Loss of Job and Divorce

Alexander Guggenberger

Course: Advanced Microeconometrics

Summer Semester 2019

University of Vienna

1 Introduction

Is there a relationship between professional performance and the stability of romantic relationships? A study from 2018 which observed relationships during the transition from education to work, found that struggling with this process is linked to higher instability of the relationship, whereas the successful transition into employment tends to stabilize it (Heintz-Martin & Zabel, 2018). However, this link exists only for male failure or success, which the authors interpret as an indicator of the persistence of traditional gender roles.

The current project is a further attempt to shed light on the issue by investigating a closely related research question. Specifically, I am interested in whether loss of job leads to an increased risk of getting divorced and whether this effect differs between the sexes, like the finding of the above cited paper suggests.

For this purpose, I will first shortly describe the data I use and the empirical strategy I apply in Section 2 which is followed by a discussion of the results including heterogeneous effects by subgroups in Section 3. Section 4 summarizes my finding and puts them into perspective with regard to the motivating paper mentioned in the introduction.

2 Data and Empirical Strategy

My data source is the National Longitudinal Surveys of Youth, from which I retrieve data on marriage status (which I binarize to married or not married), whether and for what reason a job was lost, weeks of unemployment during the year before the interview, whether a job is lined up for the job lost, number of children, income and spouse's income, in a panel format. After preparing the data, *reasonsofjobloss* has four categories; fired, lay off, any reason and valid skip (if job was not lost). I create a divorce dummy, indicating a status change from married to not married since the last interview. From 1979 to 1994, the survey was conducted annually, followed by biennial surveys until 2016. I can therefore use either only the first half of the data or drop odd years in the first half to avoid this change in time between data points. I find that results are fairly robust (see Table 1 in Section 3 and Table 4 in the appendix for a comparison). For the further analysis, I arbitrarily chose to use the first half of the data set.

I define four different treatment dummies:

- *treat1* indicates whether the individual lost their job because of a lay off or was fired, no job was lined up and this resulted in a period of unemployment

- *treat2* indicates whether the individual was unemployed at some point during the last year

- *treat3* indicates whether the individual was fired, no job was lined up and this resulted in a period of unemployment

- *treat4* indicates whether the individual lost their for any reason (including quitting)

- *treat5* indicates whether the individual lost their job because of a lay off, no job was lined up and this resulted in a period of unemployment

Under the assumption that being laid off or fired is exogenous, this specification would allow me to estimate the causal effect of losing ones job on the probability to get divorced. The specification I was heading towards was supposed to include income and difference in spouses income as controls besides year and individual fixed effects. However, income and consequently the difference to the spouse's income are not exogenous, but rather determined by a job loss. I thus tried including the lag of these variables and instrumenting income using the lagged income and the exogenous variables as controls (see Table 3). However, I finally decided to leave them out entirely in order to not complicate things too much. They will, however play a role again in the context of heterogeneous treatment effects (see Table 2). Including *children* is important as I assume that having children tends to stabilize relationships. Year and individual fixed effects control for common time trends in both the treatment and the outcome variable and individual time invariant characteristics (such as risk aversion, which would correlate negatively with both variables). This results in the following model:

$$divorce_{i,t} = \beta_0 + \beta_1 * treat_{i,t} + \beta_2 * children_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t} \quad (1)$$

Where *treat* is one of the above defined indicators and γ_t and δ_i denote time and individual fixed effects respectively.

3 Results

Table 1: Coefficients for Different Treatment Definitions

	(1) layoff or fired	(2) unemployed	(3) fired	(4) anyreason	(5) layoff
divorce					
treat	0.190*	0.0383	0.467***	0.136*	0.0650
	(0.0789)	(0.0436)	(0.125)	(0.0537)	(0.0943)
year	0.115***	0.115***	0.115***	0.116***	0.115***
	(0.00460)	(0.00466)	(0.00459)	(0.00461)	(0.00460)
kids	-0.425***	-0.425***	-0.425***	-0.423***	-0.426***
	(0.0265)	(0.0265)	(0.0265)	(0.0265)	(0.0265)
N	43557	43557	43557	43557	43557

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results of estimating the above stated equation are presented in Table 1. The numbers are qualitatively what I expected (Note however that these coefficients must not be interpreted as marginal effects due to the logit specification): Having children stabilizes marriages, and over the years, getting divorced becomes more common.

Being fired has the highest and most significant effect on getting divorced, although one must keep in mind that being fired is particularly not exogenous, meaning that this coefficient cannot be interpreted as the causal effect. It is easy to argue how an individual is more likely to get fired and to get divorced in hard times (omitted variable bias), or how a divorce is demanding in terms of psychical capacity, thus reducing performance at work and leading to being fired (reverse causality). One approach to check this causality is to look at the order of these events over time, I plot and discuss the corresponding graph below (Figure 1).

Just being unemployed, however, has no significant effect. The lower, but significant effects of *anyreason* and *layedofforfired* both also include being fired. Indeed, including the indicator for being fired in the corresponding regressions makes the actual treatment dummy in both of them insignificant. Column 5 shows the effect of being laid off on the probability to get divorced, which was the most promising treatment definition, as being laid off is supposedly exogenous. However, the coefficient is not significant.

Consequently, I will only focus on the impact of being fired on getting divorced in the further analysis. In terms of marginal effects, we are talking about a 0.79 percentage point increase, which, as compared to the baseline probability of getting divorced of 1.70 percent (among those observations who were not fired), amounts to a predicted 46.30 percent increase in the probability of getting divorced conditional on being fired.

Table 2 reports the effect by subgroups. The difference between males and females is only marginal, as opposed to what the motivating paper suggests. Besides methodological issues, it might be that the corresponding social norms differ between the US and Germany. Interestingly, there is no effect of having children for women, only for men, which is somewhat counter intuitive. Also, both subgroup estimates are larger than the overall estimate, which I cannot explain.

Column 3 and 4 show the effect by earning more or less than than their spouse in the year before they were fired. The effect is higher if the fired individual was the one contributing more to before-job loss joint income, which makes sense as in such cases, the financial distress caused by the job loss is higher for the couple.

The remaining question is, whether the observed relation is causal or not.

Table 2: Heterogenous Treatment Effects

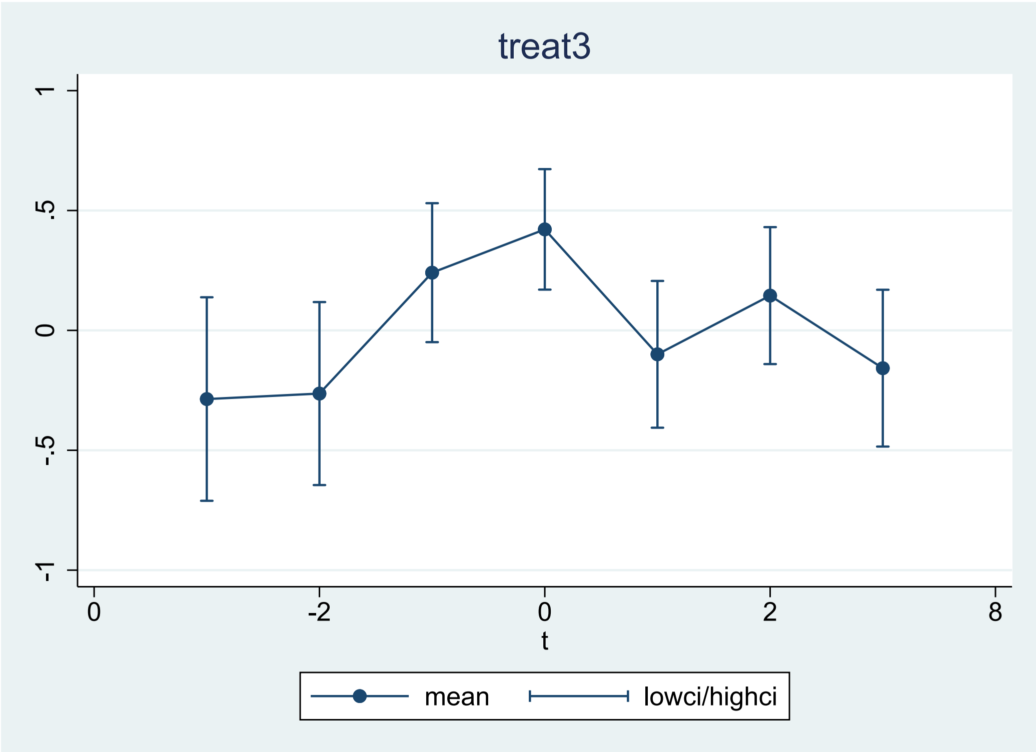
	(1) male	(2) female	(3) higher inc than spouse	(4) lower inc than spouse
divorce				
treat3	0.506**	0.494**	0.803*	0.491**
	(0.176)	(0.182)	(0.314)	(0.178)
year	0.153***	0.0568***	0.200***	0.0818***
	(0.00688)	(0.00647)	(0.0134)	(0.00670)
kids	-1.138***	0.0656	-1.542***	-0.0635
	(0.0563)	(0.0373)	(0.0621)	(0.0392)
N	18483	25074	6518	19646

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 1 below shows a plot of the coefficients lags and leads of the coefficients of the treatment indicator. I arbitrarily chose to observe seven years around the actual job loss and normalized the effect by subtracting their mean. If being fired were exogenous and causal for the increase in probability of getting divorced, I would expect to observe a sudden increase of the estimate at t=0. Obviously, this is not the case here. Although the peak is in the year of the job loss, the probability clearly already starts increasing the year before. Considering that some time passes between the decision to get divorced and the actual divorce, this discrepancy gets even more striking. I can therefore not reject the objection, that the observed relation between being fired and getting divorced is driven by mechanisms other than the causal effect that I was looking for.

Figure 1: Event Study



4 Conclusion

Motivated by a paper (Heintz-Martin & Zabel, 2018) that showed significant effects of struggling with or succeeding in the transition from school to work on relationship stability for men but not for women, the aim of this project was to find a similar pattern between job loss and divorce using US panel data and juxtapose the results. My central insights are that such a statistical association cannot be found using other causes of job loss than being fired, especially not when using being laid off, which would be the most trustworthy regarding exogeneity. The effect of being fired on the probability of getting divorced is only slightly smaller for men than for women, but noticeably larger for those earning more than their spouse in the year before the job loss compared to those who do not. However, the causality from being fired to getting divorced must be doubted, given that the dependence is smaller but already measurable one year before the individual was fired, which rules out direct causality for these cases, except unplausible anticipation effects.

Possible explanations for this discrepancy between mine and the motivating paper's results are the, albeit similar, effectively quite different settings and research questions. Reasons to continue or end a extramarital romantic relationship might be different than for a marriage, my sample covers also middle aged and older adults who might behave differently then adolescents and young adults.

Finally, this project highlights the importance of not jumping to conclusions when learning any empirical findings. External validity need not be given, and it might not be possible to abstract from the narrow context of the specific study.

References

Heintz-Martin, V., & Zabel, C. (2018). The stability of partnerships across the transition from education to employment. *Journal of Youth Studies*, 1–18.

Appendices

Table 3: What to do with Income?

	(1)	(2)	(3)	(4)	(5)	(6)
	divorce	divorce	divorce	divorce	divorce	divorce
divorce						
treat3	1.535	0.591***	0.467***	0.454***	1.395	0.672***
	(0.925)	(0.123)	(0.125)	(0.126)	(0.885)	(0.182)
year	0.0811	0.0431***	0.115***	0.0878***	0.150***	0.171***
	(0.0513)	(0.00376)	(0.00459)	(0.00527)	(0.0447)	(0.00937)
kids	-0.850***		-0.425***	-0.436***	-0.631***	-1.151***
	(0.214)		(0.0265)	(0.0268)	(0.187)	(0.0382)
numjobs	-0.265					
	(0.199)					
ivinc	0.0000111					
	(0.0000342)					
ivdinc	-0.0000343*					
	(0.0000161)					
inc				0.0000110***	-0.0000124	
				(0.00000231)	(0.0000300)	
dinc					-0.0000316*	
					(0.0000157)	
L.inc						-0.00000214
						(0.00000419)
L.dinc						-0.00000292
						(0.00000246)
N	445	48320	43557	41010	508	15712

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Results if Odd Years are Dropped

	(1) layoff or fired	(2) unemployed	(3) fired	(4) anyreason	(5) layoff
divorce					
treat	0.00518	-0.136*	0.516**	-0.0186	-0.235
	(0.111)	(0.0601)	(0.168)	(0.0743)	(0.137)
year	-0.0568***	-0.0586***	-0.0566***	-0.0569***	-0.0571***
	(0.00378)	(0.00386)	(0.00377)	(0.00379)	(0.00378)
kids	-0.211***	-0.215***	-0.209***	-0.211***	-0.212***
	(0.0337)	(0.0337)	(0.0337)	(0.0337)	(0.0337)
N	21227	21227	21227	21227	21227

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$