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Who is bowling alone? Quantile treatment effects of unemployment on social participation

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This article examines heterogeneity in the effect of unemployment on social participation. Whereas existing studies on this relationship essentially estimate mean effects, we use quantile regression methods to provide a broader and more complete picture. To account for the potential endogeneity of job loss, we estimate quantile treatment effects (on the treated) based on entropy balancing and focus on unemployment due to plant closures. Using German panel data, we show that the effect of unemployment varies across the distribution of public social activities. It is large and negative for individuals in the middle and lower part of the distribution of public activities, whereas those participating a lot are not affected. By contrast, the effect of unemployment on private social participation is virtually zero for individuals at the lower part of the outcome distribution and weakly positive in the middle. Our findings suggest that active labor market policies should account for target-group specific elements, tailored to those individuals which are most adversely affected by unemployment.

Keywords: unemployment; social participation; plant closure; quantile treatment effects; entropy balancing

JEL Classification Numbers: J65, C21, I31

1 Introduction

It is well-established that unemployment has severe consequences for various aspects of individuals' life, such as subjective well-being, health outcomes and patterns of social participation (e.g., Winkelmann and Winkelmann (1998), Sullivan and von Wachter (2009)

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and Kunze and Suppa (2017), respectively).[1] Both pecuniary and non-pecuniary channels through which unemployment affects these aspects have been emphasized in the literature. Examples include the material hardship associated with the loss in income but also the loss of social, psychological and non-pecuniary benefits provided by employment (e.g., Jahoda, 1982).

However, while the average (or mean) effects on the life of those directly affected are well documented, distributional effects of unemployment for various outcomes (such as well-being, health, etc.) have received less attention. In fact, only a few recent studies characterize the consequences of unemployment (or job loss) for different parts of the outcome distribution, see Korkeamäki and Kyyrä (2014) for earnings, Binder and Coad (2015a,b) for individuals' life satisfaction and Schiele and Schmitz (2016) for different measures of health outcomes. The results from these studies indicate that the effect of unemployment varies significantly across the respective outcome distribution under consideration. With respect to social participation, existing studies find that the effect of unemployment may vary with both individual and contextual factors, such as social status, region, employment status (of the partner) and the local unemployment rate, see, e.g., Sonnenberg (2014), Dieckhoff and Gash (2015), Kunze and Suppa (2017). Moreover, both the empirical literature on the effect of unemployment on life satisfaction (e.g., Winkelmann and Winkelmann, 1998, Gielen and van Ours, 2014) as well as theoretical considerations regarding the effect of unemployment on the level of social support (e.g., Tattarini *et al.*, 2018)[2] point to the existence of effect heterogeneity with respect to the initial distribution of unemployment and social participation. Yet, a systematic analysis of the distributional effects of unemployment on social participation, trying to identify causal effects, is missing so far. To close this gap in the literature is the contribution of the present paper.

The literature on social capital has highlighted the importance of social participation for various non-economic and economic outcomes (as e.g., better employment prospects and health, or increased growth and judicial efficiency), see, e.g., Putnam (2001), Alesina and La Ferrara (2000), Bauernschuster *et al.* (2014), Satyanath *et al.* (2017). Moreover, social participation is considered to be a crucial dimension of human well-being which requires further analysis (e.g., Sen, 2000, Stiglitz *et al.*, 2009). The severe impact of unemployment on social participation, however, has recently been emphasised by Kunze and Suppa (2017).[3] According to their findings, unemployment has a negative and lasting effect on public social activities but also implies a retreat of individuals into private life, which, in turn, limits the access to information (e.g., about vacancies) associated with a broader and

[1] Note that some studies on the relationship between unemployment and health, however, do not find any causal effect, e.g. Schmitz (2011).

[2] See section 2 for descriptive statistics and more details on this link.

[3] See also Kunze and Suppa (2020) for an analysis of the effect of unemployment on social participation of indirectly affected partners. Moreover, Sonnenberg (2014) provides a survey of the sociological literature on the effect of unemployment and social participation. According to the main findings from this literature, unemployment tends to lower social participation (see also Dieckhoff and Gash (2015)).

more heterogeneous network. The present paper complements this literature by estimating distributional effects of unemployment on the level of social participation.

The main challenge in identifying a causal effect of unemployment on social participation is to account for the potential endogeneity of job loss. For example, estimates may suffer from bias due to reversed causality if an unobservable individual shock reduces social participation and thus individuals' performance on the job. Using data from the German Socio-Economic Panel (SOEP), we focus on plant closures as arguably exogenous reason for entry into unemployment in order to account for this problem. To estimate unconditional quantile treatment effects, i.e. the unconditional effect of unemployment across the distribution of social participation, we apply quantile regression techniques proposed by Firpo (2007), in which we replace common propensity score methods by entropy balancing (Hainmueller, 2012) in order to achieve a more effective balance of conditioning variables.

We follow Kunze and Suppa (2017) and measure social participation by five distinct indicators which are grouped according to whether they are carried out in private or public. Specifically, we use the frequencies of attending cultural events; cinema, pop concerts and the like; performing volunteer work (all carried out in public); social gatherings; and helping out friends (both private). The underlying variables are aggregated into two indices by using principal component (factor) analysis. These outcome measures are preferred over single outcome variables as they are continuous variables, which are necessary to employ quantile regression methods.[4]

Our results show that unemployment stretches the distribution of public social participation to lower values. The estimated coefficients of unemployment on the lower six deciles of the distribution of public social participation activities are large and negative, whereas the effects on the upper three deciles are much smaller and not statistically significant. Consequently, if the identifying assumptions hold, adverse effects of unemployment particularly apply to individuals who participated less already before they became unemployed. By contrast, the effect of unemployment on private social participation is essentially zero for individuals at the lower part of the outcome distribution (the three lowest quantiles), while the estimated coefficients are positive for the remaining quantiles and particularly large at the center of the distribution (a strong and statistically significant effect at the median). As the estimated average treatment effects on the treated are much smaller than the distributional effects that are found for certain parts of the population, our findings highlight the importance of using quantile regression methods to analyze the full picture on the relationship between unemployment and social participation. Altogether, our findings suggest that individuals with low participation (before unemployment) are those who are most adversely affected by unemployment. Hence, policy makers should especially focus on active labour market policies for those individuals with low levels of social participation

[4]By making use of these social participation measures, we assume that the primary aim of each single activity is to get in contact with other individuals in the real world (Putnam, 2001).

and weak social networks (target-group specific efforts) in order to help these individuals to establish and maintain their social network as well as to provide them with crucial information, which, in turn, may positively affect their job search behavior and their labor market opportunities.

The main reason we focus on unconditional treatment effects is that we are interested in heterogeneity regarding the (unconditional) effect of unemployment on social participation (and not, e.g., the effect heterogeneity of unemployment conditional on high or low educational achievements, respectively). This is the most interesting object to consider from a policy perspective, in particular if social participation is considered as one specific dimension of human well-being (e.g., from a capability perspective, see, e.g., Sen (1992) and Sen (2000)).[5] In addition to such an intrinsic or ultimate importance, (more) negative effects of unemployment for already critically low values in social participation (of the unconditional distribution) may lead to social isolation, labour market detachment, and may thus also provide an additional argument in favor of uenmployment hysteresis. See Frölich and Melly (2013) for a detailed discussion of the differences between conditional and unconditional quantile treatment effects and further references.

The remainder is structured as follows. Section 2 provides a review of the related literature on unemployment and social participation as well as some conceptual considerations. Section 3 describes our econometric strategy and Section 4 our data. Section 5 presents our main results and several robustness checks. Section 6 provides complementary evidence. Section 7 concludes.

2 Unemployment and social participation: related literature and some theoretical considerations

Social participation is generally viewed as a crucial aspect of human well-being which requires further analysis (e.g., Sen, 2000, Stiglitz *et al.*, 2009). Moreover, from the literature on social capital it is well known that social participation is an important determinant of various economic outcomes, like for instance, higher wages, better employment prospects, better health or higher growth (e.g., Putnam, 2001, Alesina and La Ferrara, 2000, Durlauf and Fafchamps, 2005, Bauernschuster *et al.*, 2014).[6] Consequently, many studies have an-

[5] See also Suppa (2018), who suggests a measure for deprivation in social participation based on a capability perspective. His measure essentially seeks to identify individuals, who exhibit normatively alarming low (unconditional) levels of social participation. More specifically, he suggests to consider an individual to be deprived in social participation if he or she is observed not to participate in any social activity. Similar arguments also apply when studying the unconditional distributions of, say, health or education (e.g., Schiele and Schmitz (2016)).

[6] Satyanath *et al.* (2017), however, emphasize the important role of social capital in determining the rise of the Nazi Party in Germany. They use historic data on association density in interwar Germany and show that denser networks are positively related to increased party entry and therefore electoral success. There findings represent a prominent example for the observation that social capital may also be associated with

alyzed different factors that influence social participation. According to Alesina and La Ferrara (2000), for example, participation in various social activities is significantly reduced by income inequality and racial as well as heterogeneity. Kunze and Suppa (2017) find negative and lasting effects of unemployment for public social activities and, at the same time, an increase in private social activities (such as meeting friends and neighbours).[7] These latter effects clearly limit the access to information (e.g., about vacancies) resulting from a broader and more heterogenous network. More recently, Pohlan (2019) studies the impact of job loss on a number of outcome variables (both economic and social ones) which may affect exclusion from society. She finds that job loss has particularly strong effects on individual's perception about how well they are integrated in society, on life satisfaction, on the access to economic resources and on an individual's mental health.[8] Moreover, she shows that the strength of the effects vary with socioeconomic factors such as having a partner or education. The focus of this literature, however, is mainly on estimating mean effects. Our paper complements these studies by arguing that the effect of unemployment might differ over the distribution of social participation. Our estimations therefore provide a broader and more complete picture.

Our work is also related to a growing literature using quantile regression approaches to analyze the consequences of job loss and unemployment. Korkeamäki and Kyyrä (2014) study the effect of job loss due to mass layoffs and plant closure on earnings using quantile regression. They show that displacement has the strongest effect at the lower end of the earnings distribution and turns out to be small or negligible at the upper end. Binder and Coad (2015a,b) use quantile regression techniques to analyze heterogenous effects of unemployment along the distribution of several measures of well-being. They find that unemployment indeed has a differential effect over the distributions of life satisfaction, mental health and a general measure of subjective well-being. Specifically, individuals with high life satisfaction or mental health turn out to be less affected when becoming unemployed.[9] However, as these studies do not distinguish between the reason for unemployment, a causal interpretation of these results is only possible by imposing rather strong assumptions. Schiele and Schmitz (2016) use quantile regression methods to analyze the effects of job loss due to plant closure across the distributions of various health measures. They show that individuals in the middle and lower part of the distributions of physical

negative effects.

[7]See also Bauernschuster *et al.* (2014) who do not find any significant effect of the internet use on several aspects of social capital.

[8]Note however that Pohlan (2019) does not find any effect of unemployment on social participation, which stands in contrast to some of the results found by Kunze and Suppa (2017). Possible explanations for these differences may be the use of a different data set or an alternative measurement of social participation activities (i.e., the conceptualization of the social participation indicators).

[9]Similarly, Clark and Lepinteur (2019) find that, on average, the experience of unemployment during early adulthood significantly lowers individuals' well being at age 30 and that the effect is strongest for those individuals at the bottom of the subjective well-being distribution whereas the happiest are not affected. Hence, well-being can be considered as a buffer against adverse life events.

and mental health are adversely affected by job loss whereas there is no effect at the upper end of the distribution. The results of theses studies indicate that unemployment and job loss have heterogenous effects on several outcome variables throughout the distributions of these variables. The present paper complements this literature by studying the (potentially) heterogenous effects of unemployment on social participation.

Finally, our work connects to the literature on the non-monetary costs and the subjective well-being associated with unemployment. A common presumption in this literature is that the loss of social contacts is responsible for a large part of these non-monetary costs (e.g., Winkelmann and Winkelmann, 1998).[10] Winkelmann (2009), for example, studies the (average) effect of social participation on life satisfaction. He finds that participation increases life satisfaction but also that participation itself cannot dampen the decline in subjective well-being associated with an unemployment experience. Binder and Coad (2011) are the first to analyze distributional effects of social relations (and other factors such as health or income) on subjective well-being. They show that coefficient estimates decrease over the (conditional) distribution of happiness, implying that the positive effect of an active social life is much stronger at the bottom of the distribution (even though it is still high in the upper quantiles). Hence, a functioning social life can explain high levels of subjective well-being even for the happiest in the distribution. Similarly, Neira *et al.* (2019) study the impact of several dimensions of social capital (i.e., trust, social networks and civic engagement) on life satisfaction, thereby focussing on distributional effects by using quantile regression techniques. They find heterogenous effects on the different quantiles of the subjective well-being distribution. More precisely, effects turn out to be stronger for the least happy individuals as compared to the happiest. These studies emphasize the consequences of changes in social contacts and participation for subjective well-being. The present paper adds to this literature by pointing out the distributional consequences of unemployment on social participation (and thus social captital), with potentially important distributional implications for the non-monetary costs of unemployment.

From a theoretical point of view, there are many different channels through which unemployment may directly or indirectly affect social participation, such as financial and time constraints as well as changes in social norms or job prospects, see Kunze and Suppa (2017) for a detailed overview of these mechanisms. However, as the focus of the existing literature is essentially on mean effects, differential effects that apply only to certain parts of the distribution might be overlooked. Indeed, the effect of unemployment on social participation may not be the same for different subgroups of the population. The results of previous studies suggest that the effect may vary with both individual and contextual factors, such as social status, region, employment status (of the partner) and the local unemployment rate (e.g., Sonnenberg, 2014, Kunze and Suppa, 2020)).

[10]Explanations of such an effect focus on variations in individuals' subjective well-being due to status and identity effects, see, e.g., Clark (2003) and Hetschko *et al.* (2014).

Moreover, heterogeneity with respect to the initial distribution of social participation can be motivated by several findings. From an empirical perspective, the effect of unemployment on life satisfaction has been found to be heterogeneous by previous research (see Winkelmann and Winkelmann (1998), Gielen and van Ours (2014) and references cited above). From a theoretical perspective, one mechanism to expect effect heterogeneity with respect to social participation is the following: Since social participation can be seen as an investment activity for building up a stock of social capital (Glaeser *et al.*, 2002) and social support (which is often seen as one form of social capital, e.g., Irwin *et al.* (2008)), higher levels of social participation are associated with higher levels of social support. If social support helps individuals to cope with a shock like unemployment it may, among other things, also prevent individuals from withdrawing from social life.[11] In fact, social support has long been hypothesised to play a critical role in coping with the experience of unemployment, but mostly with respect to its psychological consequences (e.g., Komarovsky, 1940 [2004], pp. 129–130). Moreover, since the mid-1970s this so-called buffering effect of social support, which is presumed to moderate the effects of various shocks (including unemployment) on mental health, received more systematic attention in sociological research (Gore, 1978, Lin *et al.*, 1985).[12] More recent studies in this line of research provides novel evidence in favor of the buffering hypothesis (Milner *et al.*, 2016, Tattarini *et al.*, 2018).[13]

Yet, we do not have regularly collected survey instruments for social support in our data, so we cannot directly test this hypothesis. Occasionally, the SOEP, however, asks respondents for people who may support them in specific situations.[14] The respondents can then enumerate up to 5 persons or report that they do not have any person to turn to in that particular situation. In 2011 these items are collected together with our social participation measures, which allows us at least to probe whether higher quantiles of social participation are actually associated with higher levels of perceived social support.

As a simple measure of social support, we consider the average number of individuals available to the respondent in the different situations. Figure 1 shows the average level of this social support measure across the population within the quantiles of public and private social participation, respectively. Clearly, higher levels of social participation are associated

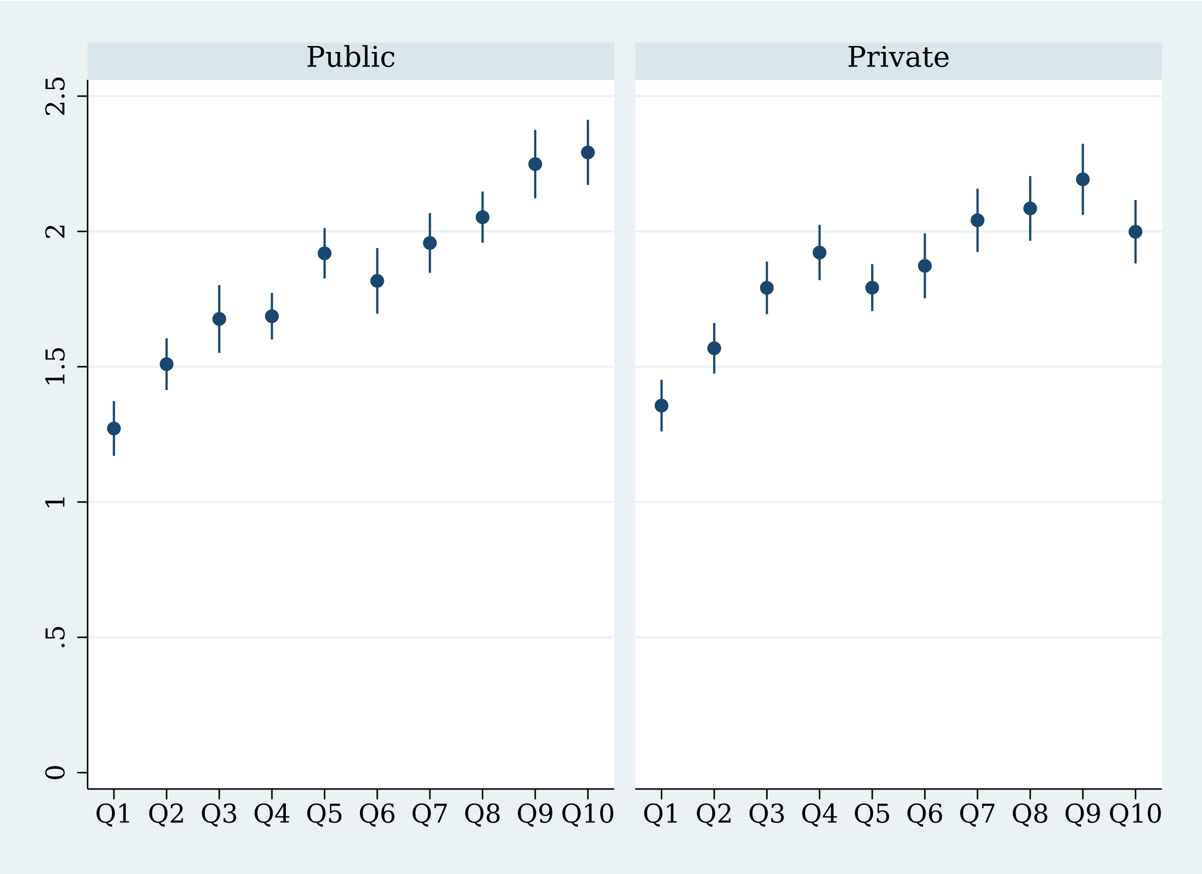
[11]Social Support can be partitioned into different forms, including emotional, instrumental, informational, companionate, and esteem support (Gottlieb and Bergen, 2010).

[12]However, this line of research produced inconsistent findings, at least partly resulting from different measurement approaches for social support. Moreover, methodological concerns have been raised as well, like social support being responsive to unemployment itself and thus being endogenous (Atkinson *et al.*, 1986).

[13]Also, the American Psychological Association, in fact, recommends to 'Make Connections' to build resilience as 'Good relationships with close family members, friends or others are important. [...]'. See `https://www.apa.org/helpcenter/road-resilience` for more details.

[14]In detail these questions are: (1) With whom do you talk about personal thoughts and feelings, or about things you wouldn't tell just anyone?, (2) Who supports your advancement in your career or educational training and fosters your progress?, (3) Now a hypothetical question: If you were to need long-term care (for example, in the case of a bad accident), who would you ask for help?, (4) With whom do you occasionally have arguments or conflicts that weigh upon you?, (5) Who can you tell the truth even when it is unpleasant?

Figure 1: Average level of social support by quantile of public and private social participation



Notes: Data from SOEP v34 (2011). Standard errors account for both primary sampling units and strata. The estimation uses survey weights. The construction of the social participation indices is explained in section 3. Social support is measured by the mean number of persons available to the respondent in different adverse circumstances, see footnote 14.

with higher social support. Based on the evidence and the descriptive patterns, we thus expect the causal effect of unemployment on social participation to vary with the (initial) distribution of our social participation measures. A thorough analysis of these (potential) effects is the contribution or this paper.

3 Empirical strategy

3.1 General idea and framework

The aim of our analysis is to identify quantile treatment effects on the treated (QTT), i.e. the effect of unemployment on different points of the distributions of our measures of social participation for those individuals who have lost their job due to a plant closure. This enables us to identify potential effects even if the average treatment effect on the treated (ATT) remains unchanged. We adopt the framework of Firpo (2007) which combines the estimation of unconditional quantiles with propensity score weighting techniques in order to account for selection on observed variables. From a methodological point of view, however, we replace conventional propensity score methods by entropy balancing (see Hainmueller (2012) and Marcus (2013)), which is a reweighting technique that has been shown to be more effective in balancing the conditioning variables than common propensity score methods. Specifically, entropy balancing determines weights in order to balance pre-specified moment conditions for covariates between treated and non-treated individuals (in our case the same mean and variance). At the same time efficiency is achieved by remaining close to uniform weights to avoid loss of information.[15] As the main focus of our analysis is to examine if the effect of unemployment varies along the distribution of social participation activities for treated individuals, we use the framework and methods suggested by Firpo (2007) to estimate *unconditional* quantile treatment effects on the treated – in contrast to *conditional* treatment effects on the treated which would allow us to study effects conditional on covariates.[16]

The general framework can be summarized as follows. Let Y, D and X denote the outcome variable, i.e. a continuous measure of either private of public social participation activities, the treatment variable, i.e. unemployment due to a plant closure, and a set of conditioning variables, respectively. Then Y^0 denotes the level of social participation in a situation where individuals are continuously full-time employed with the same employer, whereas Y^1 is the measure of our social participation indices for individuals that experience

[15] Other advantages of entropy balancing are its computational efficiency and its versatility (as weights can be passed to almost any estimator). Moreover, as in related approaches, entropy balancing reduces model dependency through orthogonalised treatments. Section 5.2, however, shows that our main results are robust against using inverse probability weighting instead of entropy balancing.

[16] See Frölich and Melly (2013) for technical details in deriving and estimating unconditional quantile treatment effects and a discussion on the differences between conditional and unconditional effects.

unemployment due to a plant closure. The observed outcome is then given by $Y = Y^1 D + Y^0(1-D)$. The effect of unemployment on the outcome distribution at quantile τ, $\Delta^{\tau}_{D=1}$, is then obtained by the difference between the τ quantile of the outcome distribution when individuals experience unemployment due to a plant closure ($Q^{\tau}_{Y^1|D=1}$) and the τ quantile of the potential outcome distribution in the (hypothetical) situation where these individuals are continuously employed ($Q^{\tau}_{Y^0|D=1}$):

$$\Delta^{\tau}_{D=1} = Q^{\tau}_{Y^1|D=1} - Q^{\tau}_{Y^0|D=1} \tag{1}$$

These QTTs are defined for all $\tau \in (0,1)$ and, thus, in principle allow for the identification of effects over the entire distribution of social participation Firpo (2007).

3.2 Identification

Identification of QTTs in the above framework is essentially based on a selection-on-observables (or unconfoundedness) assumption, which states that potential levels of social participation must be independently distributed from unemployment, conditional on X. As unemployment due to plant closure can be considered as being largely exogenous to individuals, unconfoundedness is likely to hold in our case. The main reason is that a plant closure is generally not related to individuals' characteristics or abilities. Rather, it is likely to be caused by developments of the overall economy or wrong management decisions which are not at the responsibility of single individuals which are affected by it via unemployment. However, it may be possible that individuals anticipate a plant closure, which, in turn may result in a gradual leaving process of some workers, for example the better educated and skilled ones, prior the closing. To account for this kind of selection into unemployment which might be related to the level of social participation, we use information on predetermined individual, job and firm-characteristics to control for these factors. Hence, we assume unemployment due to plant closures to be randomly assigned conditional on X and estimate the counterfactual distribution of treated individuals by using the observed outcome of non-treated individuals.

In addition, to infer from distributional effects of unemployment on social participation to individual effects, one has to assume rank preservation. According to this assumption, the relative rank of an individual in the outcome distribution must be the same whether or not the individual receives the treatment. Test for rank preservation and also the weaker form of rank similarity have been suggested by Frandsen and Lefgren (2018), Dong and Shen (2018) and Autor *et al.* (2017). While the results of these studies indicate that rank preservation might not hold in some applications, we argue that this may not be the case in the context of unemployment and social participation. Specifically, there are at least two reasons why it may be plausible to assume that people rank similarly in the distributions of social participation in case they experience unemployment due to plant closure as well as in the hypothetical situation if these individuals are continuously employed. First, social participation is also determined by factors which are not directly affected by unemployment, for example by personality traits or by the provision of public infrastructure for various activities (e.g., opera, theaters, etc.). Second, our findings of large adverse effects at the lower part of the distribution of public social participation and no effects at the upper part are most likely explained by the observation that people with an initially active social life are better diversified and shielded against adverse effects, whereas those with an initially poor social life are the ones which are most adversely affected. However, even if the assumption of rank preservation is violated, distributional aspects may also be very informative and relevant, sometimes even more than individual effects (Firpo, 2007). With regard to unemployment and social participation, for example, large negative effects at the lower part of the distribution of public social participation and no or positive effects at the upper part would indicate that higher rates of unemployment may increase the share of individuals which are excluded from society and may therefore lack relevant information about vacancies to become reemployed. This, in turn, may, among other things, increase the risk of dependency on social welfare are thus increase public costs (Pohlan, 2019).

Finally, identification requires a common support assumption and uniqueness of quantiles. As our sample is restricted to the region of common support in the estimation and as our social participation measures are continuous and take on a broad range of values, both assumptions are likely to hold. All estimations are carried out with the Stata command ivqte by Frölich and Melly (2010).[17]

4 Data

The empirical analysis uses data from the German Socio-Economic Panel (SOEP), which is a representative longitudinal study of private households in Germany with annually about 20,000 participating individuals, see, e.g., Goebel *et al.* (2019).[18] We restrict our sample to individuals aged 18 to 64. As our measures of social participation are collected from 1990 onwards but are not available in each year (see below), the data from the waves 1990-2017 provide the main source of our data set. However, observations are dropped if either the outcome, the treatment or conditioning variables are missing. Hence, the actual sample sizes varies with each model to be estimated. The largest sample consists of $64,331$ observations from $21,218$ different individuals.

Out treatment variable is unemployment due to plant closure, which is constructed by combining information on the reason for a job termination (including for example own resignation, dismissal, plant closure, and end of a temporary job) with information on an

[17] We thank Blaise Melly for helpful suggestions on how to modify the command in order to estimate QTTs.

[18] More specifically, we use the SOEP, version 34, SOEP, 2019, `http://dx.doi.org/10.5684/soep.v34`.

individuals' employment status. A plant closure can occur between any two survey periods that include the measurement of our social participation variables. This leaves us with a total of ten treatment periods: 1990–1992, 92–94, 94–96, 96–97, 97–99, 99–01, 05–07, 07–09, 09–11 and 15–17.[19] Hence, the treatment variable takes on the value one (at the end of each treatment period) for individuals that have become unemployed because their place of work has closed and zero for individuals that are continuously full-time employed with the same employer. Thus we exclude all observations with unemployment for other reasons than plant closures and estimate the effects of unemployment due to a plant closure as opposed to being continuously employed with the same employer.

Our analysis is based on five social participation variables: The frequency of attending cultural events such as concerts, theatre, lectures, etc. (*culture*); attending cinema, pop music concerts, dancing, disco, sports events (*cinema*); attending social gatherings (*socialising*); helping out friends (*helping*) and performing volunteer work (*volunteer*). These activities represent both crucial dimensions of social participation and investments in social capital (e.g., Alesina and La Ferrara, 2000). While the activities cinema, culture and volunteer capture both informal (cinema and culture) and formal (volunteer) aspects of connecting individuals in the public sphere, the variables socialising and helping capture essentially informal dimensions of social participation taking place in the private sphere. Following the existing literature, these activities are aggregated into two indices by using principal component analysis.[20] Table 1 shows the underlying social participation variables and the waves in which information on the respective activities have been gathered.[21]

Table 1: Underlying social participation variables

Question	**Variable**
Gathered in 85, 86, 88, 90, 92, 94, 96, 97, 99, 01, 05, 07, 09, 11, 15, 17	
Going to the movies, pop music concerts, dancing, disco, sports events	Cinema
Going to cultural events (such as concerts, theatre, lectures, etc.)	Culture
Volunteer work in clubs or social services	Volunteer
Meeting with friends, relatives or neighbours	Socialise
Helping out friends, relatives or neighbours	Helping

Notes: Responses categories are *at least once a week*, *at least once a month*, *less often*, *never*. During 1990 these items were only collected in East-Germany.

Even though the effect of unemployment on the unconditional distribution of social participation does, in principle, not depend on covariates[22], the inclusion of such variables in the estimation seems useful as it may reduce the variance of the estimator and makes the

[19]Note that we do not consider the periods 01–05 and 11–15 as four-year changes are not comparable to the remaining periods.

[20]The factor analysis suggests two underlying factors according to the eigenvalue criterion. The items culture, cinema and volunteer do only load on the first factor whereas socialising and helping only load on the second factor. See also Bauernschuster *et al.* (2014) and Kunze and Suppa (2017) for similar aggregation procedures.

[21]Note that we only use the responses to these questions when they are recorded on a 4-point-scale (ranging from 'weekly' and 'monthly' to 'less frequently' and 'never').

[22]Note, that the distributions of $Y^0|D=1$ and $Y^1|D=1$ do not depend on X. Therefore, the QTTs could, in principle, be estimated without any conditioning variables.

unconfoundedness assumption more credible. While unemployment due to plant closure can be considered to be largely exogenous to an individual, there may still be confounding factors so that the unconfoundedness assumption might hold only conditional on some covariates X (Kassenböhmer and Haisken-DeNew, 2009). In some cases, for example, a plant closure may be anticipated if it results from a preceding period of downsizing which, in turn, may be caused by bad management decisions or macroeconomic developments. During a period of downsizing, some employees might leave the firm before the actual closure: On the one hand the management might force some employees to leave, e.g., those with a low performance or a low productivity. To address this issue, we control for education, working experience, occupational position, gross labor income, unemployment experience. On the other hand some employees might voluntarily leave the sinking ship and try to find a new job elsewhere. However, both the ability and the willingness of employees to search for a new job clearly depends on their outside options. These outside options, in turn depend on many factors, such as sex and ethnic background (in case of racial discrimination in the labor market), education, working experience, age, occupation, spatial flexibility, the dependence on income from (own) employment, and local labor market conditions. Hence, we also control for sex, German nationality, migration background, age, state of residence, living with partner, the number of children, individuals health (workdisability), whether there is a care needing person in the household and for the following shocks: childbirth, and separation, divorce or death of the partner. In addition, we control for the year of the interview as well as firm size and sector, which is motivated by different numbers of insolvencies across time, industry sector and firms of different sizes (Schiele and Schmitz, 2016). All control variables are measured at the pre-treatment interview, i.e. before unemployment.

Finally, to capture unobservable but time-invariant factors which affect the outcomes and might, at the same time, be correlated with unemployment (e.g., personality traits) we also include lagged levels of social participation, i.e. pretreatment outcomes of private and public social participation.

Altogether, the final estimation samples contain between 230 and 450 personyear observations which suffered from unemployment due to plant closure. Table 2 provides an overview of the variables used in our analysis and reports descriptive statistics of the controls by treatment status both before and after reweighting. The corresponding estimation samples are restricted to the available number of waves and observations for each dependent variable and model.

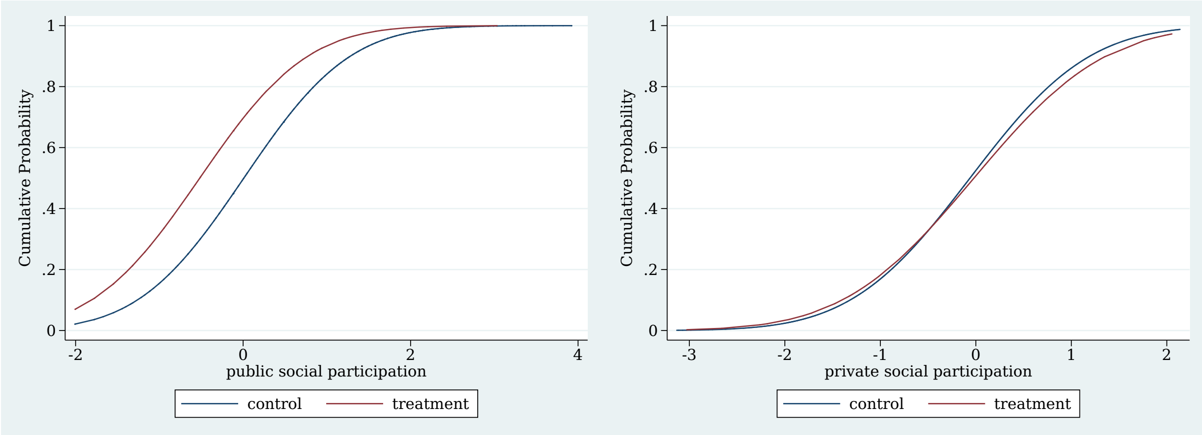
Table 2: Descriptive statistics by treatment status before and after weighting

	Treated		Control			
			Unbalanced		Balanced	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Female	0.346	(0.477)	0.323	(0.468)	0.346	(0.476)
Living with partner	0.680	(0.468)	0.662	(0.473)	0.678	(0.467)
Non-German (nationality)	0.195	(0.397)	0.115	(0.319)	0.195	(0.396)
Migration background	0.281	(0.451)	0.176	(0.381)	0.281	(0.449)
Years of education	11.383	(2.196)	12.461	(2.794)	11.351	(2.192)
Log real net equivalence income	7.212	(0.383)	7.420	(0.428)	7.192	(0.382)
Gross labour income	1869.680	(904.458)	2827.342	(1991.010)	1864.474	(903.639)
Work disability	0.065	(0.247)	0.057	(0.231)	0.065	(0.246)
Working experience	21.532	(11.393)	18.955	(10.752)	21.471	(11.376)
Has been unemployed before	0.394	(0.490)	0.298	(0.457)	0.393	(0.488)
Person needing care in hh	0.022	(0.146)	0.017	(0.129)	0.022	(0.145)
Shock: child born	0.009	(0.093)	0.016	(0.124)	0.009	(0.093)
Shock: separated, divorced or death	0.017	(0.131)	0.016	(0.124)	0.017	(0.130)
Public social participation	-0.479	(0.935)	0.002	(0.995)	-0.478	(0.934)
Private social participation	-0.193	(1.007)	-0.038	(0.975)	-0.192	(1.006)
Age groups						
Age $\leq$ 30	0.126	(0.332)	0.164	(0.371)	0.127	(0.333)
Age 31–40	0.208	(0.407)	0.265	(0.441)	0.207	(0.405)
Age 41–50	0.329	(0.471)	0.317	(0.465)	0.328	(0.470)
Age 50+	0.338	(0.474)	0.254	(0.435)	0.337	(0.473)
Number of children						
No child	0.636	(0.482)	0.582	(0.493)	0.637	(0.481)
1 child	0.182	(0.387)	0.203	(0.403)	0.182	(0.385)
2 children	0.126	(0.332)	0.161	(0.368)	0.125	(0.331)
2+ children	0.056	(0.231)	0.053	(0.224)	0.056	(0.230)
Firm size						
Less than 20	0.277	(0.449)	0.212	(0.408)	0.278	(0.448)
Between 20 and 200	0.377	(0.486)	0.267	(0.442)	0.376	(0.484)
Between 200 and 2000	0.212	(0.410)	0.232	(0.422)	0.212	(0.409)
More than 2000	0.130	(0.337)	0.256	(0.437)	0.130	(0.336)
Self-employed (no employees)	0.004	(0.066)	0.034	(0.181)	0.004	(0.066)
Sector according to NACE Rev1.1						
Sector A-B	0.026	(0.159)	0.020	(0.139)	0.028	(0.164)
Sector C	0.017	(0.131)	0.006	(0.076)	0.017	(0.130)
Sector D	0.411	(0.493)	0.306	(0.461)	0.410	(0.492)
Sector E	0.017	(0.131)	0.014	(0.116)	0.017	(0.130)
Sector F	0.160	(0.368)	0.081	(0.273)	0.160	(0.367)
Sector G	0.152	(0.359)	0.099	(0.298)	0.151	(0.358)
Sector H	0.035	(0.183)	0.017	(0.130)	0.035	(0.183)
Sector I	0.048	(0.213)	0.062	(0.242)	0.048	(0.213)
Sector J	0.022	(0.146)	0.045	(0.207)	0.022	(0.145)

Sector K	0.052	(0.222)	0.070	(0.255)	0.052	(0.222)
Sector L	0.004	(0.066)	0.099	(0.299)	0.004	(0.066)
Sector M	0.004	(0.066)	0.060	(0.238)	0.004	(0.066)
Sector N	0.022	(0.146)	0.087	(0.282)	0.022	(0.145)
Sector O	0.022	(0.146)	0.034	(0.180)	0.022	(0.145)
Sector P-Q	0.009	(0.093)	0.001	(0.034)	0.009	(0.093)
Occupational position						
Training, internship, etc.	0.004	(0.066)	0.002	(0.040)	0.004	(0.066)
Unskilled/Semi-skilled worker	0.563	(0.497)	0.293	(0.455)	0.561	(0.496)
Skilled worker	0.043	(0.204)	0.037	(0.188)	0.040	(0.195)
Master craftsman	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Self-employed	0.017	(0.131)	0.100	(0.300)	0.017	(0.130)
Clerk low skilled	0.100	(0.300)	0.087	(0.282)	0.099	(0.299)
Clerk middle skilled	0.165	(0.372)	0.218	(0.413)	0.164	(0.371)
Clerk high skilled	0.108	(0.311)	0.177	(0.382)	0.108	(0.311)
Civil servant	0.000	(0.000)	0.086	(0.281)	0.005	(0.074)
State						
Baden-Wuerttemberg	0.113	(0.317)	0.131	(0.337)	0.113	(0.317)
Bavaria	0.074	(0.262)	0.143	(0.350)	0.074	(0.261)
Berlin	0.026	(0.159)	0.030	(0.170)	0.026	(0.159)
Brandenburg	0.074	(0.262)	0.045	(0.207)	0.074	(0.261)
Bremen	0.013	(0.113)	0.006	(0.074)	0.013	(0.113)
Hamburg	0.009	(0.093)	0.013	(0.114)	0.009	(0.093)
Hesse	0.082	(0.275)	0.069	(0.254)	0.082	(0.275)
Mecklenburg-Western Pomerania	0.061	(0.239)	0.029	(0.167)	0.061	(0.239)
Lower Saxony	0.069	(0.254)	0.082	(0.275)	0.069	(0.254)
North Rhine-Westphalia	0.160	(0.368)	0.198	(0.399)	0.160	(0.367)
Saxony	0.095	(0.294)	0.077	(0.266)	0.095	(0.293)
Saxony-Anhalt	0.095	(0.294)	0.049	(0.217)	0.095	(0.293)
Schleswig-Holstein	0.017	(0.131)	0.024	(0.152)	0.017	(0.130)
Thueringia	0.065	(0.247)	0.050	(0.218)	0.065	(0.246)
Year of interview						
1992	0.238	(0.427)	0.101	(0.302)	0.239	(0.426)
1994	0.195	(0.397)	0.095	(0.293)	0.195	(0.396)
1996	0.082	(0.275)	0.098	(0.298)	0.082	(0.275)
1997	0.091	(0.288)	0.088	(0.283)	0.091	(0.287)
1999	0.043	(0.204)	0.089	(0.285)	0.043	(0.203)
2005	0.082	(0.275)	0.132	(0.339)	0.082	(0.275)
2007	0.078	(0.269)	0.130	(0.336)	0.078	(0.268)
2009	0.100	(0.300)	0.116	(0.320)	0.099	(0.299)
2015	0.091	(0.288)	0.151	(0.358)	0.091	(0.287)
Observations	231		38674		38674	

Notes: Data from SOEP v34 1990–2017). The first four columns present means and standard deviations before treatment for treated and controls. The last two columns show means and standard deviations for the reweighted control group according to entropy balancing.

Figure 2: Cumulative density functions by treatment status



Notes: Data from SOEP v34 (1990–2017). The figure shows the cumulative distribution functions (normal approximation) of our two outcome measures, i.e. public (left) and private (right) social participation, for treated individuals and all control individuals.

Figure 2 illustrates the cumulative distribution functions of our two outcome measures for both unemployed individuals due to a plant closure as well as individuals without a job loss. Clearly, the functions differ by treatment status. While the unemployed participate less in public social activities than the employed throughout the whole distribution, the effect seems to be smaller and ambiguous with respect to private social activities. More precisely, the unemployed participate less than the employed at the lower part of the distribution whereas the opposite holds for the upper part of the distribution. However, these descriptive patterns do not account for selection into unemployment based on confounding factors, such as age, education or work experience. The estimation of unconditional quantile treatment effects accounting for this issue is the aim of the next section.

5 Empirical results

5.1 Baseline

Table 3 provides the results for the estimated effects of unemployment on our two outcome measures of social participation. Specifically, columns (1) and (2) report the effects for public social participation activities whereas columns (3) and (4) report the corresponding results for private activities. For reasons of comparability, the first row shows the results for the average treatment effects on the treated (ATT) for unemployment due to plant closure. The ATT is estimated using standard inverse probability weighting. In columns (1) and (3), we report the ATT when covariates are not controlled for. In the remaining specifications (columns (2) and (4)), we explicitly control for differences in pretreatment individual and household as well as firm characteristics and pretreatment outcomes of public and private participation (see section 4).

Consider first the results on public social participation. When we do not control for any confounders (1), the average difference in public social participation by unemployment due to plant closure equals −0.54. This suggests that, on average, those who experience unemployment participate less. However, once differences in pretreatment individual, household, and firm characteristics as well as pretreatment outcomes are controlled for (2), the effect becomes smaller and is −0.11 (roughly corresponding to one tenth of a standard deviation which is around 1), but still remains significant. This finding suggests that, on average, there is a substantial and adverse effect of unemployment due to plant closure on public social participation activities. This is in line with Kunze and Suppa (2017) who study the average effect of unemployment on the same measure of public social participation.

If we look at the QTT results, however, we also find evidence for negative effects of unemployment due to plant closure on the distribution of public social participation. Moreover, a comparison of columns I and II reveals that the estimated QTTs turn out to be considerably smaller when individual, household and firm characteristics are controlled for, indicating that there is some selection into unemployment due to plant closure. The focus will thus be on the specification with all controls (column (2)) in the following. As can be inferred from column (2), the negative effects seem to apply only to the middle and the lower part of the distribution. Specifically, the estimated coefficients for the first six quantiles are considerably larger than the average treatment effect on the treated and statistically significant in most cases. The size of these effects roughly corresponds to two tenth of a standard deviation. By contrast, coefficients in the upper part of the distribution are small and not significant.

We now look at the results for private social participation. The specification without controls in column (3) mirrors the descriptive pattern shown in figure 2. While the average effect turns out to be small and insignificant (0.005), there are larger and negative effects in the lower part of the distribution (statistically significant for the second decile) and positive effects in the upper part of the distribution (statistically significant for the seventh decile). However, this pattern changes when selection into unemployment due to plant closure is taken into account (column (4)). In this case the average treatment effect on the treated turns out to be much larger and becomes statistically significant (0.109), consistent with existing evidence. Distributional effects, however, are either zero or very small in the lower part of the distribution (the first three deciles) and much larger in the middle and upper part of the distribution. A statistically significant effect is found for the particularly pronounced effect at the median, which roughly equals three tens of a standard deviation.

Altogether, our results show that the impact of unemployment is different at different parts of the distribution of public and private social participation. The adverse effects of unemployment due to plant closure for public social participation are concentrated at the bottom part and in the middle of the distribution, thereby stretching the whole distribution of public participation to considerably lower values, whereas the estimated effects for private participation suggest that unemployment impacts, if at all, primarily in the middle of

Table 3: Main Results

	Public		Private	
	(1)	(2)	(3)	(4)
ATT	-0.540***	-0.110**	0.005	0.109*
	(0.046)	(0.049)	(0.050)	(0.064)
Q_1	-0.329***	-0.222***	0.000	0.000
	(0.071)	(0.030)	(0.010)	(0.025)
Q_2	-0.605***	-0.148**	-0.043**	0.000
	(0.002)	(0.066)	(0.019)	(0.131)
Q_3	-0.809***	-0.228*	-0.010	0.019
	(0.073)	(0.120)	(0.047)	(0.052)
Q_4	-0.664***	-0.282**	0.000	0.141
	(0.073)	(0.143)	(0.065)	(0.088)
Q_5	-0.457***	-0.148	-0.172	0.344*
	(0.097)	(0.136)	(0.165)	(0.189)
Q_6	-0.392***	-0.222**	0.019	0.019
	(0.077)	(0.090)	(0.026)	(0.047)
Q_7	-0.479***	-0.003	0.105**	0.141
	(0.035)	(0.022)	(0.053)	(0.098)
Q_8	-0.551***	-0.091	0.029	0.208
	(0.105)	(0.179)	(0.092)	(0.152)
Q_9	-0.661***	-0.119	0.141	0.134
	(0.075)	(0.108)	(0.190)	(0.268)
N	64331	38907	64331	38907

Notes: Data from SOEP v34 (1990–2017). Indicated levels of significance are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors based on bootstrapped standard errors (500 replications, clustered at individual level) in parentheses. The ATT is estimated using standard inverse probability weighting. Quantile treatment effects are estimated using the approach suggested by Firpo (2007), in which weights are determined by entropy balancing. Columns (1) and (3) give the effect without any controls for public and private social participation activities, respectively. In columns (2) and (4) we control for all variables listed in table 2. Controls variables are measured at $t-2$.

the distribution.

Assuming rank preservation, our results suggest that those individuals who did not participate much in public activities already before they became unemployed are the ones most adversely affected by unemployment, whereas there is no effect for those with an active social life in public. Moreover, as there is no evidence in favor of a positive effect of unemployment on private social participation for individuals at the lower part of the distribution, individuals who did not participate much before unemployment (the most adversely affected ones) also do not intensify private relationships and may thus lack comfort and distraction.

These findings illustrate that the effect of unemployment on social participation is quite substantial, in particular for those individuals at the lower parts of the outcome distributions, which, in turn, points to potentially large and heterogonously distributed costs of unemployment in the first year after entry into unemployment.

5.2 Sensitivity checks

We consider several sensitivity checks in order to demonstrate that our findings are robust to assumptions and choices made.

Estimator. In a first step we check the robustness with respect to the estimator. More precisely, we replace entropy balancing with propensity score methods (inverse probability weighting) and use the estimator suggested by Firpo (2007). Formally, this method differs from entropy balancing as it assigns different weights to each observation. Specifically, the weights for observations in the control group are given by $1/(1-PS(X))$ in inverse probability weighting, where $PS(X)$ is the propensity score. Table 4 shows the results for both public and private social participation (columns (1) and (3)). Clearly, both the qualitative and quantitative effects are very similar to the results in the main specifications so that our main results are generally confirmed.[23]

Sample. In a second step, we check the robustness of our findings with respect to the selection of our sample. Specifically, we additionally include individuals that are part-time employed before they are (potentially) affected by unemployment. As can be inferred from Table 4 (columns (2) and (4)), our main results do not change much. The effects for public social participation turn out to be more pronounced at the lower half of the outcome distribution, whereas the effect of private social participation becomes smaller and insignificant. This latter effect may be attributed to differing time constraints faced by full-time and part-time employed.

[23]Note that the propensity score is estimated by local logit regression with smoothing parameters (window width λ and bandwidth h) equal to one and infinity (global smoothing), respectively (as in Binder and Coad (2015b)). However, we also used the cross-validation procedure (based on a random sample of 10% of our data to reduce computational time) in order to select these parameters. As in Schiele and Schmitz (2016), results (not shown) based on these selected parameters turn out to be very similar.

We also checked for gender- and regional-specific effects by estimating separate models for males and females as well as for individuals from East and West Germany. However, these estimation results (not shown) turned out to be mixed. This may be due to the small number of observations, small gender- and regional-specific effects (if existent at all), or the fact that gender roles and gender-specific behaviour are constantly changing. Tentative results suggest that the qualitative findings regarding public social participation are more pronounced for men than for women, whereas the opposite is true for private social participation. Moreover, effects on public social participation are much larger on average and along the whole distribution for East Germany than for individuals from West Germany, for which a significantly negative effect is only found at the lowest part of the distribution. Regarding private social participation, effects tend to be stronger for individuals from West Germany with a particular strong and significant effect at the top of the distribution.

6 Further results

All plant closures. So far the focus of our analysis was on the distributional effects of unemployment on social participation. However, the literature on the consequences of unemployment is closely connected to the literature on job loss. Hence, to compare our findings with this line of research, we also provide the estimation results for the case in which the treatment group includes not only those individuals who experience unemployment due to plant closure but also those with a job loss (but no unemployment spell) due to plant closure. Columns (1) and (4) of table 5 show that both average and distributional effects are smaller as compared to the main results and become insignificant in many cases. Furthermore, regarding public social participation, the strongest and significant effects are found around the middle of the distribution (quantiles 0.3 to 0.7; as compared to quantiles 0.1 to 0.6 for the main results). Consequently, as behavioral responses turn out to be different, the actual experience of unemployment (as compared to the experience of a job loss) seems to be a crucial determinant of both the average and distributional effects on social participation. Possible explanations for these differences are financial concerns, differing time constraints or identity utility.

All reasons for unemployment. Finally, to further analyze the plausibility of our assumptions, we also consider the effect of unemployment due to all reasons for entering unemployment, including, e.g., 'retirement', 'being fired' or 'mutual agreement'.[24] However, as many of these reasons are either voluntary or endogenous, the unconfoundedness assumption is likely to be violated. Hence, we expect a substantial change of our results. Indeed, columns (2) and (5) of table 5 show that, the effects tend to be smaller across the whole distribution for both public and private social participation. Furthermore, for private ac-

[24]Different reasons for entering unemployment have been studied, e.g., by Winkelmann and Winkelmann (1998) or Kassenböhmer and Haisken-DeNew (2009).

Table 4: Robustness results

	Public		Private	
	(1) IPW	(2) Part-time	(3) IPW	(4) Part-time
ATT	-0.110**	-0.110**	0.109*	0.109*
	(0.049)	(0.049)	(0.064)	(0.064)
Q_1	-0.222***	-0.222***	0.000	0.000
	(0.036)	(0.072)	(0.022)	(0.024)
Q_2	-0.151*	-0.214***	0.000	0.000
	(0.088)	(0.043)	(0.127)	(0.127)
Q_3	-0.228**	-0.226**	0.019	0.035
	(0.109)	(0.109)	(0.081)	(0.058)
Q_4	-0.282**	-0.271**	0.141	0.092
	(0.132)	(0.128)	(0.089)	(0.066)
Q_5	-0.148	-0.159	0.344*	0.035
	(0.128)	(0.113)	(0.185)	(0.180)
Q_6	-0.222**	-0.103	0.019	0.023
	(0.094)	(0.093)	(0.054)	(0.052)
Q_7	-0.003	-0.004	0.141	0.035
	(0.040)	(0.037)	(0.094)	(0.064)
Q_8	-0.091	-0.226	0.208	0.154
	(0.174)	(0.141)	(0.159)	(0.201)
Q_9	-0.119	-0.063	0.141	0.134
	(0.099)	(0.092)	(0.263)	(0.249)
N	38907	47876	38907	47876

Notes: Data from SOEP v34 (1990–2017). Indicated levels of significance are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors based on bootstrapped standard errors (500 replications, clustered at individual level) in parentheses. The ATT is estimated using standard inverse probability weighting. Quantile treatment effects are estimated using the approach suggested by Firpo (2007); models (1) and (3) use inverse probability weighting, whereas models (2) and (4) use entropy balancing and, compared to our main results, additionally include individuals working part-time prior to an unemployment spell. All models include the control variables listed in table 2. Control variables are measured at $t-2$.

tivities, the effect of unemployment turns out to be even negative for some parts of the lower half of the outcome distribution (quantiles 0.3 to 0.5). A significant and positive effect is only found for the 0.7 quantile. For public activities, the effects turn out to be less significant. However, similar to our main results, the strongest effect is still located at the bottom of the outcome distribution (quantile 0.2). The behavioral differences between the (voluntarily) unemployed due to all reasons and those who are unemployed due to a plant closure may be explained by better job prospects and a weaker social norm (in particular for public activities) for the voluntarily unemployed. Moreover, these individuals may not need any support from friends or family, e.g., if they have sufficient resources for consumption smoothing. Consequently, the focus on exogenous unemployment entries is crucial for our identification strategy as well as for similar study designs.

Quantile treatment effects. So far the focus of our analysis has been on estimating QTTs. Now, we also present the results for the unconditional quantile treatment effects (QTE), being defined as the difference between the τ quantile of the potential outcome distribution in the (hypothetical) situation where all individuals experience unemployment due to plant closure and the respective quantile of the potential outcome distribution in the (hypothetical) situation where all individuals are continuously employed. Columns (3) and (6) of table 5 present the results when using the estimator suggested by Firpo (2007). Comparing these estimates with our main results reveals that the coefficients tend to be larger throughout the whole distribution for public social activities. Yet, the strongest and statistically significant effects can be found (as for the QTTs) at the lower half of the distribution (quantiles 0.2 and 0.3).[25] For private social activities, however, estimates are larger in the middle and at the bottom of the distribution, but much smaller at the top (and even negative for the 0.8 quantile). Also, the effect at the middle of the distribution is no longer statistically significant. Altogether, even though the effects are of less statistical significance and estimation of QTEs tends to require stronger assumptions, the conclusions of our main results seem to hold equally for these findings.[26]

7 Concluding Remarks

This paper is the first to provide causal evidence on heterogenous effects of unemployment on social participation with respect to the distributions of both public and private social participation. We use quantile regression methods which enables us to identify potential effects of unemployment on social participation that only apply to certain parts of the out-

[25]Note, however, that there is an additional strong and negative effect for the 0.8 quantile.

[26]Note that we have also experimented with the recently proposed estimator by Powell (2019). For public social participation the qualitative effects for the QTEs turn out to be very similar, i.e., the strongest negative effects for the lower part of the distribution (quantiles 0.2 and 0.3; positive but not significant estimates at the top). For private activities, however, we find significant positive and strong effects throughout the distribution.

Table 5: Further results

	Public			Private		
	All plant closures	All reasons	QTE	All plant closures	All reasons	QTE
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-0.084***	-0.078***	-0.110**	0.015	0.021	0.109*
	(0.032)	(0.019)	(0.049)	(0.037)	(0.025)	(0.064)
Q_1	-0.003	0.000	-0.097	0.000	0.000	0.000
	(0.030)	(0.084)	(0.120)	(0.004)	(0.006)	(0.180)
Q_2	-0.145	-0.222***	-0.228**	-0.024	0.000	0.442
	(0.105)	(0.072)	(0.106)	(0.030)	(0.016)	(0.286)
Q_3	-0.107*	-0.060	-0.661**	-0.010	-0.010	0.184
	(0.059)	(0.090)	(0.282)	(0.044)	(0.014)	(0.180)
Q_4	-0.184*	-0.104	-0.558*	0.000	-0.007	0.353
	(0.108)	(0.080)	(0.316)	(0.061)	(0.042)	(0.239)
Q_5	-0.169***	-0.003	-0.228	0.096	-0.033	0.165
	(0.063)	(0.037)	(0.197)	(0.163)	(0.126)	(0.201)
Q_6	-0.003	0.000	-0.110	0.000	0.000	0.203
	(0.013)	(0.042)	(0.108)	(0.025)	(0.009)	(0.142)
Q_7	-0.125*	-0.101**	-0.433**	0.012	0.062*	0.148
	(0.070)	(0.042)	(0.182)	(0.057)	(0.038)	(0.157)
Q_8	-0.003	-0.062	-0.228	0.033	0.010	-0.184
	(0.104)	(0.064)	(0.259)	(0.107)	(0.015)	(0.205)
Q_9	-0.039	-0.088	-0.320	0.029	0.105	0.036
	(0.096)	(0.060)	(0.388)	(0.029)	(0.113)	(0.283)
N	38690	39818	38907	38690	39818	38907

Notes: Data from SOEP v34 (1990–2017). Indicated levels of significance are * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard errors based on bootstrapped standard errors (500 replications, clustered at individual level) in parentheses. The ATT is estimated using standard inverse probability weighting. Quantile treatment effects are estimated using the approach suggested by Firpo (2007), in which weights are determined by entropy balancing. Columns (1) and (4) present the results when all individuals that experienced a plant closure (but necessarily an unemployment spell) are included in the treatment group. Columns (2) and (5) show the results when the treatment group includes individuals with all reasons for unemployment (not just due to a plant closure). Columns (3) and (6) display quantile treatment effects (QTEs) using the estimator suggested by Firpo (2007). All models include the control variables listed in table 2. Control variables are measured at $t-2$.

come distributions. To estimate causal effects, we focus on plant closures as exogenous reason for unemployment.

We show that unemployment stretches the distribution of public social participation to lower values. The estimated coefficients of unemployment on the lower six deciles of the distribution of public social participation activities are large and negative, whereas the effects on the upper three deciles are much smaller and not statistically significant. Consequently, adverse effects of unemployment particularly apply to individuals who participated less already before they became unemployed. Furthermore, unemployment does not lower public social participation for individuals who already participated much. By contrast, we find that the effect of unemployment on private social participation is essentially zero for individuals at the lower part of the outcome distribution (the three lowest quantiles), while the estimated coefficients are positive for the remaining quantiles and particularly large at the center of the distribution (a strong and statistically significant effect at the median).

Our results emphasize the importance of using quantile regression methods to analyze the effect of unemployment on social participation, in particular as estimates of the average treatment effect on the treated are much smaller in our setup than the distributional effects that apply only to certain parts of the population. Altogether, our findings suggest that individuals with low participation (before unemployment) are those who are most adversely affect by unemployment because they strongly reduce their levels of participation in public activities but at the same time do not increase private participation which, in turn, may provide comfort and distraction.

The important policy recommendation resulting from our analysis is that policy makers should especially focus on active labour market policies for those individuals with low levels of social participation and weak social networks (target-group specific efforts) in order to support these individuals in establishing and maintaining their social network as well as to provide them with crucial information, which, in turn, positively affects their job search behavior and opportunities. Moreover, our results suggest that measures for the unemployed, which further weaken social support and social participation, such as (high) mobility requirements, should be viewed with caution.

Our paper can be considered as a first step to analyze distributional effects of various determinants of social participation. Future research should, e.g., provide a better understanding of heterogenous effects of unemployment on political participation or spillover effects on other family members (see Alesina and Giuliano (2011) and Kunze and Suppa (2020),[27] respectively, for an analysis of average effects). Furthermore, a better understanding of commonly adopted coping strategies with unemployment, especially for those individuals that are most adversely affected, and their effects on individuals well-being and labour market outcomes would be valuable.

[27] See also Marcus (2013) and Nikolova and Ayhan (2019) for a similar analysis on the (average) effect of unemployment on health and subjective well-being of spouses.

References

Alesina, A. and Giuliano, P., 2011. Family ties and political participation, *Journal of the European Economic Association*, 9 (5), 817–839.

Alesina, A. and La Ferrara, E., 2000. Participation in heterogeneous communities, *The Quarterly Journal of Economics*, 115 (3), 847–904.

Atkinson, T., Liem, R., and Liem, J.H., 1986. The social costs of unemployment: Implications for social support, *Journal of Health and Social Behavior*, 27 (4), 317.

Autor, D.H., Houseman, S.N., and Kerr, S.P., 2017. The effect of Work First job placements on the distribution of earnings: An instrumental variable quantile regression approach, *Journal of Labor Economics*, 35 (1), 149–190.

Bauernschuster, S., Falck, O., and Woessmann, L., 2014. Surfing alone? The internet and social capital: Evidence from an unforeseeable technological mistake, *Journal of Public Economics*, 117 (C), 73–89.

Binder, M. and Coad, A., 2011. From average Joe's happiness to miserable Jane and cheerful John: using quantile regressions to analyze the full subjective well-being distribution, *Journal of Economic Behavior & Organization*, 79 (3), 275–290.

Binder, M. and Coad, A., 2015a. Heterogeneity in the relationship between unemployment and subjective wellbeing: A quantile approach, *Economica*, 82 (328), 865–891.

Binder, M. and Coad, A., 2015b. Unemployment impacts differently on the extremes of the distribution of a comprehensive well-being measure, *Applied Economics Letters*, 22 (8), 619–627.

Clark, A.E., 2003. Unemployment as a social norm: Psychological evidence from panel data, *Journal of Labor Economics*, 21 (2), 323–351.

Clark, A.E. and Lepinteur, A., 2019. The causes and consequences of early-adult unemployment: Evidence from cohort data, *Journal of Economic Behavior & Organization*, 166, 107–124.

Dieckhoff, M. and Gash, V., 2015. Unemployed and alone? Unemployment and social participation in Europe, *International Journal of Sociology and Social Policy*, 35 (1/2), 67–90.

Dong, Y. and Shen, S., 2018. Testing for rank invariance or similarity in program evaluation, *The Review of Economics and Statistics*, 100 (1), 78–85.

Durlauf, S.N. and Fafchamps, M., 2005. Social Capital, *in:* P. Aghion and S. Durlauf, eds., *Handbook of Economic Growth*, Elsevier, *Handbook of Economic Growth*, vol. 1, chap. 26, 1639–1699.

Firpo, S., 2007. Efficient semiparametric estimation of quantile treatment effects, *Econometrica*, 75 (1), 259–276.

Frandsen, B.R. and Lefgren, L.J., 2018. Testing rank similarity, *The Review of Economics and Statistics*, 100 (1), 86–91.

Frölich, M. and Melly, B., 2010. Estimation of quantile treatment effects with stata, *Stata Journal*, 10 (3), 423–457(35).

Frölich, M. and Melly, B., 2013. Unconditional quantile treatment effects under endogeneity, *Journal of Business & Economic Statistics*, 31 (3), 346–357.

Gielen, A.C. and van Ours, J.C., 2014. Unhappiness and job finding, *Economica*, 81 (323), 544–565.

Glaeser, E.L., Laibson, D., and Sacerdote, B., 2002. An economic approach to social capital, *Economic Journal*, 112 (483), 437–458.

Goebel, J., Grabka, M.M., Liebig, S., Kroh, M., Richter, D., Schröder, C., and Schupp, J., 2019. The german socio-economic panel (SOEP), *Jahrbücher für Nationalökonomie und Statistik*, 239 (2), 345–360.

Gore, S., 1978. The effect of social support in moderating the health consequences of unemployment, *Journal of Health and Social Behavior*, 19 (2), 157.

Gottlieb, B.H. and Bergen, A.E., 2010. Social support concepts and measures, *Journal of Psychosomatic Research*, 69 (5), 511–520.

Hainmueller, J., 2012. Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies, *Political Analysis*, 20, 25–46.

Hetschko, C., Knabe, A., and Schöb, R., 2014. Changing identity: Retiring from unemployment, *Economic Journal*, 124 (575), 149–166.

Irwin, J., LaGory, M., Ritchey, F., and Fitzpatrick, K., 2008. Social assets and mental distress among the homeless: Exploring the roles of social support and other forms of social capital on depression, *Social Science & Medicine*, 67 (12), 1935–1943.

Jahoda, M., 1982. *Employment and Unemployment: A Social-Psychological Analysis*, The Psychology of Social Issues, Cambridge University Press.

Kassenböhmer, S.C. and Haisken-DeNew, J.P., 2009. You're fired! The causal negative effect of entry unemployment on life satisfaction, *Economic Journal*, 119, 448–462.

Komarovsky, M.a., 1940 [2004]. *The Unemployed Man and His Family: The Effect of Unemployment upon the Status of the Man in fifty-nine Families*, Classics in gender studies, AltaMira Press.

Korkeamäki, O. and Kyyrä, T., 2014. A distributional analysis of earnings losses of displaced workers in an economic depression and recovery, *Oxford Bulletin of Economics and Statistics*, 76 (4), 565–588.

Kunze, L. and Suppa, N., 2017. Bowling alone or bowling at all? the effect of unemployment on social participation, *Journal of Economic Behavior & Organization*, 133, 213–235.

Kunze, L. and Suppa, N., 2020. The effect of unemployment on social participation of spouses: evidence from plant closures in Germany, *Empirical Economics*, 58, 815–833.

Lin, N., Woelfel, M.W., and Light, S.C., 1985. The buffering effect of social support subsequent to an important life event, *Journal of Health and Social Behavior*, 26 (3), 247.

Marcus, J., 2013. The effect of unemployment on the mental health of spouses - Evidence from plant closures in Germany, *Journal of Health Economics*, 32 (3), 546–558.

Milner, A., Krnjacki, L., Butterworth, P., and LaMontagne, A.D., 2016. The role of social support in protecting mental health when employed and unemployed: A longitudinal fixed-effects analysis using 12 annual waves of the hilda cohort, *Social Science & Medicine*, 153, 20–26.

Neira, I., Lacalle-Calderon, M., Portela, M., and Perez-Trujillo, M., 2019. Social capital dimensions and subjective well-being: A quantile approach, *Journal of Happiness Studies*, 20 (8), 2551–2579.

Nikolova, M. and Ayhan, S.H., 2019. Your spouse is fired! How much do you care?, *Journal of Population Economics*, 32, 799–844.

Pohlan, L., 2019. Unemployment and social exclusion, *Journal of Economic Behavior & Organization*, 164, 273 – 299.

Powell, D., 2019. Quantile treatment effects in the presence of covariates, *The Review of Economics and Statistics*, forthcoming.

Putnam, R., 2001. *Bowling Alone*, Simon & Schuster.

Satyanath, S., Voigtländer, N., and Voth, H.J., 2017. Bowling for fascism: Social capital and the rise of the nazi party, *Journal of Political Economy*, 125 (2), 478–526.

Schiele, V. and Schmitz, H., 2016. Quantile treatment effects of job loss on health, *Journal of Health Economics*, 49, 59 – 69.

Schmitz, H., 2011. Why are the unemployed in worse health? The causal effect of unemployment on health, *Labour Economics*, 18 (1), 71–78.

Sen, A.K., 1992. *Inequality Reexamined*, Russell Sage Foundation book, New York: Russell Sage Foundation, 3rd ed.

Sen, A.K., 2000. *Social exclusion: Concept, application, and scrutiny*, *Social development papers*, vol. No. 1, Manila: ADB.

Sonnenberg, B., 2014. Dependencies and mechanisms of unemployment and social involvement: Findings from the Socio-Economic Panel Study, *Dissertation, FU Berlin*.

Stiglitz, J.E., Sen, A.K., and Fitoussi, J.P., 2009. Report by the commission on the measurement of economic performance and social progress, Tech. rep., Commission on the Measurement of Economic Performance and Social Progress.

Sullivan, D. and von Wachter, T., 2009. Job displacement and mortality: An analysis using administrative data, *The Quarterly Journal of Economics*, 124, 1265–1306.

Suppa, N., 2018. Walls of glass. Measuring deprivation in social participation, OPHI Working Paper Series 117, Oxford Poverty and Human Development Initiative, Oxford.

Tattarini, G., Grotti, R., and Scherer, S., 2018. The buffering role of the family in the relationship between job loss and self-perceived health: Longitudinal results from Europe, 2004–2011, *Health & Place*, 52, 55–61.

Winkelmann, L. and Winkelmann, R., 1998. Why are the unemployed so unhappy? Evidence from panel data, *Economica*, 65 (257), 1–15.

Winkelmann, R., 2009. Unemployment, social capital, and subjective well-being, *Journal of Happiness Studies*, 10 (4), 421–430.