

# Effects of Parental Divorce on Teenage Children's Risk Behaviors: Incidence and Persistence

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Published online: 18 August 2015

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**Abstract** It is generally difficult to separate the effects of divorce from selection when analyzing the effects of parental divorce on children's risk behaviors. We used propensity score matching and longitudinal data methods to estimate the effects of parents' divorce on their children's binge drinking, alcohol consumption, tobacco use, marijuana use, and hard drug use. The children were between 12 and 18 years old in the first survey and between 18 and 24 years old in the second survey. Our results suggest that parental divorce significantly increased the probability of risk behaviors in their children. Moreover, many of these adverse impacts persisted over time, especially among teenage girls.

**Keywords** Divorce · Children's outcome · Propensity score · Random effects probit

## Introduction

Divorce rates in the United States increased rapidly in the 1970s and have since remained relatively high. Since 2000, these rates have been hovering around 3.5–4.0 divorces

annually per 1000 people. These figures indicate that a considerable number of children are experiencing family disruptions. Research has shown that an individual's experiences early in life may have serious effects later in life. The potential instability and insecurity in a child's life caused by a family breakup may continue for a long time. This insecurity could induce substance abuse, crime, and low educational outcomes. Results from many studies show that children from divorced families have worse outcomes than children from intact families. For example, Mohanty and Ullah (2012) argued that one of the reasons children from divorced families earn less during their adulthood was the stress associated with their parental family structure. Others have found that children in to-be-divorced families have lower test scores and more behavioral problems (e.g., Cherlin et al. 1991; McLanahan 1985).

Parental divorce may affect children's outcomes through a number of mechanisms. These include the emotional impacts on the child of the change in family structure, change in economic resources available to achieve the child's best outcomes, and change in parental inputs (e.g., guidance, amounts of direct and indirect time spent with child). For example, female-headed families tend to have lower incomes, have less time to devote to children, have smaller social networks, and live in poorer neighborhoods—factors that may contribute to poorer outcomes for children. However, recent research casts doubt on the effects of divorce on female income levels (Ananat and Michaels 2008; Page and Stevens 2004). These papers indicated that unobservable factors may cause divorced females to have lower incomes than married females. Divorce can also cause disruptions and emotional stress for children through parental separation, hostility, and residential/school dislocation. It can also lead to immediate reduction in time and parenting inputs from the nonresident

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parent (Steele et al. 2009). In addition, females tend to increase their labor participation after divorce (Tamborini et al. 2012), which may contribute to reduced time with their children.

Although these mechanisms could lead to negative outcomes for the child, divorce could also produce positive outcomes in some cases. For example, the potential negative effects of parental conflicts or abuse could be reversed by parental separation. A number of studies have found evidence that, in cases of severe parental conflicts or abuse, divorce actually improved children's behavior and well-being (e.g., Jekielek 1998; Morrison and Coiro 1999).

Understanding the relation between divorce and children's outcomes is crucial in designing effective public policies that can influence family structures (Painter and Levine 2000). This is important because most current policies have not been able to directly address the underlying reasons for parental divorce. If divorce is related to poor outcomes in children, it might be concluded, for instance, that the correct policy prescription is to discourage divorce by increasing the cost of divorce. Furthermore, if divorce is seen as having a large negative effect on children's outcomes, it may be considered prudent for public policy to consider adding the cost of such negative outcomes to the damages that can be claimed.

Unobserved confounding factors represent an important challenge in determining the causal effects of divorce on children's outcomes because children's outcomes may well be influenced by the same family attributes that are conducive to divorce. For example, the relative disadvantage observed among children from divorced families may be due to differences between the types of people who get divorced and those who do not. Hence, there may be factors that simultaneously affect both divorce and children's outcomes. For instance, parents' characteristics, time use, and behavior may affect both the probability of divorce and the child's behavior. Similarly, living conditions could affect both the probability of divorce and children's outcomes.

The analyses most commonly used in assessing the effects of divorce on children's outcomes are generally cross-sectional and longitudinal in nature. Many cross-sectional analyses tend to ignore the fact that a divorced family structure may be related to unobserved disadvantages that can also cause poor children's outcomes. Mednick et al. (1987) found that children from divorced families were more likely to commit crimes but that this relationship vanished when additional control variables such as the father's criminal record and social class were included in the models. Thus, in the absence of experimental data, it is difficult to determine, using only cross-sectional data, how children would have fared if the parents had not divorced (Corak 2001; Steele et al. 2009).

Moreover, without a randomized controlled trial, it is also not possible to be completely certain that one has controlled for all the variables that could potentially influence both family structure and children's outcomes (McLanahan and Sandefur 1994). Other studies have resorted to using instrumental variables. For example, Ananat and Michaels (2008) used instrumental variable estimation to account for unobservable traits when analyzing the effects of divorce on females' incomes. In contrast, Page and Stevens (2004) used fixed effects estimation using a large longitudinal data set. Interestingly, the effects of divorce vanished in these studies after accounting for unobservable traits.

As a genuine experimental design on divorce is obviously not possible, one of the best alternative approaches is to use quasi-experimental methods with longitudinal data; therefore, in this study, we used longitudinal data from the US National Longitudinal Study of Adolescent Health (Add Health). Our aim in this study was to examine whether children from divorced families were more likely to engage in risk behaviors such as substance abuse. In addition, we investigated not only the short-term but also the medium-term effects of divorce on teenagers' risk behaviors. We call these two effects the "incidence effect" and the "persistence effect," respectively, in our analysis.

To take into account the selection issues, we used propensity score matching, in addition to longitudinal data estimation, to remove systematic differences between divorced families (the treatment group) and married families (the control group). In our matched sample, each child lived with both biological parents when they were born. After some time, half of the children experienced their parents getting divorced while continuing to live with one parent (usually the mother). The other half continued to live with both parents, i.e., the family remained intact. We estimated several average treatment effects based on the matched samples, employing the information contained in the estimated propensity scores and our longitudinal data. As a robustness check, we also used the OLS and bivariate probit models on the unmatched sample.

Our results provide some new insights into the effects of divorce on the incidence and persistence of teenagers' risk behaviors. In particular, we found that children aged 12–18 years from divorced families were more frequently involved in binge drinking, alcohol consumption, tobacco use, and marijuana use than their counterparts from married families. All these frequencies increased as the children grew older. A noteworthy difference was that the frequencies of alcohol consumption among children from both family types tended to converge over time, while the frequencies of tobacco and marijuana use among children from divorced families remained substantially higher than those from intact families. We conducted separate analyses on males and females and found that the persistence of the

adverse effects of divorce was particularly pronounced for teenage girls.

The rest of the paper is structured as follows. The following section briefly reviews the literature on the effects of divorce on children's outcomes. This is followed by sections on the methods, data, and results. The final section of the paper contains the discussion and conclusion.

## Literature Review

The majority of studies on the effects of divorce on children's outcomes have concentrated on measurements of child well-being. Amato and Keith (1991) conducted a meta-analysis of studies published from the 1950s through the 1980s dealing with the long-term consequences of divorce on adult well-being. Their study indicated that children from divorced families scored significantly lower than children from married families on a variety of indicators of well-being, including measures of academic achievement, self-concept, conduct, psychological adjustment, social relations, and the quality of relationships with the mother and father. This study was updated by Amato (2001) with a focus on studies published in the 1990s. All of these papers used cross-sectional data and so it is possible that there may have been unobservable traits correlated with both divorce and outcomes that could have biased the results.

As previously noted, several studies have attempted to assess the effects of divorce on children's outcomes using more robust estimation methods. For instance, Cherlin et al. (1998) used fixed effects and random effects models to estimate the effects of divorce on the mental health problems of offspring. Fomby and Cherlin (2007) used random effects models, among others, to capture the effects of divorce on children's well-being. Boutwell and Beaver (2010) used propensity score matching to estimate the effects of divorce on children's self-control. Corak (2001) used difference-in-differences estimation and two quasi-experiments to measure the effects of divorce on offspring's income, marriage, and divorce. Amato and Sobolewski (2001) and Hawkins et al. (2007) used structural equation modeling to explore the effects of divorce on children's well-being, while Caceres-Delpiano and Giolito (2012) used difference-in-differences methods with US census data to assess the effects of divorce on children's criminal behavior.

A number of studies have also examined the effects of divorce on the use of tobacco, alcohol, and other drugs. For example, Brown and Rinelli (2010) used the Add Health data set and logistic regression to test whether family structure was associated with smoking and drinking among adolescents. Wolfinger (1998) used a bivariate probit model to assess the effects of divorce on smoking and

drinking among adolescents. Griesbach et al. (2003) estimated the odds ratios for smoking between children from divorced and married families in seven European countries.

This paper contributes to the literature by further assessing the robustness of the results of the studies mentioned above through examining the relationship between divorce and children's risk behaviors. In contrast to past studies, we covered a wide range of outcomes including binge drinking, alcohol consumption, tobacco use, marijuana use, and hard drug use. We also conducted separate analyses on males and females and provided new insights into the effects of divorce on not only the incidence but also the persistence of teenagers' risk behaviors.

## Data and Methods

Add Health is a survey that explores the causes of health-related behaviors of representative adolescents in grades 7 through 12 in the US and their outcomes in young adulthood, and is the largest, most comprehensive survey of adolescents ever undertaken. Data at the individual, family, school, and community levels were collected in two waves in 1995 and 1996. In 2001, Add Health respondents aged 18–24 years were reinterviewed in a third wave to investigate how experiences during adolescence affect outcomes and behaviors in young adulthood. Not all of the students were included in all three waves. Therefore, to include the maximum number of students and to have samples from at least two different years, we chose Wave 1 (1995 survey) and Wave 3 (2001 survey) from the Add Health database.

Our data sample consists of children from both divorced and married families. Our definition of a divorced family is where the child lived with either biological parent in 1995, and the biological parents had previously lived together. Our definition of a married family is where the child lived with both biological parents in 1995, and the biological parents still lived together in 2001. Cohabitation is treated as marriage. Hence, we excluded the following individuals from the sample: those with deceased parents, those whose parents did not live together when the child was born, and those whose parents separated between 1995 and 2001.

Table 1 shows the means of variables from the interview with the mother in 1995, when the children were between 12 and 18 years of age. These variables were used to estimate the propensity score (i.e., the probability of divorce), which was then used to create the matched data sample.<sup>1</sup> The results in the table were divided into

<sup>1</sup> To include the 1538 mothers who did not record when their marriage/cohabitation started, the 1067 who did not record their income, and the 180 who did not record their age, we performed regression imputation in Stata.

**Table 1** Means of matching variables for divorced and married families (whole sample)

	Unmatched sample (N = 8392)			Matched sample (N = 4044)		
	Divorced	Married	abs(t) <sup>a</sup>	Divorced	Married	abs(t) <sup>a</sup>
Start of marriage <sup>b</sup>	77.64	77.42	10.45	77.53	77.57	1.21
Age	40.33	42.63	24.86	40.99	40.71	1.76
Hispanic	0.13	0.18	6.94	0.14	0.12	1.32
Black	0.26	0.13	20.75	0.16	0.16	0.13
Other race	0.10	0.13	6.72	0.06	0.07	1.58
Middle school	0.16	0.19	3.95	0.12	0.12	0.39
University	0.20	0.27	9.52	0.26	0.26	0.11
Work	0.75	0.69	8.09	0.80	0.80	0.27
Importance of religion	1.66	1.47	13.03	1.65	1.68	0.80
Household income <sup>c</sup>	35.70	53.90	20.20	42.01	45.06	1.94
Alcohol use	28.31	21.22	7.67	27.53	30.05	1.27
Urban	0.31	0.27	5.35	0.29	0.30	0.17
Rural	0.19	0.17	2.79	0.19	0.19	0.36
West	0.23	0.27	5.74	0.22	0.23	1.06
Midwest	0.27	0.25	2.38	0.29	0.31	1.30
South	0.38	0.33	5.44	0.36	0.33	1.92
Income <sup>2</sup>	2887.72	5652.20	5.46	3549.92	5221.06	1.49
Age <sup>2</sup>	1655.06	1846.80	24.10	1706.03	1684.55	1.57
Age · Hispanic	5.57	7.80	8.24	5.52	4.89	1.47
Age · Black	10.35	5.59	17.81	6.74	6.61	0.28
Age · Other race	3.05	4.43	6.43	2.55	3.05	1.49
Income · Hispanic	3.94	6.08	5.80	4.27	4.23	0.06
Income · Black	7.70	6.60	2.57	6.07	5.39	1.17
Income · Other race	2.24	5.45	8.62	2.39	3.05	1.61

<sup>a</sup> Absolute value of the *t*-statistic from a *t*-test of differences in the mean

<sup>b</sup> We subtracted 1900 from this variable

<sup>c</sup> Household income was coded as the midpoint of the interval to which the household belongs

unmatched and matched samples. The means of the variables for each sample were presented for divorced mothers and married mothers. We used four different methods to estimate the effects of parents’ divorce on children’s outcome. We used OLS and bivariate probit on the unmatched sample and the standard probit and random effects probit on the matched sample.

Propensity score matching was used to mitigate the selection bias, but this cannot eliminate the possibility of omitted variable bias. The aim of matching is to create a homogeneous sample in which each individual from a divorced family is comparable to a similar individual from a married family. If matching is successful, then a *t*-test of the differences in the means of the matching variables in the matched sample will not be rejected. The matching variables exhibited in Table 1 are defined as follows: “Start of marriage” (or cohabitation) is the year the parents married (or commenced cohabitation). “Age” is the age of the mother when she completed the questionnaire. “Hispanic,” “Black,” and “Other race” are dummy variables for race, with “White” as the base. “Middle school” and “University” are dummy variables for education,

with “High school” as the base. The indicator variable “Work” is coded as 1 if the mother was working and 0 otherwise. “Importance of religion” is a scale variable from 1 to 4 that took the value 1 if the mother considered religion to be very important and 4 if she considered it not important at all or had no religion. “Household income” is the yearly income at the time of the survey. “Alcohol use” is the number of days the mother drank alcohol in the past year. “Urban” and “Rural” are dummy variables for location, with “Suburb” as the base. “West,” “Midwest,” and “South” are geographic dummies, with “Northeast” as the base. To create a homogeneous matched sample, we followed the strategy used by Dehejia and Wahba (1999) and included higher-order polynomials and interaction terms in the propensity score model. We included income squared, age squared, and interaction terms between income, age, and race dummies. We used nearest-neighbor matching with caliper  $0.25\sigma$ , where  $\sigma$  is the standard deviation of the propensity score (see Guo and Fraser 2010).

Table 1 shows the means of the unmatched and matched samples in both divorced and married families, based on the characteristics of the mother, and a *t*-test of the

differences of the means. Comparing the average values of the variables describing the mothers, we see that the null hypotheses of equal means were rejected in all cases in the unmatched sample, but were not rejected in the matched sample at the 0.05 level. In the unmatched sample, 26 % of the Black mothers were divorced and 13 % were married, while in the matched sample, these numbers were 16 and 16 %, respectively. Hence, the propensity score model provided a reasonably good balance of the covariates between divorced and intact families. The outcome measures we considered were as follows: binge drinking = 1 if the child had five or more drinks in a row during the past 12 months, 0 otherwise; alcohol drinking = 1 if the child drank alcohol during the past 12 months, 0 otherwise; cigarette smoking = 1 if the child smoked cigarettes during the past 12 months, 0 otherwise; marijuana use = 1 if the child used marijuana during the past 12 months, 0 otherwise; hard drug use = 1 if the child used cocaine, LSD, heroin, or any other hard drug during the past 12 months, 0 otherwise.

We used OLS and bivariate probit models on the unmatched sample. For the OLS models, the variables in Table 1 were used as covariates together with a dummy variable taking the value 1 if the child's parents were divorced and 0 otherwise. Likewise, we estimated bivariate probit models in which the outcome variables and the divorce variable were assumed to follow a bivariate normal distribution. The covariates in the divorce equation were the same as those in Table 1, while in the outcome equation, age and age squared of the mother were excluded, and the age of the child was included. Age and age squared of the mother were then used as exclusion restrictions.

We used the propensity score to match the treated individuals to the control individuals. We then calculated the treatment effect as the average difference in outcomes of the matched samples between children from divorced samples and children from married samples. To further take into account the control variables and compare the results across the different time periods, we followed Chiswick and Mirtcheva (2013) and estimated probit models on the matched sample. Specifically, we estimated separate probit models for the 1995 survey and 2001 survey data, as these years represent two of the waves in the longitudinal data we employed. In addition, to take advantage of the longitudinal structure of our data and take into account unobserved heterogeneity, we estimated a random effects probit model (Greene 2008) using both the 1995 and 2001 survey data. In this random effects probit analysis, each dependent variable was coded as 1 if the individual had a risk behavior outcome in the previous 12 months and 0 otherwise. We included the following covariates in the model: propensity score, the age of the student, and a dummy for divorce (treatment) (i.e.,

divorce = 1 if the student is from a divorced family and 0 if the student is from a married family). We also included a period variable as follows:  $p_t = 0$  for the 1995 survey and  $p_t = 1$  for the 2001 survey. Moreover, we included an interaction term between time period and divorce so that we could derive the treatment effect estimates for both 1995 and 2001 and compare these with the standard probit model results.

For the probit models estimated separately for 1995 and 2001, the treatment effects were estimated as:

$$TE = \Phi(\bar{x}_{it}\hat{\beta} | \text{divorce} = 1) - \Phi(\bar{x}_{it}\hat{\beta} | \text{divorce} = 0),$$

where

$$\bar{x} = (1, \text{divorce}, \overline{age}, \overline{ps}) \\ \beta = (\beta_0, \beta_1, \beta_2, \beta_3)$$

$\Phi(\cdot)$  is the cumulative distribution function (CDF) of the standard normal. Divorce = 1 if the child comes from a divorced family and 0 otherwise.  $\overline{age}$  is the mean age of the adolescents in the sample and  $\overline{ps}$  is the mean propensity score in the sample.  $\beta$  is a vector of parameters.

The treatment effects in the random effects probit model were calculated as:

$$TE = \Phi(\bar{x}_{it}\hat{\alpha}\sqrt{1-\hat{\rho}} | \text{divorce} \\ = 1) - \Phi(\bar{x}_{it}\hat{\alpha}\sqrt{1-\hat{\rho}} | \text{divorce} = 0),$$

where

$$\bar{x} = (1, \text{divorce}, p_t, \text{divorce} \cdot p_t, \overline{age}, \overline{ps}) \\ \alpha = (\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5)$$

$\overline{age}$  and  $\overline{ps}$  are defined above and  $p_t = 1$  if  $t = 1995$  and 0 if  $t = 2001$ . The term  $\sqrt{1-\hat{\rho}}$  is the scaling factor for normalization in the estimation of the random effects probit model (Arulampalam 1999).  $\hat{\rho}$  is the proportion of the total variance contributed by the longitudinal-level variance component.

To be able to compare our results with those from other studies, we used the probabilities from the random effects probit models to calculate the odds ratios (OR). In all models, we applied nonparametric bootstrapping to the whole process to calculate the standard deviation of the treatment effects. A random sample of children who participated in both Wave 1 and Wave 3 of the Add Health survey was drawn for each iteration. A propensity score for the probability of divorce was then estimated based on the characteristics of the mother. A nearest-neighbor matching algorithm was used to select the adolescents with similar backgrounds, and the probit models were used to estimate the probability of their binge drinking, alcohol consumption, tobacco use, marijuana use, and hard drug use. Finally, the average treatment effects were estimated and their standard errors were derived using the bootstrap covariance matrix.



## Results

### Effects Estimated from the Matched Sample

Table 2 shows the mean values for the outcome variables for males and females in the matched sample. The columns in the table represent results for adolescents from divorced families and married families in 1995, when the children were between 12 and 18 years old, and in 2001, when they were between 18 and 24 years old.

In 1995, 35 % of males from divorced families engaged in binge drinking compared with 25 % of males from married families; this difference was statistically significant. The differences in incidence between divorced and married families for alcohol consumption, tobacco use, and marijuana use were also statistically significant. No statistical significance was observed for hard drug use. The outcome incidence levels increased from 1995 to 2001 for males from both divorced and married families. The only statistically significant differences in incidences between males from divorced and married families in 2001 were for tobacco and marijuana use.

In 1995, when female participants were aged between 12 and 18 years, 31 % of the sample from divorced families engaged in binge drinking compared with just 20 % of girls from married families; this difference was statistically significant. In 2001, the proportion that engaged in binge drinking had increased to 46 and 42 % for those from divorced and married families, respectively. In general, in the 1995 sample, females from divorced families had a higher incidence of binge drinking, alcohol consumption,

tobacco use, and marijuana use than those from married families. In the 2001 sample, the level of the outcomes had increased for every outcome for females from both divorced and married families. However, a higher percentage of females from divorced families engaged in tobacco use and marijuana use compared with females from married families. No significant differences at the 0.01 level were observed for binge drinking, alcohol consumption, or hard drug use.

There are both similarities and differences between the male and female samples. For example, in 1995, males had a higher incidence of binge drinking than females, but the incidence of other outcomes was at the same level for both males and females. In 2001, males had a higher incidence of binge drinking, tobacco use, and marijuana use than females. Table 6 in the Appendix shows the frequency of risk behaviors from the unmatched sample. We can see that there is little difference between the outcomes in the two tables.

### Effects of Divorce on Teenagers' Risk Behaviors from Regression Modeling

Table 3 reports results from the OLS and bivariate probit models on the unmatched samples and from the standard probit and random effects probit models on the matched samples. In the 1995 sample, the effects of divorce were significant for binge drinking, alcohol consumption, tobacco use, and marijuana use. The treatment effect estimates suggested that the probability of engaging in binge drinking, for example, was on average 9 % higher for

**Table 2** Frequency of risk behaviors (matched samples)

	1995				2001			
	Divorced	Married	Diff <sup>a</sup>	abs(t) <sup>b</sup>	Divorced	Married	Diff <sup>a</sup>	abs(t) <sup>b</sup>
<b>Males</b>								
Binge drinking	0.35	0.25	0.10**	4.08	0.60	0.59	0.01	1.25
Alcohol consumption	0.55	0.41	0.14**	5.15	0.75	0.77	-0.02	1.56
Tobacco use	0.23	0.15	0.08**	5.38	0.42	0.33	0.09**	4.22
Marijuana use	0.21	0.12	0.09**	4.60	0.35	0.26	0.09**	5.12
Hard drug use	0.08	0.05	0.03	2.21	0.11	0.11	0.00	0.35
<b>Females</b>								
Binge drinking	0.31	0.20	0.10**	6.39	0.46	0.42	0.04	1.06
Alcohol consumption	0.55	0.42	0.12**	6.53	0.76	0.71	0.05	2.46
Tobacco use	0.23	0.15	0.07**	5.33	0.37	0.27	0.10**	5.41
Marijuana use	0.19	0.12	0.07**	4.89	0.22	0.18	0.04**	3.01
Hard drug use	0.06	0.05	0.01	0.99	0.08	0.07	0.01	0.84

<sup>a</sup> Difference between outcomes for divorced and married families (i.e., the average treatment effect)

<sup>b</sup> The absolute value of the *t*-statistic from a *t*-test of differences in the mean

\*\* *p* < 0.01

males from divorced families than for males from married families in the same age group. The effects were small and nonsignificant for the use of hard drugs. In the 2001 sample, when the children were aged between 18 and 24 years, there were no significant differences between males from divorced and married families with regard to binge drinking and alcohol consumption. The differences for tobacco use and marijuana use were roughly similar to those from 6 years earlier. There were small differences in the results from the four different models with matched and unmatched samples, suggesting the robustness of our estimates.

In 1995, the results for females were qualitatively similar to the results for males. There were significant differences of around 10 % for binge drinking, alcohol consumption, tobacco use, and marijuana use, but no significant difference for hard drug use. In 2001, the effects were higher for binge drinking and alcohol consumption, similar for tobacco use, and lower for marijuana use. For hard drug use, there were few effects. The results were again similar in the four different models with matched and unmatched samples. For the random effects probit models, the individual random effects were all significantly different from zero at the 0.01 level (see Tables 8 and 9 in the Appendix), suggesting that unobserved heterogeneity mattered in our estimation.

When estimating the random effects probit model with longitudinal data from 1995 and 2001, the interaction terms of period and divorce allowed us to estimate treatment effects with the same model taking account of the correlation for each individual between the periods. Let  $TE_{1995}$  be the treatment effect in 1995 and  $TE_{2001}$  be the treatment effect in 2001. Then, using the results from the random effects probit model in Table 3, we defined the effects of divorce on adolescents' outcomes as incidence or persistence. If  $TE_{2001} = 0$  and  $TE_{1995} > 0$ , the effect of divorce is merely a transitory incidence effect. However, if  $TE_{2001} > 0$  and  $TE_{1995} > 0$ , the effect of divorce can be deemed to be persistent, and may have long-term consequences.

The estimates of the random effects probit model in Table 3 suggest that the results for both binge drinking and alcohol consumption for males could be characterized as incidental rather than persistent. In contrast, the results for tobacco use and marijuana use appeared to be persistent. These effects were very similar for 1995 and 2001. We failed to reject the hypothesis of equal effects in 1995 and 2001 for either tobacco use or marijuana use. For females, the effects on tobacco and marijuana use were also found to be persistent.

**Table 3** Effects of divorce on adolescents' outcomes using OLS and bivariate probit (BP) on the unmatched samples and standard probit (SP) and random effects probit (REP) on the matched samples

	1995				2001			
	OLS	SP	REP	BP	OLS	SP	REP	BP
<b>Males</b>								
Binge drinking	0.09** (0.02)	0.07** (0.02)	0.13** (0.03)	0.07** (0.02)	0.00 (0.02)	-0.02 (0.02)	-0.03 (0.03)	-0.01 (0.02)
Alcohol consumption	0.13** (0.02)	0.10** (0.02)	0.14** (0.03)	0.11** (0.02)	-0.02 (0.02)	-0.02 (0.02)	-0.03 (0.03)	-0.02 (0.02)
Tobacco use	0.07** (0.01)	0.06** (0.02)	0.10** (0.02)	0.05* (0.02)	0.09** (0.02)	0.08** (0.02)	0.09** (0.03)	0.09** (0.02)
Marijuana use	0.08** (0.01)	0.04* (0.02)	0.09** (0.02)	0.06** (0.01)	0.09** (0.02)	0.09** (0.02)	0.11** (0.02)	0.09** (0.02)
Hard drug use	0.02 (0.01)	0.01 (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.02)	0.01 (0.01)
<b>Females</b>								
Binge drinking	0.11** (0.01)	0.10** (0.02)	0.11** (0.03)	0.10** (0.02)	0.04* (0.02)	0.03 (0.02)	0.04 (0.03)	0.05** (0.02)
Alcohol consumption	0.12** (0.02)	0.12** (0.02)	0.13** (0.03)	0.10** (0.02)	0.04* (0.02)	0.04* (0.02)	0.06* (0.03)	0.04** (0.01)
Tobacco use	0.09** (0.01)	0.09** (0.02)	0.12** (0.02)	0.08** (0.01)	0.10** (0.02)	0.11** (0.02)	0.10** (0.02)	0.11** (0.02)
Marijuana use	0.08** (0.01)	0.06** (0.02)	0.07** (0.02)	0.06** (0.01)	0.05** (0.01)	0.05* (0.02)	0.06** (0.02)	0.06** (0.01)
Hard drug use	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.02)	0.01 (0.01)

Standard errors in parentheses

\*  $p < 0.05$ ; \*\*  $p < 0.01$

As a sensitivity analysis, we followed Altonji et al. (2008) and constrained the correlation coefficient in the bivariate probit to different values. This approach allows researchers to estimate the treatment effects under various hypothesized degrees of selection, rather than relying on weak or questionable instrumental variables. Comparison between the conventional estimates and hypothetical estimates based on Altonji et al. (2008) provides useful insights into the plausibility and robustness of the conventional estimates. The estimation results are reported in Table 10 in the Appendix. We considered a wide range of possible correlations; to save space, we report results with the correlation coefficient constrained to  $-0.90$ ,  $0.00$ , and  $0.90$ . As expected, the estimated divorce parameter generally decreased when the correlation (between parents' divorce and subsequent children's risky behaviors) was increased, with the potential confounding factors possibly contributing to both events. At the same time, we stress that the relevant marginal effects that are comparable to the probit estimates on the matched samples are the average treatment effects on the treated group. For instance, the average treatment effect on female binge drinking in 1995 is estimated to be  $0.10$  when the correlation coefficient is not restricted. Under the restriction of zero correlation, this estimated effect increases to  $0.11$ . However, under a hypothesized strong correlation of  $0.9$  ( $-0.9$ ), the corresponding estimate is  $0.09$  ( $0.08$ ). This result demonstrates the robustness of our estimates, even under implausibly high degrees of endogeneity.

Overall, the estimated results are rather stable in all the risk behaviors because the decreases in the estimated divorce parameters are offset by an increase in the correlations. This suggests that our results are robust because altering the correlations between the extremes does not alter the conclusion of the study.

### Comparison with Other Studies

Past studies that have analyzed the effects of divorce on alcohol, tobacco, and drug use have used various models and reported a range of statistics.

Table 4 reports the 95 % confidence intervals for the odds ratios from the random effects probit model. The odds

ratios were calculated with the same probabilities used to calculate the TEs shown in Table 3. Table 5 reports the odds ratios from four other studies that examined smoking and drinking. The first study in Table 5, by Brown and Rinelli (2010), used the same Wave 1 data from the Add Health data set used in our study. Hence, their findings can be compared with our findings on alcohol consumption and tobacco use. These are exhibited in the 1995 column in Table 4. For alcohol consumption, the odds ratios from our random effects probit model are in the intervals  $[1.27, 2.17]$  and  $[1.25, 2.15]$  for males and females, respectively, while the results in Brown and Rinelli (2010) were  $1.37$ ,  $1.36$ , and  $1.93$  for their three family types compared with a family with both biological parents. These results were inside our 95 % confidence interval. The odds ratios for smoking in Brown and Rinelli (2010) were between  $1.34$  and  $1.97$ , which was also inside the 95 % confidence interval of our study for males, but the lowest number was slightly below the lower limit of our confidence interval.

Griesbach et al. (2003) reported the odds ratios for smoking among 15-year-olds in two different living arrangements compared with a married family in seven European countries. The odds ratios varied from  $1.12$  to  $1.99$  for an adolescent living in a single-parent family and from  $1.41$  to  $3.50$  for an adolescent living in a stepfamily. Therefore, our results in Table 4—an odds ratio between  $1.28$  and  $2.50$  for males and between  $1.47$  and  $2.71$  for females—fall in the middle of the odds ratios for these countries. Wolfinger (1998) estimated the odds ratios in comparing a single-mother family (where the child lived with its mother) and a stepfamily (where the child lived with his/her mother and her new partner). The results given in Wolfinger (1998) were for adults whose parents had divorced before they were 16 years old. These results can therefore be compared with our results from 2001, when the Add Health children were aged between 18 and 24 years. The odds ratios for binge drinking among males were  $1.76$  and  $1.00$  in Wolfinger (1998) and within the interval  $(0.67, 1.15)$  in our study. The results for females were  $0.84$  and  $1.11$  in Wolfinger (1998), which were generally within the interval  $(0.92, 1.46)$  in our research. For smoking, the results from Wolfinger (1998) were well inside our 95 % confidence interval. Furthermore, we

**Table 4** 95 % confidence interval for the odds ratios (OR) from the random effects probit model (risk factors following divorce compared with risk factors when living with both biological parents)

	1995		2001	
	Males	Females	Males	Females
Binge drinking	[1.27, 2.17]	[1.25, 2.15]	[0.67, 1.15]	[0.92, 1.46]
Alcohol use	[1.39, 2.29]	[1.35, 2.19]	[0.62, 1.14]	[0.94, 1.66]
Tobacco use	[1.28, 2.50]	[1.47, 2.71]	[1.16, 1.82]	[1.25, 2.09]
Marijuana use	[1.23, 2.63]	[1.18, 2.54]	[1.27, 2.19]	[1.06, 1.90]
Hard drug use	[0.66, 2.06]	[0.48, 2.36]	[0.68, 1.66]	[0.51, 1.53]



**Table 5** Odds ratios (OR) from comparable articles in the related literature

Authors: Brown and Rinelli (2010)							
Data: Add Health Wave 1, 1995							
Method: Logistic regression on cross-sectional data							
Age of children: 12–18 years							
OR relative to married biological parents							
	Drinking			Smoking			
Married stepfamily:	1.37			1.34			
Single-mother family:	1.36			1.35			
Cohabiting stepfamily:	1.93			1.97			
Authors: Griesbach et al. (2003)							
Data: From seven European countries in 1998 (Austria, Denmark, Finland, Germany, Norway, Scotland, Wales)							
Method: Logistic regression on cross-sectional data							
Age of children: 15 years							
OR of smoking relative to married family							
	Aus	Den	Fin	Ger	Nor	Scot	Wales
Single-parent family:	1.80	1.20	1.99	1.25	1.33	1.14	1.12
Stepfamily:	2.22	2.44	3.50	2.27	2.32	1.77	1.41
Author: Wolfinger (1998)							
Data: National Opinion Research Council General Social Survey: 1977–1994							
Method: Bivariate probit on pooled cross-sectional data							
Age: Adults							
Parents divorced before the child was aged 16 years							
We calculated the marginal effects based on predicted probabilities of being a smoker or a problem drinker (Table 2).							
OR of smoking and problem drinking relative to married family							
	Problem drinking		Smoking				
	Male	Female	Male	Female			
Single-mother family:	1.76	0.84	1.58	1.78			
Stepfamily:	1.00	1.11	1.58	1.36			
Author: Jeynes (2001)							
Data: National Educational Longitudinal Survey in 1992							
Method: Logistic regression on cross-sectional data							
Age of children: 12th grade							
OR for children whose parents divorced during the previous 4 years (1988–1992) vs. children living in intact family							
Alcohol consumption: 1.15							
Binge drinking: 1.13							

calculated the odds ratios in Jeynes (2001) using the fact that the odds ratio is equal to  $\exp(b)$ , where  $b$  is the estimated coefficient of divorced vs. married families in a logistic regression. The estimated odds ratios in Jeynes

(2001) were 1.13 for binge drinking and 1.15 for alcohol consumption in divorced families compared with married families. Comparing with our confidence intervals for 2001, these results were inside the 95 % confidence

interval for females but just outside the upper 95 % confidence limit for males.

## Summary and Discussion

In this study, we applied a variety of methods, including matching and longitudinal estimation techniques, to longitudinal data to examine the effects of divorce on teenage children's risk behavioral outcomes. Specifically, we used propensity score matching and longitudinal data to select a sample of teenagers, half of which were from divorced families and half from married families. We then used four methods to estimate the effects of divorce on these children's binge drinking, alcohol consumption, tobacco use, marijuana use, and hard drug use.

The results generally suggest the following:

- 1) Children from divorced families had about a 10 % higher probability of engaging in binge drinking, alcohol consumption, tobacco use, and marijuana use when they were aged 12–18 years.
- 2) The frequencies of engaging in binge drinking, alcohol consumption, tobacco use, and marijuana use increased by age for both male and female adolescents from both divorced and married families.
- 3) The effects of divorce were persistent for tobacco use and marijuana use for both males and females.
- 4) The effects of divorce on teenage girls were also persistent for alcohol consumption and possibly binge drinking; however, this did not apply to teenage boys.
- 5) There was little effect of divorce on hard drug use for either males or females.

What are the possible explanations for the significant effects of divorce on adolescents' risk behaviors? In the literature, divorce is generally linked to a stressful life transition, which normally requires certain adjustments by both the adults and the children. Causes of this stress may include decreased material well-being and less time spent with one of the parents. The parent who loses custody of the child also loses control over the resources provided for the child's maintenance. This arrangement provides an incentive for this parent to hide income in order to pay less child support (Del Boca 2003; Weiss and Willis 1985). Other economic difficulties also arise when parents separate; for example, the cost of achieving a certain living standard is higher for one adult than for two, and direct costs, such as moving costs, are incurred during the separation process. These economic consequences can affect the child's well-being. In addition, the parent who loses custody usually spends less time with the child after separation (Del Boca 2003), which usually also means less

involvement. This is important because Neymotin (2014) showed that parental involvement could lead to better child behavioral outcomes. These factors all contribute toward creating stress for the child, as confirmed by Kraft and Luecken (2009), who measured higher levels of the stress hormone cortisol in children from divorced families than in those from married families.

In this study, we examined a wider range of outcomes including binge drinking, alcohol consumption, tobacco use, marijuana use, and hard drug use, and conducted separate analyses on males and females. Lastly, we provided new insights into the effects of divorce on not only the incidence but also the persistence of teenagers' risk behaviors. Our findings suggest that policy makers should reject notions based on assumptions that children are naturally resilient and can survive divorce with little impact on their lives. While not the focus of this study, investment in children from divorced families to avoid risk behaviors can potentially offer a high payoff to society as a whole. A significant number of children in the US live apart from their fathers and receive little money and attention from them. Receipt of money from the noncustodial parent by the custodial parent is largely dependent upon which state they live in (Folbre 2010). In addition, according to Folbre (2010), social security benefits are not provided to the spouse for those married less than 10 years, although the majority of divorces take place within this period. Hence, public policies that could help the financial situation of children from divorced families (e.g., increasing cash assistance to single mothers) could potentially alleviate some of the detrimental effects of divorce on children's behavior and outcomes. Increased public resources could also be directed toward counseling and monitoring of children and their parents soon after divorce. Efforts and support systems such as these for children of divorced families could help them during their transition. Evaluating the effectiveness of support systems and policies that could prevent the occurrence of divorce would also be a good area for future research.

As previously discussed, not all of the children were included in all three waves of the Add Health data. Therefore, to include the maximum number of children and to have samples from at least two different years, we used Wave 1 and Wave 3 in this study. Future research could test whether our results are sensitive to the inclusion of Wave 2 of the Add Health data. Our findings are also dependent upon the quality of the data, the variables measured in the survey, and the choice of variables used in the models. Given that our data are from surveys, our analyses are based upon quasi-experiments and econometric modelling. As with all observational studies and unlike randomized controlled experiments, unmeasured or unobserved confounding variables may be present. In

addition, there were many respondents in our data who did not complete the surveys. We tried to account for some of the missing variables by imputation. However, if the reason for the data missingness was related to the probability of divorce, or the risk factors, then it is possible that this could bias our results. Future studies should test the robustness of our findings with other data sources.

**Acknowledgments** The Research Council of Norway, Grants 190306/I10 and 233800/E50, provided financial support for this research. This research uses data from Add Health, a program project designed by J. Richard Udry, Peter S. Bearman, and Kathleen Mullan

Harris, and funded by a grant P01-HD31921 from the National Institute of Child Health and Human Development, with cooperative funding from 17 other agencies. Special acknowledgment is due Ronald R. Rindfuss and Barbara Entwisle for assistance in the original design. Persons interested in obtaining data files from Add Health should contact Add Health, Carolina Population Center, 123 W. Franklin Street, Chapel Hill, NC 27516-2524 (addhealth@unc.edu).

## Appendix

See Tables 6, 7, 8, 9 and 10.

**Table 6** Frequency of risk behaviors (unmatched samples)

	1995				2001			
	Divorced	Married	Diff <sup>a</sup>	abs(t) <sup>b</sup>	Divorced	Married	Diff <sup>a</sup>	abs(t) <sup>b</sup>
<b>Males</b>								
Binge drinking	0.34	0.26	0.07**	4.78	0.58	0.60	-0.02	1.36
Alcohol consumption	0.53	0.44	0.09**	5.35	0.74	0.77	-0.03	2.34
Tobacco use	0.22	0.16	0.07**	5.07	0.42	0.32	0.10**	6.25
Marijuana use	0.21	0.14	0.07**	5.40	0.35	0.26	0.09**	5.96
Hard drug use	0.08	0.06	0.02**	2.65	0.11	0.10	0.01	1.07
<b>Females</b>								
Binge drinking	0.30	0.21	0.09**	6.82	0.44	0.44	0.00	0.30
Alcohol consumption	0.54	0.45	0.10**	5.91	0.74	0.74	-0.01	0.35
Tobacco use	0.21	0.14	0.08**	6.30	0.36	0.27	0.10**	6.45
Marijuana use	0.18	0.11	0.07**	6.55	0.22	0.18	0.04**	3.24
Hard drug use	0.05	0.05	0.01	1.09	0.07	0.06	0.01	0.82

<sup>a</sup> Difference between outcomes for divorced and married families (i.e., the average treatment effect)

<sup>b</sup> The absolute value of the *t*-statistic from a *t*-test of differences in the mean

\*\*  $p < 0.01$

**Table 7** Estimates of correlations between the error terms in the bivariate probit model

	1995			2001		
	$\rho$	std( $\rho$ )	$p > \chi^2$	$\rho$	std( $\rho$ )	$p > \chi^2$
<b>Males</b>						
Binge drinking	-0.30	0.17	0.12	0.05	0.17	0.75
Alcohol consumption	-0.04	0.17	0.81	0.07	0.19	0.71
Tobacco use	-0.23	0.19	0.45	-0.01	0.18	0.94
Marijuana use	-0.26	0.19	0.26	0.21	0.17	0.23
Hard drug use	0.01	0.28	0.97	0.16	0.22	0.55
<b>Females</b>						
Binge drinking	-0.19	0.17	0.42	0.03	0.16	0.84
Alcohol consumption	-0.20	0.17	0.25	0.30	0.17	0.07
Tobacco use	-0.17	0.18	0.38	-0.20	0.16	0.27
Marijuana use	-0.32	0.17	0.12	0.12	0.19	0.53
Hard drug use	-0.27	0.26	0.32	-0.06	0.27	0.78

**Table 8** Estimated coefficients from random effects probit model for males

	Binge	Alcohol	Tobacco	Marijuana	Hard drugs
$\alpha_0$ Constant	-3.98** (0.41)	-3.44** (0.43)	-3.12** (0.60)	-2.48** (0.48)	-2.72** (0.52)
$\alpha_1$ Divorce	0.40** (0.09)	0.44** (0.09)	0.62** (0.14)	0.52** (0.12)	0.11 (0.14)
$\alpha_2$ Period	0.45** (0.14)	0.35** (0.14)	0.96** (0.21)	0.61** (0.17)	0.26 (0.19)
$\alpha_3$ Divorce-period	-0.48** (0.11)	-0.55** (0.11)	-0.24 (0.14)	-0.08 (0.13)	-0.13 (0.16)
$\alpha_4$ Age	0.18** (0.02)	0.19** (0.03)	0.06 (0.04)	0.04 (0.03)	0.03 (0.03)
$\alpha_5$ Prop score	0.06 (0.04)	0.08 (0.05)	-0.01 (0.08)	0.02 (0.06)	0.07 (0.06)
$\sigma_u$ Sdev rand eff	0.87** (0.06)	0.95** (0.06)	1.51** (0.10)	1.10** (0.08)	0.82** (0.11)
N # observations	3128	3128	3128	3128	3128

$\sigma_u$  is the standard deviation of the random effect

\*\*  $p < 0.01$  Standard errors in parentheses

**Table 9** Estimated coefficients from random effects probit model for females

	Binge	Alcohol	Tobacco	Marijuana	Hard drugs
$\alpha_0$ Constant	-3.10** (0.35)	-3.80** (0.40)	-3.81** (0.58)	-1.89** (0.45)	-2.13** (0.62)
$\alpha_1$ Divorce	0.45** (0.09)	0.50** (0.09)	0.76** (0.14)	0.46** (0.12)	0.24 (0.17)
$\alpha_2$ Period	0.32** (0.13)	0.09 (0.13)	0.51* (0.20)	0.48** (0.17)	0.61** (0.23)
$\alpha_3$ Divorce-Period	-0.32** (0.11)	-0.23 (0.11)	-0.19 (0.14)	-0.15 (0.13)	-0.34 (0.20)
$\alpha_4$ Age	0.12** (0.02)	0.21** (0.02)	0.10** (0.03)	0.01 (0.03)	-0.02 (0.04)
$\alpha_5$ Prop score	0.05 (0.04)	0.07 (0.05)	-0.01 (0.07)	0.00 (0.06)	-0.03 (0.08)
$\sigma_u$ Sdev Rand Eff	0.69** (0.06)	0.85** (0.04)	1.44** (0.10)	0.94** (0.08)	0.91** (0.15)
N # observations	3046	3046	3046	3046	3046

\*\*  $p < 0.01$  Standard errors in parentheses

$\sigma_u$  is the standard deviation of the random effect

**Table 10** Estimates of divorce parameters, standard deviations, and marginal effects (average treatment effects of the treated) when correlation is restricted in the bivariate probit model

	1995				2001			
	Unrestricted	-0.90	0.00	0.90	Unrestricted	-0.90	0.00	0.90
$\rho$								
Males								
Binge drinking	0.80 (0.44) [0.07]	1.69** (0.03) [0.07]	0.23** (0.05) [0.08]	-1.24* (0.03) [0.05]	0.33 (0.53) [-0.01]	1.26** (0.03) [0.01]	-0.02 (0.05) [-0.01]	-1.34** (0.04) [-0.02]

Table 10 continued

$\rho$	1995				2001			
	Unrestricted	-0.90	0.00	0.90	Unrestricted	-0.90	0.00	0.90
Alcohol consumption	-0.02 (0.61) [0.11]	1.58** (0.03) [0.13]	0.28** (0.05) [0.11]	-1.15** (0.03) [0.09]	-0.13 (0.46) [-0.02]	1.21** (0.04) [-0.01]	-0.07 (0.05) [-0.02]	-1.43** (0.04) [-0.02]
Tobacco use	1.27** (0.26) [0.05]	1.77** (0.04) [0.03]	0.22** (0.05) [0.06]	-1.24** (0.04) [0.04]	0.23 (0.61) [0.09]	1.64** (0.03) [0.09]	0.24** (0.05) [0.09]	-1.22** (0.03) [0.07]
Marijuana use	0.98** (0.26) [0.06]	1.83** (0.04) [0.05]	0.27** (0.05) [0.07]	-1.22** (0.04) [0.05]	0.36 (0.45) [0.09]	1.70** (0.03) [0.09]	0.26** (0.05) [0.09]	-1.20** (0.03) [0.07]
Hard drug use	0.88** (0.34) [0.01]	1.89** (0.05) [0.00]	0.12 (0.07) [0.01]	-1.40** (0.05) [0.01]	-0.21 (1.37) [0.01]	1.79** (0.05) [0.00]	0.05 (0.06) [0.01]	-1.41** (0.04) [-0.01]
Females								
Binge drinking	1.13** (0.28) [0.10]	1.80** (0.04) [0.09]	0.35** (0.05) [0.11]	-1.16** (0.03) [0.08]	0.69 (0.44) [0.05]	1.46** (0.03) [0.06]	0.13** (0.05) [0.05]	-1.27** (0.03) [0.02]
Alcohol consumption	0.92** (0.30) [0.11]	1.61** (0.03) [0.13]	0.26** (0.05) [0.10]	-1.24** (0.03) [0.08]	-0.15 (0.43) [0.04]	1.46** (0.03) [0.06]	0.13** (0.05) [0.04]	-1.45** (0.03) [0.05]
Tobacco use	0.89** (0.33) [0.08]	1.89** (0.04) [0.06]	0.35** (0.05) [0.08]	-1.17** (0.04) [0.06]	0.96* (0.39) [0.11]	1.73** (0.03) [0.11]	0.32** (0.05) [0.11]	-1.17** (0.03) [0.08]
Marijuana use	1.03** (0.25) [0.06]	1.91** (0.04) [0.05]	0.32** (0.05) [0.07]	-1.21** (0.04) [0.05]	0.88** (0.27) [0.06]	1.77** (0.04) [0.05]	0.23** (0.05) [0.06]	-1.25** (0.03) [0.03]
Hard drug use	0.88** (0.32) [0.01]	1.94** (0.06) [-0.01]	0.10 (0.07) [0.01]	-1.46** (0.06) [0.00]	0.43 (0.34) [0.01]	1.88** (0.05) [0.00]	0.09 (0.07) [0.01]	-1.44** (0.05) [0.00]

$\rho$  is the restricted correlation coefficient

Standard errors in parentheses

Marginal effects (average treatment effects of the treated) in brackets

The average treatment effects of the treated are calculated as

$TE = P(risk|x, divorce = 1) - P(risk|x, divorce = 0) = \frac{\Phi_2(\bar{x}'\hat{\alpha}, \bar{x}'\hat{\beta} + \hat{\delta}, \rho)}{\Phi(\bar{x}'\hat{\alpha})} - \frac{\Phi_2(-\bar{x}'\hat{\alpha}, \bar{x}'\hat{\beta}, -\rho)}{1 - \Phi(\bar{x}'\hat{\alpha})}$ , where  $\Phi_2$  is the CDF of the bivariate normal,  $\Phi$  is the CDF of the normal,  $\bar{x}'$  are the mean of the variables used in both the divorce and risk equations,  $\alpha$  are the estimated parameters in the divorce equation,  $\beta$  are the estimated parameters in the risk equation,  $\delta$  is the estimated divorce parameter in the risk equation

\*  $p < 0.05$ ; \*\*  $p < 0.01$

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