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YOU'LL NEVER WALK ALONE: UNEMPLOYMENT, SOCIAL NETWORKS AND LEISURE ACTIVITIES

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Abstract

We analyse how unemployment affects individuals' social networks, leisure activities, and the related satisfaction measures. Using the LISS panel, a representative longitudinal survey of the Dutch population, we estimate the effects by inverse propensity score weighting in a difference-in-differences design in order to deal with unobserved heterogeneity and unbalanced covariate distribution between treated and control units potentially associated with the dynamics of the outcome variables. We find that, after job loss, individuals increase their network size by strengthening their closest contacts within the family, spending more time with neighbors, and making more use of social media. Although they devote their extra leisure time mostly to private activities, our results do not support the hypothesis of social exclusion following unemployment.

JEL Class.: I31, J01, J64.

Keywords: Unemployment, job loss, social exclusion, leisure, social satisfaction, doubly robust difference-in-differences.

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You'll never walk alone: Unemployment, social networks and leisure activities

Mattia Filomena and Matteo Picchio

1 Introduction

Unemployment entails both economic and non-economic costs, and for this reason it has often attracted the attention not only of economists but also of psychologists and sociologists. In labour economics, a large body of literature has focused on the magnitude and duration of the consequences of unemployment spells on future labour market and health outcomes. For instance, the "scarring effects" literature argues that past unemployment increases the likelihood of further unemployment and lower wages later in life.[1]

Unemployment also has detrimental effects on health (Picchio and Ubaldi, 2023), and both economic deprivation and lost latent benefits should be considered when interpreting results (Janlert and Hammarström, 2009). Previous studies have suggested that physical health worsens when unemployment rates fall, because of increasing unhealthy behaviours like smoking, overeating, and taking less physical exercise (Ruhm, 2000, 2003). Moreover, the experience of parental unemployment during childhood may harm children's physical health later in life, with possible mediation channel in higher alcohol and tobacco consumption (Ubaldi and Picchio, 2023). Also mental health and life satisfaction may be significantly compromised by job loss (Picchio and Ubaldi, 2023), and these psychological scars have been widely analyzed by the empirical literature (see e.g. Clark et al., 2001; Clark and Lepinteur, 2019; Kassenboehmer and Haisken-DeNew, 2009; Strandh et al., 2014). For instance, Winkelmann and Winkelmann (1998) argued that the non-monetary costs of unemployment associated with reduced well-being are even larger than the income losses, and they are primarily due to a loss of social con-

[1] See, among others Arulampalam et al. (2001), Gregg (2001), Gregory and Jukes (2001), Gregg and Tominey (2005), Mroz and Savage (2006), Cockx and Picchio (2013), Guvenen et al. (2017), De Fraja et al. (2021), Filomena et al. (2022). See Filomena (2023) for a systematic review of the literature on the scarring effects of unemployment.

tacts and reduced self-esteem. Moreover, Nikolova and Ayhan (2019) highlighted that the unemployment effect is significant also for the partner's life satisfaction, and it extends beyond the loss of consumption opportunities because it may be related to social values attached to labour market participation.

The psychological and sociological literature provides a framework in which to interpret the relation between unemployment and the social values attached to labour market participation. According to the latent deprivation theory (Jahoda, 1981), unemployment causes deprivation not only of manifest economic resources but also of five latent psychological needs which are usually satisfied by employment: a time structure, social contacts, participation in collective purposes, status and identity, and regular activity. The absence of those functions is expected to cause, along with financial constraints, a decline in mental health. Moreover, in hypothesizing the positive relationship between employment and healthy psychological development, Jahoda (1982) asserted that even unsatisfactory employment is preferable to unemployment.[2] Thus, while employment is important for well-being, because it increases an individual's perception of self-worth and his/her self-esteem, unemployment leads to an increased feeling of helplessness (Goldsmith et al., 1996a,b).

As suggested by Brand (2015), job loss and unemployment may be also associated with new patterns of interaction with family members and friends, and the disruption of social and family ties. These themes have received less attention from the economic literature, and the effects of unemployment on social contacts are not straightforward. On the one hand, unemployment may lead to (i) lower level of income, thereby reducing public activities and social interactions because of tighter financial constraints; (ii) lower levels of self-acceptance, goal and meaning in life, unemployment stigmatization, and self-isolation, causing a retreat into private life in order to avoid social contacts and public activities (Kunze and Suppa, 2017; Rözer et al., 2020); (iii) reduced satisfaction and less ability to cope with difficulties (Pohlan, 2019). On the other hand, unemployment may positively affect social participation due to the increased amount of leisure, which allows unemployed individuals to spend more time on home production, caring for others, and socializing (Krueger and Mueller, 2012; Kunze and Suppa, 2017). As regards relationships with friends and family members, social scientists and psychologists have

[2]Gundert and Hohendanner (2014) detected a considerably lower risk of feeling socially excluded among employed workers than among unemployed ones. However, fixed-term and temporary agency workers display lower levels of social well-being with respect to permanent employees. This may be due to different perceived life-course predictability, which the authors consider important for social affiliation.

reported mixed research results: according to Rözer et al. (2020), strong ties are likely to be strengthened or, at least, not affected (Atkinson et al., 1986; Gallie et al., 2003), whereas Jackson (1999) argued that the unemployed suffer from less social support from close relatives and authority figures.

We contribute to this literature by providing evidence on the effects of unemployment on a very rich set of outcomes related to social networks and leisure time. In order to do so, we consider several aspects of an individual's social contacts and activities and provide a clearer and more complete picture of how a job loss may affect social inclusion. We first focused on the network size by analyzing the number of contacts, as in Pohlan (2019). Then, we differentiated the network size in several directions to highlight possible heterogeneous effects according to the strength of the tie and the type of relationship. For example, we distinguished between friends and very close friends and between amount of contacts and very close contacts, without family members or considering only family members. Moreover, we looked at the frequency with which individuals spent time with their family, neighbors, and friends. In addition, to take into account the way in which individuals were engaged in social interactions, we focused on the use of social media. Moreover, because Kunze and Suppa (2017) suggested that unemployment may alter individuals' preferences for public or private events, we considered several outcomes related to changes in the average time devoted to leisure activities. Finally, unlike previous research, which had mainly focused on overall measures of life satisfaction, mental health, and perceived social status (see e.g. Winkelmann, 2009; Kassenboehmer and Haisken-DeNew, 2009), we exploited more detailed information to quantify individuals' satisfaction along several dimensions, namely satisfaction with (i) social contacts, which should capture the sense of emptiness, loneliness and trust in personal contacts; (ii) amount of leisure time; and (iii) leisure activities.

Our empirical analysis exploited a representative longitudinal survey of the Dutch population – the Longitudinal Internet Studies for the Social Sciences (LISS) panel – which is administered by CentERdata of Tilburg University. From the methodological point of view, our strategy to identify the unemployment effects followed the one used in Pohlan (2019). We used doubly robust estimators for the average treatment effect on the treated (ATT) in a difference-in-differences (DID) research design, which is consistent if either a propensity score model or an outcome regression (OR) model is correctly specified (Sant'Anna and Zhao, 2020). The first difference in the outcome regression model allowed us to eliminate the omitted variables bias generated by individual fixed-effects additively entering the conditional mean of the outcome of interest. The propensity score model is particularly useful when the parallel trend assumption may fail because the distribution of observed characteristics, which are thought to be associated with the dynamics of the outcome variable, differs between the treated and comparison group (Abadie, 2005). To balance predetermined observed characteristics of the treated and untreated units, we used the improved doubly robust DID estimator recently proposed by Sant'Anna and Zhao (2020). To estimate the ATT, this combines the outcome regression (OR) procedure (e.g. Heckman et al., 1997) with Abadie's (2005) Inverse Probability Weighting (IPW) approach.

The paper is organized as follows. Section 2 describes the dataset, the sample used in the empirical analysis, and the empirical method. Section 3 reports our findings. Section 4 concludes.

2 Method

2.1 Data and variables

To answer our research questions, we focused on a sample of individuals in the Netherlands obtained from the Social Integration and Leisure core study of the Longitudinal Internet Studies for the Social Sciences (LISS) panel. The LISS panel is administered by CentERdata of Tilburg University.[3] The Social Integration and Leisure core study is carried out once a year and its questionnaire collects information on a broad range of leisure activities, social contacts, and satisfaction measures.[4] Some background variables on general characteristics, like demography, family composition, education, labour market position, retirement status, and earnings are instead collected on a monthly basis. We exploited this information on the labour market status to determine if the interviewee was employed or unemployed at the moment in which the Social Integration and Leisure questionnaire was administered.

We exploited all the available waves of the Social Integration and Leisure core study up to the COVID-19 pandemic outbreak, covering the time span 2008-2019. First, we built several *Social Network* measures by using information on (i) the number of contacts

[3] See Knoef and de Vos (2009) for an evaluation of the representativeness of the LISS panel and Scherpenzeel (2011, 2010) and Scherpenzeel and Das (2010) for methodological notes on the LISS panel design.

[4] See https://www.dataarchive.lissdata.nl/study_units/view/6 (last accessed on 20/07/2023) for more information on this questionnaire.

and very close contacts reported by each interviewee (all friends, without family members, and considering only family members outside of the household); (ii) how often the interviewee spent the evening with his/her family, neighbors, or friends; (iii) the number of hours per week of social media use, as a measure of friend relationship through chat, video calls, and internet communities.[5] Thus, we were able to consider the overall network size (contacts) and stronger ties (very close contacts) of the interviewees, the amount of time directly spent with other people or by means of online interactions. Second, we considered different types of *Leisure Activities*, namely (i) how many minutes per week were spent watching TV or reading books; (ii) how many books had been read in the last 30 days; (iii) how many hours per week were devoted to sports activities; (iv) how many hours per week were spent using a computer, navigating the Internet, and searching on websites. Third, while previous literature had mostly relied on how people are satisfied with their life as a whole, we exploited more detailed questions and were able to quantify individuals' *Satisfaction* with regard to their social contacts, amount of leisure time, and how they spend it. The respondents ranked their satisfaction on a 0 to 10 scale, where 0 was "not at all satisfied" and 10 meant "completely satisfied".

We matched these variables with background information gathered by the LISS panel, at both the individual and the household levels. At the individual level, we gathered information on gender, age, marital status, employment status, and education. At the household level, we exploited information on the number of household members, the number of children living in the household, the type of dwelling (self-owned or not), and urban characteristics of the place of residence. A more detailed description of both outcome and control variables is provided in Table 1.

Our goal was to estimate the effect of unemployment, meant as experiencing job loss. Therefore, adopting Pohlan's (2019) approach, for each wave from 2008 until 2018 we retained only 17-64 year-old employed individuals (employees, workers in the family business, or self-employed persons) observed both in wave t_0 and in the next consecutive wave t_1.[6] We considered interviewees as experiencing a job loss, i.e. as the treated units, if in the subsequent consecutive wave the individual declared that he/she was not working because either he/she was unemployed, or taking care of household chores, or was an unpaid worker receiving unemployment benefit. By contrast, the control group was composed of all interviewees who were employed both in wave t_0 and in the next

[5] Social media may be of help for the unemployed to maintain their social contacts (Feuls et al., 2014).

[6] We excluded retirees, individuals who had partial work disability, and those involved in voluntary work.

Table 1: Description of variables

Variable	Definition
Dependent variables	
Social network	
Number of friends	Number of friends (and close friends) of the interviewee (overall, without family members, and family members outside of the household)
Social events	How often the interviewee spent evenings with his/her family, neighbors, or friends (1 = never/don't know; 2 = about once a year; 3 = a number of times a year; 4 = about once a month; 5 = a few times a month; 6= one or twice a week; 7 = almost every day)
Social media	Average time spent using social media (chatting, video calling, visiting internet forums, using WhatsApp, Telegram, Snapchat, Skype or similar), weekly hours
Leisure Activities	
TV	Average time spent watching television, weekly minutes
Book reading	Average time spent reading books, weekly minutes
Books	Number of books read in the last 30 days, for study or for pleasure
Sports	Average time spent on sports activities, weekly hours
PC	Average time spent using a computer at home, at school, or somewhere else, weekly hours
Internet	Average time spent using Internet at home, at school, or somewhere else, weekly hours
Web searching	Average time spent searching for information on the Internet (for hobbies, work, day-trips, etc.), weekly hours
Satisfaction	
Social contacts	How satisfied was the interviewee with his/her social contacts? (from 0 to 10; 0 = not at all, 10 = completely satisfied)
Leisure amount	How satisfied was the interviewee with the amount of leisure time that he/she had? (from 0 to 10; 0 = not at all, 10 = completely satisfied)
Leisure activities	How satisfied was the interviewee with how he/she spent his/her leisure time? (from 0 to 10; 0 = not at all, 10 = completely satisfied)
Treatment variable	
Unemployment	Dummy = 1 for becoming unemployed between two consecutive interviews. It included: job seekers following job loss, first-time job seekers, those exempted from job seeking after a job loss, those who took care of the housekeeping, unpaid workers receiving unemployment benefit.
Control variables	
Individual characteristics	
Female	Dummy = 1 if the interviewee was a woman
Age	Age of the interviewee
Age square	Age square of the interviewee
Marital status	Dummy = 1 if the interviewee was single
Education level	From primary education to university
Self-owned dwelling	Dummy = 1 if the interviewee was a homeowner
Year of the interview	From 2008 to 2019
Household characteristics	
Members	Number of household components
Children	Number of children living in the household
Urban character	Surrounding address density per km^2 (1 = very or extremely urban (1,500 or more); 0 = not urban (less than 1,500))
Female × Members	Interaction between female and number of household members
Female × Children	Interaction between female and number of children living in the household

Source: Social Integration and Leisure, LISS panel administered by Centerdata (Tilburg University, the Netherlands).

consecutive wave t_1. In the empirical analysis, we exploited each pair of waves t_0 and t_1, with $t_0 = 2008, \ldots, 2018$. The final sample was made up of 23,756 control units and 605 treated units, which pertained to 6,014 different individuals repeatedly observed across t_0 and t_1 pairs of waves.

2.2 Identification and estimation

In order to estimate the effect of experiencing unemployment on individuals' social networks, leisure activities, and the related levels of satisfaction, previous studies have mostly employed fixed effects models (see e.g. Kassenboehmer and Haisken-DeNew, 2009; Kunze and Suppa, 2017; Eckhard, 2022). Although controlling for time-constant unobserved heterogeneity helps to remove spurious correlation from the estimate of the unemployment effect, in this framework there are further endogeneity concerns. First, people may anticipate the job loss, so that it may exert its effects on social networking and leisure activities already at time t_0. Second, there may be feedback effects or reverse causality: for instance, people with few social contacts may be more likely to lose their job and less likely to find a new one because of a deterioration of their social skills and then of their performance, or because individuals who are dissatisfied with their job, leisure, or social relationships may decide to quit voluntarily. Previous studies have argued that social contacts are important for job search behaviours and success (Ioannides and Loury, 2004). Thus, people less involved in social activities with family, friends, or neighbors, as well as individuals who spend less time on social forum or web searching, may have fewer chances of obtaining information about vacancies and be more likely to experience longer unemployment spells due to unobserved personal traits.

The use of a conventional DID estimator would be based on strong assumptions to identify the unemployment effect; the average outcomes for treated and control units should follow parallel paths over time in absence of the treatment. This assumption may be implausible if the pre-treatment characteristics of treated and untreated individuals are unbalanced between the two groups and they are associated with the dynamic of the outcome variable Abadie (2005).

We now describe our analysis. As in Pohlan (2019), we considered that differences in observed characteristics may create non-parallel outcome dynamics; we deviated from the canonical DID analysis; and we used inverse propensity score weighting in a DID approach (Abadie, 2005). More precisely, we used the improved doubly robust DID (DR-

DID) estimator recently proposed by Sant'Anna and Zhao (2020), which is consistent if either the propensity score model or the OR model are correctly specified. To estimate the ATT, it combines the OR procedure (e.g. Heckman et al., 1997) and Abadie's (2005) Inverse Probability Weighting (IPW) approach. The first difference in the OR model eliminates the omitted variables bias generated by individual fixed-effects additively entering the conditional mean of the outcome of interest. The propensity score model is particularly useful when the parallel trend assumption may fail because the distribution of observed characteristics, which are thought to be associated with the dynamics of the outcome variable, differs between the treated and comparison group (Abadie, 2005). The improved DR-DID estimator attains double robustness in terms of both consistency and inference.[7]

Sant'Anna and Zhao (2020) considered the estimand

$$\tau = E\Big[\big(w_1(D) - w_0(D, X; \pi)\big)\big(\Delta Y - \mu_{0,\Delta}(X)\big)\Big] \tag{1}$$

where

- ΔY is the first difference with respect to time of the outcome variable;
- $\mu_{d,\Delta}(X) = \mu_{d,t_1}(X) - \mu_{d,t_0}(X)$ is the first difference of the true OR $m_{d,t}(x) \equiv E[Y_t|D = d, X = x] = X'\beta_{0,t}$, with $d, t = 0, 1$;
- $w_1(D) = D/E(D)$ and $w_0(D, X; \pi) = \frac{\pi(X)(1-D)}{1-\pi(X)} \Big/ E\Big[\frac{\pi(X)(1-D)}{1-\pi(X)}\Big]$, with $\pi(X)$ an arbitrary model for the true, unknown propensity score.

The estimand in Equation (1) is a weighted average of the regression-adjusted temporal differences in the outcome variable, with weights w_0 depending on the propensity score which, in our framework, is the individual probability of job loss between two consecutive waves. More in detail, it weights-down the distribution for the untreated for those values of the covariates which are over-represented among the control group, and weights-up the same distribution for those values of the covariates which are instead under-represented.

Sant'Anna and Zhao's (2020) improved DR-DID estimator is a three-step estimator. In the first step, a logit model for the probability of job loss is estimated using Graham

[7]In the terminology of Sant'Anna and Zhao (2020), double robust consistency means that the estimand identifies the ATT even if either, but not both, the propensity score model or the OR model are misspecified. Similarly, double robustness for inference implies that the exact form of the asymptotic variance of the estimator does not depend on which of the two models is correctly specified.

et al.'s (2012) Inverse Probability Tilting (IPT) estimator with a set of covariates X_i. We included in X_i predetermined individual and household characteristics. We also plugged into X_i all the social network measures, leisure activities, and satisfaction levels evaluated at time t_0, so as to control and balance the treated and untreated units also for the pre-treatment values of the outcomes of interest.[8] In the second step, the OR parameters for the control group are estimated by weighted least squares, with weights given by the propensity scores estimated in the first step. In the third step, the estimated propensity scores and the fitted values of the regression models are plugged into the sample analogue of τ specified in Equation (1).

The improved DR-DID estimator identifies the ATT under the assumption that, in the absence of the treatment, the average conditional outcome of the treated and control units would have evolved in parallel. By conditioning the working models on predetermined individual/household characteristics and on the pre-treatment values of all the outcome variables of interest, we allowed for time trends specific to each of these control variables. Although we balanced the treated and untreated units on the basis of the outcome variables, i.e. social networks, leisure activities, and the related levels of satisfaction, at time t_0, thereby ensuring that the identified impacts were not due to different pre-treatment levels of the outcomes variables feeding back on the probability of job loss, our identification strategy was affected by a limitation.[9] Between two consecutive years t_0 and t_1, individuals may suffer a shock in some of their unobserved characteristics jointly affecting the realization of the outcome variable and the employment status at time t_1. In order to attribute a causal interpretation to the estimated effects, we had to rule out this possibility.

A further assumption that should be satisfied is the standard overlap condition (see for instance Assumption 3.2 in Abadie (2005) or Assumption 3 in Sant'Anna and Zhao (2020)). In our empirical analysis, we had evidence that the overlap condition was satisfied: we found that the support of the propensity score for the treated units was a subset of the support of the propensity score for the untreated units.

To assess if the estimated propensity scores adequately balance the covariate distributions of treated and untreated units, we report in Table 2 the average of all the covariates contained in X by treatment status and with and without IPT. Columns (1)-(3) show that,

[8] Differently from Pohlan (2019), our dataset had no information on individual employment histories and job and firm characteristics that may be of help in avoiding self-selection issues due to different reasons for job loss (lay-offs, expired temporary contracts, voluntary quits, or plant closures).

[9] This limitation also affects the analysis in Pohlan (2019).

before weighting, those interviewees who would lose their job in the next period were systematically different from the controls, especially in terms of leisure activities and individual/household characteristics. After reweighting using IPT, the weighted averages of the controls perfectly match those of the treated (columns (5)-(7)): treated and control units are exactly balanced in terms of moments of order one. Rubin (2001) suggested a further distributional condition that should be satisfied if the distributions of the covariates in the two groups are to be considered reasonably balanced: the ratio of the variances of the residuals obtained by regressing each of the covariates on the linear index of the estimated propensity score should be close to 1. Columns (4) and (8) report these ratios. They show that the fraction of variables which, according to Rubin (2001), are "bad" (ratio lower than 0.5 or larger than 2) or of "concern" (ratio is either between 0.5 and 0.8 or between 1.25 and 2) decreases from 28% to 6%. Rubin's (2001) B, i.e. the standardized difference in the means of the propensity scores between the treated and the untreated units, decreases from 65.1 to 0.0, whereas Rubin's (2001) R, i.e. the ratio of the variances of the propensity scores for the treated and the untreated units, is within the 0.5-2 interval to be considered sufficiently balanced. These diagnostic statistics suggest that IPT weighting is able to balance quite well the distribution of covariates of treated and untreated units.

3 Results

3.1 Main findings

Table 3 reports the estimated ATT for all the outcome variables analyzed, i.e. changes in social network measures, in leisure activities, and in satisfaction levels. Differently from Pohlan (2019), we find a positive effect of becoming unemployed on network size. This effect is particularly marked in the case of close friends, suggesting a strengthening of the closest ties. When we distinguish between friends who are family members and those who are not, we find that it is the strengthening of the ties with family members which drives the results. Moreover, job losers significantly spend more evenings with their neighbors and more time on social media (+56 minutes per week). These effects may be explained by tighter financial constraints following unemployment: individuals who become unemployed receive more support from their closest contacts, reduce direct interactions by increasing the use of social networks, and cut secondary expenses, such

Table 2: Averages of covariates by treatment with and without balancing

	Unweighted				IPT weighted			
	Control Average (1)	Treated Average (2)	Difference in averages (3)	Ratio of variances (4)	Control Average (5)	Treated Average (6)	Difference in averages (7)	Ratio of variances (8)
Initial level of outcomes								
Social network								
# of friends	3.172	3.273	0.101	0.95	3.273	3.273	0.000	0.98
# of close friends	2.627	2.636	0.009	0.98	2.636	2.636	0.000	0.99
# of friend excluding family members	1.452	1.542	0.090	1.07	1.542	1.542	0.000	1.02
# of close friends excluding family members	1.047	1.058	0.011	0.95	1.058	1.058	0.000	0.95
# of friends among family members	1.726	1.747	0.021	0.95	1.747	1.747	0.000	0.95
# of close friends among family members	1.583	1.587	0.004	0.93	1.587	1.587	0.000	0.96
Evenings spent with family in a week	4.548	4.498	-0.050	1.07	4.498	4.498	0.000	1.03
Evenings spent with neighbors	3.188	3.162	-0.026	1.04	3.162	3.162	0.000	0.99
Evenings spent with friends	3.771	3.625	-0.147**	1.05	3.625	3.625	0.000	1.03
Social media (hours per week)	3.370	3.681	0.311	0.52★	3.681	3.681	0.000	0.44★★
Leisure activities								
TV (minutes per week)	965.202	1048.018	82.816***	0.91	1048.018	1048.018	0.000	0.71★
Book reading (minutes per week)	191.082	198.924	7.842	0.90	198.924	198.924	0.000	0.87
# of books (last 30 days)	1.332	1.220	-0.113	0.52★	1.220	1.220	0.000	0.91
Sports (hours per week)	2.065	1.852	-0.214**	0.86	1.852	1.852	0.000	0.99
PC (hours per week)	6.957	8.009	1.052***	1.14	8.009	8.009	0.000	0.76★
Internet (hours per week)	10.343	11.443	1.100**	1.19	11.443	11.443	0.000	0.85
Web searching (hours per week)	2.607	2.714	0.106	1.21	2.714	2.714	0.000	1.02
Satisfaction								
Social contacts (0-10)	7.203	6.962	-0.241***	1.09	6.962	6.962	0.000	0.82
Leisure amount (0-10)	6.552	6.489	-0.063	1.20	6.489	6.489	0.000	1.06
Leisure activities (0-10)	6.904	6.630	-0.274***	1.26★	6.630	6.630	0.000	1.01
Individual characteristics								
Female	0.500	0.587	0.087***	1.02	0.587	0.587	0.000	1.00
Age (years)	44.362	46.170	1.808***	1.10	46.170	46.170	0.000	1.00
Age square	2087.646	2264.964	177.318***	1.15	2264.964	2264.964	0.000	1.02
Primary education	0.030	0.055	0.025***	1.73★★	0.055	0.055	0.000	0.99
Intermediate secondary education	0.162	0.208	0.046***	1.22	0.208	0.208	0.000	0.98
Upper secondary education	0.078	0.114	0.037***	1.45★	0.114	0.114	0.000	0.99
Intermediate vocational education	0.295	0.304	0.009	1.02	0.304	0.304	0.000	0.99
Higher vocational education	0.305	0.223	-0.082***	0.82	0.223	0.223	0.000	1.00
University	0.131	0.096	-0.035***	0.75★	0.096	0.096	0.000	1.01
Single	0.218	0.276	0.058***	1.18	0.276	0.276	0.000	1.00
Self-owned dwelling	0.801	0.704	-0.097***	1.34★	0.704	0.704	0.000	1.01
Wave 2008	0.119	0.078	-0.041***	0.67★	0.078	0.078	0.000	1.00
Wave 2009	0.097	0.101	0.004	1.04	0.101	0.101	0.000	1.00
Wave 2010	0.100	0.079	-0.021*	0.81	0.079	0.079	0.000	1.00
Wave 2011	0.088	0.078	-0.010	0.89	0.078	0.078	0.000	1.00
Wave 2012	0.093	0.124	0.031**	1.33★	0.124	0.124	0.000	0.99
Wave 2013	0.087	0.126	0.039***	1.42★	0.126	0.126	0.000	0.99
Wave 2014	0.086	0.140	0.054***	1.47★	0.140	0.140	0.000	0.99
Wave 2015	0.086	0.106	0.020	1.22	0.106	0.106	0.000	1.02
Wave 2016	0.079	0.048	-0.031***	0.62★	0.048	0.048	0.000	1.00
Wave 2017	0.086	0.074	-0.012	0.87	0.074	0.074	0.000	1.03
Wave 2018	0.079	0.046	-0.033***	0.63★	0.046	0.046	0.000	1.00
Household characteristics								
# of household members	2.837	2.636	-0.200***	0.99	2.636	2.636	0.000	1.02
# of children	1.034	0.886	-0.148***	0.92	0.886	0.886	0.000	0.99
Urban area	0.402	0.435	0.033	1.03	0.435	0.435	0.000	1.00
Female × # of household members	1.396	1.607	0.211***	1.07	1.607	1.607	0.000	1.01
Female × # of children	0.508	0.565	0.058	1.13	0.565	0.565	0.000	1.01
Mean bias	9.2				0.0			
Median bias	10.1				0.0			
Rubin's (2001) B[(a)]	65.1				0.0			
Rubin's (2001) R[(b)]	0.98				0.78			

Notes: The reported statistics were computed on 605 treated and 23,756 untreated individuals. *** p-value< 0.01; ** p-value< 0.05; * p-value< 0.1. Significance tests on the difference of the averages were based on a regression of the variable on the job loss indicator. The tests were robust to heteroskedasticity and within-individual correlation. Columns (4) and (8) show the ratio of the variances of the residuals orthogonal to the linear index of the propensity score in the treated group over the control group. ★★ indicates that variables are "bad", i.e. the ratio is smaller than 0.5 or larger than 2. ★ indicates that variables are of "concern", i.e. the ratio is either between 0.5 and 0.8 or between 1.25 and 2 (Rubin, 2001).

(a) Rubin's (2001) B is the standardized difference in the means of the propensity scores between the treated and the untreated units.

(b) Rubin's (2001) R is the ratio of the variances of the propensity scores for the treated and the untreated units.

as going out to a restaurant or a pub, by spending more time with their neighbors. The increase in the number of evenings spent with neighbors could also be explained by the fact that job losers spend more time at home or in the vicinity, making it more likely for them to establish or strengthen their social relationships with neighbors.

Table 3: Main estimation results

	ATT	Treated	Controls
Δ *in Social Networks*			
Number of friends	0.123**	605	23,756
	(0.061)		
Number of close friends	0.155**	605	23,756
	(0.065)		
Number of friends (no family members)	-0.008	605	23,756
	(0.045)		
Number of close friends (no family members)	0.034	605	23,756
	(0.045)		
Number of friends (family members)	0.133***	605	23,756
	(0.051)		
Number of close friends (family members)	0.126**	605	23,756
	(0.052)		
Evenings spent with family	-0.054	586	23,350
	(0.051)		
Evenings spent with neighborhood	0.136**	588	23,219
	(0.053)		
Evenings spent with friends	0.051	585	23,255
	(0.048)		
Use of social media (hours per week)	0.937**	586	22,953
	(0.383)		
Δ *in Leisure Activities*			
TV (minutes per week)	178.949***	605	23,756
	(30.572)		
Book reading (minutes per week)	51.169***	605	23,756
	(15.601)		
Number of books (last 30 days)	0.117	601	23,654
	(0.073)		
Sports (hours per week)	0.376***	601	23,662
	(0.093)		
PC (hours per week)	3.731***	600	23,619
	(0.485)		
Internet (hours per week)	3.877***	595	23,374
	(0.619)		
Web searching (hours per week)	0.087	586	22,953
	(0.145)		
Δ *in Satisfaction*			
Social contacts (0-10)	0.015	580	23,172
	(0.056)		
Leisure amount (0-10)	0.851***	592	23,505
	(0.085)		
Leisure activities (0-10)	0.117*	596	23,582
	(0.066)		

Notes: Standard errors clustered at individual level are reported in parentheses. *** p-value< 0.01; ** p-value< 0.05; * p-value< 0.1.

As regards the effect of unemployment on leisure activities, we find that sports activities are positively affected, with an increase of about 23 minutes per week. This contrasts with the previous evidence in Kunze and Suppa (2017), who found that in Germany the effect of unemployment on active participation in sports was nil. Moreover, job loss leads to more hours spent watching TV (+179 minutes per week), reading books (+51 minutes per week), using the PC (+224 minutes per week) and browsing the Internet (+233 minutes per week). The activity of searching the Internet for information on hobbies, work, day-trips, etc. is instead not affected by unemployment.

Finally, the last panel of Table 3 shows that unemployment does not modify satisfaction with social contacts, but it positively and significantly affects satisfaction with the amount of leisure and, although with less statistical significance, with the way in which leisure time is spent. The significant increase in the amount of time devoted to private activities (e.g. watching TV) may suggest that job losers suffer from the stigma generated by unemployment, which reduces self-esteem, leading to self-isolation and a retreat into private life and interests. However, considering that unemployment strengthens the network size at the level of family ties, increases the time spent with neighbors and interactions via social media, and that the satisfaction with social contacts is unchanged, our findings do not support the hypothesis that job loss causes social exclusion.

3.2 Heterogeneity analysis

Becoming unemployed may exert different effects on social networks, leisure activities, and related satisfaction measures depending on individual and socioeconomic characteristics.

First, unemployment effects may differ between genders because unemployment events may be differently perceived by men and women, with different psychological, health and financial implications. On the one hand, the single-breadwinner social norm still persists, and it has prioritized men's attention to the obligation to provide financially for their family members (Thébaud, 2010). Therefore, a job loss, and the consequent limitation of the ability to fulfil breadwinning obligations, may impact more on men because it may hit their self-esteem more strongly (Eckhard, 2022). Indeed, the meta-analysis in Picchio and Ubaldi (2023) showed that male health is more impaired by unemployment. On the other hand, the sociological literature has pointed out that job loss and unemployment may shape familial obligations, with women responding to the financial instability generated by their job loss by making great efforts to care for their families (Damaske, 2022), thus markedly affecting their social networks and the way in which they organize their leisure activities. Columns (1) and (2) of Table 4 report the unemployment effect for men and women, respectively. We find that the overall increase in evenings with neighbors and in time spent on social media is essentially driven by men, whereas these effects are smaller in magnitude and not significantly different from zero for women. Men reacted more strongly to job loss also in terms of time spent on the analysed leisure activities analysed, especially in terms of watching TV (+250 minutes per week for men against +122 for women), reading (+61 minutes per week for men against +42 for women), and sports (+30 minutes per week for men against +18 for women). This suggests that men and women use the extra free time caused by the job loss differently, with men more focused on typical leisure activities than women.[10]

Second, the consequences of unemployment on social networks and leisure may differ between older and younger individuals. On the one hand, older individuals may find it more difficult to make new contacts because their peers already have stable networks and may be less open to new social contacts. On the other hand, older individuals may have longer-lasting social ties, which may possibly become more durable relationships (Rözer et al., 2020), or they may enjoy family life more than younger individuals. Younger and older people may have different life perspectives: while young people need a higher frequency of social interactions, for older people it is the quality of their social interactions which matters most, rather than their frequency (van Ours, 2021). Moreover, older individuals may be less financially constrained than younger people, which may help them to face the income losses due to unemployment without major changes in their leisure activities. Nevertheless, the experience of a job loss for older workers is often a one-way street out of the labour force or into long-term unemployment, whereas young people typically have higher re-employment chances, so that older job losers tend to change their behaviour in terms of leisure activities more intensively. Columns (3) and (4) in Table 4 shows that the overall effect of unemployment on the number of close friends, especially family members, is induced by the elderly. The number of friends or of close friends is instead unchanged for job losers younger than 50. People older than 50 reduces the frequency of evenings spent with friends when they lose their job, and their use of social media increases (+44 minutes per week), but not as much as it does for younger job losers (+76 minutes per week). As regards leisure activities, we find that younger job losers increase their time spent using the PC (+272 minutes per week) and Internet (+298 minutes per week) much more than the elderly (+172 and +165 minutes per week, respectively). Older job losers devote more time than younger ones to reading (+88 minutes per week) and to sports (+28 minutes per week). For older job losers, unemployment also positively impacts on satisfaction not only with the amount of leisure time, but also with leisure activities.

[10]We also investigated whether job losers reacted differently in terms of hours of voluntary work and informal care-giving, with no effect overall and no difference between men and women.

Table 4: Estimation results by different individual characteristics

	Men	Women	Age $<$ 50	Age $\geq$ 50	Single	Married	Lower educated[a]	Higher educated[b]	Not Urban Area[c]	Urban Area[d]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Δ *in Social Networks*										
Number of friends	0.134	0.101	0.020	0.242***	0.136	0.105	0.071	0.193**	0.189**	0.036
	(0.101)	(0.075)	(0.084)	(0.087)	(0.108)	(0.073)	(0.084)	(0.089)	(0.078)	(0.096)
Number of close friends	0.163	0.134*	0.057	0.283***	0.149	0.147*	0.111	0.227**	0.235***	0.055
	(0.106)	(0.081)	(0.088)	(0.096)	(0.118)	(0.078)	(0.089)	(0.093)	(0.086)	(0.099)
Number of friends (no family members)	0.012	-0.027	-0.006	-0.028	0.113	-0.057	-0.098*	0.107	0.051	-0.088
	(0.075)	(0.057)	(0.061)	(0.068)	(0.089)	(0.054)	(0.059)	(0.071)	(0.059)	(0.070)
Number of close friends (no family members)	0.062	0.008	0.037	0.023	0.145	-0.007	-0.084	0.194***	0.087	-0.033
	(0.072)	(0.058)	(0.062)	(0.065)	(0.092)	(0.052)	(0.057)	(0.071)	(0.060)	(0.068)
Number of friends (family members)	0.124	0.130**	0.033	0.267***	0.016	0.168***	0.175**	0.084	0.132*	0.135*
	(0.085)	(0.064)	(0.067)	(0.079)	(0.089)	(0.062)	(0.070)	(0.076)	(0.070)	(0.076)
Number of close fiends (family members)	0.101	0.135***	0.032	0.258***	0.010	0.160**	0.200***	0.039	0.141**	0.109
	(0.087)	(0.067)	(0.069)	(0.083)	(0.092)	(0.064)	(0.072)	(0.077)	(0.071)	(0.079)
Evenings spent with family	-0.103	-0.013	-0.123*	0.028	-0.064	-0.060	0.013	-0.149**	-0.046	-0.072
	(0.082)	(0.065)	(0.071)	(0.072)	(0.096)	(0.061)	(0.069)	(0.073)	(0.070)	(0.074)
Evenings spent with neighborhood	0.263***	0.051	0.212***	0.058	0.142	0.140**	0.019	0.293***	0.180***	0.077
	(0.078)	(0.072)	(0.075)	(0.075)	(0.111)	(0.062)	(0.071)	(0.079)	(0.068)	(0.088)
Evenings spent with friends	0.119	0.009	-0.009	-0.138*	0.014	0.054	0.065	0.028	0.124**	-0.035
	(0.080)	(0.060)	(0.065)	(0.071)	(0.097)	(0.055)	(0.069)	(0.067)	(0.063)	(0.076)
Use of social media (hours per week)	1.241**	0.683	1.266**	0.732**	1.653	0.591*	0.685	1.273***	1.127*	0.754
	(0.514)	(0.543)	(0.643)	(0.334)	(1.083)	(0.336)	(0.586)	(0.442)	(0.588)	(0.490)
Δ *in Leisure Activities*										
TV (minutes per week)	249.850***	122.467***	177.794***	178.924***	189.360***	173.602***	217.559***	134.949***	185.708***	172.002***
	(55.533)	(33.932)	(44.405)	(40.521)	(50.084)	(37.843)	(48.948)	(30.747)	(38.510)	(49.093)
Book reading (minutes per week)	61.461***	42.108**	22.582	87.647***	-4.464	69.061***	58.966***	42.468*	64.772***	35.325
	(23.367)	(21.062)	(20.795)	(23.818)	(24.134)	(19.919)	(21.371)	(22.400)	(22.022)	(21.597)
Number of books (last 30 days)	0.246*	0.028	0.084	0.169*	-0.017	0.181**	0.117	0.109	0.269**	-0.074
	(0.129)	(0.087)	(0.106)	(0.096)	(0.133)	(0.086)	(0.075)	(0.137)	(0.106)	(0.091)
Sports (hours per week)	0.501***	0.297**	0.278**	0.468***	0.260	0.435***	0.336**	0.394***	0.415***	0.317**
	(0.153)	(0.116)	(0.109)	(0.158)	(0.161)	(0.114)	(0.131)	(0.133)	(0.126)	(0.140)
PC (hours per week)	4.415***	3.317***	4.527***	2.869***	4.699***	3.319***	2.851***	4.785***	3.678***	3.834***
	(0.761)	(0.630)	(0.697)	(0.650)	(1.051)	(0.525)	(0.616)	(0.761)	(0.634)	(0.744)
Internet (hours per week)	4.079***	3.686***	4.972***	2.752***	4.516***	3.591***	2.850***	5.210***	4.077***	3.719***
	(0.883)	(0.821)	(0.978)	(0.681)	(1.167)	(0.741)	(0.736)	(1.083)	(0.913)	(0.830)
Web searching (hours per week)	0.193	0.055	0.213	0.022	0.602*	-0.123	0.046	0.073	0.111	0.057
	(0.244)	(0.174)	(0.193)	(0.214)	(0.342)	(0.154)	(0.191)	(0.223)	(0.184)	(0.234)
Δ *in Satisfaction*										
Social contacts (0-10)	0.015	0.020	-0.058	0.111	-0.136	0.081	-0.044	0.098	-0.016	0.063
	(0.084)	(0.075)	(0.082)	(0.075)	(0.118)	(0.063)	(0.080)	(0.077)	(0.068)	(0.094)
Leisure amount (0-10)	0.725***	0.949***	0.764***	0.988***	0.967***	0.822***	0.802***	0.924***	0.742***	1.002***
	(0.144)	(0.102)	(0.117)	(0.122)	(0.167)	(0.097)	(0.111)	(0.131)	(0.117)	(0.123)
Leisure activities (0-10)	0.062	0.161*	0.090	0.175**	0.006	0.160**	0.101	0.156	0.122	0.113
	(0.102)	(0.086)	(0.096)	(0.088)	(0.139)	(0.073)	(0.087)	(0.103)	(0.092)	(0.094)

Notes: Standard errors clustered at individual level are reported in parentheses. *** p-value< 0.01; ** p-value< 0.05; * p-value< 0.1.

[a] Education level = primary school, intermediate secondary school, or intermediate vocational education.

[b] Education level = upper secondary school, higher vocational education, or university.

[c] Moderate, slightly, and non urban areas = Surrounding address density per km^2 less than 1,500.

[d] Very or extremely urban areas = Surrounding address density per km^2 of 1,500 or more.

Third, the negative effects of unemployment may be buffered by having a partner (Paul and Moser, 2009). In the case of job loss, the spouse can offer social support and help in stabilizing the household's financial situation. Furthermore, the spouse also provides emotional support that may be helpful in avoiding social exclusion after the unemployment occurrence. Moreover, partnered job losers may have a lower degree of flexibility in terms of geographical mobility because of family considerations (Kassenboehmer and Haisken-DeNew, 2009) and are less likely to accept a job offer elsewhere. We therefore hypothesize that partnered job losers may experience a greater strengthening of their closest contacts, especially among family members, compared to single job losers. The results in columns (5) and (6) of Table 4 support our hypothesis. We indeed find that, while single job losers do not experience significant changes in their social contacts, partnered job losers see an increase in the number of the closest contacts within their family and in the evenings spent with their neighbors. While both groups show a greater use of computer, Internet, and TV, and a higher level of satisfaction with the amount of leisure, after becoming unemployed, only partnered job losers significantly engage more in sports activities (+26 minutes per week) and read more (+69 minutes per week).

Fourth, financial consequences after unemployment may impact higher- and lower-educated individuals differently. Higher-educated job losers may have more savings and more chances of quickly finding a new position after the job loss (Riddell and Song, 2011). If so, also their social networks and leisure behaviours may be less affected than those of lower-educated job losers, who may be less able to cope with the negative effects of unemployment and may experience the greatest need for support (Rözer et al., 2020). Columns (7) and (8) in Table 4 show the results after splitting the sample between low-educated and high-educated individuals.[11] The unemployment gradient differs by educational level especially in terms of social networks. On the one hand, low-educated job losers receive more support from contacts and close contacts among family members, but they interact less with friends outside the family circle. On the other hand, highly-educated job losers see an increase in their social networks in terms of close friends outside their family, in the evenings spent with their family and neighbors, and in the time devoted to social media interactions (+ 76 minutes per week). The unemployment effect on leisure activities and satisfaction does not vary significantly between low- and high-educated job losers.

[11] We included in the low-educated group those interviewees with at most a primary or intermediate secondary/vocational education, and in the high-educated group those with higher-level diplomas (see notes of Table 4).

Finally, previous studies suggest that urban characteristics may affect quality of life, life satisfaction, and social participation (Li and Kanazawa, 2016; Vogelsang, 2016; Olsen et al., 2019). Thus, the unemployment effect on social networks and leisure activities may vary depending on the environment in which people live. For instance, living in a very urban place may make it more difficult to go out and make new friends due to higher costs of living, but it may provide more alternative leisure activities. Moreover, living in a low-populated area may lead to reduced direct interactions with friends and fewer opportunities to engage in public activities. However, the strength of ties in smaller communities may guarantee higher social support after job loss (Leana and Feldman, 1991). The results in columns (9) and (10) of Table 4 were obtained after splitting the sample according to the population density of the place where respondents lived. We find that the social networks of people living in densely-populated areas are not affected by unemployment, whereas job losers living in low population-density areas experience an increase in their number of friends and close contacts. Moreover, they spend more evenings with their neighbors and friends.

3.3 Sensitivity analysis

To test the robustness of our main findings, we performed a series of sensitivity analyses using alternative DID estimators. The results are set out in Table 5. In column (1) we report the effects estimated using the traditional DID, without therefore weighting observations in order to balance treated and untreated units on the basis of information predetermined with respect to the treatment. Column (2) reports the results obtained by using the IPW-DID proposed by Abadie (2005), which does not involve an OR model. In column (3), the weights of Abadie's (2005) estimator are normalized to sum up to 1. This normalization may solve instability problems due to propensity score estimates relatively close to one (Sant'Anna and Zhao, 2020). Finally, column (4) shows the results obtained by using a second DR-DID estimator proposed by Sant'Anna and Zhao (2020). While the one used in the benchmark analysis employed inverse probability tilting (Graham et al., 2012) to estimate the propensity score – which leads to a DR-DID estimator which Sant'Anna and Zhao (2020) showed to be both DR consistent and DR for inference – the one used to obtain column (4) was based on the conditional maximum likelihood estimator for estimating the propensity scores. All these alternative estimators deliver unemployment effects that are extremely similar to the benchmark ones.

Table 5: Sensitivity analyses using different estimators

	DID (Traditional) (1)	IPW-DID (Abadie, 2005) (2)	IPW-DID (Standardized weights) (3)	IPW-DR-DID (Sant'Anna and Zhao, 2020) (4)
Δ *in Social Networks*				
Number of friends	0.121**	0.123**	0.122**	0.123**
	(0.061)	(0.061)	(0.061)	(0.061)
Number of close friends	0.157**	0.155**	0.155**	0.155**
	(0.064)	(0.065)	(0.065)	(0.065)
Number of friends (no family members)	-0.009	-0.009	-0.009	-0.008
	(0.045)	(0.045)	(0.045)	(0.045)
Number of close friends (no family members)	0.037	0.034	0.034	0.034
	(0.045)	(0.045)	(0.045)	(0.045)
Number of friends (family members)	0.132**	0.133**	0.133**	0.133**
	(0.051)	(0.051)	(0.051)	(0.051)
Number of close friends (family members)	0.126**	0.126**	0.126**	0.127**
	(0.053)	(0.052)	(0.053)	(0.053)
Evenings spent with family	-0.054	-0.054	-0.054	-0.054
	(0.051)	(0.051)	(0.051)	(0.051)
Evenings spent with neighborhood	0.141***	0.137**	0.137**	0.136**
	(0.053)	(0.053)	(0.053)	(0.053)
Evenings spent with friends	0.050	0.053	0.053	0.051
	(0.048)	(0.048)	(0.048)	(0.048)
Use of social media (hours per week)	0.899**	0.939**	0.939**	0.937**
	(0.383)	(0.383)	(0.383)	(0.383)
Δ *in Leisure Activities*				
TV (minutes per week)	177.529***	178.993***	178.988***	178.985***
	(30.312)	(30.660)	(30.658)	(30.581)
Book reading (minutes per week)	50.539***	51.319***	51.319***	51.145***
	(15.641)	(15.622)	(15.622)	(15.606)
Number of books (last 30 days)	0.100	0.119	0.119	0.117
	(0.075)	(0.073)	(0.073)	(0.073)
Sports (hours per week)	0.377***	0.376***	0.376***	0.376***
	(0.093)	(0.093)	(0.093)	(0.093)
PC (hours per week)	3.706***	3.736***	3.735***	3.731***
	(0.479)	(0.488)	(0.487)	(0.485)
Internet (hours per week)	3.827***	3.885***	3.885***	3.879***
	(0.621)	(0.620)	(0.620)	(0.619)
Web searching (hours per week)	0.081	0.085	0.085	0.087
	(0.145)	(0.146)	(0.146)	(0.145)
Δ *in Satisfaction*				
Social contacts	0.016	0.013	0.013	0.015
	(0.056)	(0.056)	(0.056)	(0.056)
Leisure amount	0.850***	0.852***	0.852***	0.851***
	(0.085)	(0.085)	(0.085)	(0.085)
Leisure activities	0.122*	0.117*	0.117*	0.117*
	(0.066)	(0.066)	(0.066)	(0.066)

Notes: Standard errors clustered at individual level are reported in parentheses. *** p-value< 0.01; ** p-value< 0.05; * p-value< 0.1.

4 Conclusions

Apart from the well-known negative unemployment effects on future labour market outcomes, experiencing unemployment may also have non-monetary costs because it affects individuals' psychological dimensions and social participation. In this paper, we have examined the impact of becoming unemployed on individuals' social networks, leisure activities, and related levels of satisfaction. We have estimated the effect by applying inverse probability score weighting in a difference-in-differences setting on a Dutch sample, focusing on several dimensions of social networking and everyday-life activities.

In contrast to the common beliefs that unemployment causes social exclusion and isolation, we find that the Dutch job losers experienced an increase in their overall network size, which was driven by the strengthening of their closest contacts within family. At the same time, significant changes relate to the way in which individuals engage in their social interactions; i.e. through a marked increase in the use of social media. As regards changes in the frequency of social relationships, our results highlight a statistically significant increase in the evenings spent with neighbors, whereas the number of evenings spent with family and friends is not affected. Furthermore, in line with Kunze and Suppa's (2017) finding, we detect a significant increase of leisure time spent on private activities, such as using a PC and Internet or watching TV. Time devoted to sport activities was also found to increase after job loss. The results concerning changes in satisfaction levels reveal that job losers declare an increase in satisfaction with the amount of leisure time at their disposal. The effect heterogeneity analyses show that the increase in the overall network size is driven by older job losers, by people living in low populated areas, and by higher-educated individuals. In particular, the former two groups experienced an increase in the ties with family members, whereas higher-educated job losers reported an increase in the number of close friends and spent more time with their neighbors. A greater use of social media consequent on job loss is observed for men, younger, higher-educated individuals and those not living in urban areas. Although job losers invest more leisure time in private activities following unemployment, our findings on the network size, interactions, and social satisfaction do not support the hypothesis of self-isolation and social marginalization in the Netherlands.

Our analysis has two main limitations. First, the lack of information on individual employment histories in our dataset prevented us from exploiting job and firm characteristics that might have helped us avoid self-selection issues according to different reasons of job loss. Moreover, regardless of the reason for job loss, there may be unobserved shocks between two consecutive years affecting both social outcomes and employment status, which were not captured in our empirical analysis, generating biases of reverse causality.

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