Does unemployment lead to loneliness?

Alexander Bennett

Purti Sadhwani

Sjur Løne Nilsen

January 2023

Abstract

This study investigates the relationship between unemployment and loneliness by utilising Propensity Score Matching as a method to control for other factors, including past experiences of unemployment. The paper finds a small yet significant effect of unemployment on loneliness. The study also delves deeper into the relationship by examining differences across regions and gender, and by identifying specific aspects of loneliness. The results could offer valuable insights for policy makers responsible for labour market policies.

This paper is the end product of a project in the course Research Module: Applied Microeconomics at the University of Bonn. We would like to thank our supervisors Prof. Dr. Thomas Dohmen and Sonkurt K. Sen for their support and knowledge.

1 Introduction and motivation

This paper examines loneliness and its relationship with unemployment. More specifically, whether unemployment is a causal explanation for feelings of loneliness. The structure is as follows: this section gives an overview of the literature surrounding the consequences and causes of loneliness and motivates why the link with unemployment should be of interest. Section 2 describes the chosen dataset. Section 3.1 explains the issues of causal interpretation when identifying the impact of unemployment and 3.2 outlines the chosen empirical approach. Section 4 presents these results and finally section 5 provides discussion on scope to expand on the results and critiques of our approach.

Loneliness is defined to be the "discrepancy between a person's desired and actual social relationships" (Masi et al. 2011). It is a subjective feeling that reflects perceived social isolation and is an innately emotionally unpleasant experience which everyone is susceptible to. As a social species, humans fundamentally demand the presence of others, and specifically those who value them and can be trusted (Cacioppo & Patrick 2008). Loneliness, and its associated aversive state is a signal to change behaviour. By experiencing feelings of vulnerability, it forces the formation of social connections necessary to avoid damage and to reproduce (Hawkley & Cacioppo 2010, Cacioppo et al. 2006). Loneliness is therefore not always a bad thing when transient, but when prolonged it causes problems. Loneliness was previously labelled as a "public health epidemic" (Rimmer 2018) and is of increasing concern after the COVID-19 pandemic due to the social distancing regulations (Payne 2021). Policymakers are becoming more concerned about loneliness and in 2018 Britain appointed a Minister of Loneliness to campaign and raise awareness on its impacts.

There is robust literature available regarding the physical and mental health consequences of loneliness. Researchers have emphasized three pathways through which loneliness may affect health. Firstly, due to the lack of valuable interactions with others, the lonely may start unhealthy habits like smoking and decreased physical activity (Shankar et al. 2011). Secondly, loneliness is linked to lower self-esteem and can predict increases in depression (McAvay et al. 1996, Cacioppo et al. 2006) and suicidal behaviour (Rudatsikira et al. 2007). Finally, feeling lonely is associated with raised stress levels and blood pressure (Grant et al. 2009, Hawkley & Cacioppo 2010). All three channels indicate that loneliness may be an important risk factor for health issues and Holt-Lunstad et al. (2010) claim that loneliness has an impact on health comparable with smoking and greater than obesity. Later work finds that lonely adults are at increased risk of premature mortality

(Holt-Lunstad et al. 2015). Therefore, it is of importance to try and understand the causes of loneliness.

There have been several attempts to find out what characterises people that are lonely. Research has shown that loneliness is “approximately 50 % heritable and 50% environmental” (Boomsma et al. 2005). A common theme that has been found is that loneliness is experienced more by people in old age (Yang & Victor 2011), those with disabilities (Macdonald et al. 2018) and migrants (Ten Kate et al. 2020). It is also well documented that individual factors including the lack or loss of a partner can cause more loneliness (Stack 1998, Van Baarsen 2002). Differences in loneliness levels can further be linked to differences in characteristics of regions in Germany (Buecker et al. 2021). The increased spotlight on unemployment and loneliness throughout the COVID-19 pandemic led Payne (2021) to portray results indicating that areas with higher unemployment rates experienced higher rates of loneliness. Although this is a correlation, Morrish & Medina-Lara (2021) provide a systematic review of the relationship between loneliness and unemployment, claiming that unemployment develops aspects such as “enforced isolation or diminished sense of belonging”, leading to loneliness. Furthermore, losing out on social connections that one had at work and the lack of income make it difficult to participate socially. Also this is exacerbated by the stigma associated with unemployment, which may lead to embarrassment and less social interactions. They find a 40 % increase in the likelihood of reporting loneliness when unemployed.

Conversely, there is also scope for an effect of loneliness on unemployment through reduced productivity and motivation. This effect is reinforced by Von Soest et al. (2020) who conducted a longitudinal study and claimed that loneliness is a key predictor of higher midlife unemployment in Europe. There are parallels in Morrish et al. (2022), who reiterate this relationship and by using a propensity score matching technique, find that experiencing loneliness increases the probability of being unemployed in the future by 17.5 percentage points, with a stronger effect on prolonged loneliness. Furthermore, there is a well documented literature on the negative relationship between unemployment and mental health (Murphy & Athanasou 1999, Farré et al. 2018). The bidirectionality implies a self-reinforcing relationship between loneliness and unemployment, and with both being detrimental to health and well-being, there is a need for a better understanding of the mechanisms behind their interaction.

2 Data

We collected our sample from the German Socio-Economic Panel (SOEP) between 2013 and 2017. We sample on three conditions. First, to make sure that we are looking at labour market participants, we require individuals to be between 22 and 67 years old in 2017 and that they were employed in 2013. Second, we remove people who have stated that they are in bad health. At last, we removed every observation with missing data, obtaining a sample of 5529 individuals. 418 individuals experienced unemployment during the four-year period, and they make up our treatment group. 5111 individuals stayed in the same job during the same period and work as our control group. Our last condition could induce selection effects, as people who might have missing data, could have similar characteristics. [1]

SOEP contains several types of questions, which provide us with three different types of variables. Answers to questions about unemployment duration, household income, age and years of education are contained in numerical variables. Categorical variables indicate participants' gender, whether they live in east Germany or not, and employment status. At last, we have the variables collected from a Likert scale answer, producing ordinal numbers. The questionnaire asks of the degree they would rate their health. It also asks three questions related to the subject of loneliness: how often they feel left alone, socially isolated and that the company of others is missing. All scored in a 1 (Bad / Very often) to 5 (Good / Never) interval. We generate an aggregate loneliness variable, taking the average of all three answers. For the rest of this paper, we emphasise that low levels of the loneliness variable, represents more frequent feelings of loneliness.

As we consider the effect of unemployment on loneliness, we want to obtain a treatment variable representing the exposure of unemployment in the observed period. This is constructed by subtracting the answer of unemployment experience in 2013, from the answer in 2017, obtaining a measure in years. Using this, we assign 1 to every worker with durational unemployment in the period, and 0 to the workers that stayed in the same job. This divides our sample into a treatment group, those who experienced unemployment in 2013 to 2017, and a control group, those who did not.

Since loneliness is an emotion and difficult to measure, we must use ordinal data to measure it. There are two main challenges associated with using ordinal data in statistical methods. Firstly, interpreting the distance between scale points, e.g. "[1] Very often" and

[1] A t-test comparing the variables of our obtained sample with the group of 1 806 individuals who were dropped because of missing values, only age and education were the statistically different.

“[2] Often”, is challenging as it depends on how respondents understand and answer the question. Another drawback is what is known as response bias. Individuals may have different reference points. Trying to compare the responses of an extrovert and an introvert may be difficult because they have a different reference point for what "often" means and a different impression of what it feels like to be "left out." The generated aggregate loneliness variable helps us to make the answers more comparable across individuals. Although it is a good alternative for a measure of loneliness in the dataset, this does not mean that it is a perfect one. Standardising the variable will further help us with interpreting the size of the effect.

Although our variables provide relevant insights to our research question, simplifying complex concepts like experienced unemployment and unobservable self-assessed emotions like loneliness, together with a limited sample, may render our result inaccurate.

Table 1 shows how the different variables are balanced between the individuals expe-

Table 1: Descriptive Statisitcs, Treated and Control

	Balance table			
	Mean		t-test	Variance
	Treated	*Control*	*t*	*ratio*
age	41.0	42.7	(-3.61)	1.14
age^2	1777.3	1909.0	(-3.35)	1.1
$marital\_status$	0.58	0.64	(-2.24)	.
$years\_of\_edu$	12.0	13.1	(-7.47)	0.75
$health$	2.50	2.33	(3.73)	1.12
log_hhinc	7.81	8.07	(-10.8)	0.98
$unemp\_exp$	1.28	0.43	(11.7)	3.71
$east\_ger$	0.32	0.23	(3.77)	.
sex	0.69	0.71	(-0.57)	.
$empl\_sec = 2$	0.11	0.24	(-6.11)	.
$empl\_sec = 3$	0.21	0.23	(-1.24)	.
$empl\_sec = 4$	0.07	0.08	(-0.81)	.
$empl\_sec = 5$	0.08	0.06	(1.98)	.
$empl\_sec = 6$	0.02	0.01	(2.30)	.
$empl\_sec = 7$	0.17	0.15	(-0.09)	.
$empl\_sec = 8$	0.11	0.08	(2.27)	.
$empl\_sec = 9$	0.10	0.04	(5.52)	.
$aggregate\_loneliness$	3.89	4.13	(7.08)	1.59
Observations	5529			
Treated / Control	418 / 5 111			
MeanBias/MedBias	19.3/16.7			

riencing unemployment and individuals who stayed in their job. The t-test in combination with the variance ratio, indicates that the distribution of these variables across the two groups are different. Especially, we observe that those that stay in their job through the whole period have on average one more year of education and have experienced nearly 10 months less of unemployment in their lifetime, compared to those exposed to unemployment in the observed period. Also, individuals who experience unemployment in the period, have a lower average loneliness level than the control group, but both groups' answers are skewed to the left. The table raises several questions. Are lonely people more likely to become unemployed? Are unemployed people more likely to become lonely? Or are these effects only due to the covariates? In the next section we will address these questions further and present one method that could potentially isolate the effect of unemployment on loneliness.

3 Method

3.1 Challenges

The relationship between unemployment and loneliness raises two concerns. Firstly, our analysis is prone to reverse causality. We might observe the effect of unemployment on loneliness and the effect of loneliness on unemployment simultaneously as lonely individuals might have a higher probability of suffering from job loss, and vice versa. Our second concern is that individuals are selected into treatment (unemployment) by endogenous factors. Those who become unemployed may have compositional differences in observable characteristics such that the unemployed tend to be lonelier than their employed counterparts. This problem, also known as selection bias, is in conventional methods solved by using controls.

To avoid that such an analysis does get contaminated by reverse causality, a potential solution is to make sure that unemployment was realised exogenously. To achieve this, the literature exploits the closure of plant facilities as exogenous entry into unemployment (Marcus 2013). Arguing that this method would remove bias, individuals from closed plants are now comparable with workers in plants in the same sector that were not closed. Failing to obtain such a data set led us to consider other methods. Moreover, as we cannot randomise the assignment of treatment i.e. unemployment experience, we therefore need to ensure that we take the degree of exogenous unemployment into account.

Randomness and exogenous job loss motivates the use of a propensity score matching

(PSM) procedure. In the next section we will elaborate the use of PSM and discuss how it deals with the bidirectional relationship between loneliness and unemployment (reverse causality), and the nonrandom assignment of unemployment (selection effects).

3.2 Empirical analysis

Our approach in order to isolate the impact of unemployment on loneliness is to use PSM. PSM attempts to emulate randomisation of treatment, by conditioning on selected observable characteristics. Thus, the untreated individuals can be compared to the treated with respect to the control variables.

There are two important assumptions that need to be satisfied, in order for PSM to give a causal interpretation (Caliendo & Kopeinig 2008). The first being unconfoundedness, implying that the covariates should be independent of the treatment or the anticipation of the treatment. The second being the overlap condition, which makes sure that there is sufficient overlap between the covariates of the treatment and the control group. Together these conditions secure the strong ignorability treatment assignment, which states that after matching, the treatment variable is independent of the covariates.

In order to use PSM, our empirical process must satisfy the mentioned assumptions. First, the sample is limited to only include those who are employed in 2013. We then estimate the probability of experiencing unemployment between 2013 and 2017 using characteristics that are fixed in 2013. As these are measured before the assignment of the treatment, it requires us to assume that the probability stays constant over time, or changes in the same way for the entire population. We argue that this strong assumption holds as our selected covariates are likely to stay constant for the majority of our sample. We also allow for the unemployment risk to move the same way for the whole sample as government policies and economic cycles should influence everyone equally. The probability estimation utilises a probit model, indicating that the covariates follow a normal distribution. The probit is defined in equation (1).

$$E(unemployment_i|X_i) = Pr(unemployment_i = 1|X_i) = \phi(\beta_i X_i) \tag{1}$$

Furthermore, the covariates were chosen based on known risk factors to unemployment and loneliness. That is they are related to both the treatment and the outcome. In equation (1) the covariate vector X_i includes: age, age squared, health, education, gender, marital status, log of household income, previous unemployment experience, location dummy and employment sector[2]. We include the square of age to allow for some non-linearity in age effects. Furthermore, we include self reported health as those in better health may be less likely to experience unemployment (Hesselius, 2007), but also those with poor health are more likely to report feeling lonely (Russell et al., 1980). Additionally, the employment sector is important as some industries may be more prone to fluctuations in unemployment (US bureau of labour statistics, 2023). However, we are only able to include observable confounding factors, but it could be the case that there are unobservable factors affecting unemployment and loneliness, violating the unconfoundedness assumption, and leading to biased treatment effects. One potential component could be an individual's prior labour market participation. This is not directly observed and could affect unemployment and loneliness. We argue that previous unemployment experience can act as a proxy for this.

Based on the probit regression we estimate the propensity score (unemployment risk) for every observation in the sample, and resample with a matching process. The propensity score is simply the estimated probability that an individual is treated, based on the covariates. We match individuals in the treatment and control group who had similar propensity scores, where one remained employed throughout 2013 to 2017 and the other experienced unemployment at some point in the period. To make sure that those with close propensity scores were matched, we used the caliper matching technique. We define a maximum tolerance level of 0.001, which requires matching within a range of 0.001 around each individual's propensity score. This eliminates outliers having an incomparable propensity score. Furthermore, we use no replacement in order to ensure that each individual in the control group is only matched to one individual in the treatment. We are able to do this due to many individuals in the control group and few in the treated (Caliendo & Kopeinig 2008).

Our matching procedure creates a sample of individuals in the treatment and control who have similar unemployment risk. Thus, we are exploiting the randomness in the timing of unemployment as their risk is the same, but it is only realised for the treated individuals. As the treatment is now arguably exogenous, we compare the average loneliness levels in 2017 of those in the treatment to those in the control group, taking into consideration the standard deviation.

[2]These covariates were chosen on the basis of Morrish et al. (2022).

4 Results

Table 2 shows the probit model and the obtained matching quality. The covariates are significant except for age, marital status and gender, but they are considered to be important and have been motivated in section 3.2. Employment sector estimates show varying significance, but have to be regarded altogether. The mean of each employment sector is simply the proportion of the group in that sector, and similar proportions are achieved. The signs of a successful matching procedure is also indicated by the standardised mean and median bias, which is relatively low [3]. Furthermore, the covariates have a low t-test score and together with variance ratios close to 1, the two groups' covariates have similar distributions.

Table 2: Propensity Score Matching

	Probit estimates		**Balance after matching**			
	Unemp	s.e.	Mean *Treated*	Mean *Control*	t-test *t*	Variance *ratio*
age	-0.047**	(0.022)	41.1	40.0	(1.48)	0.91
age^2	0.000	(0.000)	1788	1710	(1.35)	0.96
marital_status	0.072	(0.062)	0.58	0.59	(-0.29)	.
years_of_edu	-0.032**	(0.013)	12.1	12.1	(0.27)	1.1
health	0.102***	(0.033)	2.46	2.43	(0.43)	1.07
log_hhinc	-0.412***	(0.067)	7.85	7.84	(0.01)	1.07
unemp_exp	0.090***	(0.014)	0.94	0.76	(1.5)	0.96
east_ger	0.103*	(0.060)	0.30	0.28	(0.39)	.
sex	-0.013	(0.063)	0.69	0.68	(0.31)	.
empl_sec = 2	-0.380***	(0.109)	0.11	0.10	(0.69)	.
empl_sec = 3	-0.278***	(0.098)	0.22	0.24	(-0.68)	.
empl_sec = 4	-0.374***	(0.126)	0.07	0.08	(-0.27)	.
empl_sec = 5	-0.204	(0.131)	0.08	0.08	(0.26)	.
empl_sec = 6	0.053	(0.214)	0.02	0.03	(-0.23)	.
empl_sec = 7	-0.289***	(0.107)	0.18	0.17	(-0.09)	.
empl_sec = 8	-0.231*	(0.121)	0.11	0.10	(-0.57)	.
empl_sec = 9	-0.046	(0.130)	0.09	0.09	(-0.25)	.
constant	3.271***	(0.687)				
Observations = 5504		psR2 = 0.007	MeanBias/MedBias = 3.7/2.2			

Standard errors in parentheses, estimated with psmatch2

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[3] Recommended to be below 5% (Caliendo & Kopeinig 2008)

Table 3: Average Treatment Effects, With groups

Sample	Observations T	Observations C	ATT	SE	P>|z|
All	393	5 111	-0.202 **	(0.080)	0.012
Men	264	3 614	-0.229 **	(0.096)	0.018
Women	117	1 497	-0.368***	(0.140)	0.009
East Ger	104	1 218	-0.165	(0.151)	0.275
West Ger	274	3 893	-0.232**	(0.095)	0.014

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Treated individulas might not sum to total beacuse of the caliper matching procedure excluding treated individuals with not a sufficient match

Table 3 presents the main findings. When the sample is not restricted, we observe the average treatment effect on the treated (ATT). This is the difference in standardised average loneliness levels between individuals that have experienced unemployment during the period (treatment) and those that stayed employed in the same period. This gives us the insight of how our treated individuals would have answered if they were not treated. ATT does not give us inference on the control group. We find the sign of the ATT is negative, indicating that the experience of unemployment leads to more frequent feelings of loneliness. Specifically, experiencing unemployment increases frequency of loneliness by 0.2 standard deviations at the 5% significance level. This effect is in line with the hypothesised direction.

Additionally, we provide more robustness checks through sampling by different groups. Table 3 also shows that women have a larger ATT than men. One argument for this would be that women are more likely to report feeling lonely than men and acknowledge loneliness more often than men (Borys & Perlman 1985). However, both show negative effects, and might be similar as they have overlapping confidence intervals. Furthermore, when splitting the sample into East and West Germany, both have negative ATT, but only West Germany has significant results. The lack of a finding for East Germany may be due to the small sample, but it is also possible that as East Germany has higher rates of unemployment (Bundesministerium 2018), there is less of a stigma surrounding it, implying individuals are less likely to feel as lonely. Overall, the significance across groups indicates that not only one group is driving the relationship in the sample, and that this effect is experienced throughout different groups.

Furthermore, by varying the outcome and treatment variables we conduct further robustness checks in order to yield insights about which types of emotions and unemployment experiences drive our results. Table 4 portrays the results when deconstructing aggregate loneliness back into the three differing questions. We find that only the feeling of being 'socially isolated' and feeling that 'company of others is missing' show significant changes close to the effect of the aggregate loneliness level. The insignificance of feeling 'left out' could be due to several reasons. It might be that "left out" is a more abstract concept than the others. Also the tone of the question could reflect negative social status, which could be harder for individuals to admit.

Table 4 also varies the treatment variables. The 'currently unemployment' treatment variable is defined as those having experienced unemployment throughout 2013 to 2017, and also being unemployed and actively searching work at the time of survey in 2017. As the individuals were unemployed when answering loneliness questions, we would predict that these individuals may feel more lonely. The results support this idea as being currently unemployed increases the frequency of feelings of loneliness by 0.79 standard deviations at the 1% significance level, which is a stronger difference than in the main specification. This could indicate that our results in our main model might be only due to those individuals. In order to check this speculation, we condition on those who are employed in 2017, but experienced unemployment in 2013 to 2017. The variable 'back in job' shows that these individuals have insignificant results, which suggests our speculation is true. Therefore, we can argue that experiencing unemployment does lead to feeling lonely more often; however,

Table 4: Average Treatment Effects, Varying treatment and outcome

Variations	Observations T	C	ATT	SE	P>|z|
Aggregate Loneliness	393	5 111	-0.202 **	(0.080)	0.012
Left out	393	5 111	-0.049	(0.079)	0.53
Socially Isolated	393	5 111	-0.243***	(0.082)	0.003
Company Missing	393	5 111	-0.215 ***	(0.076)	0.005
Currently unemployed	106	4 928	-0.790 ***	(0.150)	0.000
> 2 years unemp!	28!	5 111!	-0.892!**	(0.388!)	0.022!
Back in job	255	4928	-0.071	(0.095)	0.462
> 2 y. Back in job!	11!	4928!	-1.113!**	(0.505!)	0.027!

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

! - inexplicable results, sample size is too low, kept to show potential variations current unemployment has the most negative effect on loneliness. This suggests that when returning to a job, the negative impact on the feelings of loneliness reduces.

There are further specifications focusing on those experiencing more than 2 years of unemployment in the period, but the obtained sample size is clearly too small to make any meaningful inference and we leave this as inspiration to future research on the effect of unemployment duration on loneliness levels.

5 Discussion and Critique

Our results show that there is evidence of unemployment affecting loneliness levels, which should be relevant for policy making. We point out two implications of our result. The first being that experiencing unemployment could have a negative impact on loneliness. This could be worsened by the introduction of zero-hour contracts, which could increase the frequency of unemployment in the economy. Secondly, as echoed by the literature, loneliness is an important component in individuals' health. The detrimental effects of unemployment are emphasised and potentially exacerbated by the increasing loneliness levels which can have negative consequences on one's health. This would suggest that policymakers should increase their focus on aiding individuals to avoid unemployment, and during unemployment provide sufficient arenas for social interaction. However, it should be noted that the external validity of the results is limited to only countries with a similar economic outlook.

Considering our results, there are several remarks and limitations with our approach. Some concerns are due to the matching process, and some are due to the available data. PSM is dependent on covariates, and there are both issues with our selected observables and the potential unobservables. The controls in our analysis are observed before the treatment assignment that is unemployment experience. It is, at the same time possible that these individual characteristics change during the observed period. Health and age evidently affect an individual's current unemployment status but we cannot account for such changes as it would violate the unconfoundedness assumption. Furthermore, in any propensity score analysis, there is potential for bias from unmeasured confounders. This is mitigated by a careful selection of covariates in the propensity score. However, there are still unobservables like mental health that could be an important predictor for both loneliness and unemployment.

PSM works especially well with a large number of covariates. However, it is dependent on having a large sample as well, because a small sample complicates the matching procedure by yielding a larger difference between matches (Li et al. 2018). For that reason, our small sample of treated individuals restricts us from increasing the model complexity leading to a bias-variance trade off. A larger sample could have offered a lower bias and thus a higher precision. Nevertheless, as we are dealing with a variance-bias tradeoff, we have been cautious about not using too many variables. This helps us keep the common support, limits the variance (Bryson et al. 2002), along with allowing us to have sufficient overlap between the controls and treatment groups. Further research in the area can find more robust results with a larger dataset available.

A final limitation of our model is both the self-perceived loneliness measure and assignment of treatment. Self reported measures suffer from reliability issues. People might overstate or understate the measure and the interpretation might vary with age, region and other factors. Individuals may find it difficult to rate their innate loneliness on a Likert scale, thus, they may be inclined to answer the question with either what they think the researcher wants to hear or what they believe is socially desirable and acceptable. This social desirability bias is a large limitation of using a self-reported loneliness level. Furthermore, for our treatment, it is important to remember that unemployment is not a binary experience for a person, hence our binary variables will generalise a rather complex situation that might differ across individuals and how the individual became unemployed remains unanswered in our paper.

6 Conclusion

In this paper we have investigated the relationship between unemployment and loneliness, and more specifically we have tried to identify the causal relationship of unemployment on loneliness. By arguing that these two factors are subject to bidirectionality, we motivated the use of PSM. Our findings indicate lower levels of loneliness for those who experienced unemployment during 2013 and 2017, suggesting that unemployment indeed made them lonelier than before. Further specification across groups, and varying the treatment variable, allowed us to find the effect across groups, and that the timing of the unemployment experience itself could alter the results. Our paper suggests that policy makers should take these findings into account when regulating working contracts, and when providing unemployment benefits. Further research could look into the role of unemployment duration on loneliness, and the mechanisms of why unemployment causes loneliness.

References

Boomsma, D. I., Willemsen, G., Dolan, C. V., Hawkley, L. C. & Cacioppo, J. T. (2005), 'Genetic and environmental contributions to loneliness in adults: The netherlands twin register study', *Behavior genetics* **35**(6), 745–752.

Borys, S. & Perlman, D. (1985), 'Gender differences in loneliness', *Personality and Social Psychology Bulletin* **11**, 63–74.

Buecker, S., Ebert, T., Götz, F. M., Entringer, T. M. & Luhmann, M. (2021), 'In a lonely place: Investigating regional differences in loneliness', *Social Psychological and Personality Science* **12**(2), 147–155.

Bundesministerium (2018), 'Jahresbericht zum stand der deutschen einheit 2018'.
URL: *https://www.bmwk.de/Redaktion/EN/Publikationen/jahresbericht-zum-stand-der-deutschen-einheit-2018.pdf*

Cacioppo, J. T., Hughes, M. E., Waite, L. J., Hawkley, L. C. & Thisted, R. A. (2006), 'Loneliness as a specific risk factor for depressive symptoms: cross-sectional and longitudinal analyses.', *Psychology and aging* **21**(1), 140.

Cacioppo, J. T. & Patrick, W. (2008), *Loneliness: Human nature and the need for social connection*, WW Norton & Company.

Caliendo, M. & Kopeinig, S. (2008), 'Some practical guidance for the implementation of propensity score matching', *Journal of economic surveys* **22**(1), 31–72.

Farré, L., Fasani, F. & Mueller, H. (2018), 'Feeling useless: the effect of unemployment on mental health in the great recession', *IZA Journal of Labor Economics* **7**(1), 1–34.

Grant, N., Hamer, M. & Steptoe, A. (2009), 'Social isolation and stress-related cardiovascular, lipid, and cortisol responses', *Annals of Behavioral Medicine* **37**(1), 29–37.

Hawkley, L. C. & Cacioppo, J. T. (2010), 'Loneliness matters: A theoretical and empirical review of consequences and mechanisms', *Annals of behavioral medicine* **40**(2), 218–227.

Holt-Lunstad, J., Smith, T. B., Baker, M., Harris, T. & Stephenson, D. (2015), 'Loneliness and social isolation as risk factors for mortality: a meta-analytic review', *Perspectives on psychological science* **10**(2), 227–237.

Holt-Lunstad, J., Smith, T. B. & Layton, J. B. (2010), 'Social relationships and mortality risk: a meta-analytic review', *PLoS medicine* **7**(7), e1000316.

Li, F., Morgan, K. L. & Zaslavsky, A. M. (2018), 'Balancing covariates via propensity score weighting', *Journal of the American Statistical Association* **113**(521), 390–400.

Macdonald, S. J., Deacon, L., Nixon, J., Akintola, A., Gillingham, A., Kent, J., Ellis, G., Mathews, D., Ismail, A., Sullivan, S. et al. (2018), "the invisible enemy': disability, loneliness and isolation', *Disability & Society* **33**(7), 1138–1159.

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.

Masi, C. M., Chen, H.-Y., Hawkley, L. C. & Cacioppo, J. T. (2011), 'A meta-analysis of interventions to reduce loneliness', *Personality and social psychology review* **15**(3), 219–266.

McAvay, G. J., Seeman, T. E. & Rodin, J. (1996), 'A longitudinal study of change in domain-specific self-efficacy among older adults', *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences* **51**(5), P243–P253.

Morrish, N. & Medina-Lara, A. (2021), 'Does unemployment lead to greater levels of loneliness? a systematic review', *Social Science & Medicine* **287**, 114339.

Morrish, N., Mujica-Mota, R. & Medina-Lara, A. (2022), 'Understanding the effect of loneliness on unemployment: propensity score matching', *BMC Public Health* **22**(1), 1–15.

Murphy, G. C. & Athanasou, J. A. (1999), 'The effect of unemployment on mental health', *Journal of Occupational and organizational Psychology* **72**(1), 83–99.

Payne (2021), 'Mapping loneliness during the coronavirus pandemic'.
URL: *https://www.ons.gov.uk/peoplepopulationandcommunity/wellbeing/articles/mappinglonelinessduringthecoronaviruspandemic/2021-04-07*

Rimmer, A. (2018), 'Rcgp calls for national campaign to tackle loneliness'.

Rudatsikira, E., Muula, A. S., Siziya, S. & Twa-Twa, J. (2007), 'Suicidal ideation and associated factors among school-going adolescents in rural uganda', *BMC psychiatry* **7**(1), 1–6.

Shankar, A., McMunn, A., Banks, J. & Steptoe, A. (2011), 'Loneliness, social isolation, and behavioral and biological health indicators in older adults.', *Health psychology* **30**(4), 377.

Stack, S. (1998), 'Marriage, family and loneliness: A cross-national study', *Sociological perspectives* **41**(2), 415–432.

Ten Kate, R. L., Bilecen, B. & Steverink, N. (2020), 'A closer look at loneliness: why do first-generation migrants feel more lonely than their native dutch counterparts?', *The Gerontologist* **60**(2), 291–301.

Van Baarsen, B. (2002), 'Theories on coping with loss: The impact of social support and self-esteem on adjustment to emotional and social loneliness following a partner's death in later life', *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences* **57**(1), S33–S42.

Von Soest, T., Luhmann, M. & Gerstorf, D. (2020), 'The development of loneliness through adolescence and young adulthood: Its nature, correlates, and midlife outcomes.', *Developmental psychology* **56**(10), 1919.

Yang, K. & Victor, C. (2011), 'Age and loneliness in 25 european nations', *Ageing & Society* **31**(8), 1368–1388.