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Examining The Causal Effect of Unemployment on Mental Health in the Netherlands

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Abstract

Many people experience mental health problems in the Netherlands and its economic costs are extremely high. The negative relationship between unemployment and mental health is well established in the empirical literature. However, evidence on the causal effect of unemployment on mental health is not as extensive due to endogeneity of unemployment and the context-dependent effects. This causality was examined in the Netherlands, for which there was no evidence yet. In addition, heterogeneity on the basis of gender, age, and partnership, was analyzed. The results help to design policies that focus on the high prevalence of mental health.

The LISS survey panel data was used to compare individuals who became unemployed at some time to individuals who were continuously employed during that same time. These were made more similar in important characteristics by the use of propensity score matching. A difference-in-difference strategy was then implemented to follow their change in mental health over time.

The results showed a strong negative correlation between unemployment and mental health. However, there was no evidence on the causal effect of unemployment on mental health. The impact was not different for men and women. The decline in mental health was slightly larger for younger individuals and for singles, as compared to older people and cohabiting individuals, respectively. No effects were statistically significant.

Becoming unemployed doesn't decline an individual's mental health. The results suggests that people with worse mental health are more likely to become unemployed, which explains the correlation. It is thus recommended that policy design should focus on increasing the mental health of workers with poor mental health. Further research should focus on the effect of unemployment duration and of cumulative unemployment experiences.

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1. Introduction

A self-evident effect of job loss is the reduction of income (Jacobson et al., 1993), but the consequences of unemployment reach far beyond economic elements. For example, it leads to subsequent job insecurity (Stevens, 1997) and an increased divorce risk (Charles & Stephens, 2004). The relationship between unemployment and mental health has been studied extensively as well. The empirical evidence consistently shows that unemployment is associated with poor mental health (e.g., Artazcoz et al., 2004; Theodossiou, 1998).

Poor mental health has a high prevalence. Approximately 18.6% of people in the Netherlands had a mental health problem in 2016 (Organisation for Co-operation and Economic Development [OECD] & European Union [EU], 2018). In addition, it has major economic consequences. Poor mental health is associated with impaired physical health (Prince et al., 2007), increased mortality and suicide rates (OECD & EU, 2018), but also with reduced work productivity and non-employment (Bubonya et al., 2017). The total costs of the mental health problems in the Netherlands were estimated at €35 billion in 2015, equal to 5.1% of the gross domestic product (GDP) (OECD & EU, 2018).

The World Health Organization (WHO) acknowledges the importance of mental health and designs proposals and initiatives to focus on mental health (WHO, 2013, 2019). The negative correlation between unemployment and mental health suggests that unemployment could lead to a deterioration in mental health. This information helps to design policies regarding mental health. Hence, it is important and relevant to analyze whether unemployment has a causal effect on mental health.

However, the current literature shows three main obstacles. First, it is difficult to identify this causal effect. There is extensive evidence that unhealthy employees are more likely to end up unemployed than healthy workers, and that healthy jobseekers have a higher probability to re-enter employment (García-Gómez et al., 2010; Stewart, 2001). In addition, there are unobserved characteristics that affect both unemployment risk and mental health, such as academic ability and personality traits, that could bias the results. In order to account for the endogeneity of unemployment, longitudinal data and advanced econometric methods are needed. So far, the majority of empirical research regarding this topic used cross-sectional data. The evidence on the relationship between unemployment and mental health has been convincing, but causality analysis is not much done.

Second, the causal studies that have been published show some divergence in results. While most studies found that unemployment had a significant negative impact on mental health, various analyses reported no significant effect (see, e.g., Cygan-Rehm et al., 2017; Marcus, 2013; Schmitz, 2011). Previous research has shown additionally that the effect size is very sensitive to the context of analysis. For example, Voßemer et al. (2018) presented evidence that a more altruistic unemployment benefits scheme helps to diminish the negative effect of unemployment on life satisfaction. Research in Greece revealed that the negative unemployment effect on mental health was larger during a financial crisis than during the period right before (Drydakis, 2015).

Third, numerous studies concluded that the effect size depends on certain individual characteristics as well, which allows for heterogeneity. For example, a study in the UK reported a negative effect size that was generally larger for younger individuals than for older people (Gathergood, 2013). It is important to emphasize that the heterogenous effects depend on the setting as well. Strandh et al. (2013) found, for example, a differential effect size between men and women in Ireland, but no difference in Sweden.

In short, three things are important when studying the effect of unemployment on mental health. It is necessary to use an adequate method and data to identify a causal effect. It is critical to assess this effect in many different contexts. Last, it is relevant to examine the presence of heterogeneity. This is not yet done in the Netherlands. Hence, the aim of this thesis is to estimate the effect of unemployment on mental health in the Netherlands. This research also aims to identify possible heterogenous effects. The following will thus be examined.

What is the short-term causal effect of unemployment on mental health in the Netherlands?

Does the effect size of unemployment on mental health vary by gender?

Does the effect size of unemployment on mental health vary by age?

Does the effect size of unemployment on mental health vary by cohabitation?

The Dutch LISS panel, which contains annual data on health, and monthly updates on background characteristics and employment status from 2008, is used to obtain a representative sample. Propensity score matching (PSM) is combined with difference-in-difference (DID) to estimate the causal effect of unemployment on mental health. PSM makes sure that the individuals that become unemployed are compared to (almost) identical individuals that do not become unemployed, i.e., continuous employment. DID analyzes how mental health of these two groups has changed.

This thesis contributes to the existing literature in two main ways. First, the study is highly informative for policy design relating to unemployment. The study examines whether unemployment contributes to changes in mental health. This can be incorporated into a policy design that aims to mitigate the mental health costs related to unemployment. If the reason for mental health decline becomes clear, then policies can be implemented to offset this negative experience. Second, the causal effect is analyzed in the Dutch context, which has not been done before. As explained above, this is important since the context influences the effect size a lot. Heterogenous effects are examined as well. These also depend on the setting.

This thesis is set up as follows. Section 2 provides a theoretical framework with current empirical findings and a pathway to the hypotheses. Section 3 describes the data. Section 4 explains the methodology of the study. Section 5 presents the results and section 6 concludes.

2. Theoretical Framework

2.1. Concepts

2.1.1. Unemployment

Unemployment is defined by the International Labour Organisation (ILO) (2013) as “those of working age who were not in employment, carried out activities to seek employment during a specified recent and were currently available to take up employment given a job opportunity” (p. 56). Although slight differences exist, this is the generally accepted definition across countries. Statistics Netherlands (CBS) implements it as well (CBS, n.d.). The definition suggests unemployment is an involuntary position.

The unemployment rate in the Netherlands has somewhat increased from 5.0% in 2010 to 7.4% in 2014, but declined steadily after that, with an unemployment rate of 3.4% in 2019 (OECD, 2020). Compared to other high-income countries, the Dutch unemployment rate is relatively low (OECD, 2020). In the past ten years a little over one-third of all unemployment was considered long-term employment, meaning a duration of at least 12 months (OECD, 2020). When individuals become unemployed, they are entitled to receive unemployment benefits in most countries. How high this is in relation to previous labor earnings says something about the level of unemployment protection in a country. The Netherlands has a relatively high level of unemployment protection (OECD, n.d.).

The Dutch labor market is characterized by a high level of part-time workers. In 2019, 37.0% of employment was part-time employment (OECD, 2020). In comparison, Germany and France had a part-time employment rate of merely 22.0% and 13.4%, respectively (OECD, 2020).

2.1.2. Mental health

Mental health was long interpreted as the absence of mental disorders. However, as the WHO highlighted the importance of mental health and its widespread costs and effects, it characterized mental health as an integral part of health, and defined it as “a state of well-being in which an individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and is able to make a contribution to his or her community” (WHO, 2004, p. 12). Hence, mental health comprises three central concepts. Emotional well-being, relating to happiness and positive feelings, psychological well-being, relating to an individual’s effective functioning such as autonomy and self-acceptance, and lastly social well-being, relating to an individual’s functioning to to society such as social acceptance and coherence. Keyes used this to define positive mental health as the presence of emotional well-being combined with psychological and social well-being (Keyes, 2005, 2007). He then studied the relationship between positive mental health and mental illness, and found surprisingly that even though the two concepts are related, they can exist independently. This was also found in the Netherlands (Lamers et al., 2011).

The unemployment rate among people with a mental disorder in the Netherlands is 7%, approximately twice as high as the unemployment rate of people without ill health (OECD, 2014). 40% of the people with mental ill health that are working have a part-time job. Moreover, workers with a mental disorder that attend work are less productive than workers without mental ill-health. Related to demographics, mental health problems are more prevalent among women, low educated people, and divorced people and widows (Driessen, 2011).

2.2. Theory on unemployment and mental health

Many theories have been formulated that try to explain the unemployment effect on mental health. Merging different parts from these together results in one general overarching model. This theoretical model states that unemployment mainly affects mental health through the two major needs for employment, similar to Nordenmark and Strandh (1999).

First, there is an economic need for employment. Employment provides economic resources, which enable consumption, and give an individual a sense of agency, power, and the ability to plan for the future. The economic deprivation and uncertainty due to unemployment necessitate an individual to adjust their standard of living and restrict an individual's control over their life, leading to distress and poor mental health (Fryer, 1986, 1992).

Second, there is a psychosocial need for employment. Employment provides certain latent benefits, such as time structure, social contacts, and a social identity, role and status (Ezzy, 1993; Jahoda, 1982; Warr, 1987). Ezzy (1993) contends that an individual perceives their position in a society as either positive or negative due to the social meaning that is attached to it. Since employment is the norm in today's Western society, becoming unemployed coincides with a decline in subjective social status, leading to a deterioration in mental health.

These components form the building blocks of the theoretical model. Unemployment affects mental health mainly through the economic need and psychosocial need for employment. The experience of unemployment can be conceptualized as a process of loss (Sage, 2018). Then, becoming unemployed coincides with a loss of these met needs, leading to deterioration in mental health. The importance of employment depends on the social context in which the individual is situated. In accordance with unemployment as a process of loss, stronger economic and psychosocial need for employment is then associated with a larger negative effect on mental health.

2.3. Difficulty of identifying the causal effect

However, in practice it is difficult to identify a causal effect of unemployment on mental health due to the endogeneity of job loss. There is direct selection of unhealthy individuals into unemployment. The idea behind this mechanism is that workers with poor mental health have, on average, higher rates of absenteeism and presenteeism than workers with good mental health (Bubonya et al., 2017), and hence are more likely to enter unemployment. The presence of reverse causality also has empirical support (García-Gómez et al., 2010; Lindholm et al., 2001; Riphahn, 1999). A related observation is that unhealthy jobseekers have a lower probability to re-enter employment, and subsequently have longer unemployment durations (Stewart, 2001). Additionally, there are unobservable individual characteristics that affect both mental health and employment risk. Examples are personality traits and genetic frailty. Longitudinal data and advanced econometric methods are necessary to account for this endogeneity of unemployment, which enables identification of the causal effect.

2.4. Empirical evidence on the causality

The results across the empirical literature relating to the unemployment effect on mental health are presented and discussed next.

Various empirical analyses have indicated that unemployment has indeed a negative effect on mental health. Green (2011) observed a significant effect of unemployment on mental health in Australia, and Krug and Eberl (2018) in Germany. Some empirical assessments focused on unemployment due to plant closure. This implies that variation in unemployment is exogenous. Marcus (2013) examined this in Germany for cohabiting individuals and their spouses, Riumallo-Herl et al. (2014) analyzed it in both the USA and Europe for older workers, and Drydakis (2015) used plant closures to study the unemployment effect in Greece during times of a financial crisis. All three analyses reported a significant negative effect on mental health. Kuhn et al. (2009) examined the effect of job loss on public health costs. They found that job loss due to plant closure led to increased expenditures on hospitalization and drug prescription related to mental health for men, but not for women. Schaller and Stevens (2015) found a significant negative effect of involuntary job loss on mental health in the USA.

In contrast, some studies reported a non-significant effect (e.g., Schmitz, 2011). This does not necessarily imply that the results so far are inconclusive. The insignificance reported in Schmitz (2011) could be due to the methodology in place. He examined the causal effect of unemployment in Germany in the beginning of the 21st century. He separated unemployment due to plant closure from other reasons in order to obtain a causal effect, and he applied a fixed effects model. Schmitz (2011) found no evidence of a negative causal effect. Similarly, Marcus (2013) analyzed the same effect in the same time and place, and with the same data. He used unemployment due to plant closure as well, but implemented a non-parametric matching method in combination with difference-in-difference. Marcus (2013) observed a highly significant negative effect. This suggests that the non-significance of Schmitz (2011) could be due to the chosen methodology.

Moreover, the reported effect sizes are rather divergent. Several studies suggest that the context of analysis is important. Riumallo-Herl et al. (2014) examined the effect of unemployment due to plant closure and observed an increase in depressive symptoms scores of 28.2% in the USA and of merely 7.5% in Europe. They also described that the USA had, on average, a much lower level of unemployment protection than European countries have, suggesting that a country's unemployment protection system would be important for the effect size. Drydakis (2015) examined the effect of unemployment due to plant closure on mental health in Greece from 2008 to 2013. He observed that the effect size is larger during the financial crisis (2010-2013) than right before this (2008-2009). Therefore, the country's position in the economic cycle during the analyzed time period could be of importance. Accordingly, the empirical evidence demonstrates that the context and setting in which the unemployment effect is analyzed influences the estimates greatly.

In short, the scarce empirical evidence generally reports a negative unemployment effect on mental health, with context-dependent effect sizes. This is in line with the previously described theory. For example, in a country with a high level of unemployment protection economic need for employment is relatively weak, compared to a country with a low level of unemployment protection. The effect size in the first country is then smaller than in the second country. The theory and the supporting empirical evidence construct the first hypothesis which states that unemployment, on average, decreases individual's mental health.

2.5. Heterogeneity

The presence of heterogenous effects is justified by the theory as well. However, the empirical literature regarding heterogeneity is still limited.

2.5.1. Gender

Strandh et al. (2013) assessed the role of gender in the effect of unemployment on mental health. They concluded that there was no difference between men and women in Sweden, a very egalitarian country. The effect size was larger for men than it was for women in Ireland, where there was gendered division related to the family and economic situation. In the Netherlands, men work more and earn more than women, while women spend more time on household tasks and the nursing of the children (Portegijs et al., 2018a, 2018b). This difference is especially apparent when they become parents. This is similar to the socially defined optimal situation, although the ideal gender positions are slightly more egalitarian than what is observed in practice. This indicates that the social norm for men is employment, while women could identify with social roles mainly related to nurturing, in addition to being employed. Hence, women may have less of a need for employment than men do, suggesting a smaller effect size for women. The second hypothesis therefore states that the effect of unemployment on individual's mental health is, on average, more negative for men than for women.

2.5.2. Age

Gathergood (2013) investigated the unemployment effect in the UK. He observed that the overall negative effect of unemployment on mental health was significant, with larger effect sizes for people aged 30-50 years, and smaller effect sizes for individuals who were younger and older. Breslin and Mustard (2003) assessed the effect in Canada from 1994 to 1996. The results suggested that there was a negative effect of unemployment on mental health for individuals aged 31-55 years, while there was no significant effect for adults that were 30 years or younger. The theory Family responsibilities due to parenthood increase the economic need for employment. The average age at which both men and women become parents in the Netherlands is approximately 30 years (CBS, 2020). Hence, parents have increased financial pressure mostly in their thirties and forties. This implies a greater need for employment between 30 and 50 years of age, suggesting an effect size that is U-shaped with respect to age. Thus, the third hypothesis states that the effect of unemployment on individual's mental health is, on average, more negative for people aged 30-49 than for younger and older individuals. In this thesis the term ‘middle-aged’ is used for the 30-to-49 age group. Younger and older individuals are then people who are not in this age group.

2.5.3. Cohabitation

Milner et al. (2016) studied the role of social support in the unemployment effect on mental health. They used longitudinal Australian survey data on individuals who experienced both employment and unemployment, and applied a fixed effects model. They observed that the decline in mental health due to unemployment was larger for individuals with low perceived social support. Pearlin et al. (1981) claimed that social support could help mitigate the effect of job disruption on depression. Spouses or cohabiting partners can provide a huge amount of social support (Sherbourne & Hays, 1990). Additionally, Tattarini et al. (2018) reported that the unemployment effect on self-perceived health was smaller for cohabiting men than for singles. This was especially true when the partner was employed. Hence, it can be assumed that cohabiting individuals have a lower need for employment than singles. Thus, the fourth hypothesis states that the effect of unemployment on individual’s mental health is, on average, more negative for singles than for individuals with a cohabiting partner.

3. Empirical Strategy

3.1. Theory

3.1.1. Difference-in-Difference

The aim of this thesis is to study the effect of unemployment on mental health. To examine this propensity score matching (PSM) and difference-in-difference (DID) techniques are combined. This study focuses on the average treatment effect on the treated (ATT), defined as the change in mental health due to experiencing unemployment for those who actually experience unemployment. Assume a treatment group $(D = 1)$ of individuals who experience unemployment between period $t - 1$ and t, and a control group $(D = 0)$ of individuals who are continuously employed. Let Y^1 and Y^0 denote mental health outcomes of treatment and non-treatment, respectively. The standard ATT is then defined as in equation (1).

$$ATT = E[Y_t^1 \mid D = 1] - E[Y_t^0 \mid D = 1] \tag{1}$$

The second term on the right-hand side is not observed. The DID design solves this by assuming that in absence of treatment, treated and control individuals would experience the same trend in outcome. This is the common trend assumption, which is formulated in equation (2).

$$E[Y_t^0 - Y_{t-1}^0 \mid D = 1] = E[Y_t^0 - Y_{t-1}^0 \mid D = 0] \tag{2}$$

The ATT under a DID is then identified as is specified in equation (3). Hence, the DID strategy accounts for time-invariant unobservable individual-specific fixed effects and common period effects.

$$ATT = E[Y_t^1 - Y_{t-1}^1 \mid D = 1] - E[Y_t^0 - Y_{t-1}^0 \mid D = 0] \tag{3}$$

However, treatment participation in this study is not random. Certain characteristics influence both the probability of becoming unemployed and mental health status, such as educational attainment (Browning et al., 2006; Hoeymans et al., 2004). There is selection bias. Consequently, the holding of the common trend assumption cannot be assumed. DID needs to be complemented by another evaluation method. One possibility is matching.

3.1.2. Propensity score matching

Matching assumes that conditioning on a set of characteristics X that are unaffected by treatment, the potential non-treatment outcome Y^0 is independent of treatment participation. Equation (4) specifies this conditional independence assumption (CIA) (Lechner, 2000).

$$Y^0 \perp D \mid X \tag{4}$$

The idea of matching is then that treated individuals are compared to non-treated individuals with the same observable characteristics X (i.e., they are 'matched' on the set of covariates X) (Dehejia & Wahba, 2002). As a result, any difference in outcome between these two groups is connected to treatment participation. Matching thus deals with selection on observables.

In addition to the CIA, the (weak) common support assumption must be satisfied. This ensures that for each treated individual, there is at least one untreated individual with similar X characteristics (Caliendo & Kopeinig, 2008).

$$P(D = 1 \mid X) < 1 \tag{5}$$

With a large number of relevant covariates X, finding individuals with the same characteristics is difficult due to the curse of high dimensionality. Rosenbaum and Rubin (1983) suggest implementing propensity score matching (PSM). This entails conditioning on the probability of treatment participation as a function of X, called the propensity score $P(X)$.[1] It reflects an individual's probability of treatment participation, given his/her observed characteristics X. The CIA is then defined as follows.

$$Y^0 \perp D \mid P(X) \tag{6}$$

Combining DID and PSM leads to the following identifying assumption (Smith & Todd, 2005).

$$E_{P(X)|D=1}[Y_t^0 - Y_{t-1}^0 \mid P(X), D = 1] = E_{P(X)|D=1}[Y_t^0 - Y_{t-1}^0 \mid P(X), D = 0] \tag{7}$$

This states that no unobserved variables should exist that simultaneously affect the probability of experiencing unemployment and influence changes in mental health, implying that in the absence of treatment, the mental health of treated individuals and matched controls follows the same trend.

[1] $P(X) = P(D = 1|X)$.

Thus, PSM allows to minimize selection bias, while DID additionally accounts for time-invariant unobservable individual-specific fixed effects and common time effects. The accompanying ATT estimator can be expressed as follows (Heckman et al., 1997).

$$ATT^{DID-PSM} = \frac{1}{N_{D_1}} \sum_{i \in D_1 \cap S} \left[\left(Y_{i,t}^1 - Y_{i,t-1}^1 \right) - \sum_{j \in D_0 \cap S} w_{ij} \left(Y_{j,t}^0 - Y_{j,t-1}^0 \right) \right] \tag{8}$$

N indicates the number of treated individuals, D_1 (D_0) the treatment (control) group, S the area of common support, and w_{ij} the weight assigned to the control individuals based on the matching strategy.

3.2. Procedure

3.2.1. Propensity score

The propensity score is estimated by means of a probit regression, with treatment participation as the dependent variable and a set of conditioning variables X as the regressors. The explanatory variables are measured before treatment (i.e. at time period $t-1$), as all the conditioning variables must be unaffected by treatment. Since the propensity score is extremely skewed, the linear index of the propensity score is used. This helps to identify differences in propensity scores in the extremes more precisely, leading to better matching results in those areas (Lechner, 2000).

The probit model is specified such that the balancing property of the covariates is satisfied. That is, conditional on the propensity score, there are no significant differences in the covariates X between the treatment and control group. This is analyzed by dividing the sample into strata such that within each stratum the mean linear propensity score is not significantly different between the treatment and control group. Then, the covariate means must not significantly differ between treated and controls in each stratum (Becker & Ichino, 2002). On overview of the t-statistics for all covariates in all strata can be found in Appendix A, Table A1.

In addition, common support is subjectively assessed by looking at a density graph of propensity scores of treated and non-treated observations, and numerically by comparing the minima and maxima of the propensity score between the treated and untreated group.

3.2.2. Matching

Next, treated and control observations with similar linear propensity scores are matched using kernel matching.[2] With kernel matching, a weighted average of all control observations is used to obtain a counterfactual ('match') for each treated individual. The control observations are given a weight on basis of the relative distance of their propensity score to the propensity score of the treated individual. Kernel matching results in lower variance (Caliendo & Kopeinig, 2008). Matching is done for each year separately. This ensures that individuals in the same time period are compared to each other.

The Epanechnikov kernel with a bandwidth of 0.06 is applied. This only uses the control observations that are within the bandwidth for each treated individual (Galdo et al., 2008). The choice of bandwidth follows from Silverman (1986) and Heckman et al. (1997). The reasoning behind the choice of kernel matching is described in the next section.

The balance of the covariates after matching must be analyzed. A two-sample t-test assesses whether the covariate means between treatment and control group are significantly different (Rosenbaum & Rubin, 1985). The matching quality can also be assessed with the standardized bias (SB), which is calculated as the difference in means between treated and controls as a percentage of the square root of the average of the variance in the treatment and control group (Rosenbaum & Rubin, 1985).[3] Although no official threshold is defined, a standardized bias below 5% is often considered good (Caliendo & Kopeinig, 2008).

3.2.3. Estimating ATT

Finally, the ATT is estimated over the pooled sample. Recall that propensity score estimation is over the pooled sample, matching for each year separately, and the ATT estimation again over the pooled sample. The standard errors of the ATT are obtained by bootstrapping over all three steps with 200 replications.

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[2] The program "*psmatch2*" in Stata, implemented by Leuven and Sianesi (2003), is used.

[3] $SB = 100 * \frac{\bar{X}_T - \bar{X}_C}{\sqrt{0.5 * (V_T(X) - V_C(X))}}$

4. Data

4.1. Data description

The analysis is conducted with Dutch longitudinal survey data from the Longitudinal Internet Studies for the Social Sciences (LISS) panel. This is administered by CentERdata (Tilburg, The Netherlands). A true probability sample of households was drawn from a population register by CBS. Households with no PC or stable internet access were given this. It is a representative sample of Dutch-speaking individuals. Although there is some misrepresentation of the Dutch population with regards to certain characteristics, it is assumed that the data is representative of the research population, namely the Dutch labor force (Knoef & De Vos, 2009; Van Der Laan, 2009).[4] The panel fills in questionnaires on a monthly basis and receives financial compensation for each completed questionnaire. A longitudinal survey, covering principal topics such as health and education, is carried out every year. The modules 'Health' and 'Work & Schooling' are used for this thesis, in addition to the monthly updated background variables. Data is retrieved from 2008 to 2019.

In this study individuals in the sample are repeatedly observed for two consecutive years, i.e., at time $t-1$ and time t. As health data is not available for the year 2014, time $t-1$ is defined for the years 2008-2012, and 2015-2018. Hence, there are nine possible sequences for which data is collected.

4.1.1. Sample selection

The sample comprises the treatment group and the control group. The treatment group consists of individuals who are employed at time $t-1$, experience job loss in period $(t-1, t]$, and are still unemployed at time t. The control group consists of individuals who are continuously employed in period $[t-1, t]$. People that are at some point in this time period out of the labor force are thus excluded from the sample. The definition of unemployment by the ILO, described in the theoretical framework, is used to specify unemployment.[5]

There are a few exclusion criteria. First, person-spells with relevant missing data are excluded.[6] Second, individuals under the age of 18 and above the age of 64 are excluded. Minors are only allowed to work a certain amount of hours per week. Individuals close to the legal retirement age might look at

[4] More information about the LISS panel can be found at www.lissdata.nl.

[5] The sample size before the exclusion criteria was 52916 (T=840, C=52076).

[6] Individuals who report a change in gender or birthyear are excluded as well.

unemployment as less of a burden than the rest of the working age individuals. Third, employment only comprises employees. Self-employed people and individuals working in a family business are excluded. Their employment prospective is different from 'traditional' employees. Furthermore, self-employed individuals have a completely different unemployment benefit scheme in the case of job loss as compared to employees in the Netherlands, which could influence the estimated effect (Directorate-General for Employment, Social Affairs and Inclusion, n.d.). Fourth, if the reason for job loss was reported as health-related or voluntary (e.g., resignment), the individual is excluded.

This results in a sample size of 245 treated individuals and 13,491 untreated individuals, summing to a total of 13,736 person-spells. The number of treated and non-treated individuals per year is shown in Table 1. It is noticeable that the fraction of individuals becoming unemployed gradually increases with a peak in year 2013, whereafter it decreases steadily. This is similar to the path of unemployment rate in the Netherlands (OECD, 2020).

Table 1: Number of treated and non-treated per year.

Year	Treated	Controls	% Treated
2009	35	1830	1.88
2010	26	1570	1.63
2011	24	1641	1.44
2012	32	1473	2.13
2013	49	1636	2.91
2016	26	1169	2.18
2017	21	1361	1.52
2018	22	1375	1.57
2019	10	1436	0.69
Total	245	13491	1.78

4.2. Variables

4.2.1. Dependent variable

Mental health, the outcome of interest, is measured with the Mental Health Inventory (MHI-5). It is a subscale of the 36-Item Short Form Health Survey (SF-36) (Ware & Gandek, 1998). It assesses the respondent's experienced frequency of five emotions and feelings in the past month, comprising three negative emotions and two positive feelings.

This past month …

1. … I felt very anxious.
2. … I felt so down that nothing could cheer me up.
3. … I felt calm and peaceful.
4. … I felt depressed and gloomy.
5. … I felt happy.

The respondents report the frequency on a six-point Likert scale, from zero to five with respective options *never*, *seldom*, *sometimes*, *often*, *mostly*, and *continuous*. The scale of the negative feelings is reversed, such that a higher score indicates a more desirable mental state. The scores of the five mental states are summed up individually, after which the score is scaled on a 0-100 range by multiplying the sum by four. A higher score thus indicates a more positive mental health state (Driessen, 2011). The MHI-5 had a Cronbach's alpha of 0.84 in the sample. This indicates that the internal consistency of the instrument is considered good (Revicki, 2014).

An advantage of the MHI-5 instrument is that respondents are not asked to directly report mental health problems, as a study by Bharadwaj et al. (2017) concluded that people have a tendency to underreport these.

The MHI-5 was found to be a good and valid instrument to measure mental health (McCabe et al., 1996; Ware & Gandek, 1998). It is mainly suitable for identifying the prevalence of anxiety disorders and mood disorders (Rumpf et al., 2001). It is also strongly correlated with seeking mental health care (Hoeymans et al., 2004). A disadvantage is that the MHI scale has no formal threshold that indicates the presence/absence of mental health problems (Hoeymans et al., 2004; Kelly et al., 2008). Recently, Statistics Netherlands defined the cut-off point at 60 (Driessen, 2011). The instrument is thus best used to compare certain groups of individuals, or look at the change over time.

4.2.2. Treatment variable

Employment status is measured using the variable indicating primary occupation, which is self-reported on a monthly basis. Someone is considered to be employed when in paid employment. Being unemployed is defined as being a job seeker or being exempted from job seeking following job loss.[7] All other possibilities are labeled as not in labor force (NILF) and are not in the sample. The monthly data allows to track employment status between two yearly time points, making treatment assignment more accurate. It is important to note that the measurement is subjective, as it indicates self-reported primary occupation during the month. This implies that people with marginal part-time jobs are most likely defined as NILF.

4.2.3. Conditioning variables

The identification strategy builds on the assumption that the model includes all variables that simultaneously influence the probability of entering unemployment and changes in mental health status. The characteristics can be divided into three main categories. An overview of all conditioning variables with their respective LISS code can be found in Appendix B, Table B1.

First, the conditioning variables include demographic characteristics, such as gender and age. Age in years is measured with both a linear and quadratic term. Educational attainment is quantified with a dummy variable, which specifies whether an individual has a HBO and/or WO (i.e., college or university) degree or not. Moreover, parenthood and cohabitation are separately accounted for with dummy variables.

Second, there is controlled for job and labor market characteristics. Personal net monthly income is adjusted to 2015 prices using the GDP deflator (World Bank, n.d.). The natural logarithm is taken of income in order to resemble the skewed distribution of income and reduce the significance of possible outliers. Job tenure is measured in years. Three dummy variables are used to control for having a permanent contract, for working at a public firm, and for being a white-collar worker. Moreover, economic sector and job uncertainty are measured with factor variables, comprising five and four categories, respectively.

Third, the individual's health status is accounted for. Self-perceived health indicates the individual's subjective general health and is measured in five categories, with a higher category

[7] Employed: belbezig = 1; unemployed: belbezig = 4,5,6.

indicating better health.[8] Mental health, measured with the MHI-5 score as described above, is included as well. Having a chronic disease is measured with a dummy variable. Lastly, absenteeism is added as a dummy variable, indicating not working a full week due to the individual's health. Time dummies indicating the survey years are included as well.

4.3. Descriptive statistics

4.3.1. Mental health

Figure 1 displays the distribution of the mental health score by employment status. This cross-sectional comparison shows that employed people have on average a better mental health status than unemployed individuals. This is in line with the general belief of a negative correlation between unemployment and mental health (e.g., Paul & Moser, 2009). In addition, the MHI-5 score of unemployed individuals is more dispersed than that of employed individuals.

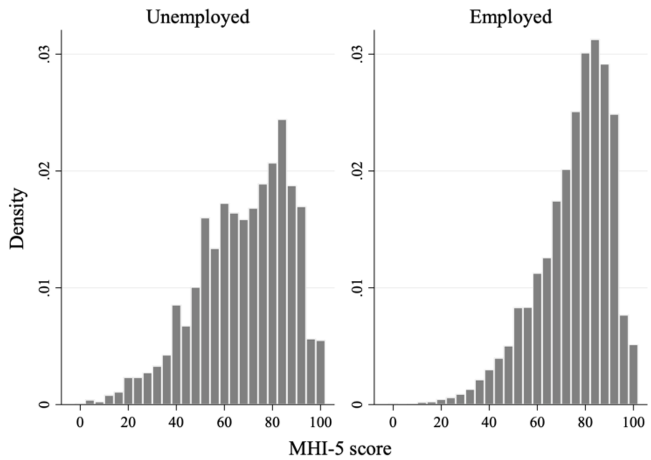

Figure 1: Distribution of the MHI-5 scores for unemployed and employed individuals.

[8] However, in this study it is considered a cardinal measure, following the work of e.g., Böckerman and Ilmakunnas (2009) and Ronchetti & Terriau (2019, 2021).

Table 2 contains the summary statistics. Looking at the mental health status before and after potential treatment, it can be seen that people entering unemployment at time t already have, on average, worse mental health at time $t-1$, as compared to individuals who are continuously employed during this period. However, the difference in mental health levels between treated and untreated individuals does not increase over time, and even shrinks slightly.

Table 2: Summary statistics.

	Treated		Non-Treated	
	Mean	SD	Mean	SD
Age	48.192	11.210	44.959	10.651
Male	0.498	0.501	0.507	0.500
Tertiary education	0.331	0.471	0.419	0.493
Parent	0.469	0.500	0.531	0.499
Couple	0.718	0.451	0.762	0.426
Net monthly income (ln)	7.293	0.959	7.431	0.627
No uncertainty	0.102	0.303	0.217	0.412
Low uncertainty	0.298	0.458	0.517	0.500
Some uncertainty	0.396	0.490	0.222	0.416
High uncertainty	0.204	0.404	0.044	0.205
Tenure	11.241	12.077	12.813	10.602
Permanent contract	0.747	0.436	0.920	0.271
(Semi-)public company	0.249	0.433	0.405	0.491
Primary sector	0.016	0.127	0.014	0.117
Secondary sector	0.204	0.404	0.162	0.369
Tertiary sector	0.302	0.460	0.250	0.433
Quaternary sector	0.273	0.447	0.447	0.497
Other sector	0.204	0.404	0.127	0.332
White collar	0.776	0.418	0.810	0.392
Self-perceived health	3.065	0.680	3.240	0.702
Chronic disease	0.241	0.428	0.228	0.419
Absenteeism	0.171	0.378	0.053	0.224
Mental health ($t-1$)	70.286	19.146	76.307	14.971
Mental health (t)	71.886	18.083	76.283	15.254
Observations	245		13491	

Note: The mean and standard deviation (SD) are given. All variables are measured at time $t-1$, unless stated otherwise.

4.3.2. Conditioning variables

The summary statistics of Table 2 display that treated and controls differ with respect to multiple characteristics. Compared to workers continuing employment, workers becoming unemployed in the near future are approximately 3 years older. In addition, a smaller percentage has finished higher education. Treated individuals report a much higher level of job uncertainty. 60% of treated individuals report some uncertainty or high uncertainty, in contrast to only 27% of non-treated individuals. Also, the treated have less permanent contracts and don't work in public firms as much. Related to health, treated individuals have a much higher rate of absenteeism (11.8 percentage points), and report a lower SPH than non-treated individuals.

5. Results

5.1. Propensity score estimation

The propensity score estimation is presented in Table 3. It shows that the probability of becoming unemployed is higher for younger and older employees (i.e., the age effect is U-shaped). Having longer tenure or a permanent contract reduces the risk of job loss. In addition, the probability of job loss is higher for employees with higher job uncertainty, and lower for employees that work in the quaternary sector. Moreover, poor prior health is indicative of risking unemployment.

Table 3: Probit model for experiencing unemployment.

	Coefficient	Standard Error
Age	–0.059***	0.022
Age squared	0.001***	0.000
Male	–0.041	0.065
Tertiary education	–0.021	0.067
Parent	0.010	0.063
Couple	–0.026	0.068
Net monthly income (ln)	–0.052	0.039
Tenure	–0.009***	0.003
Permanent contract	–0.565***	0.083
(Semi-)public company	–0.131	0.086
Low uncertainty	0.027	0.093
Some uncertainty	0.393***	0.094
High uncertainty	0.842***	0.112
Primary sector	–0.098	0.247
Secondary sector	–0.015	0.097
Tertiary sector	–0.116	0.086
Quaternary sector	–0.396***	0.100
White collar	0.144*	0.078
Self-perceived health	–0.030	0.048
Chronic disease	–0.159**	0.073
Absenteeism	0.515***	0.093
Mental health	–0.006***	0.002
Year dummies	Yes	
N	13736	
Log-likelihood	–1041.651	

Note: All explanatory variables are measured before treatment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The region of common support is visualized by Figure 2 (Lechner, 2002). It can be seen that the area of common support is relatively large, i.e., for all treated individuals at least one non-treated individual exists with the same propensity score. When constraining PSM to the region of common support according to Leuven and Sianesi (2003), one must exclude all treated observations with a propensity score that is higher than the maximum or lower than the minimum propensity score of the non-treated individuals. Implementing this leads to the exclusion of zero treated individuals. However, a more critical approach is used in this thesis to account for year-exact matching. The definition of common support by Leuven and Sianesi (2003) is applied to each year separately. By this definition 3 treated observations are excluded.

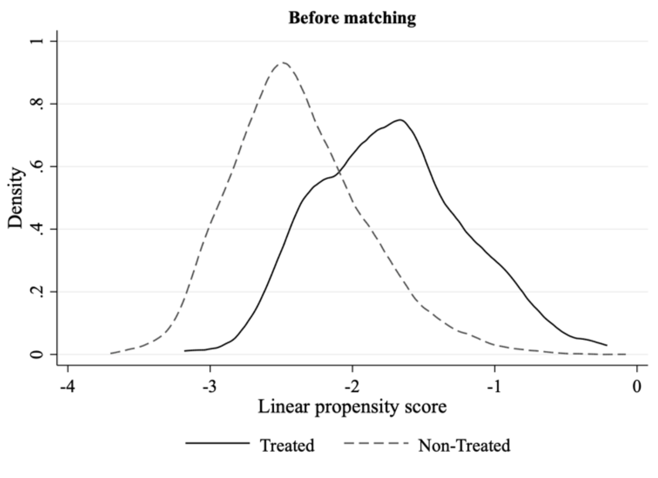

Figure 2: Distribution of the linear propensity score before matching.

5.2. Matching quality

The optimal matching method depends on the research question and data. There are a lot of comparable non-treated individuals available in this sample.[9] Hence, it could be beneficial to use multiple control observations in the matching process to decrease variance (Caliendo & Kopeinig, 2008). The matching quality of kernel matching, 3-to-1 nearest neighbor caliper matching, and radius matching are compared briefly. The Pseudo R-squared and the p-value of the likelihood ratio test come from the probit regression that estimate the propensity scores. The Pseudo R^2 of the unmatched sample indicates that the conditioning variables explain some variation in treatment. Its value is nearly zero in all the matched samples. The p-value of the unmatched sample indicates that the conditioning variables are jointly significant at the 1% level. In the matched samples there is no evidence of joint significance.

[9] Figure A1 shows the frequency histogram of the linear propensity scores for treated and non-treated individuals.

The standardized bias indicates how similar the distributions of the covariates are between treated and controls. The mean and median bias drop considerably in the matched samples, as compared to the original sample. These measures suggest that matching ensures balance of the covariates and pre-treatment differences between treated and matched controls. Of these three matching methods, kernel matching performs the best. Hence, this is the method of choice in this thesis.

Table 4: matching quality summary.

Sample	Pseudo R^2	$P > \chi^2$	Mean bias (%)	Median bias (%)
Unmatched	0.153	0.000	20.072	15.387
Kernel matching [a]	0.001	1.000	0.909	0.853
3-NN caliper matching [b]	0.005	1.000	2.556	2.571
Radius matching [c]	0.001	1.000	1.027	0.981

Note: Pseudo R^2 is from the probit model estimating the propensity scores. P-value is of the likelihood ratio test of joint significance of all conditioning variables. Bias indicates standardized difference in means between treated and control.

[a] Epanechnikov kernel with bandwidth 0.06. [b] 3-to-1 nearest neighbor matching with caliper 0.25 of standard deviation of estimated linear propensity score. [c] Radius matching with caliper 0.25 of standard deviation of estimated linear propensity score.

After matching, the distribution of the propensity scores between treated and controls became more similar. This is presented in Figure 3.[10] Balancing of the covariates succeeded as well, shown in Table 5. Before matching, many covariate means were significantly different between treated and non-treated individuals. Matching eliminated all significant mean differences between treated and controls, as the two-sample t-test is not significant for any covariate. In addition, PSM led to a massive reduction in standardized bias, where each covariate has a standardized bias below the threshold of 5% after matching. Because of exact matching on year, the difference in means and standardized bias of the year dummies after matching are zero. They are therefore excluded from Table 5. The quality of matching was considered sufficient.

[10] The corresponding graphs for nearest neighbor matching and radius matching are displayed in Appendix A, Figure A2 and A3, respectively.

Table 5: Covariate balancing: mean characteristics before and after kernel matching.

Variable	Sample	Treated	Control	Difference	Std. bias (%)	Bias reduction (%)
Age	Unmatched	48.192	44.959	3.233***	29.567	
	Matched	48.013	47.872	0.140	1.283	95.661
Age squared	Unmatched	2447.604	2134.749	312.856***	32.188	
	Matched	2430.621	2419.950	10.671	1.098	96.589
Male	Unmatched	0.498	0.507	–0.009	–1.822	
	Matched	0.496	0.483	0.013	2.532	–38.968
Tertiary education	Unmatched	0.331	0.419	–0.089***	–18.382	
	Matched	0.333	0.329	0.005	0.955	94.805
Parent	Unmatched	0.469	0.531	–0.062*	–12.367	
	Matched	0.467	0.461	0.006	1.182	90.442
Couple	Unmatched	0.718	0.762	–0.044	–10.036	
	Matched	0.721	0.725	–0.004	–0.924	90.793
Net income	Unmatched	7.293	7.431	–0.137***	–16.941	
	Matched	7.292	7.284	0.008	1.010	94.038
Tenure	Unmatched	11.241	12.813	–1.572**	–13.833	
	Matched	11.408	11.111	0.297	2.614	81.103
Permanent contract	Unmatched	0.747	0.920	–0.173***	–47.747	
	Matched	0.754	0.754	0.000	–0.055	99.885
(Semi-)public company	Unmatched	0.249	0.405	–0.156***	–33.684	
	Matched	0.250	0.248	0.002	0.472	98.599
Low uncertainty	Unmatched	0.298	0.517	–0.219***	–45.625	
	Matched	0.304	0.312	–0.008	–1.701	96.272
Some uncertainty	Unmatched	0.396	0.222	0.174***	38.296	
	Matched	0.396	0.394	0.002	0.463	98.791
High uncertainty	Unmatched	0.204	0.044	0.160***	50.000	
	Matched	0.196	0.195	0.001	0.218	99.564
Primary sector	Unmatched	0.016	0.014	0.002	1.957	
	Matched	0.017	0.013	0.003	2.766	–41.339
Secondary sector	Unmatched	0.204	0.162	0.042*	10.857	
	Matched	0.200	0.206	–0.006	–1.463	86.525
Tertiary sector	Unmatched	0.302	0.250	0.052*	11.610	
	Matched	0.304	0.310	–0.006	–1.279	88.984
Quaternary sector	Unmatched	0.273	0.447	–0.174***	–36.772	
	Matched	0.275	0.271	0.004	0.782	97.873
White collar	Unmatched	0.776	0.810	–0.035	–8.626	
	Matched	0.779	0.777	0.002	0.555	93.566
Self–perceived health	Unmatched	3.065	3.240	–0.175***	–25.288	
	Matched	3.071	3.053	0.018	2.582	89.790
Chronic disease	Unmatched	0.241	0.228	0.013	3.128	
	Matched	0.237	0.243	–0.005	–1.183	62.180
Absenteeism	Unmatched	0.171	0.053	0.119***	38.203	
	Matched	0.154	0.149	0.005	1.579	95.867
Mental health	Unmatched	70.286	76.307	–6.022***	–35.039	
	Matched	70.550	70.649	–0.099	–0.578	98.350

Note: All variables are measured at time $t-1$. The year dummies are not reported. The 'Difference' column denotes significance of a two-sample t-test of equality of means. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

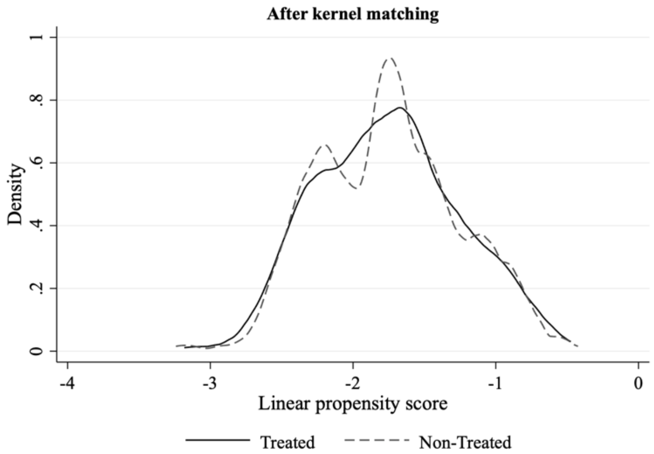

Figure 3: Distribution of the linear propensity score after kernel matching.

5.3. ATT estimates

Table 6 displays the estimated effect of experiencing unemployment on mental health. The first equation is essentially a mean comparison of mental health after treatment between treated and controls. The mental health score of people who have become unemployed is approximately 4.4 points lower than the score of employed individuals. This is statistically significant at the 1% level. The second equation applies the same method to assess whether there already was a difference in mental health between treated and controls before treatment occurred. Treated individuals have, on average, a mental health score that is 6.0 points smaller than mental health of controls. This is again statistically significant at the 1% level.

A difference-in-difference specification accounts for time-invariant differences in mental health and other important covariates between treated and controls. Matching makes mental health of treated and controls more comparable over time. Hence, PSM-DID is implemented to estimate the causal effect of unemployment on mental health. It was found that, on average, experiencing unemployment is associated with a decrease in mental health of –0.129 points, as compared to continuous employment. This is not statistically significant. Consequently, this does not support the first hypothesis that unemployment negatively impacts mental health.

Table 6: The effect of unemployment on mental health: main results.

	Correlation	Correlation	PSM-DID
	MHI_t	MHI_{t-1}	ΔMHI_t
Treatment	–4.397***	–6.022***	–0.129
	(1.160)	(1.228)	[1.186]
N_t/N_c	245/13491	245/13491	240/13491
Matching	No	No	Yes

Note: The table presents the effect of an unemployment experience on mental health. Robust standard errors in parentheses; bootstrapped standard errors (200 repetitions) in brackets. Significance: *10%, **5%, ***1%. N_t = number of treated, N_c = number of controls. Numbers refer to person-spells.

5.4. Robustness analysis

A number of robustness checks are performed. First, mental health is measured differently. A binary outcome variable, equal to 1 if the individual reported medication use for anxiety or depression and 0 otherwise, is used. This variable is more objective and indicative of the presence of a specific mental illness. Becoming unemployed is associated with a 1.6 percentage point increase in the probability of medication use, as compared to staying employed. This effect is not significant.

Robust standard errors are displayed as well. There is an ongoing discussion on how to estimate the standard errors with propensity score matching. Hence, a second approach is used to assess whether the results are robust to the standard error technique. The bootstrapped standard error is 1.186, while the robust standard error is 1.222. The ATT estimate is insignificant with both standard errors.

Next, two different matching techniques are used, namely 3-to-1 nearest neighbor caliper matching and radius matching. The first method entails that each treated individual is matched to three comparison individuals with the closest propensity scores, provided that the distance between the propensity score of the treated individual and the comparison individual is not too large. Radius matching uses *all* control observations within a given interval around the propensity score of each treated individual. The maximum tolerated distance (‘caliper’) is set to 0.25 of the standard deviation of the estimated linear propensity score, following the recommendation of Rosenbaum and Rubin (1985). With the use of nearest neighbor matching and radius matching, unemployment decreases mental health with 0.736 points and 0.249 points, respectively. These ATT estimates are more negative than the ATT estimate with kernel matching, but both are statistically insignificant and the results are still similar. This suggests that the results are robust to the matching method.

The propensity score is also estimated with a smaller set of conditioning variables. The use of a large set of conditioning variables can reduce the region of common support, as a more specific propensity score makes finding matches with similar propensity scores more difficult. Also, the variance of the propensity score estimates can increase when irrelevant variables are added, which makes the ATT estimates less precise (Caliendo & Kopeinig, 2008). Hence, a more parsimonious specification of the propensity score model is implemented to assess the sensitivity to the set of conditioning variables. Following the procedure implemented by Marcus (2014), the propensity score model is estimated by means of a stepwise probit regression with forward selection, only including the variables that are significant at the 10% level. This results in a smaller set of conditioning variables Z. The corresponding probit regression that estimates the propensity scores is displayed in Appendix A, Table A2.[11] The ATT estimate increases in absolute size (i.e., becomes more negative), but it is still highly insignificant.

In addition, treatment is only considered in case of unemployment due to company closure. If an individual experiences a mental health shock leading to job loss, the ATT estimate is biased because it doesn't take into account this reverse causality. Job loss due to plant closure is considered an exogenous reason for unemployment, implying that this treatment participation is unrelated to individual's health (and individual characteristics in general). The effect of unemployment due to plant closure on mental health is slightly larger than the ATT of the original treatment, but the results are both statistically insignificant.

Moreover, person-spells are now defined over 2 years instead of 1 year. That is, the treatment group is employed at $t-2$ and unemployed at time t, while the control group is continuously employed over this period. The corresponding outcome of interest is $\Delta Y_t = Y_t - Y_{t-2}$. For this sample the years 2009, 2011, 2013, 2015, 2017, and 2019 are used. Many empirical studies on the unemployment effect on mental health have used two-year-periods (see e.g., Marcus, 2013; Riumallo-Herl et al., 2014; Schmitz, 2011). This robustness analysis ensures that the absence of an unemployment effect is not due to the specification of the treatment interval. The impact on mental health, a decrease of 1.274 points, is now more severe than the effect of the original estimation. However, it is still not statistically significant. Hence, the non-significant effect in this thesis is not due to the shorter person-spells.

As a last sensitivity analysis, the unemployment effect is examined over a longer term. An individual is considered treated if he/she is employed at $t-1$, unemployed at t, and stays unemployed until $t+1$. The sequence is E-U-U (E = employed, U = unemployed). Control observations are continuously employed over the same period (E-E-E). The outcome is then $\Delta Y_{t+1} = Y_{t+1} - Y_{t-1}$.

[11] The conditioning variables Z include age, age squared, net income (ln), tenure, permanent contract, some uncertainty, high uncertainty, quaternary sector, chronic disease, absenteeism, mental health, year 2012, and year 2018.

Becoming long-term unemployed leads to a decrease in mental health of 1.875 points, as compared to staying employed. This effect is more negative than the main ATT, although statistically insignificant.

This long-term outcome is also examined when treatment is defined like job loss. Treatment is similar to long-term unemployment, but treated individuals can be both employed and unemployed in $t + 1$ (E-U-E/U). The outcome and control sequence are built the same way as described above. The ATT estimate is non-negative and insignificant. Compared to continuous employment, job loss is associated with a 0.790-point increase in mental health.

Table 7: Robustness analysis.

Difference with main specification	ATT	S.E.	N_t/N_c
Outcome: medication use for anxiety or depression	0.016	0.012	238/13296
Robust standard errors	–0.129	1.222	240/13491
Matching method			
Nearest neighbor matching	–0.736	1.582	241/13491
Radius matching	–0.249	1.082	241/13491
Z conditioning variables	–0.456	1.230	241/13491
Treatment: plant closure	–0.275	2.109	76/11886
Two-year person-spells $[t-2, t]$	–1.274	1.423	174/6159
Outcome: ΔY_{t+1}			
Treatment: unemployment	–1.857	1.749	101/10397
Treatment: job loss	0.790	1.548	168/10397

Note: Bootstrapped standard errors (S.E.) (200 repetitions). Significance: *10%, **5%, ***1%. N_t = number of treated, N_c = number of controls. Numbers refer to person-spells.

5.5. Heterogeneity analysis

Although no significant effect of unemployment on mental health was identified for the overall sample, significant effects could still exist for certain subgroups. The theory that underpins this is detailed in the theoretical framework. Heterogenous effects based on gender, age, and cohabitation are examined. The conditional average treatment effects on the treated (CATT) are specified in Table 8.

While the ATT for men is approximately zero, the impact on mental health for women is more negative, at –0.362 points. Neither conditional effects are statistically significant. The second hypothesis, which articulates that unemployment leads to a stronger decrease in mental health for men than for women, is rejected.

Next, people aged 50 and above are examined separately from individuals aged 30–49. Individuals younger than 30 are excluded from this analysis. The number of treated individuals under 30 is low, which makes the results for this subgroup useless. The results are intriguing. For middle-aged people is becoming unemployed, compared to staying employed, associated with a decrease in mental health of 3.802 points. This is significant at the 10% level. For individuals above 50, mental health *improves* by 2.543 points, although this is not significant. The difference in effect size of 6.3 points between the two groups is considered relevant. This shows support in favor of the third hypothesis, which states that the effect of becoming unemployed on mental health is more detrimental for younger individuals than for older individuals. However, it must be kept in mind that the results for neither subgroups on their own were statistically significant at the conventional 5% level.

At last, people who live with their partner (independent of marital status) are analyzed separately from individuals who don't live with a partner. The results show that experiencing unemployment for singles is associated with an average reduction in mental health of –2.324 points on the 100-point MHI scale, in comparison to single individuals who stay employed. The ATT estimate for individuals living with their partner is 0.667 points. Both estimates are statistically insignificant, as well as the difference between them. However, the difference of approximately 3 points could have some meaning in practice. Nonetheless, the hypothesis cannot be accepted based on statistical significance.

Table 8: Conditional average treatment effect on the treated (CATT).

Group of interest	ATT	S.E.	N_t/N_c
By gender			
Male	0.042	2.053	116/6841
Female	–0.362	1.529	120/6650
By age			
50+ years	2.543	1.713	125/5271
30–49 years	–3.802*	1.983	93/6916
By cohabitation			
Single	–2.324	3.166	64/3206
Partner	0.667	1.324	172/10285

Note: The table presents the effect of an unemployment experience on mental health for the subgroups. Bootstrapped standard errors (S.E.) (200 repetitions). Significance: *10%, **5%, ***1%. N_t = number of treated, N_c = number of controls. Numbers refer to person-spells.

6. Discussion & Conclusion

6.1. Interpretation of the results

6.1.1. Overall effect

The results showed that unemployed individuals have a significantly lower mental health score than employed individuals. This negative correlation is in line with the general conclusion of previous literature. However, the analysis did not find a causal effect of unemployment on mental health. This finding was robust to various sensitivity measures. This is in contrast with the earlier described theory and empirical evidence. However, potential reasoning for the non-effect does have common ground with the theory and evidence. First, it is likely that characteristics of the labor market and the unemployment benefits scheme in the Netherlands make the effect smaller. The Netherlands has a relatively high level of unemployment protection. Previous studies declared that this diminishes the effect size (Riumallo-Herl et al., 2014; Voßemer et al., 2018). In addition, the general theory suggests that individuals with a stronger attachment to their work would experience a larger decline in mental health in case of unemployment. The part-time employment rate in the Netherlands is much higher than in other countries (OECD, 2020). Consequently, the mental health effect of unemployment is smaller than in other countries on the basis of environmental characteristics. It could also be possible that unemployment declines at a later stadium than at the point it was measured. The average unemployment duration in a person-spell was 5.5 months. The negative effect is then potentially not yet powerful, as the unemployed individual still gets unemployment benefits. This thesis also analyzed the effect of long-term unemployment, compared to continuous employment. This results in a larger decline in mental health, but the estimate was not statistically significant. However, the difference does suggest that this link should be explored more thoroughly. These results suggest that the correlation between unemployment and mental health is due to health selection effects.

6.1.2. Subgroup analysis

The analysis does not find evidence that the unemployment effect depends on gender. The CATT estimates for men and women were insignificant, as well as their difference. This is contrary to the outlined hypothesis that the negative effect is stronger for men than for women in the Netherlands. A potential explanation is that the social norm for men and women is most divergent during parenthood. However, more than half of the treated individuals is at least 50 years old when they transition to unemployment. It is still possible that the impact on mental health differs between men and women at a younger age. This would still be in line with the general theory. The underlying idea is that men have a higher need for employment than women during parenthood due to their positions in society. When the children become adults, these differences in gender norms decrease.

The unemployment impact on mental health is more negative for the middle-aged group than for individuals that are 50 years and older, with a difference of 6.3 points on the MHI scale. The mental health effect is substantial and weakly significant for the 30-to-49 age group. In contrast, individuals that are at least 50 have a non-negative and insignificant effect on mental health. This analysis supports the theory and hypothesis that people aged 30-49 experience, on average, a stronger decline in mental health due to unemployment than older individuals do. These results are also in line with the empirical evidence of Gathergood (2013).

Unemployment, as compared to staying employed, leads to lower mental health for singles and a slight increase in mental health for individuals with a cohabiting partner, although both estimates are statistically insignificant. The estimates are not significantly different either, but the difference in ATT estimates of 3 points does suggest practical relevance. This is in line with the proposed theory. A study by Milner et al. (2016) concluded that unemployment of people with high social support was associated with a much smaller decline in mental health than the decline of people with lower perceived social support. Since partners can give you financial and social support during an unemployment experience, it is expected that the mental health of people with a partner is more robust to a transition in unemployment than the mental health of single individuals.

6.2. Limitations

The biggest limitation of this thesis is the inability to verify the assumptions of the matching strategy. Although some steps can be evaluated in the matching process, such as the ability of matching to balance the covariates, the main assumption that treated and matched controls would have parallel trends in the absence of treatment cannot be tested formally. The use of an unemployment measure with exogenous variation would be ideal for interval validity. Many empirical studies have implemented unemployment due to plant closure in the strategy. The exogenous variation in unemployment cannot be explained by health, which improves the identification of the causal effect of unemployment on mental health. However, the use of unemployment due to plant closure has several pitfalls. The prevalence of plant closures is very limited, which decreases the sample size drastically (Schmitz, 2011). Also, the mental health consequences of unemployment might differ per job loss reason (Brand, 2015). Third, plant closures apply mostly to specific settings and individuals with certain specific characteristics (Browning & Heinesen, 2012; Marcus, 2013; Schmitz, 2011). The unemployment effect due to plant closure is thus difficult to generalize. Hence, there is a tradeoff between internal validity and external validity.

The assumption that treated and matched controls have parallel trends before treatment implies that there is no long-term direct health selection. Nonetheless, the methodology doesn't account for a health shock between t-1 and the point of job loss that could lead to unemployment. Hence, presence of this short-term health selection could bias the results. In the sample this period is on average 6.7 months long, with a median of 7 months. The results suggest that this bias is unlikely. The impact of unemployment due to plant closure on mental health is similar in size and significance. This definition of treatment assumes that the reason of unemployment is exogenous. In addition, employers cannot instantly dismiss workers who experienced a health shock (Uitvoeringsinstituut Werknemersverzekeringen [UWV], 2019). If employees voluntarily quit, they should be reported as NILF. Hence, it is implausible that a short-term health shock that leads to unemployment is present in this analysis. However, this is merely an assumption and should be investigated.

Another limitation is the use of self-reported data. The treatment variable is a subjective measurement of employment status and is reported by the household head instead of the individual self. In addition, there is no information on employment status in between two consecutive months. Hence, there is not a good measure of unemployment duration. Information on previous unemployment experience before the start of the panel is also not available. Duration of unemployment and the cumulative experience of unemployment are relevant characteristics, as various studies have suggested that the effect size depends on these (Janlert et al., 2015; Milner et al., 2014; Paul & Moser, 2009).

6.3. Conclusion

This thesis examined whether unemployment negatively affects mental health in the Netherlands. No evidence of a significant effect was found. There was only weak support for the negative effect of unemployment on mental health for individuals in the 30-to-49 age group. There was no different in effect size between men and women, and between singles and cohabiting partners. This study contributes to the current literature by using advanced economic methods to estimate the causal effect. Previous literature concluded that the effect depends on the labor market characteristics of the region that is being analyzed. The effect was not yet studied in the Netherlands. At last, the effect was estimated for certain subgroups. This has also not been done much.

Further research should explore the long-term effects of unemployment, as well as analyze the possibility of dynamic treatment effects. All results should be analyzed for the middle-aged individuals in particular, since they are most attached to the labor market. In addition, the causal effect of mental health on employment status should be assessed. The results of this thesis suggest that there is a health selection effect. Causal evidence on this relationship is relevant for policy design that tries to diminish the mental health problem in the Netherlands.

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Appendix

Appendix A: Assisting tables and figures

Table A1: Balancing property.

	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6
N_t/N_c	12/5873	80/5559	62/1226	43/518	41/295	7/20
Lower p-score	–3.701	–2.494	–1.890	–1.588	–1.286	–0.679
Linear p-score	2.09*	2.28*	1.270	0.790	2.45*	1.340
Variable						
Age	–0.580	–0.640	0.940	–0.040	0.700	1.610
Age squared	–0.770	–0.530	1.050	–0.090	0.500	1.760
Male	–1.820	–0.310	0.210	–0.350	1.870	2.19*
Tertiary education	–1.760	–0.470	1.120	0.820	–0.790	2.64*
Parent	0.680	–0.870	–0.040	0.840	0.180	–0.310
Couple	1.140	0.230	–0.540	–0.530	0.120	–0.130
Net income	–2.05*	–1.340	0.640	0.780	–0.500	1.370
Tenure	–1.800	–0.760	–0.170	1.140	1.470	–0.670
Permanent contract	–2.38*	–2.15*	0.890	–0.630	0.620	0.870
Public company	–0.500	–0.690	0.540	0.550	–1.030	2.72*
Low uncertainty	0.900	0.130	–1.500	–0.050	–1.010	
Some uncertainty	0.280	–0.470	1.440	–0.860	0.530	–0.960
High uncertainty	–0.090	–0.470	0.200	1.310	–0.390	0.960
Primary sector	–0.390	–0.230	–0.810	0.180	1.920	–0.580
Secondary sector	–0.200	–0.200	0.130	–0.460	0.340	1.740
Tertiary sector	1.920	–0.210	0.640	–1.320	–0.320	0.540
Quaternary sector	–1.510	0.010	–0.120	1.550	–1.010	
White collar	–1.530	–0.080	0.120	1.470	–1.070	0.320
Self–perceived health	–1.040	–0.880	1.840	0.240	–0.830	1.190
Chronic disease	0.110	1.490	–1.330	–0.790	0.530	–0.520
Absenteeism	–0.300	0.330	–1.510	0.130	1.900	0.800
Mental health $t-1$	1.740	–0.680	1.290	–0.360	–2.15*	1.130
Year 2009	–1.350	–1.380	2.11*	–0.810	1.660	2.72*
Year 2010	1.020	–0.890	1.340	–0.820	0.050	–0.580
Year 2011	0.010	–0.810	–0.820	2.50*	0.070	0.300
Year 2012	0.510	1.120	0.500	–1.490	–0.830	–0.300
Year 2015	–0.950	0.520	–0.230	0.460	–0.180	–0.850
Year 2016	–0.380	0.770	–0.390	–0.580	0.510	–0.850
Year 2017	–0.380	–0.520	–0.420	2.33*	–0.790	0.300
Year 2018	–0.870	0.690	–0.770	0.330	–0.840	

Note: The table reports the t-statistic of the two-sample t-test of equality of means. N_t = number of treated, N_c = number of controls. Lower p-score indicates the lower limit of the interval of the linear p-score in each block. An empty cell means the t-test was not applicable for that variable in that block. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2: Probit model for experiencing unemployment with Z conditioning variables.

	Coefficient	Standard Error
Age	–0.054***	0.021
Age squared	0.001***	0.000
Net income	–0.059*	0.035
Tenure	–0.009***	0.003
Permanent contract	–0.547***	0.083
Some uncertainty	0.367***	0.063
High uncertainty	0.801***	0.087
Quaternary sector	–0.392***	0.063
Chronic disease	–0.148**	0.070
Absenteeism	0.513***	0.091
Mental health	–0.006***	0.002
Year 2012	0.251***	0.074
Year 2018	–0.407***	0.130
Observations	13736	
Log-likelihood	–1049.144	

Note: All explanatory variables are measured before treatment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

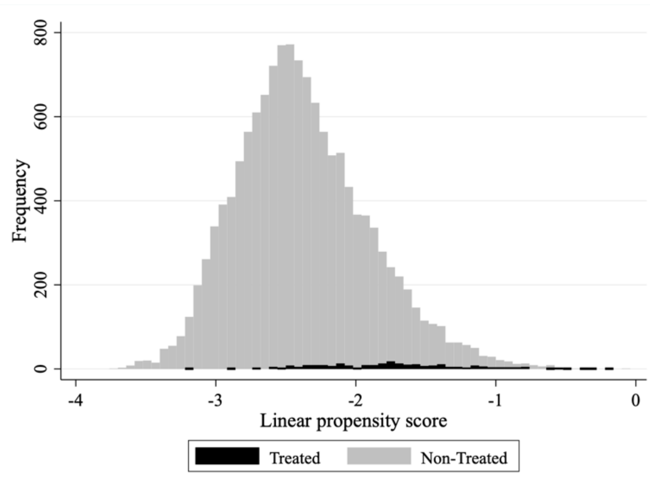

Figure A1: Histogram (frequency) of the linear propensity scores before matching.

Figure A2: Density of the linear propensity scores after nearest neighbor matching.

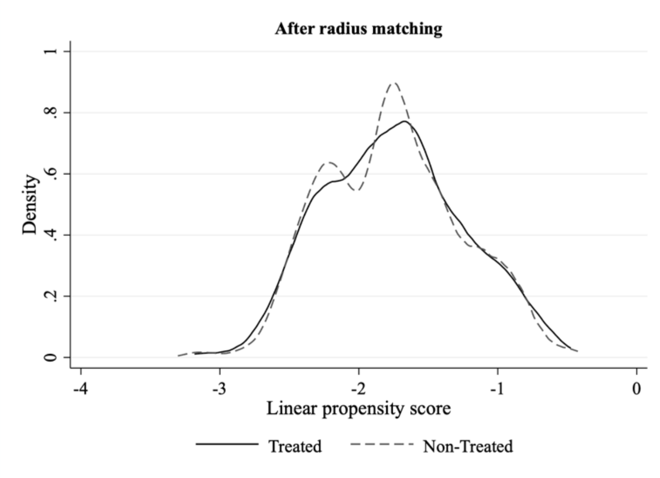

Figure A3: Density of the linear propensity scores after radius matching.

Appendix B: Data information

Table B1: Overview of the conditioning variables.

Variable	Definition	LISS variable code
Demographic information		
Male	0 = female, 1 = male	geslacht
Age	in years, second order polynomial	leeftijd
Tertiary education	1 = HBO or WO degree, 0 else	oplmet
Parent	1 = children under 18 in household, 0 else	aantalki
Partner	1 = living with partner, 0 else	woonvorm
Year	survey year dummies	
Labor market information		
Personal income	natural logarithm of personal monthly net real income (2015 = 100)	nettoink
Tenure	in years	cw##x134
Permanent contract	1 = permanent contract, 0 else	cw##x121
Public firm	1 = (semi-)public firm, 0 else	cw##x122
White collar	1 = white collar job, 0 else	cw##x404
Job uncertainty	4 categories (no, low, some, high uncertainty)	cw##x435
Sector	5 categories (primary, secondary, tertiary, quaternary, other)	cw##x402
Health information		
Self-perceived health	SPH (1–5; 1 = poor, 5 = excellent)	ch##x004
Mental health	MHI-5 (0–100)	ch##x011–015
Chronic disease	1 = long-standing disease or handicap, 0 else	ch##x018
Absenteeism	1 = not working a full week due to health, 0 else	ch##x100