3501	1

Table 5: Regression Results

	(1)	(2)
VARIABLES	Model 1	Model 2
employ	-0.0009	0.0033
	(0.005577)	(0.011623)
hs	0.0199*	0.0163
	(0.010932)	(0.011679)
col	-0.0445**	-0.0262
	(0.020607)	(0.021797)
employ_hs		0.0035
		(0.013397)
employ_col		-0.0362**
		(0.017540)
income	-0.0006***	-0.0006***
	(0.000046)	(0.000046)
children	-0.0289***	-0.0289***
	(0.003510)	(0.003511)
96.year	0.0214***	0.0213***
	(0.002592)	(0.002592)
97.year	0.0433***	0.0432***
	(0.002646)	(0.002647)
Constant	0.0884***	0.0886***
	(0.009317)	(0.009376)
Observations	17,584	17,584
R-squared	0.045	0.046
Number of id	6,440	6,440

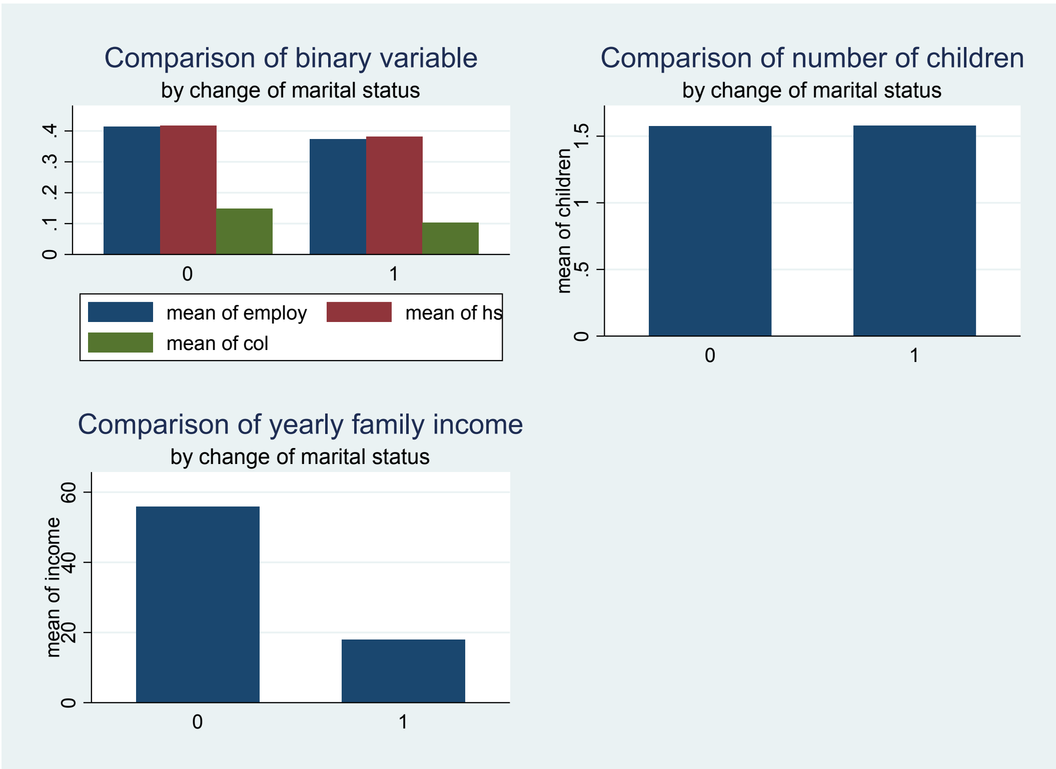
Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6: Comparison with Hypothesis, and Economic Significance

	hypothesis	model 1	model 2
employ	positive	-0.03	0.11
hs	undetermined	0.66	0.54
col	undetermined	-1.48	-0.87
income	undetermined	-1.09	-1.09
children	negative	-0.96	-0.96

Note: the displayed economic significance is elasticity for *income*, and semi-elasticity for all other variables.

Figure 1: Comparison between divorced and undivorced female



Appendix 2:

```
----------------------------------------------------------------------------------------
-------------------------------------------------------------------------------------

      name:  <unnamed>

       log:  E:\202 Econometrics\Break ice\Data\paper.smcl

  log type:  smcl

 opened on:   1 May 2017, 00:01:18

. *============================

. * final changes to panel data

. *============================

. drop if sex==1 //drop male

(25,476 observations deleted)


. drop if change==2| change==5| change==8 //drop unmarried

(10,313 observations deleted)


. gen div = 0

. replace div = 1 if change==3|change==6

(575 real changes made)

. label var div "married to divorce"


. gen employ = 0

. replace employ =1 if employment==1|employment==2

(7,263 real changes made)

. label var employ "being employed"


. replace income = income/1000

variable income was long now double

(16,894 real changes made)

. label var income "income in $1000"
```

```
. gen hs = 0

. replace hs = 1 if education>=12 & education<=15

(7,317 real changes made)


. gen col = 0

. replace col = 1 if education>=16

(2,581 real changes made)

.

. *============================

. * data description

. *============================

. tabstat div employ income children hs col, stat(mean median sd min max) ///

>        col(stat) format(%8.2f)

   variable |     mean      p50       sd      min      max

-------------+--------------------------------------------------

        div |     0.03     0.00     0.18     0.00     1.00

     employ |     0.41     0.00     0.49     0.00     1.00

     income |    54.58    44.50    57.25  -128.56  1034.93

   children |     1.57     2.00     1.37     0.00     9.00

hs |     0.42     0.00     0.49     0.00     1.00

        col |     0.15     0.00     0.35     0.00     1.00

----------------------------------------------------------------

.

. graph bar (mean) employ hs col, over (div) ///

>title("Comparison of binary variable") ///

>subtitle("by change of marital status") ///

>saving(1)

(file 1.gph saved)

. graph bar (mean) children, over (div) ///
```

```
>title("Comparison of number of children") ///

>subtitle("by change of marital status") ///

>saving(2)

(file 2.gph saved)


. graph bar (mean) income, over (div) ///

>title("Comparison of yearly family income") ///

>subtitle("by change of marital status") ///

>saving(3)

(file 3.gph saved)


. graph combine 1.gph 2.gph 3.gph, hole(4) saving(comparison)

(file comparison.gphsaved)

.

. cor div employ income children hs col

(obs=17,584)


             |      div   employ   income children       hs
-------------+---------------------------------------------
         div |   1.0000
      employ |  -0.0146   1.0000
      income |  -0.1177   0.1019   1.0000
    children |   0.0007  -0.2165   0.0080   1.0000
hs|  -0.0131   0.4161  -0.0955  -0.2562   1.0000
         col |  -0.0229   0.2650   0.2042  -0.1193  -0.3501


             |      col
-------------+---------
         col |   1.0000

. *=============================
```

```
. * empirical results

. *============================

. xtset id year

      panel variable:  id (unbalanced)

       time variable:  year, 95 to 97, but with gaps

              delta:  1 unit


. xtreg div employ hs col income children i.year, fe


Fixed-effects (within) regression            Number of obs     =    17,584

Group variable: id                           Number of groups  =     6,440


R-sq:                                        Obs per group:

within  = 0.0454                                       min =         1

    between = 0.0017                                        avg =       2.7

    overall = 0.0058                                        max =         3


F(7,11137)       =     75.61

corr(u_i, Xb)  = -0.3300                     Prob > F          =    0.0000


------------------------------------------------------------------------------

        div |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

     employ |  -.0008514   .0055768    -0.15   0.879    -.0117829    .0100801

hs |   .0199466   .0109318     1.82   0.068    -.0014817    .0413749

        col |  -.0445014   .0206067    -2.16   0.031    -.0848941   -.0041086

     income |  -.0006097   .0000465   -13.11   0.000    -.0007008   -.0005186

   children |  -.0288618   .0035104    -8.22   0.000    -.0357427   -.0219808

            |

       year |
```

```
96  |  .0213547  .0025919    8.24  0.000    .0162741   .0264354

97  |  .0432974   .002646   16.36  0.000    .0381109    .048484
           |
      _cons |   .088442  .0093174    9.49  0.000    .0701782   .1067057
-------------+----------------------------------------------------------------
sigma_u|  .20053792

sigma_e|  .13721942

       rho |  .68110276   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(6439, 11137) = 2.79              Prob > F = 0.0000


. outreg2 using table1.xls, replace bdec(4) sdec(6)

table1.xls

dir :seeout

.

. gen employ_hs = employ * hs

. gen employ_col = employ * col


. xtreg div employ hs col employ_hsemploy_col income children i.year, fe


Fixed-effects (within) regression            Number of obs     =    17,584

Group variable: id                         Number of groups  =     6,440


R-sq:                                     Obs per group:

within  = 0.0460                                   min =         1

    between = 0.0018                                    avg =       2.7

    overall = 0.0058                                    max =         3


F(9,11135)       =     59.65

corr(u_i, Xb)  = -0.3373                      Prob > F         =    0.0000
```

```
------------------------------------------------------------------------------
        div |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     employ |   .0032698   .0116234     0.28   0.778    -.0195142    .0260538
hs |    .016281    .011679     1.39   0.163    -.0066119    .0391739
        col |  -.0261601   .0217966    -1.20   0.230    -.0688853    .0165651
employ_hs |   .0035321   .0133971     0.26   0.792    -.0227286    .0297928
employ_col|  -.0361875   .0175402    -2.06   0.039    -.0705694   -.0018056
     income |    -.00061   .0000465   -13.12   0.000    -.0007012   -.0005189
   children |  -.0288611   .0035107    -8.22   0.000    -.0357427   -.0219795
           |
       year |
96  |   .0212825   .0025919     8.21   0.000      .016202    .0263631
97  |     .04316   .0026472    16.30   0.000     .0379709     .048349
           |
      _cons |   .0885609   .0093755     9.45   0.000     .0701832    .1069386
-------------+----------------------------------------------------------------
sigma_u|  .20080139
sigma_e|  .13718672
        rho |  .68177623   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(6439, 11135) = 2.78             Prob > F = 0.0000


. outreg2 using table1.xls, append bdec(4) sdec(6)
table1.xls
dir :seeout


.
.
end of do-file
```