The immediate effect of becoming unemployed on physical and mental health in the United Kingdom

Thesis

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Abstract

Background
Employment is of major importance for people in modern societies as a source of income as well as for shaping people's social life. Therefore, the impact of unemployment is a relevant concern for policymakers and researchers. In theory, unemployment can cause a deterioration in both physical and mental health, as a result of changes in lifestyle, income loss, loss of a social network and feelings of distress. In practice, a negative correlation between unemployment and health has been well established. Nevertheless, current literature shows ambiguous results on whether there is a causal link between unemployment and health, or whether this negative correlation is mostly driven by confounding and selection of unhealthy people into unemployment (reverse causality). Hence, this thesis aims to investigate the immediate impact of becoming unemployed on mental and physical health, specifically in the context of the United Kingdom.

Methods
Drawing on data from The UK household Longitudinal Study in the period 2009-2019, a difference-in-difference (DiD) model in combination with propensity score matching (PSM) was used, to be able to establish a causal relationship between unemployment and both physical and mental health. The sample includes people between the ages of 16-64, who have either experienced unemployment within a year (treatment group) or have been employed continuously during a year (control group). By employing DiD, unobserved individual fixed effects and common period effects are removed. For a DiD estimator to be valid, the common trend assumption needs to hold. As there are many confounding factors that make this assumption implausible, propensity score matching was used to match similar individuals of the treatment and control group, with respect to important confounding factors. Importantly, individuals were matched on health indicators as well, to overcome the problem of reverse causality. The SF-12 mental component summary and physical component summary served as the main outcome variables.

Results
PSM succeeded in creating a similar treatment and control group, as all included covariates were sufficiently balanced after matching. Subsequently, the average treatment effect on the treated showed a decrease in mental health of 2.442 points, which can be regarded as a small and strongly significant effect. In contrast, becoming unemployed had no impact on physical health. Effects were similar for women and men, but differed between age groups. The youngest age group (16-28) seemed to experience the steepest decline in mental health, and the oldest age group (53-64) the smallest decline. The results were robust to a different matching strategy, an alternatively constructed independent variable, and a different health outcome, namely the GHQ-caseness score. Additionally, assessment of the pre-treatment assignment health trajectories of the treatment and control group showed similar trends for both groups, confirming the likelihood that the common trend assumption holds.

Discussion
This thesis suggests that becoming unemployed has a negative effect on mental health, but not on physical health, although it might be that the effect on physical health only becomes apparent in the long-term. Future research that looks at the long-term would therefore be valuable, in addition to research that investigates which factors specifically make people more likely to experience a health decline as a result of unemployment. The main policy implications of this thesis are that the government, employers, and health professionals should increase efforts to prevent unemployment as much as possible and support and assist people that become unemployed, to lessen the burden on health.

Contents

1. Introduction

Employment is incredibly important for most people in modern societies (Nordenmark & Strandh, 1999). It is not only a primary source of income, but also of significance in shaping an individual's social identity (Jahoda, 1982). Consequently, the impact of unemployment on individuals and society as a whole is a serious concern for policymakers and researchers. Periods of high unemployment rates in the 1930s and from 1980 onwards have motivated researchers to investigate the impact of unemployment and provided them with the necessary data for research (Wilson & Walker, 1993).

Most recently, the COVID-19 pandemic has rekindled worries about the potential damage that unemployment causes. The pandemic and the resulting protection measures in place in countries, such as the closing of shops and social distancing measures, have severely impacted the global economy, which is for instance reflected in increasing unemployment rates (International Monetary Fund, 2020). One of the countries that has been severely hit by the COVID-19 pandemic is the United Kingdom. As of June 2021, the country has over 4,5 million confirmed cases of the coronavirus and with more than 125.000 reported deaths, the UK has the highest number of COVID-19 deaths in Europe (European Centre for Disease Prevention and Control, 2021). Economically, the consequences of the pandemic are clearly visible as well. The unemployment rate in the UK was estimated at 5.0% in January 2021, which is an increase of 1.1 percentage points in just a year. In total, this amounts to 1.7 million people being unemployed (Office for National Statistics, 2021a).

Unemployment can affect society in numerous ways. Most notably and undisputable is the financial impact for individuals and their families, caused by the loss of income. Moreover, high unemployment rates have budgetary consequences for the government due to a loss of tax revenue and increased use of social services (Parliament of Australia, n.d.). Less straightforward, unemployment may affect the health of individuals in a negative way. This would further increase the costs of unemployment for the individual and the country, both directly, through increased health care costs, and indirectly through decreased productivity (Harris & Morrow, 2001). The association between health and unemployment has been researched extensively throughout the years. Consistently, this research points towards a negative correlation between both mental and physical health and unemployment. The unemployed are reported to have an increased risk of depression, anxiety disorders and alcohol abuse (Paul & Moser, 2009; Herbig et al., 2013). Furthermore, higher rates of overall mortality, as well as mortality caused by cardiovascular diseases are seen. Lastly, unemployed people are more likely to take medication, visit a physician and have higher hospital admission rates (Jin et al., 1997).

Although a negative correlation between unemployment and health is evident, the driver of this correlation is less apparent. On the one hand, theory suggests that unemployment might cause worse health. First off, loss of income could force people to forgo essential medical care or adapt a cheaper, but less healthy lifestyle. Moreover, the psychological impact of job loss could cause mental illness and eventually even physical health conditions (Stauder, 2019). On the other hand, evidence demonstrates that the selection hypothesis explains at least in part why unemployed people are in worse health: people with mental or physical health conditions are more likely to become unemployed. Moreover, they are more likely to stay unemployed, thereby increasing the chance of healthy individuals to return on the labor market (García-Gómez et al., 2010; Lindholm et al., 2001). Thirdly, confounders might bias the relationship between health and unemployment. For instance, socioeconomic status (SES) causes people to be more at risk of becoming unemployed (Doku et al., 2019). In addition, the socioeconomically disadvantaged are less healthy. The fact that SES is associated with both unemployment risk and health status might distort the association between unemployment and health.

Disentangling the mechanisms that explain the correlation between health and unemployment and identifying their impact is important to get a better understanding of this relationship. Moreover, it can help to better inform policy. In particular, investigating the causal relationship between unemployment and health is beneficial for two reasons. Firstly, it can provide relevant information to policymakers, as a causal effect of unemployment on health should be considered when evaluating the costs of unemployment. Higher costs on a healthcare and societal level are reason for policymakers to increase efforts to battle unemployment. In addition, evidence of unemployment resulting in worse health may be important knowledge for healthcare providers. This information could be an incentive to develop preventive and supportive programs specifically targeting recently or long-term unemployed people to lessen the health consequences.

Literature investigating a causal relationship between unemployment and health is significantly scarcer than research on just the association. This is most likely the result of the empirical challenges that come with trying to design an experiment that can convincingly prove causation. The limited literature that is available on causation shows ambiguous results. Some research finds a negative effect of unemployment on mental health (Gathergood, 2013; Gebel & Voßemer, 2014) and others do not find a causal effect (Schmitz, 2011; Ronchetti & Terriau, 2019). These inconclusive results could be due to many factors specific to the studies. For instance, the studies use data from different countries. Importantly, only Gathergood (2013) uses UK data for their research. Moreover, the researchers employ different empirical strategies to investigate a causal link between unemployment and health. Regardless, the scarcity of available research and the ambiguity of the results create opportunity for more research on this topic. In combination with the fact that only one study uses data from the United Kingdom, this leads to the following research question:

What is the immediate effect of becoming unemployed on physical and mental health in the United Kingdom?

Reader's guide

The theory behind the causal effect of unemployment on health and evidence on a causal link will be discussed in the 'Background' chapter. Moreover, country specific factors that influence the impact of unemployment on health, specifically in the UK context, will be evaluated. Lastly, potential confounding factors that might bias the relationship between unemployment and health will be assessed. Subsequently, the empirical strategy will be explained in the 'Methods' section. Thereafter, a description of the dataset and the variables that will be used in the models will be provided in the 'Data' section. The findings from the different analyses will be presented in the 'Results' chapter. In the 'Discussion' section, these finding will be elaborated on. Moreover, the strengths and limitation of the empirical strategy will be discussed. Lastly, the policy implications of the results and future research suggestions will be provided.

2. Background

In this chapter, the relationship between unemployment and health will be further explored. Firstly, the causation hypothesis will be explained in detail and evidence for this hypothesis will be discussed. Secondly, country specific factors that might affect the impact of unemployment on health will be examined and information on how these factors might play a role in the context of the United Kingdom will be presented. Lastly, the confounders that might bias the relationship between unemployment and health will be discussed.

The causation hypothesis

As mentioned in the introduction, one of the hypotheses as to why a correlation between unemployment and health is found, is that becoming unemployed might cause a deterioration in health. This potential causal link is what this thesis aims to establish. There are multiple explanations for the causation hypothesis.

Firstly, the most straight-forward mediating factor is the loss of income, or manifest deprivation, that is the result of becoming unemployed (Jahoda, 1982). As a consequence of a significant reduction in income, individuals are forced to change their lifestyles to reduce spending (Korpi, 2001). They could have to cancel a gym or sport club membership, thereby decreasing their daily amount of exercise. Moreover, they may not be able to afford healthy foods, such as fresh vegetables, as these are more expensive. In worse cases, a loss of income might lead individuals to forgo medical therapies that are not covered by health insurance (Stauder, 2019). All these lifestyle changes could cause a deterioration in physical health. In addition, income loss might affect mental health. If people need to use their savings, this leads to the feeling of a loss of agency over life, inability to plan for the future and it makes people more vulnerable to future economic hardship (Stauder, 2019). Moreover, financial restrictions may result in the need to move house, which at the same time could disrupt an individual's social network (Gebel & Voßemer, 2014). Furthermore, each of the factors mentioned above could lead to distress.

Secondly, Jahoda (1982) argues that individuals suffer from latent deprivation caused by job loss. She says that employment fulfills important psychological needs of people. She believes that employment provides a social network, a social identity, and the feeling of participating in a collective. Furthermore, it provides a time structure and regular activity. It is likely that when these important aspects of psychological health fall away in unemployment, this leads to a decrease in mental well-being (Nordenmark & Strandh, 1999). In contrast, it is conceivable that people adapt to unemployment in the long-run, for example by attempting to fulfill these psychological needs in different ways.

Aside from the direct impact of manifest deprivation on physical health, the distress caused by manifest and latent deprivation might have an indirect effect on physical health (Stauder, 2019). Distress and other mental health problems are known to cause an increase in unhealthy behaviors such as smoking and weight gain (Marcus, 2014). Subsequently, these unhealthy behavioral patterns mediate the development of an abundance of diseases, such as diabetes mellitus, cardiovascular disease, cancer, and COPD (CDC, 2020). Noteworthy, these indirect effects on physical health might take time to develop and manifest. Therefore, an effect on physical health might only be visible in the long-run. Moreover, since the financial benefits people receive when becoming unemployed reduce over time, the financial impact on physical health will increase over time (Stauder, 2019). Together with the fact that people might adapt to unemployment in the long-run, Stauder (2019) proposes a u-shaped effect of unemployment on mental health.

Evidence on the causation hypothesis

As mentioned in the introduction, proving causation in a methodologically sound way is difficult. This is because of the bias of reverse causality, meaning the selection of unhealthy individuals into unemployment, and the presence of confounding that might bias the relationship between health and unemployment. To establish a causal relationship, researchers predominantly use either an instrumental variable approach or propensity score matching in combination with a difference-in-difference approach. The purpose of using an instrumental variable is to ensure that entry into unemployment is caused exogenously, thereby overcoming the problem of reverse causality and confounding bias. The instrumental variable that is most often utilized is plant closure. It is argued that getting laid off because of a plant closure is not related to an individual's characteristics, therefore exogenous to the health of that individual as well as confounding factors that might bias the relationship between unemployment and health (Brand, 2015). The other empirical strategy most often used is propensity score matching in combination with a difference-in-difference estimator (PSM-DiD). The matching is done to create a similar treatment and control group, thus allowing to control for confounders. Moreover, it overcomes the problem of reverse causality by including lagged health variables. The difference-in-difference model is used to account for individual and time fixed effects that might bias the relationship.

Below, firstly three studies that use plant closure as an instrumental variable will be discussed. These studies were the most relevant to this thesis, considering they investigated a similar age group and had relatively high methodological quality. Following, the only three studies that use PSM-DiD will be discussed. Lastly, the study of Gathergood (2013) will be evaluated, as it is the only one using UK data. Given that the results of the studies vary, with some reporting a causal effect and others finding no effect, it is interesting to analyze whether the country they research, the empirical strategy they adopt, or the outcome measures they use might explain some of the differences in results.

Evidence using plant closures as an instrumental variable

Starting, Schmitz (2010) uses data from the German Socio-Economic Panel (SOEP). Taking unemployment because of plant closure and measuring the effect on health satisfaction, mental health, and hospital visits, he finds no effects on health for any of the outcome variables. Similarly, Browning et al. (2006) find no effects. They used a sample of the male population of Denmark to see the effect of displacement on hospitalization for stress-related diseases. Displacement was defined as being laid off in the context where a firm laid off at least 30% of their workers at once. To account for the fact that displaced employers might have found a new job relatively quickly, they also analyzed a subgroup that was unemployed for at least 10% of the year after displacement. Nonetheless, they found no significant effects on health. The stress-related diseases they included for their outcome variable were diagnoses of physical diseases that they believed to be linked to stress and depression, such as hypertension and other cardiovascular diseases as well as gastritis and peptic ulcers. Although stress and depression are indeed linked to increased risk of cardiovascular diseases, the same does not hold for gastritis and peptic ulcers. While before the discovery of the H. pylori bacterium, stress was believed to be the cause of these diseases, it is now well known that the majority of gastritis and peptic ulcer cases are caused by H. pylori, NSAID use or smoking (Turner, 2015). Therefore, in my opinion, hospitalization due to gastritis or a peptic ulcer is an inappropriate outcome measure. In contrast to Schmitz (2010) and Browning et al. (2006), Kuhn et al. (2007) found effects on two health outcomes, using Austrian data. They measured the effect of job loss induced by plant closure on expenditures on medical treatments, expenditures on antidepressants and related drugs and hospitalization due to mental health problems. They found that unemployment has a significant effect on antidepressant drug expenditures and expenditures on related drugs. Additionally, they found that unemployment increases hospitalization due to mental problems for men, but not for women.

Despite the frequent use of plant closures as an identification strategy, the interpretation of those results should happen with caution (Brand, 2015). Firstly, looking at plant closures significantly limits the study population. People working at these types of places are often blue-collar workers located in specific areas. Therefore, although using plant closures raises internal validity, the generalizability of the results decreases. Secondly, the selected controls in these studies should be similar to individuals laid off due to plant closures. The three studies mentioned above did this by either controlling for relevant factors that might differ between the treatment and control group (Schmitz, 2010) or by matching treatment individuals to controls with similar characteristics (Browning et al., 2006; Kuhn et al., 2007). Thirdly, taking plant closures as an instrumental variable might not completely remove reverse causality, as more qualified and healthier workers may resign and start working elsewhere when hearing about the impending closure. Likewise, when considering displacement, it is possible that less healthy workers are more easily displaced. Lastly, individual job loss may have a different impact on someone than job loss in the context of plant closures. Individual layoff in a time of economic expansion brings about questions of capability and integrity of the worker by employers and people in the worker's social network (Brand, 2015). Moreover, the stress around one's competency and the stigma around getting laid-off can cause mental illness. This is in stark contrast with the situation of mass layoffs and plant closures in economic recession, where job loss is more obviously not the result of the worker's functioning, but of external factors. The psychological consequences in this scenario may therefore be less.

Evidence using PSM-DiD

The oldest of the three articles is by Böckerman and Ilmakunnas (2009). They assessed the relationship between unemployment and self-assessed health as measured by the question 'How is your health in general' in Finnish data. They used a few different techniques, one of them being the PSM-DiD approach. They found no effect of becoming unemployed on self-assessed health. As they only had one outcome measure that consists of a single question on health, it might be that this outcome measure was not sensitive enough to detect changes in health because of unemployment. Similarly, Ronchetti and Terriau (2019) found no effect using French panel data. They employed PSM-DiD to investigate the effect of unemployment on self-perceived health. For self-perceived health they used the same question as Böckerman and Ilmakunnas (2009), in addition to a dummy variable that equals 1 if the individual answers the question with 'very good' or 'good' and equals 0 if the individual answers the question with 'fair', 'bad' or 'very bad'. For both these outcome measures the authors found no significant effects. Although the authors used two outcome measures, one is an adaptation of the other. Therefore, their outcome measures are still very limited. In contrast, Gebel and Voßemer (2014) found a significant effect of a transition between employment and unemployment on psychological health but not on physical health. Like Schmitz (2010), they used German SOEP data. However, different from the other two studies using PSM-DiD, aside from investigating the transition from employment to unemployment, they also looked at the transition from unemployment back to employment. They measured psychological health using the question 'How satisfied are you with your life, all things considered', with possible answers ranging from 0 to 10. Physical health was measured with a similar question and the same 10 answer options. They found significant effects of a similar effect size for both the effect of unemployment and re-employment on psychological health, but found no effect of either of the two employment transitions on physical health. Given the fact that they only examined the short-term effect of employment transitions (one year), it could be that an effect on physical health was not yet pronounced enough to be measured.

Industry-age-year unemployment rates as an instrumental variable (Gathergood, 2013)

The only study that uses UK panel data is by Gathergood (2013). Opposed to the articles mentioned above, he uses a different identification strategy. To ensure that unemployment is caused exogenously, he used industry-age-year unemployment rates to predict the risk of unemployment of an individual. Consequently, he used this predicted unemployment as an instrumental variable for unemployment. Two outcome measures for psychological health were used, namely the General Health Questionnaire and whether an individual is receiving treatment for anxiety-related conditions. The results showed that unemployment worsens both the GHQ score and increases anxiety-related conditions. The results of the study should be interpreted with caution as using industry-age-year unemployment rates as an instrument for unemployment is questionable. One of the most important conditions for using an instrumental variable is that the instrument only has an effect on the outcome through the independent variable of interest, in this case unemployment. However, as the author himself mentioned, the unemployment rate in the area influences how people perceive unemployment. High local unemployment rates are associated with a smaller deterioration in health when becoming unemployed, which is called the social norm effect (Clark, 2003). This social norm effect implies that industry-age-year unemployment rates not only influence the likelihood of unemployment of an individual, but also have an effect on that individual's health through how they perceive unemployment. This could impact the results.

Concluding, the studies discussed are very heterogenous both in study design and the data they use. It seems there is no clear reason why some studies found an effect and others did not. The fact that some studies found no significant effects might be explained by the poor choice of outcome measures. Moreover, the use of data from different countries might explain some differences, as there might be country specific factors that influence how large the impact of unemployment is on health. This is explained in the following section.

Country specific factors influencing the impact of unemployment on health

Firstly, the health insurance policy in a country may be of importance. Individuals living in countries where insurance is not or less affordable or where the unemployed get dropped from public insurance, may be more prone to forgo necessary healthcare than individuals living in countries where this is not the case (Stauder, 2019). As discussed before, this could result in worse physical health outcomes. Secondly, the social safety net in place in a country might influence the relationship between unemployment and health. The social safety net determines to what extent individuals carry the financial burden of unemployment. As the loss of income that comes with job loss is one of the explanations as to why unemployment might cause worse health (Jahoda, 1982), it is important to understand how large the impact of income loss is in the country of interest, relative to other countries. As the data that will be used in this study is from the United Kingdom, below, these country specific factors will be further explored in the context of the UK.

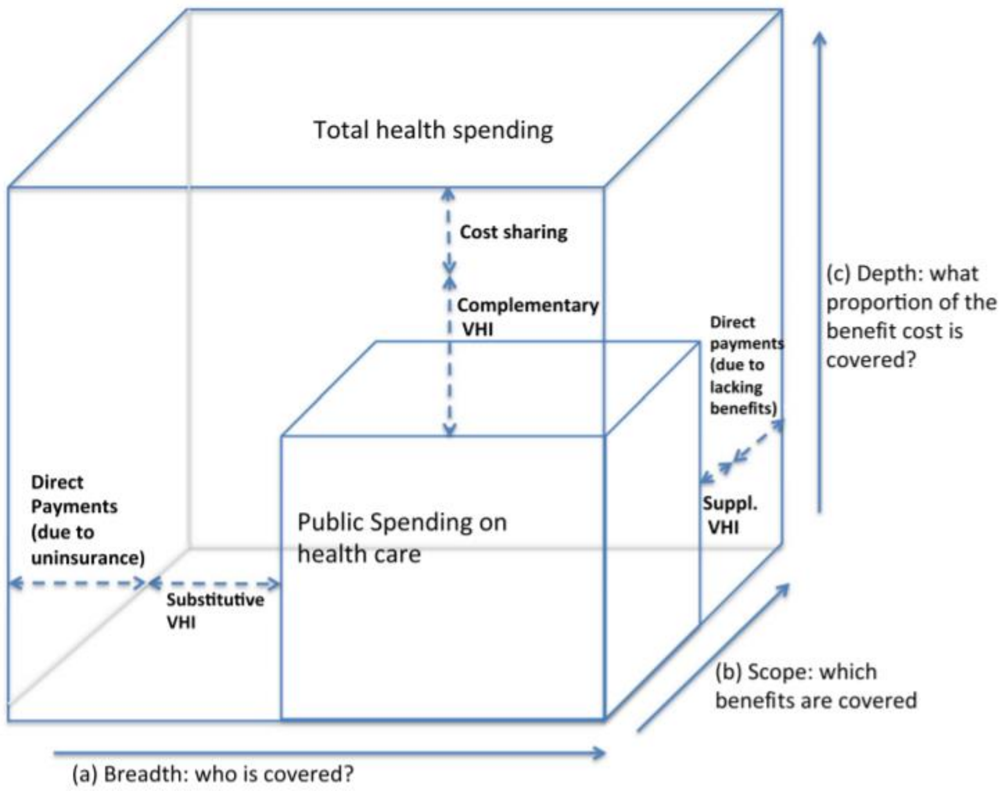
Factors influencing the impact of unemployment on health in the UK context

Starting, the impact of unemployment on health care use will be discussed. In the United Kingdom the NHS ensures free healthcare for all residents. In this case, a way to get a sense of the impact of unemployment on healthcare use, is to examine the reliance of individuals in the UK on out-of-pocket (OOP) expenditures. Rice et al. (2018) have looked at this for ten high income countries, one of them being the UK. For their research, they created an analytical framework based on the three-dimensional cube most commonly used by the WHO (World Health Report, 2010). As depicted in figure 1, they look at three dimensions to determine OOP expenses. Firstly, direct payments due to uninsurance, which in the case of the UK will be 0, as the NHS covers all UK residents. Secondly, the amount of cost sharing, for example in the form of deductibles or co-payments. Lastly, they look at direct payments due to lacking benefits. The NHS has no explicitly excluded benefits as they aim to provide healthcare necessary to meet all reasonable requirements (Mason, 2005). Therefore, Rice et al. (2018) argue that any OOP spending in the UK must come from cost sharing. Focusing on cost sharing, primary and secondary care are free at the point of use in the UK. The only co-payments are therefore for prescription drugs and dental care. They find that although OOP spending has grown in recent years (2004-2014), relative to other high income countries OOP expenditure is still very low. Additionally, people on low-income schemes or those who receive Universal Credit, a payment to assist with living costs, are exempted from co-payments (NHS, 2020). The low OOP expenditures in the UK are also reflected in the percentage of adults that report healthcare access problems due to costs. This number has been steadily low over the years and in 2016 it was the lowest among the 10 reviewed countries (Rice et al. 2018). In conclusion, the health insurance policy conditions in the United Kingdom are relatively favorable for the unemployed compared to other countries.

Secondly, the social safety net in the UK will be discussed. A measure used to assess the impact of unemployment in terms of income loss is by investigating the net replacement rate in unemployment (Ronchetti & Terriau, 2019). This measures the proportion of income that is maintained after unemployment, taking into account unemployment benefits, income tax, social contributions paid and other benefits that might be received (OECD.stat., 2021). Opposed to the gross replacement rate that only expresses unemployment benefit levels as a percentage of previous gross earnings, the net replacement rate in unemployment is a more all-encompassing measure (Ronchetti & Terriau, 2019). In the UK, this rate was 59% in 2001 and dropped to 48% in 2019. In comparison, Germany had a net replacement rate of 59% in 2019, France 65%, the Netherlands 71% and Denmark 83% (OECD.stat., 2021). Therefore, it can be concluded that the net replacement rate is relatively low in the UK compared to other OECD countries. This makes the financial impact of job loss relatively high.

Figure 1

The three dimensions that determine out-of-pocket spending



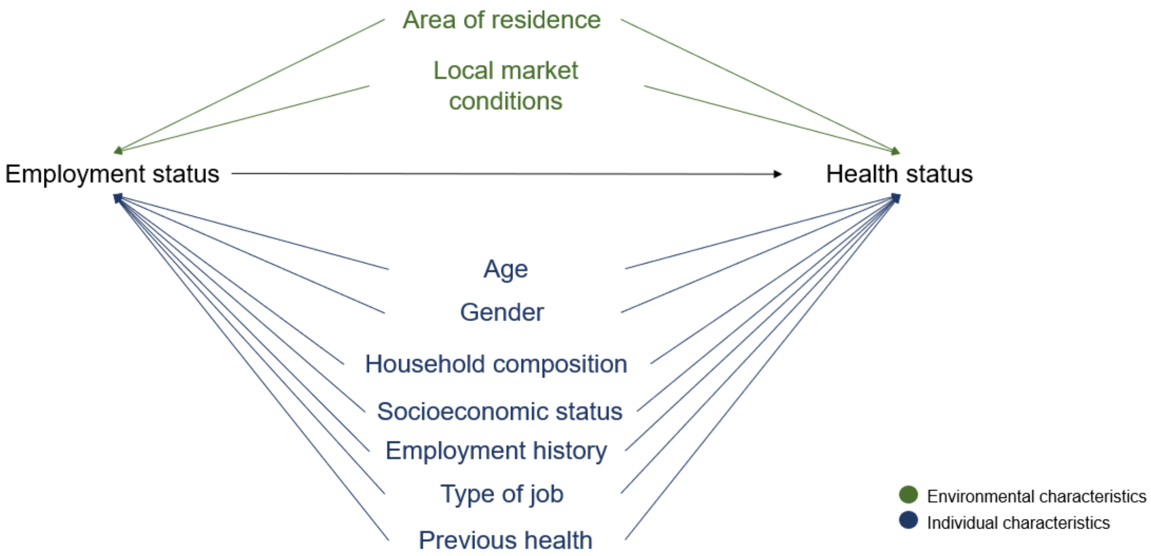
Note. Adapted from Rice et al. (2018).

Confounding effect

As mentioned in the introduction, confounding might alter the relationship between unemployment and health. Confounding is defined as bias that occurs because of a common cause of exposure and outcome (Suttorp et al., 2015). Controlling for these confounding factors is necessary to ensure that the real effect of exposure on outcome is not obscured. To be able to properly account for confounding in the analysis, theoretical knowledge is needed to identify the presence of confounding. Confounders that might obscure the relationship between unemployment and health will be discussed below. Additionally, a visual representation of the different variables and their relationships is shown in the form of a directed acyclic graph (DAG) (figure 2).

Figure 2

Directed Acyclic Graph of the relationship between unemployment and health



Firstly, several individual characteristics can be identified as potential confounders. To start off, gender and age are often used in statistical models and are likely to influence both the risk of becoming unemployed and health status (Norström et al., 2019). Moreover, socioeconomic status appears to be of importance. Lower socioeconomic status causes people to be at a higher risk of becoming unemployed (Doku et al., 2019). In addition, the socioeconomically disadvantaged are less healthy (Wang & Geng, 2019). Moreover, household composition is a possible confounder, as being married or having kids might influence the type of job or number of working hours one has. Likewise, it has an impact on health, both directly and indirectly, given that income from a spouse can compensate the lost income from the unemployed individual (Ronchetti & Terriau, 2019). Following the selection hypothesis, health status before the employment transition can influence the likelihood of becoming unemployed and evidently, previous health status is a strong predictor for current health status (Stauder, 2019). In a similar manner, employment history and previous unemployment spells can be a predictor for the likelihood of unemployment. Potentially, as explained in the causation hypothesis, these previous unemployment spells could have long-term health effects (Stauder, 2019). Additionally, the type of job may influence both the risk of unemployment and health (Gebel & Voßemer, 2014).

Aside from individual characteristics, two environmental factors can be identified as possible confounders. Area of residence can be related to the likelihood of becoming unemployed and health (Ronchetti & Terriau, 2019). In certain areas jobs security might be less, due to the types of jobs, for instance manual versus office jobs, that might be more concentrated in that area. People's health may also be related to the area they live in, for example because the pollution concentration is high. Furthermore, local market conditions are of relevance. As mentioned before, Clark (2003) showed that there seems to be a relationship between unemployment rates in the area and the impact of unemployment on health. High unemployment rates in the area or even at the household level are associated with a smaller impact of unemployment on health. Clark (2003) therefore concluded that individuals reference their employment situation to that of people around them and that this influences their experience of unemployment. This is called the social norm effect.

3. Methods

Difference-in-Difference

The problem with any experimental research trying to prove causation is that of missing data (Heckman et al., 1997). Let $D = 1$ if a person is in the treatment group and $D = 0$ if otherwise. Outcome Y_1 represents the outcome if a person receives treatment and Y_0 if the person does not receive treatment. In theory, the causal effect (Y) of a treatment can be defined as (Khandker et al., 2010):

$$Y = E(Y_1 - Y_0 | D = 1).$$

However, generally only $E(Y_1|D{=}1)$ and $E(Y_0|D{=}0)$ can be observed. In other words, one person can be in either of two states (treatment or not), but not in both. This leaves the missing data problem that the counterfactual $E(Y_0|D{=}1)$, or $E(Y_1|D{=}0)$, is not observed. In a randomized experiment this problem is solved by assigning treatment at random, creating a treatment and control group. The consequence of this randomization is that it has become plausible that the outcome in the control group $E(Y_0|D{=}0)$ is the same as what would have been the outcome in the treatment group in the absence of treatment $E(Y_0|D{=}1)$. In a randomized experiment the causal effect (Y) can thus be defined as (Khandker et al., 2010):

$$Y = E(Y_1 | D = 1) - E(Y_0 | D = 0).$$

Specifically for this research question, it is not feasible to create a randomized treatment and control group by assigning at random half of the participants to become unemployed. Therefore, to determine the effect of unemployment on health, a difference-in-difference model will be used. Difference-in-Differences (DiD) is a statistical technique used to try to mimic a randomized experiment (Rubin, 1974). Similarly to a randomized experiment, a treatment group, who experiences unemployment within the period $[t;t+1](D{=}1)$ and a control group who are continuously employed during the period $[t;t+1](D{=}0)$ are selected from longitudinal data (Ronchetti & Terriau, 2019). Assuming that these two groups are not similar in terms of health at baseline, as treatment has not been randomly assigned, this difference needs to be accounted for. This is done by not only comparing the outcome $Y_{1,t+1}$ of the treatment group with the outcome $Y_{0,t+1}$ of the control group, but by also removing from that difference the difference between the outcomes at baseline. Thus, the average effect of treatment can be defined as (Ronchetti & Terriau, 2019):

$$ATT = E(Y_{1,t+1} - Y_{1,t} | D = 1) - E(Y_{0,t+1} - Y_{0,t} | D = 0).$$

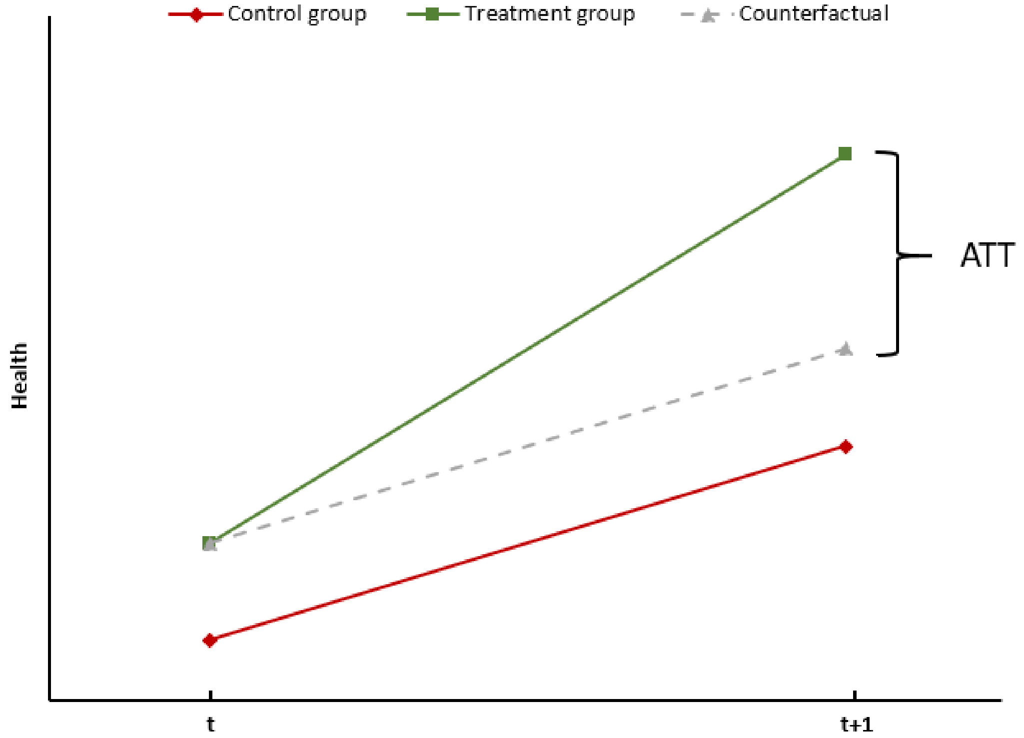
Importantly, for this equation to be appropriate, like for the equation for randomized experiments, it should be plausible to assume that, taking into account the differences between the control group and the treatment group at baseline, the outcome of the treatment group had they not received treatment should be the same as the outcome of the control group. Therefore, it is crucial that the common trend assumption holds. That is, in the absence of treatment, the treatment group would have followed the same time trend as the control group, relative to their outcomes (Gebel & Voßemer, 2014):

$$E(Y_{0,t+1} - Y_{0,t} | D = 1) = E(Y_{0,t+1} - Y_{0,t} | D = 0).$$

Thus, visually, the average effect of treatment can be calculated as depicted in figure 3:

Figure 3

Difference-in-Difference model



The regression model of the DiD estimator takes the following form:

$$Y_{it} = \alpha + \beta E_i + \gamma P_t + \delta E_i P_t + \varepsilon_{it}$$

where Y_{it} is the reported health outcome for person i at time t, E_i indicates whether the person belongs to the treatment group (1) or the control group (0) and P_t reflects whether the observation was pre-treatment assignment (0) or post-treatment assignment (1). The parameter δ is the difference-in-difference estimator.

Using a difference-in-difference approach has two noteworthy benefits. Firstly, it removes unobserved individual fixed effects, meaning differences between the treatment and control group that stay constant over time. Secondly, the comparison of trends between the control and treatment group eliminates common period effects. These are changes in the time trend, due to either shocks or an aging effect, that affect the treatment and control group in similar ways (Ronchetti & Terriau, 2019).

Propensity score matching

Propensity score matching (PSM) will be used before applying DiD, to make it more plausible that the aforementioned common trend assumption holds. As explained in chapter 2, a set of factors such as age and socioeconomic status make individuals more likely to experience unemployment and are negatively associated with health status. Therefore, it is improbable that the treatment group in absence of treatment would have followed the same time trend as the control group, if the DiD were applied without correcting for these factors. One way of correcting for this is by matching similar treatment and control individuals. Supposing that the likelihood of transitioning into unemployment is solely based on observable characteristics, matching treatment and control individuals on these observables (*X*) makes the outcomes Y_1, Y_0 independent of treatment assignment *D* (Heckman et al., 1997):

Y_0, $Y_1 \perp D|X$.

Here, "⊥" denotes independence. This is called the conditional independence assumption. If the conditional independence assumption holds, this makes the common trend assumption plausible. Thus, the effect of unemployment on health can be estimated by first matching treatment and control individuals on similar observed characteristics (Heckman et al., 1997).

As portrayed in chapter 2, many characteristics have been identified to both influence the probability of unemployment and influence the outcome. Therefore, to diminish observed heterogeneity between the treatment and control group, it is desirable to match on a broad set of covariates. However, the problem with matching on a great number of variables is that finding a comparable match becomes difficult. A solution to this problem is using PSM (Rosenbaum & Rubin, 1983). Instead of matching on the covariates itself, PSM uses propensity scores to match individuals. The propensity score is defined as the probability of being assigned to the treatment versus not, conditional on the observed covariates. Rosenbaum and Rubin (1983) demonstrate that matching on a propensity score (*P*) instead of individual covariates adequately removes the bias that results from these covariates. Therefore, the conditional independence assumption can be defined as follows (Ronchetti & Terriau, 2019):

Y_0, $Y_1 \perp D|P(X)$

Lastly, for PSM to be able to fulfil the common trend assumption, the common support condition needs to be guaranteed (Heckman et al., 1997):

$0 < P(D = 1|X) < 1$.

This means that the probability of receiving treatment or not is between 0 and 1 for each value of *X*. Imposing this condition means that there is enough overlap of the propensity scores to be able to properly match each treatment individual to a control with similar enough characteristics to ensure the common trend assumption holds.

In conclusion, the conditional independence assumption and the common support condition allow PSM to be used to fulfill the common trend assumption. Therefore, the average treatment effect of unemployment on health can be estimated using a combination of DiD and PSM:

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

where D_1 and D_0 represent respectively the treatment and control group, w_{ij} the Kernel density matching weights, and S the area of common support.

Aside from removing the effect of confounders, the advantage of using PSM is that the problem of reverse causality is minimized (Ronchetti & Terriau, 2019). By using lagged health variables as a characteristic in the propensity score calculations, individuals in the treatment and control group are matched on these health characteristics. This ensures that people in the treatment and control group are similar in terms of health up until a few months before assigning treatment (the occurrence of the unemployment event). Therefore, only health conditions that develop within these few months and subsequently resulted in unemployment, might bias the relationship between unemployment and health.

Implementation of PSM
The implementation of propensity score matching happens in two steps. First, the propensity score (the probability of becoming unemployed) is calculated for each individual (Imbens & Wooldrige, 2009). To explain the probability of becoming unemployed in the period *t*;*t*+1, a logistic regression is used. The independent variables are factors that explain the likelihood of being in the treatment or control group. The dependent variable is a binary variable indicating whether people belong to the treatment group or control group, meaning whether they experienced a transition from employment to unemployment or not. As stated by Caliendo and Kopeinig (2008), a reasonable choice regarding what variables to use in the explanatory model should be informed by theory and previous empirical research. The variables that will be incorporated in the logistic regression for this research are based on the theory discussed in chapter 2 and depicted in the Directed Acyclic Graph (figure 2). Importantly, all variables will be measured before treatment (at time *t*), to avoid the influence of treatment assignment on these variables. The logistic regression reads as follows:

$$\text{Logit}(\Pr(\text{treatment}=1)) = \beta_0 + \beta_1 A + \beta_2 S + \beta_3 X + \beta_4 H + \beta_5 C + \beta_6 E + \beta_7 J + \beta_8 R + \beta_9 M,$$

where
- A is age
- S is gender
- X are variables that proxy socioeconomic status
- H are variables that proxy health
- C are variables that proxy household composition
- E is employment history
- J is type of job
- R is area of residence
- M are the local market conditions

Secondly, a matching algorithm matches treatment and control individuals that have similar propensity scores. There are four types of PSM estimators that can be applied to match individuals: Nearest Neighbor (NN), Caliper and Radius, Stratification and Interval, and Kernel and Local Linear (Caliendo & Kopeinig, 2008).

Nearest Neighbor
This matching estimator matches an individual from the control group to a treatment individual that is closest in terms of propensity score. When using nearest neighbor matching, first the choice between matching 'with replacement' and 'without replacement' needs to be made. Matching with replacement allows one control individual to be used more than once as a match. This decreases bias, as on average treatment individuals will be matched to a more similar control individual, which increased the quality of the match. On the other hand, it increases variance of the PSM estimator. This is because less unique control individuals will be incorporated, thus less information is used to create the counterfactual (Caliendo & Kopeinig, 2008). Important to keep in mind when matching without replacement is that the matches made depend on the order in which the observations are matched. Therefore, the order should be randomized (Caliendo & Kopeinig, 2008). Lastly, one can choose to match each treatment to more than one nearest neighbor. Again, this involves a compromise between bias and variance. Matching to more individuals reduces variances as more information is used, though it increases bias, given that also worse quality matches are used (Smith, 1997).

Caliper and Radius Matching
Caliper matching incorporates a maximum propensity score difference between the treatment and control individual. Not only does it match a treatment individual to its nearest neighbor, but a match

will also only be made if the difference in propensity score is smaller than the caliper (the propensity range). Therefore, it is a way to impose the common support condition. Here too, a trade-off between bias and variance is made. Adding a caliper reduces the risk of bad matches, thus it reduces bias. However, if some individuals cannot be matched, this increases variance (Caliendo & Kopeinig, 2008). Building on this concept, radius matching is a way to include all control individuals within the caliper as a match to the treatment individual (Dehejia & Wahba, 2002). This technique has the benefit of reducing variance, without increasing bias.

Stratification and Interval Matching
Stratification matching is different from the aforementioned matching techniques in that people are not matched individually to a similar control individual in terms of the propensity score. Instead, the common support area of the propensity scores is partitioned in several strata. Subsequently, within each strata the DiD estimator is calculated. Another name for this method is interval matching (Rosenbaum & Rubin, 1984). To determine the number of strata to use, one can check whether the propensity score is balanced between the controls and the treated in each stratum. If this is not the case, one can opt for smaller strata (Aakvik, 2001).

Kernel
Kernel (KM) is distinctly different from the matching strategies explained thus far. Whereas all other techniques use only one to a few observations to match to a treated individual, KM matches almost all control individuals to each treated individual. For this, a weighted average of the controls is used when matching (Heckman et al., 1997). The idea is to give each control a weight and let that weight differ depending on the treatment individual that needs to be matched. The weight depends on the distance of the propensity score of the control individual to that of the treatment individual for which the counterfactual is estimated. Combining all controls with the different weights depending on the treatment individual then gives a weighted average to construct the counterfactual outcome for that treatment individual. (Caliendo & Kopeinig, 2008). Not surprising, the major advantage of this technique is the low variance, because almost all information is used. In opposition, bias might occur when also bad matches are used. Therefore, imposing the common support condition is crucial (Caliendo & Kopeinig, 2008). DiNardo and Tobias (2001) note that the choice of kernel function to calculate the weights does not seem to matter. On the other hand, choosing the bandwidth parameter has important implications. The bandwidth determines how large the area around the propensity score of the treatment individual is that is given a weight. A large bandwidth means very different individuals in terms of propensity score still get a weight assigned to them. A small bandwidth indicates only propensity scores similar to that of the treatment individual get a weight (Silverman, 1986). This indicates that the choice of bandwidth again involves a trade-off between variance and bias. A large bandwidth increases bias and reduces variance. For a small bandwidth it is the other way around (Caliendo & Kopeinig, 2008).

The choice of matching algorithm depends on the data. Large sample sizes will give the same estimates for all matching techniques, since an infinite number of controls allows all treatment individuals to get an exact match (Caliendo & Kopeinig, 2008). With smaller sample sizes, the data can guide the choice of matching algorithm, depending on the common support area, the number of control observations, et cetera. Ultimately, the choice should depend on what yields the best results in terms of covariate balance (Caliendo & Kopeinig, 2008). To test how well propensity score matching has succeeded, a common approach is to estimate the standardized bias. This measure defines for each covariate as a percentage the difference between the sample means of the treated and control sample divided by the square root of the average of the sample variances in the treated and non-treated groups (Rosenbaum & Rubin, 1985). Generally, a standardized bias for each control variable below 3% is seen as satisfactory (Caliendo & Kopeinig, 2008).

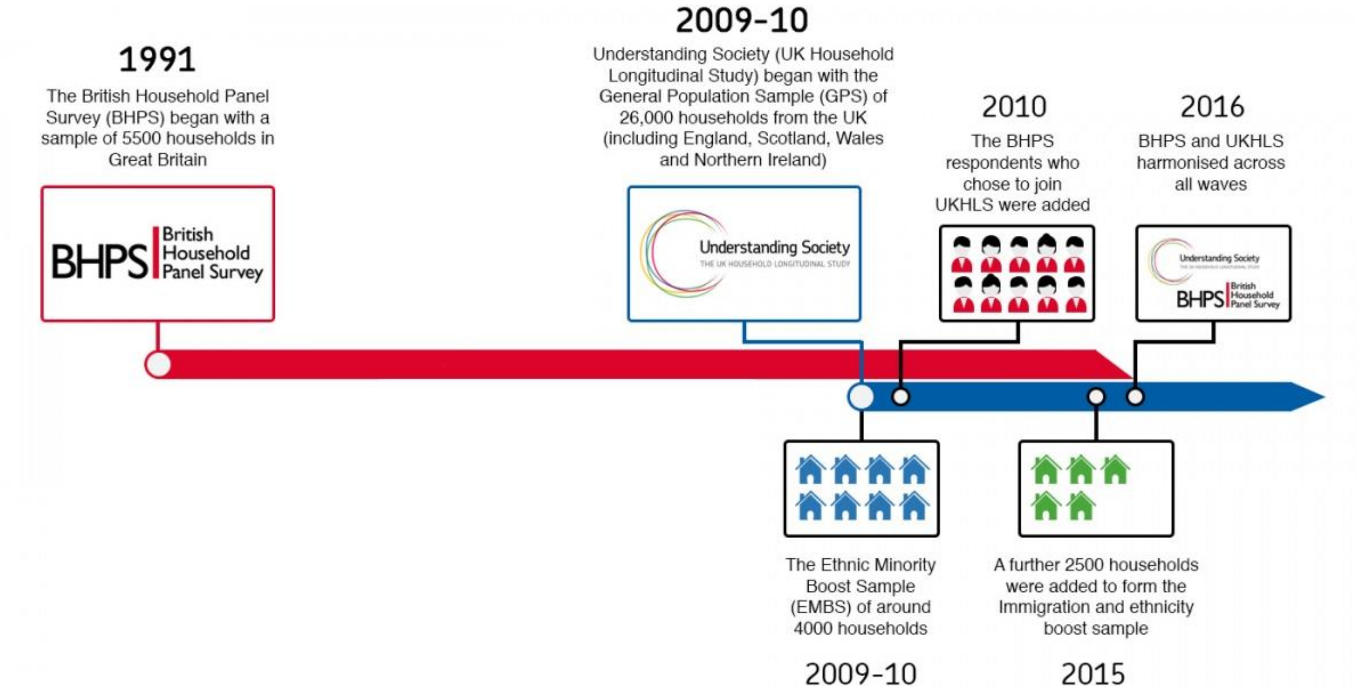
Applying different propensity score matching algorithms, kernel matching showed to be the best fit for this data. Both nearest neighbor and caliper matching could not decrease standardized bias to below 3% for all variables. Radius matching showed similar results to kernel matching, however the latter showed the best balance of covariates between control and treatment group in terms of percent standardized bias. Combined with the fact that kernel matching resulted in relatively low variance, as the data contains a high number of control observations that can be used to match, this matching algorithm was selected to match individuals before applying the DiD-model. Given that radius matching produced similar results, this method will be applied as a robustness check. As DiNardo and Tobias (2001) conclude that the choice of kernel function is of little importance, the Epanechnicov kernel has been used, seeing that this is the default option in psmatch2. For the bandwidth, first the default option of psmatch2, namely 0.06 was implemented to match. This choice of bandwidth did not lead to a satisfactory reduction in percent standardized bias. A ten times smaller bandwidth (0.006) resulted in low bias and low variance. Decreasing the bandwidth again with a factor ten resulted in a slight increase in bias compared to the bandwidth of 0.006. Thus, a bandwidth of 0.006 was chosen, as this resulted in the most optimal balancing of bias and variance.

4. Data

To answer the research question, data from *Understanding Society* – The UK household Longitudinal Study (UKHLS), will be used (University of Essex, 2020). This is a panel survey of households in the United Kingdom, conducted by the Institute for Social and Economic Research at the University of Essex. The panel is inspired by and includes components of the British Household Panel Survey (BHPS). The survey started in 2009 and currently there are 10 waves available, ranging from 2009 until 2019. The sample includes over 40,000 households of which the individual members are interviewed on a yearly basis as long as the respondent continues to live in the UK. The objective of the survey is to enable research into the short- and long-term effects of social and economic change both at the household and individual level. Therefore, interviews are conducted, both for the individual as well as for the household. The questionnaires have questions on a broad range of topics. Specifically for this study, the modules of the individual interview containing questions on demographics, employment status and health are of interest.

The data sample used for this research consists of four sub-groups (figure 4). The largest sample is the General Population Sample (GPS), consisting of 24,000 households in Great-Britain and 2,000 households in Northern Ireland. Moreover, the sample contains the Ethnic Minority Boost Sample (EMBS), which adds 4,000 households from areas with a high ethnic minority concentration, where at least one household member was from an ethnic minority group. Furthermore, 8,000 households from the British Household Panel Survey were added to the Understanding Society Survey in Wave 2. Lastly, the Immigrant and Ethnic Minority Boost Sample (IEMBS) was added in Wave 6. This sample contains 2,900 households from areas of high ethnic minority concentration, where at least one member was born outside the UK, or from an ethnic minority group (Understanding Society, n.d.).

Figure 4
Survey timeline Understanding Society.



Note. Adapted from Understanding Society (n.d.).

The General Population Sample was constructed using multi-stage stratified random sampling. Firstly, the Primary Sampling Units (PSUs) were sorted, which consist of 12 regions spanning England, Scotland, Wales, and Northern Ireland, meaning the sample contains individuals living across the entirety of the United Kingdom. These regions were then further stratified based on the proportion of household reference persons with a non-manual occupation, population density and ethnic minority density. Next, the PSUs were selected using systematic random sampling. Finally, 18 Delivery Points (addresses) were selected within each selected PSU, using systematic random sampling (Boreham et al., 2012). Areas of the EMBS and IEMBS groups were first selected based on their ethnic minority density and afterwards addresses were randomly selected. The use of multi-stage stratified random sampling and the inclusion of all regions of the United Kingdom assures that this sample is representative for the population of the UK as a whole.

To encourage as many people as possible to complete the survey each year, financial incentives were used. The incentives are as follows: Each individual gets an unconditional 10-pound gift voucher together with the invitation letter. Those adults that answer the questions via the internet, receive an additional 10 pounds in case they complete the survey within five weeks. In the event that a sample member did not partake in the previous wave, they receive a 20-pound voucher if they respond in the most recent wave (Understanding Society, n.d.).

Sample selection

Observations with an age below 16 and above 64 were dropped from the dataset. As the minimum full-time working age in the United Kingdom is 16 years (GOV.UK, n.d.) and the general age that people become qualified for State Pension is 65 years (AgeUK, 2021), this selection is a good proxy of the working population in the UK. Additionally, observations that reported any other employment status than unemployed or paid employment were dropped. The dropped observations consist of full-time students, people on maternity leave, long-term sick or disabled people, retired people, people that provide family care or care at home, people following a government training scheme, people taking care of the family business unpaid and people on an apprenticeship. The self-employed were dropped as they are not at risk of becoming unemployed in the same way that people in paid employment are.

Independent variable

The independent variable is a dummy that describes whether an observation belongs to the control group (those who report being consistently employed in the period t;t+1) or treatment group (those who report a transition from employment to unemployment in the period t;t+1). To create this variable, the current labor force status is used. This survey question asks people ‘which of these best describes your current employment situation’. Based on the answers to this question an employment dummy is created that equals 1 if the individual reports having paid employment. This can be either full time or part time employment. The dummy equals 0 if the individual reports being unemployed. Following, the treatment and control group are created. The dummy takes on the value 0 if the person reports being employed at time t as well as at time t+1 and does not report having experienced any unemployment spells between the interview at time t and t+1. The latter is done to ensure that the control group consists of individuals that were continuously employed over the year. The dummy takes on the value 1 if the person reports being employed at time t and being unemployed at time t+1.

By coding the dummy variable in this way, one person is allowed to contribute to multiple unemployment or employment spells. For instance, one individual can report being employed in wave 1, being unemployed in wave 2, being employed in wave 3 and 4, and being unemployed in wave 5. This individual would then contribute to two observations in the treatment group and one in the control group. Ultimately, it would be desirable to include only a person’s first unemployment spell in the research, as potential long-term health effects might affect later employment and unemployment observations. However, as there is no information available on people’s unemployment status before the 10 waves that this data spans, a person could in theory have been unemployed many times prior to their inclusion in this study. Thus, a second observed unemployment spell of an individual in this dataset is not substantially different from the first. Therefore, following the work of Gebel and Voßemer (2014), in this research it is preferable to include multiple unemployment observations of one person, given that this creates a larger treatment group. This is done similarly for control observations, as a first control observation of a person is not substantially different from a second or third.

Although allowing one person to contribute multiple times to the treatment or control group helps increase the number of observations in each group, it creates the potential problem that a treatment observation of one person is matched to a control observation of that same person. Therefore, the independent variable is constructed in a way that if a person is included in the treatment group once, all other observations of this person are not allowed to be control observations.

Dependent variable

The outcome health in the DiD will be assessed using two variables. To capture both mental and physical health, the SF-12 mental component summary (MCS) and physical component summary (PCS) will be used as outcome variables. The SF-12 is a generic instrument developed to assess health. It was created in a response to the widely used SF-36, a highly valid generic health measure that is relatively long and time-consuming to use, especially in large scale projects (Ware et al., 1995). The PCS and MCS are the two summary scores, in theory ranging from 0-100, that can be calculated from the SF-36 and SF-12. The scores are calculated using the weights that are given to each question depending on whether the PCS or the MCS is computed. As its name indicates, the SF-12 contains 12 items that relate to 8 health concepts. The questions are a subset of the questions used in the SF-36 and are all answered with one or multiple answer options. To ensure that the SF-12 proxies physical and mental health as well as the SF-36, twelve questions from the SF-36 were chosen that explained more than 90% of the variance in the PCS and MCS (Ware et al., 1995). The 8 health concepts and the twelve questions incorporated in the SF-12 are listed in the Appendix (table 7) (Ware et al., 1995).

The advantage of using generic health measures as indicators of physical and mental health as opposed to measuring disease incidence or hospital admission rates is that in the short-term general health might already decrease, whereas the diagnosis of a disease might only be possible in a later stage (Stauder, 2019). Therefore, for this short-term research, generic health measures are more meaningful.

Reliability and validity of the MCS and PCS

To assess the appropriateness of the SF-12 MCS and PCS as measures for mental and physical health, Ware et al. (1995) show the reliability and validity of these two measures. Firstly, Ware et al. (1995) determine the reliability in both the UK and US population. The reliability of a measure indicates how much of the variance of the scale is due to random error. One way to test this is the test-retest method, where the people are tested two times within a short time interval. Assuming that within this time interval, actual health is unlikely to change, the differences in scores between the measurements can be attributed to random error (Vilagut, 2014). The reliability of the PCS-12 was 0.86 in the UK and 0.77 for the MCS-12 (Ware et al., 1995). On average, the difference was less than one point. This indicates that for both the PCS and the MCS, the reliability is satisfactory (Nunnally & Bernstein, 1994).

Regarding validity, firstly content validity should be assessed. As the SF-12 represents, similar to the SF-36, the health concepts most often used in health questionnaires, the content validity is adequate (Ware et al., 1995). Secondly, the two factors of construct validity should be assessed, namely convergent validity and discriminant validity. Convergent validity assesses whether there is a correlation between similar measures. Ware et al. (1995) show that the SF-12 and SF-36 are highly correlated, as the correlation coefficient of the MCS between the SF-12 and SF-36 is above 0.95. The same holds for the PCS. The discriminant validity, which indicates how well the measure discriminates between known disease severity groups, is around 10% less comparing the SF-12 to the SF-36. However, the authors argue that in large groups this is an acceptable trade-off against the advantages of a shorter questionnaire (Ware et al., 1995). Concluding, together with satisfactory reliability, adequate content and convergent validity, the SF-12 MCS and PCS are appropriate as generic health measures in this thesis.

Propensity score matching variables

Below, the variables that are used in the first step of propensity score matching, namely the explanatory model, are listed as they are operationalized in the dataset. The selection of these variables has been guided by the theory discussed in chapter 2. A detailed explanation of the variables is provided in the Appendix.

- Age (linear and quadratic)
- Gender
- Highest qualification level
- Household equivalized income (linear and quadratic)
- Income from savings from rent and dividend from investments
- Marital status
- Number of children
- Previous unemployment spells
- Type of job
- SF-12 mental component summary (MCS)
- SF-12 physical component summary (PCS)
- Disability dummy
- Health condition dummy
- Regional unemployment rates
- Government Office Region

Both a linear and quadratic specification of age and income are used to match individuals, to account for the potential non-linear relationship between each of these variables and the effect of unemployment on health. It might for instance be that the difference in impact between people aged 25 and 30 is much bigger than the difference in impact between people that are 50 and 55.

5. Results

Propensity score matching

Table 1 presents the results of the logistic regression that proceeds kernel matching. The likelihood of becoming unemployed decreases as age increases. In addition, female sex, high household income, being married and having children all significantly decrease the likelihood of becoming unemployed. As expected from earlier research, being in good health significantly decreases the probability of becoming unemployed.

Table 1 Logistic regression of the probability of becoming unemployed

Independent variables	Coefficient	S.E.
Age in years (linear)	-.107**	.016
Age in years (quadratic)	.001**	.000
Female (Ref.: male)	-.305**	.052
Household equivalized income (linear)	-.001**	.000
Household equivalized income (quadratic)	.000**	.000
Income from savings and investments	.000	.000
Married (Ref.: not married)	-.367**	.060
Number of children	-.115**	.036
Highest qualification level (Ref.: Degree)		
Other higher degree	.036	.089
A-level	-.084	.078
GCSE	.120	.080
Other qualification	.390**	.106
No qualification	.122	.145
Type of job (Ref.: No paid employment)		
Management & professional	-1.065**	.172
Intermediate	-.101**	.175
Routine	-.692**	.165
1 or more previous unemployment spells (Ref.: none)	1.948**	.091
Health condition (Ref.: no health condition)	.678**	.214
Disability (Ref.: no disability)	.088	.080
SF-12 mental component summary (MCS)	-.031**	.003
SF-12 physical component summary (PCS)	-.020**	.003
Government Office Region (Ref.: North East)		
North West	.158	.154
Yorkshire and the Humber	.056	.157
East Midlands	.062	.164
West Midlands	.116	.155
East of England	.068	.170
London	.304*	.150
South East	.235	.162
South West	.061	.172
Wales	-.105	.167
Scotland	.031	.160
Northern Ireland	.146	.167
Unemployment rate	.066**	.017
Constant	2.205**	.444
Number of observations	85,763	

Notes: "Ref." = reference group; *p<.05, **p<0.01
Source: Understanding Society, 2009-2019

Using the outcome of the logistic regression, kernel matching is carried out. Table 2 and figure 5 portray the balance of most covariates in the treatment and control group, before and after matching. To make the results easier to evaluate, a dummy for highest qualification level has been created that equals 1 if the individual has passed their A-levels or obtained a degree higher than that. In addition, the variable Government Office Region has been left out of table 2 and figure 5 to make them less crowded. The balancing of all separate categories of highest qualification level and Government Office Region can be found in the Appendix. Examination shows that in the unmatched sample, treatment and control group differ substantially. Workers who are younger, male, unmarried and without children more often experience unemployment between *t* and *t*+1. Additionally, individuals with little education, low household income, little income from savings and investments and low complexity jobs are overrepresented in the treatment group as well. Moreover, the baseline health status of people in the treatment group is substantially lower and these people have been unemployed previously more often. As expected, job loss occurs more often when unemployment rates are higher. The comparison of mean standardized bias before and after matching demonstrates that kernel matching succeeds in reducing mean standardized bias to below the 3-5% threshold of Caliendo and Kopeinig (2008). Thus, propensity score matching has succeeded in creating a treatment and control group that are balanced on the selected covariates.

Figure 5
Dot chart extent of covariate imbalance in % standardized bias

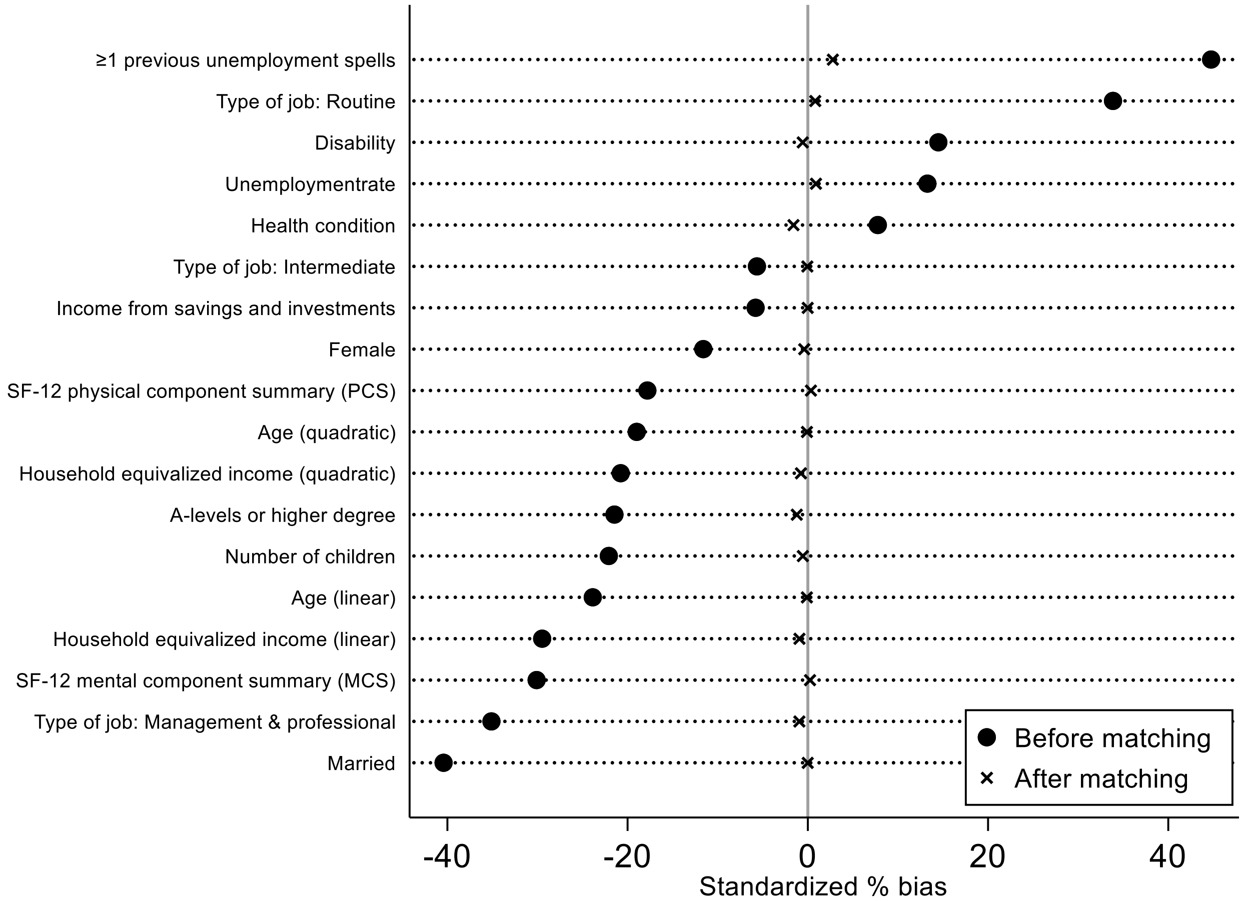


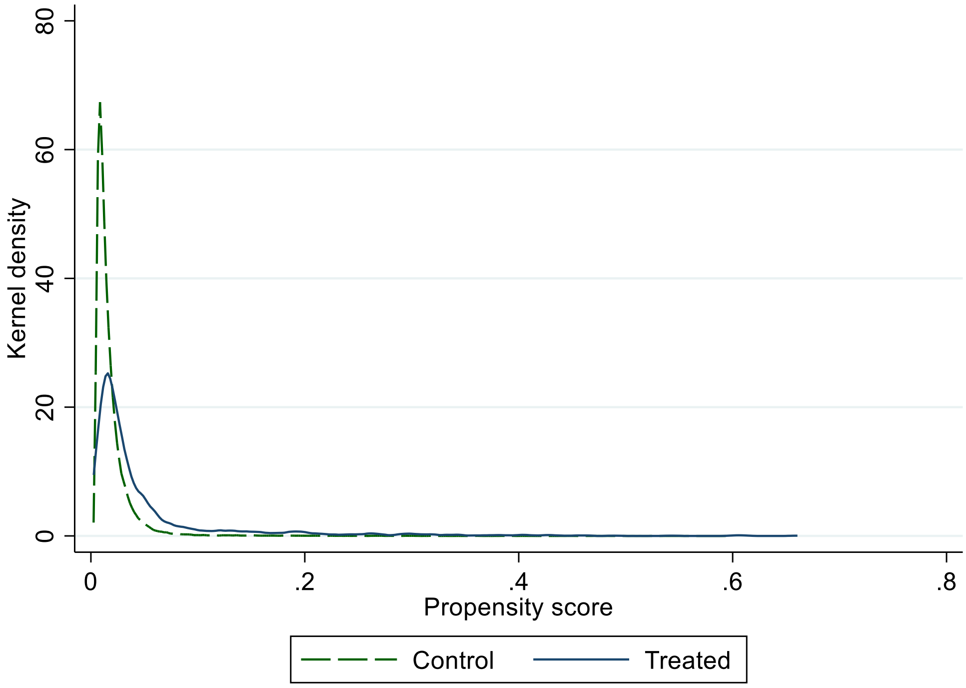
Table 2 Covariate balancing before and after matching

Covariates		Mean Treated	Mean Control	% Bias
Age (linear)	Before	39.31	42.26	-23.9
	After	39.33	39.35	-0.1*
Age (quadratic)	Before	1723.4	1912.7	-19.0
	After	1725.4	1726.5	-0.1*
Female (Ref.: male)	Before	.49	.55	-11.6
	After	.49	.50	-0.4*
Household equivalized income (linear)	Before	1694.1	1964	-29.5
	After	1697.3	1705.9	-0.9*
Household equivalized income (quadratic)	Before	3.7*10^6	4.7*10^6	-20.8
	After	3.7*10^6	3.7*10^6	-0.8*
Income from savings and investments	Before	134.64	180.94	-5.8
	After	135.05	135.22	-0.0*
Married (Ref.: not married)	Before	.54	.73	-40.4
	After	.54	.54	-0.0*
Number of children	Before	.47	.68	-22.1
	After	.48	.48	-0.6*
A-levels or higher degree (Ref.: GCSE or lower)	Before	.62	.72	-21.5
	After	.62	.62	-1.2*
Type of job (Ref.: No paid employment)				
Management & professional	Before	.32	.49	-35.1
	After	.32	.32	-0.9*
Intermediate	Before	.14	.16	-5.6
	After	.14	.14	-0.1*
Routine	Before	.51	.34	33.9
	After	.51	.51	0.8*
1 or more previous unemployment spells (Ref.: none)	Before	.12	.01	44.8
	After	.11	.11	2.8*
Health condition (Ref.: no health condition)	Before	.015	.007	7.8
	After	.015	.016	-1.6*
Disability (Ref.: no disability)	Before	.17	.12	14.5
	After	.17	.17	-0.6*
SF-12 mental component summary (MCS)	Before	46.50	49.44	-30.1
	After	46.53	46.50	0.2*
SF-12 physical component summary (PCS)	Before	51.65	53.17	-17.8
	After	51.67	51.65	0.3*
Unemployment rate	Before	6.56	6.32	13.3
	After	6.56	6.55	0.9*

Notes: All covariates are measured before treatment; "Ref." = reference group.; % bias expresses percentage standardized bias (Caliendo & Kopeinig, 2008); *%bias<3
Source: Understanding society, 2009-2019

As explained in the methods, to ensure the common trend assumption holds, not only should covariates be balanced, but the common support condition also must be imposed. One way to visually analyze the similarity of propensity scores in the treatment and control group is by depicting the density distribution of the propensity scores (Lechner, 2002) (figure 6). The kernel density plot shows that the propensity scores largely overlap and nearly all treated individuals seem to have at least one individual in the control group with the same propensity score. Consequently, when imposing the common support condition, which removes treatment observations whose propensity score is higher than the maximum score or lower than the minimum score of the controls, only 5 observations in the treatment group are dropped.

Figure 6
Kernel density plot of propensity scores, unmatched sample



Difference-in-Difference estimator

Ahead of calculating the average treatment effect on the treated (ATT), starting with analyzing the descriptive statistics offers a better understanding of the data. Table 3 displays the mean values of the SF-12 MCS and SF-12 PCS in the treatment and control group, both at time *t* (pre-treatment) and *t*+1 (post-treatment). Like what can be concluded from Table 2, before treatment assignment, the treatment group is already in worse health than the control group, both in terms of physical and mental health. These pre-treatment findings suggest that selection into unemployment contributes at least in part to the negative correlation that can be seen between unemployment and health. The difference in health between the treatment and control group increases post-treatment, regarding mental health. For physical health, the difference remains similar. In order to establish causality, next the ATT is calculated using DiD-PSM.

Table 3 SF-12 MCS and PCS pre- and post-treatment assignment (unadjusted)

	Pre-treatment	Post-treatment
	Mean (s.d.)	Mean (s.d.)
Mental health		
Treatment group	46.50 (10.49)	45.42 (11.34)
Control group	49.44 (8.94)	49.30 (9.18)
Physical health		
Treatment group	51.65 (8.94)	51.55 (9.91)
Control group	53.17 (7.82)	52.88 (8.05)

Notes: s.d.= standard deviation
Source: Understanding society, 2009-2019

Average treatment effect on the treated (ATT)

Considering the effect of becoming unemployed on mental health, which has been assessed using the SF-12 MCS, on average mental health decreases with 2.442 points (standard error (S.E.) .287)

(Panel A, table 4). To estimate the effect size, the standardized mean difference is used (Morris, 2008). The standardized mean difference is defined as the difference in mean change between post and pretest scores in the treatment and control group, divided by the pooled pretest standard deviation. In this sample, pretreatment assignment individuals report SF-12 MCS scores ranging from 1.83 to 77.09 with a mean of 49.70 and a standard deviation of 8.99. Using the standard deviation to calculate the standardized mean difference results in an effect size of -0.27. Thus, the effect of unemployment on mental health can be regarded as small and strongly significant. In contrast, physical health does not seem to suffer from job loss, as the ATT is very small (-.135) and the S.E. is twice as large as the effect (.211) (Panel A, table 4).

Table 4 Average treatment effect (ATT) and conditional average treatment effects on the treated (CATT)

	Physical Health			Mental health		
	ATT	S.E.†	N_t/N_c	ATT	S.E. †	N_t/N_c
Panel A: Average treatment effect on the treated (ATT)						
Becoming unemployed	-.135	.211	1642/ 84,116	-2.442**	.287	1642/ 84,116
Panel B: Conditional average treatment effects on the treated (CTT)						
By gender						
Men	.016	.286	825/ 37,678	-2.444**	.396	825/ 37,678
Women	-.296	.310	811/ 46,438	-2.393**	.418	811/ 46,438
By age						
16-28 years old	.668	.391	447/ 10,605	-3.354**	.580	447/ 10,605
29-40 years old	-.548	.516	293/ 21,673	-2.247**	.659	293/ 21,673
41-52 years old	-.238	.405	438/ 28,710	-2.680**	.559	438/ 29,710
53-64 years old	-.583	.458	335/ 18,156	-1.468**	.554	335/ 18,156

Notes: N_t = number of treated, N_c = number of controls. *p<.05, **p<0.01. S.E.= standard error. † No bootstrapped standard errors are reported. When estimating variance of the effect, bootstrapping is an often-used method to take into account variance due to propensity score matching and imposing common support (Caliendo & Kopeinig, 2008). Bootstrapped standard errors (100 repetitions) for the ATT showed little difference to the regular standard errors. Combined with the fact that estimated effects are all either evidently insignificant or largely significant and bootstrapping is very computationally demanding, only regular standard errors have been calculated for all other outputs.
Source: Understanding society, 2009-2019

Conditional average treatment effects on the treated

To understand the effect of becoming unemployed on health in more detail, analyzing the effect in different subgroups can be valuable. Firstly, age might have an impact on how workers perceive unemployment, as older workers experience on average longer unemployment spells (Ronchetti & Terriau, 2019). In addition, Blasco and Brodaty (2016) show that mental health effects might be larger in the male subsample. To assess the heterogeneity of the effect on health in different subgroups, separate analyses have been performed for four age groups, and gender. The explanatory models for becoming unemployed contain the same covariates as for the main analysis, except for the exclusion of gender in the explanatory model that precedes analyses of the health effects on males and females separately. Matching in all subsamples still results in satisfactory balancing of covariates, with percent standardized bias below 5% for all covariates after matching. Furthermore, imposing the common support leads to the exclusion of only a few observations.

Panel B of Table 4 reports the conditional average treatment effects on the treated (CATT) for each subgroup. Similarly to the analysis of the full sample, the effect of unemployment on physical health is insubstantial for all subgroups. Although in some subcategories a slightly negative effect, or positive effect with respect to age group 16-28, can be seen, the standard errors are too large to attach any meaning to these effects. On the other hand, the effect of becoming unemployed on mental health is substantial and strongly significant in all subgroups. Males and females are affected similarly, showing respective decreases in mental health of 2.444 and 2.393 points. These effects are comparable to the effect on the whole sample. Naturally, only the standard errors have increased slightly, which can be attributed to the decreased sample sizes of these subgroups. Concerning the different age groups, the effects on the age group 29-40 and 41-50 are of similar sizes and the same as that of the whole sample. Opposing, the mental health effects on the youngest and oldest age group in particular are notably different from the rest. The CATT on mental health of the age group from 16-28 years old is -3.354 points as a result of becoming unemployed. This is almost one point more on the SF-12 scale than in the whole sample. In contrast, becoming unemployed in the age group 53-64 years old causes a reduction in mental health of only -1.468, almost one point less than in the whole sample.

Robustness Analysis

Radius matching

As a first robustness check, the sensitivity of the ATT to the matching technique is evaluated, by using radius matching as an alternative matching algorithm. Radius matching attempts to match a treatment individual to all control individuals within the caliper. Therefore, first the optimal caliper needs to be determined. Austin (2011) recommends using 0.2 of the standard deviation of the logit of the propensity score as the caliper of width. Accordingly, the optimal caliper in this research is determined to be 0.00051. Matching resulted in adequate balancing of covariates, seeing that the standardized bias is reduced to below 3% for all covariates after matching. Panel A of Table 5 depicts the ATT of becoming unemployed on physical and mental health after radius matching. The results are highly similar to the ATT after kernel matching, implying that the findings are robust to this different matching strategy.

Table 5 ATT after radius matching & after using an alternatively constructed independent variable

	Physical Health			Mental health		
	ATT	S.E.†	N_t/N_c	ATT	S.E. †	N_t/N_c
Panel A: ATT after radius matching						
Becoming unemployed	-.141	.214	1610/ 84,116	-2.437**	.291	1610/ 84,116
Panel B: ATT using only the first treatment or control observation of a person						
Becoming unemployed	-.191	.244	1524/ 6988	-2.378**	.331	1524/ 6988

Notes: N_t = number of treated, N_c = number of controls. *p<.05, **p<0.01. S.E.= standard error.
Source: Understanding society, 2009-2019

Alternatively constructed independent variable

For the main analysis, as explained in chapter 4, the independent variable is constructed to allow one person to contribute with multiple observations to either the control group or the treatment group. This is done to increase the size of the treatment and control group, under the assumption that a first observation of a person is not substantially different from a second or third. To test whether this assumption is correct, a separate analysis is done, estimating the ATT using for the independent variable only observations that are the first contribution of a person to either the treatment or control group. Matching on this selection of observations gives satisfactory balancing of covariates, as it succeeds in decreasing standardized bias to below 3% for all covariates. Panel B of table 5 illustrates that the results are in line with the ATT of the main analysis. Thus, it appears that the construction of the independent variable using multiple observations of one person did not affect the results.

Subjective well-being: GHQ-caseness score

A third robustness check is carried out by calculating the ATT with the GHQ-caseness score as a measure of subjective well-being. This score is a popular measure in medical and psychological literature and is increasingly used in economic research (Gathergood, 2013; Clark, 2003). Therefore, incorporating this measure facilitates a more direct comparison between the estimated results and relevant literature. The GHQ is a survey that measures psychological well-being, thus it is slightly different from the SF-12 MCS, that looks at mental health. It consists of 12 questions aimed to identify whether individuals have been feeling anxious, distressed, bad tempered or other emotions related to psychological well-being (Jackson, 2007). Responses to these questions are converted to a score, by coding a 'not at all' or 'no more than usual' answer as 0 and a 'rather more than usual' and 'much more than usual' answer as 1. All these values are summed to create a scale ranging from 0 (the least distressed) to 12 (the most distressed).

The explanatory model for becoming unemployed contains all covariates that were used for the logistic regression in the main analysis, in addition to the baseline GHQ scores. Kernel matching succeeded in reducing standardized bias to below 3% for all covariates. Table 6 shows that becoming unemployed increases the GHQ score with 1.439 (S.E. .107), meaning that individuals experience a substantial decrease in subjective well-being as a result of unemployment. Using standardized mean difference, the calculated effect size is 0.53, which can be considered a medium size effect. Comparing this effect size to the effect size found in the main analysis, the impact on subjective well-being as measured by the GHQ appears to be larger than the impact on mental health as measured by the SF-12 MCS. This might be because the GHQ captures slightly different aspects of health than the SF-12 MCS, as the GHQ is a subjective well-being measure. This would imply that subjective well-being is more impacted by unemployment than mental health. Alternatively, the differences in effect sizes could be the result of the way in which the GHQ-caseness score is constructed, compared to the SF-12 MCS.

Table 6 ATT using the GHQ-caseness score

	Subjective well-being		
	ATT	S.E.†	N_t/N_c
Becoming unemployed	1.439	.107	1627/ 83,664

Notes: N_t = number of treated, N_c = number of controls. *p<.05, **p<0.01. S.E.= standard error.
Source: Understanding society, 2009-2019

Pre-treatment assignment health trajectories

When implementing difference-in-differences, a common way to increase the plausibility of the common trend assumption is by assessing whether the outcome variable followed a similar trajectory in the treatment and control group in the years prior to treatment assignment. Instead, in this research PSM has been performed to, at least in theory, make the common trend assumption more likely. However, an assessment of whether in practice this assumption has also become more plausible, for instance by investigating the trend of the outcome in the treatment and control group in the years before treatment assignment, has not been done. The reason for this is that the data available spans only 10 years. Thus, it is desirable to include all suitable observations collected in these 10 years to increase power, making it impossible to calculate health trends pre-treatment assignment for the main analysis. Therefore, a robustness check has been done using only the last five waves of the data to calculate the ATT. This leaves a substantial amount of data to estimate the pre-trend health trajectories of the treatment and control group. For this analysis, all treatment and control observations from wave 5 up to 10 have been used to create the treatment and control group. Subsequently, these observations have been matched at time *t,* similar to what has been done for the main analysis. Finally, the reported physical and mental health status of the matched individuals in the five years before matching are taken to construct the conditional health trends of the treatment and control group pre-treatment.

Figure 7

SF-12 MCS 5 years pre-treatment assignment (matched at t=0)

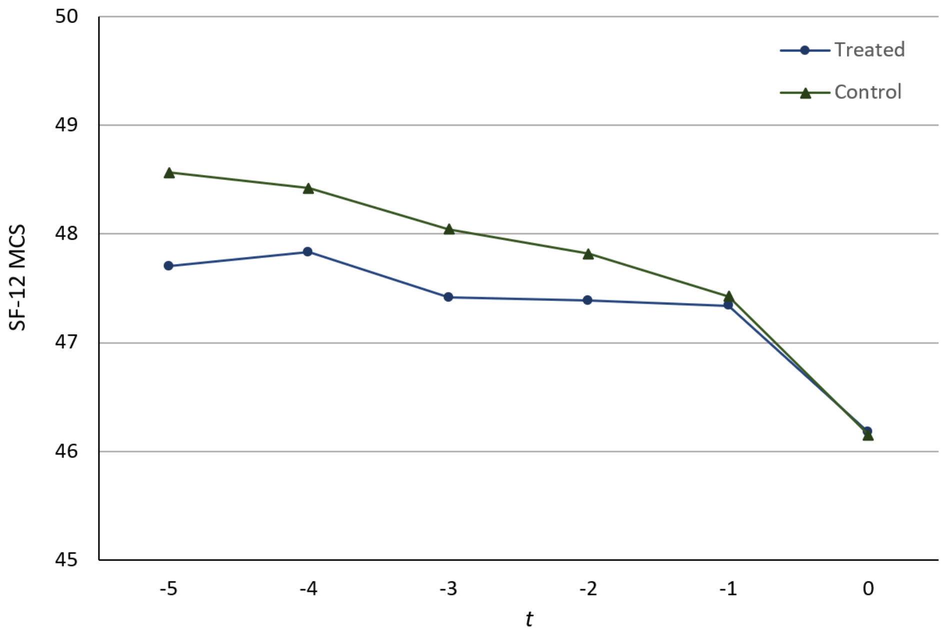
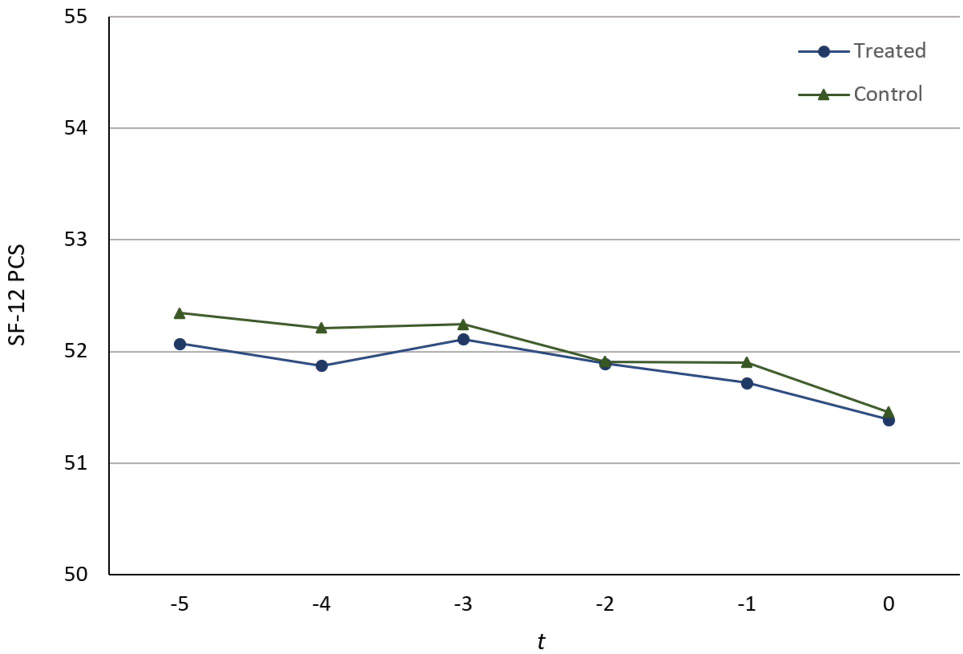


Figure 8

SF-12 PCS 5 years pre-treatment assignment (matched at t=0)



Plotting the pre-treatment health trends reveals that the trajectories of the treatment and control are mostly parallel, regarding both the SF-12 MCS and the SF-12 PCS (figure 7 and 8). Going from one year pre-treatment to five years pre-treatment only slows a slight divergence of the trends and in general the health of the treatment and control group seem to go in a similar direction. Moreover, the difference in health between the treatment and control group, with respect to the SF-12 MCS is smaller than one point at the most, which is substantially less than the treatment effect found in the main analysis. Hence, this visual assessment of parallel trends pre-treatment confirms the likelihood that the common trend assumption holds.

6. Discussion

This thesis sought to reveal the immediate impact of becoming unemployed on physical and mental health, using data from *Understanding Society* – The UK household Longitudinal Study. Through employing a combination of propensity score matching and difference-in-differences, the results from this study can be interpreted as causal effects, thereby adding meaningfully to a limited amount of literature investigating the causal relationship between unemployment and health.

The main analysis demonstrates that becoming unemployed has a small and strongly significant effect on mental health, whereas physical health does not seem to be affected. These results are in line with several other studies focusing on unemployment and health. Firstly, Gebel and Voßemer (2014) found similar results when employing the same DiD-PSM strategy as this study in German data. Including a life satisfaction scale that ranges from 0 to 10 to measure the short-term impact on psychological health, their results showed a medium sized effect (-0.45) by using the standardized mean difference to calculate the effect size. Like in this study, they found no effects on physical health in any of their analyses. Secondly, Gathergood (2013) investigated the effect of unemployment on psychological health in the UK. Using unemployment rates as an instrumental variable, they reported a small effect of 0.87 on the 12-point GHQ scale. Comparing this to ATT of the robustness analysis with the GHQ (1.439) in this study, Gatherhood (2013) reported a significantly smaller effect. This difference in effect could be due to different empirical strategies, given that, as explained in chapter 2, the instrumental variable approach of Gathergood (2013) might not capture the full effect of unemployment on health. Lastly, Kuhn et al. (2007) stepped away from self-reported health measures and instead aimed to investigate the short-term impact of job loss due to plant closures on public health costs. They found no overall increase of expenditures on medical treatments. However, expenditures on drugs specifically related to mental health problems, such as antidepressant, significantly increased with job loss. Moreover, hospitalizations as a result of mental health problems increased significantly for men. In summary, the results from the studies above all suggest that mental health is affected by unemployment. In contrast, the correlation between unemployment and physical health that is consistently found in cross-sectional data seems to be largely due to confounding and the selection of people with worse physical health into unemployment. An alternative explanation could be that physical health problems only manifest over a longer period or that the impact on physical health is too small to be detected in the short-run. The hypothesis discussed in chapter 2 on why unemployment might cause a deterioration in health provides an explanation for this line of thinking. The way in which physical health is mostly affected by job loss, is through lifestyle changes, as people can no longer afford a gym membership or healthy, often more expensive foods (Korpi, 2001). It is probable that the effects on physical health as a result of these lifestyle changes are smaller than the effects on mental health. Moreover, it is likely that these effects become noticeable only after a longer period than the few months that this study looks at. Furthermore, the indirect physical health effects following feelings of distress might take an even longer time to manifest (Stauder, 2019).

In addition, this thesis assessed the effects of unemployment on specific groups of people. First, an analysis was performed on males and females separately. It has been hypothesized that masculinity or male identity is more strongly linked to being employed than that is the case for females (Komarovsky, 1940). Furthermore, men still often earn more than their female partners, which means that financial support from a partner is less for unemployed men than for women that are married or living together (Paul & Moser, 2009). Both factors might result in a larger impact of becoming unemployed on health for men than for women. The results of the thesis do not confirm this hypothesis, as unemployment did not decrease the physical health of men or women. Furthermore, concerning mental health, the impact appears to be similar for both genders. This is in contrast with Kuhn et al. (2007), who do find some of their outcomes to be only significant in the male subsample.

Second, four separate analyses were done to estimate the effect on people aged 16 to 28, 29 to 40, 41 to 52 and 53 to 64. Paul and Moser (2009) suggest that the youngest age group and oldest age group may suffer the least from unemployment. For the former, this might be because they do not yet have the responsibility of providing for a family and for the latter because they may have more savings to fall back on (Jackson & Warr, 1984). The empirical results support this theory in part, as the impact on the oldest age group is one point less than that of the middle two age groups. Importantly, it should be noted that the inclusion criteria of the study might have also affected the results for the oldest age group. Considering observations were only included if people reported to be either in paid employment or unemployed, it might be that some older workers that lost their job decided to go into early retirement, as they did not expect to find a new job and subsequently reported their employment status to be ‘retired’. For these people, unemployment may have been more impactful than for people that felt they could find a new job fairly soon and decided to remain on the labor market. Given that the workers that went into a forced early retirement were not included in the study population, the impact of job loss on these individuals is not reflected in the results. The second assumption of Paul and Moser (2009), that younger workers are also less affected by unemployment, is not apparent from the results of this thesis. In fact, the youngest age group experiences the largest reduction in mental health as a result of becoming unemployed. Therefore, although this age group may not have to financially support a family, it could be that they face different financial pressures or that the social pressures to have a job are larger in this age group.

Strengths and limitations

Strengths

The first strength of this thesis is that it is the second study that looks at the specific situation of the United Kingdom and the first to do so with a PSM-DiD approach. The only other study that utilized UK data is Gathergood (2013). Besides, that study only looked at the effects of unemployment on psychological health. Thus, this thesis contributes usefully by being the first that inspects physical health effects of becoming unemployed in the UK. More generally, the results of this study add to the handful of studies that validly try to investigate the causal link between unemployment and health.

Second, the methodology of this thesis increases the internal validity. The difference-in-difference approach removes unobserved individual fixed effects and common period effects, which are two important aspects of bias that occur when doing longitudinal research (Ronchetti & Terriau, 2019). Even more significant for the internal validity is the use of propensity score matching on important confounding variables. The results of this thesis show that matching reduced the percent standardized bias to well below the proposed limits (Caliendo & Kopeinig, 2008), ensuring that confounding by these observables was removed. Admittedly, although bias as a result of the included variables was removed, there could be some confounding factors that have not been included in the matching procedure. The primary disadvantage of PSM and the main point of criticism is that it can only account for observed variables. Nonetheless, part of this problem is overcome by the difference-in-difference approach that removes unobserved fixed effects. Moreover, the pre-trend assessment of the outcome variables shows that there is no indication that any unobserved effects influenced the health trends of the treatment and control group differently. Therefore, it is likely that the DiD-PSM strategy removed most bias as a result of confounding. Lastly and most importantly, the internal validity of this research was increased by matching on indicators of health, as this minimizes the risk of reverse causality.

Third, the self-reported health measures used as outcome variables in this thesis are reliable and valid proxies for health (Ware et al. 1995). The use of the SF-12 MCS and SF-12 PCS therefore ensure that the outcome measures are sensitive to changes in actual health, thus making it possible to detect more minor deteriorations in health. This permits that the conclusion that physical health is not affected by job loss in the short-run can be drawn with more certainty, as we can be sure that these insignificant results are not found as a result of unresponsiveness of the outcome measure. Contrasting, other studies often use more limited outcome measures. For example, Böckerman and Ilmakunnas (2009), and Ronchetti and Terriau (2019) use one single question on general health as an indicator of self-assessed health. Considering the small effect on specifically mental health that was found in this thesis, it seems unsurprising that these studies were unable to detect an effect on health.

Lastly, the number of respondents included in this study and the PSM-DiD method increase the generalizability of the results. Given that the Understanding Society study includes over 40,000 individuals from all regions of the UK, the results are representative for the entirety of the UK, which adds to the external validity. While more studies researching this topic use panel data from a large number of participants, all studies using plant closures as an instrumental variable face the problem that their selection of workers is not representative for all workers in the country. As this thesis used a PSM-DiD model, such a selection of workers was not needed, again adding to the external validity. Importantly, generalizing the results to countries other then the UK should be done with caution. As discussed in chapter 2, the health insurance policy in a country and the social safety net might moderate how job loss impacts health. Therefore, the results of this thesis are mostly generalizable to countries that are similar in terms of those characteristics.

Limitations

The most important limitation of the methodological approach is that short-term selection into unemployment on the basis of health might still occur. As mentioned before, propensity score matching succeeded in making the treatment and control group similar at baseline and the additional robustness check of the common trend assumption showed that in the long-term there is no evidence of selection on health. Nevertheless, short-term health shocks cannot be accounted for. In theory it could be that a health shock occurred after the base-line measurements which resulted in a subsequent unemployment event. Even so, the time interval in which this could happen was fairly short (less than one year). Moreover, employment contracts and employment protection laws in the United Kingdom make this short-term health selection less likely. While the UK has less rigid employment protection than some other countries, like the Netherlands, where a worker cannot be fired by their employer because of an illness in the first two years (Rijksoverheid, n.d.), workers still enjoy some protection. If someone in the UK has been working for the same employer for at least a year, they cannot dismiss that worker for having an illness without following a procedure (Landau Law Solicitors, 2021). Firstly, the employer should consult with the workers medical advisers to learn about the medical condition and understand how to best support the worker. Secondly and most importantly, they should give the worker a reasonable time to recover (GOV.UK, 2021). These rules imply that workers are unlikely to be fired immediately after developing an illness, thus reducing the influence selection on short-term health shocks may have on the results. Moreover, the limitation of selection into unemployment as a result of a short-term health shock might have been more relevant, had this thesis found meaningful effects on physical health. In many professions a physical health shock has a more immediate and impactful effect on job performance than a mental health shock, which makes it more likely that selection based on physical health poses a risk for the validity of the results.

Recommendations

Policy implications
The results of this study have some relevant policy implications. Firstly, governments should increase efforts to support and assist the unemployed. As theory suggests, the impact of unemployment on health could be due to either a loss of income or the loss of a social network (Jahoda, 1982). The question remains whether supporting unemployed individuals by compensating them financially on the one hand or helping them strengthen their social support system on the other hand would be most effective, given that this research and other literature available are too heterogenous in terms of methodology and data to identify the impact of these two policy measures on health. Furthermore, as the results show a decrease in mental health, employers should put more effort in helping their employees cope mentally with job loss, for instance by referring them to prevention programs. Health professionals could play an important role as well, by increasing awareness of the potential mental problems that an unemployed individual might face and assisting them in how they can best deal with these problems. Health professionals could for example suggest looking for peer support to share troubles or make sure that the individual has a good support system. Moreover, the government can adopt policies to improve chances of the unemployed on the labor market or assist them in job searching, considering an important remedy for the health consequences of job loss is finding a new job (Gebel & Voßemer, 2014). However, re-employment might not be enough to undo effects of unemployment. Multiple articles suggest there may be a scarring effect of experiencing unemployment, that lasts beyond re-employment (Young, 2012; Gebel & Voßemer, 2014), which would further raise the social costs of unemployment. Therefore, attempting to prevent unemployment from happening in the first place might be the most valuable policy recommendation. For instance, governments would do well in advising employers to look for possibilities to re-train employees, before deciding to terminate the contract. In addition, governments could consider imposing rules that inhibit employers from easily firing employees.

Future research
This thesis and most other literature investigating the relationship between unemployment and health mostly analyze this relationship on the short-term. Consequently, future research that looks into the long-term impact of unemployment is needed. Especially considering physical health does not seem to be affected on the short-term, long-term research would provide valuable insights into the social costs of unemployment. Secondly, it would be worthwhile to research more in depth which individual characteristics or situations cause people to suffer more because of unemployment, considering this thesis only looks into specific gender and age groups. Other interesting aspects could be whether self-employed people experience being out of work differently, as people that reported to be self-employed were not included in the study population of this thesis. Moreover, there might be heterogeneity in how people that were previously working part-time or full-time experience unemployment. Lastly, follow up research that has specific health measures as outcome variables instead of generic health questionnaires would be relevant to create a more in depth understanding of what kind of health problems exactly people deal with. This information could then be used to offer more targeted support to people that lost their jobs.

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Appendices

Appendix I

Table 7 Concepts and questions of the SF-12

Physical Functioning
1. Does your health limit daily moderate activities?
2. Does your health limit climbing several flights of stairs?
Role-Physical
3. During the past 4 weeks, how much of the time has your physical health limited your work or daily activities?
4. During the past 4 weeks, were you limited in the kind of work or other activities because of your physical health?
Bodily Pain
5. During the past 4 weeks, how much did pain interfere with your normal work (both out and inside the home)?
General Health
6. In general, how is your health?
Energy-Fatigue
7. In the past 4 weeks, did you have a lot of energy?
Social Functioning
8. During the past 4 weeks, how much of the time have your physical health or emotional problems interfered with your social activities?
Role-Emotional
9. During the past 4 weeks, how much of the time have you accomplished less than you would like because of emotional problems?
10. During the past 4 weeks, how much of the time did you do work less carefully than usual because of emotional problems?
Mental health
11. How much of the time during the past 4 weeks have you felt calm and peaceful?
12. How much of the time during the past 4 weeks have had a lot of energy?

Appendix II - Operationalization of propensity score matching variables

Age (linear and squared)
The age of the sample member at the time of the interview is used. The age is derived from the date of birth and the derived date of the interview.

Gender
This dummy equals 0 if male and 1 if female. The derived sex (male or female) of the respondent is used. The gender of the respondent is checked across all waves and only marked as either male or female if all information corresponds or if the forename listed suggests a particular gender.

Highest qualification level
This variable is the first of three variables to adjust for socio-economic status. The highest qualification ever reported, as derived from interviews, is used. There are 6 qualification levels people can obtain: (1) degree, (2) other higher degree, (3) A-level, (4) GCSE, (5) other qualification or (6) no qualification.

Household equivalized income (linear and squared)
Monthly equivalized household net income without deductions is used. This is the second variable that is used to adjust for socio-economic status. Household income is used instead of personal income, as it is probable that not only personal income, but that of the household is available if a person encounters a health shock. This makes household income a more fitting variable to use to adjust for the confounding effect of socio-economic status. Monthly equivalized household net income without deductions is calculated by taking monthly total household net income without deductions and dividing it by the household income conversion factor. This factor is calculated by using the OECD-modified scale. This scale assigns a weight of 1 to the first household person, 0.5 to each additional adult member and 0.3 to each child below 13 years. The equivalization is performed to adjust household income to the needs of that household. This makes households of different sizes more comparable in terms of income.

Income from savings and investments
Annual income in the form of rent from savings and dividend from investments is used. This is the third variable used to adjust for socio-economic status. Like household income, this is information is derived from detailed information on personal income.

Marital Status
This variable is one of two variables to indicate household composition. The De facto marital status is used. This variable has 11 categories: (1) child under 16, (2) single and never married/in civil partnership, (3) married, (4) in a registered same-sex civil partnership, (5) separated but legally married, (6) divorced, (7) widowed, (8) separated from civil partner, (9) a former civil partner, (10) a surviving civil partner, (11) living as a couple. From these categories, a dummy variable is created that equals 0 if belonging in categories 1,2,5,6,7,8,9 or 10 and that equals 1 if belonging in categories 3, 4 or 11.

Number of children
This variable is the second of two variables to indicate household composition. It includes natural children, adopted children and stepchildren, aged 16 or below.

Previous unemployment spells dummy
Number of unemployment spells in the period from the last interview until this interview is used.

This variable counts the number of times the respondent's employment status was unemployed in a year. This is a derived variable, that considers a number of questions to deduct whether someone has experienced one or multiple unemployment spells. Using this variable, a dummy is created that takes on the value 0 if a person has 0 unemployment spells in a year and 1 if a person has 1 or more unemployment spells.

Type of job
To classify job type, the three-category version of the National Statistics Socio-Economic Classification (Three class NS-SEC) is used. The NS-SEC is an occupationally based classification. The variable is derived from information on type of employer, managerial duties, and training. The three categories of the three-class NS-SEC consist of (1) Management & professional, (2) Intermediate, (3) Routine. There are different versions of the NS-SEC, namely the three, five and eight category version. For this research, the three-category version has been chosen, as separation in more different categories will make finding a match for each individual more difficult and the extra categories do not add important extra information.

Disability and health condition dummies
A dummy for disability and a dummy for reporting to have a diagnosed health condition are the two variables included to proxy previous health. The health condition dummy equals 1 if the person answers yes regarding any of the conditions mention in the question 'has a doctor or other health professional ever told you that you have any of these conditions. The conditions included are (1) asthma, (2) arthritis, (3) congestive heart failure, (4) coronary heart disease, (5) angina pectoris, (6) heart attack or myocardial infarction, (7) stroke, (8) emphysema, (9) hyperthyroidism, (10) hypothyroidism, (11) chronic bronchitis, (12) liver condition, (13) cancer, (14) diabetes, (15) epilepsy, (16) hypertension, (17) clinical depression.

The disability dummy equals 1 if the person answers yes regarding any of the areas mentioned in the question 'do you have any health problems or disabilities that mean you have substantial difficulties with any of the following areas of your life'. The areas included are (1) mobility, (2) lifting/carrying or moving objects, (3) manual dexterity, (4) continence, (5) hearing, (6) sight, (7) communication or speech problems, (8) memory or ability to concentrate, learn or understand, (9) recognizing when you are in physical danger, (10) your physical co-ordination, (11) difficulties with own personal care, (12) other health problem or disability.

Regional unemployment rates
This variable is constructed using data from the Office for National Statistics on regional unemployment rates by age group (Office of National Statistics, 2021b). The regions specified are the twelve Government Office Regions in the UK. In the data from the Office for National Statistics, unemployment rates are reported every few months, for several age categories. For the creation of this variable, average yearly unemployment rates of the age group 16-64 per region are calculated and matched to the year in which the interview of the individual was taken.

Government Office Region
The 12 Government Office Regions are derived from the household's postcode. The regions are the following: (1) North East, (2) North West, (3) Yorkshire and the Humber, (4) East Midlands, (5) West Midlands, (6) East of England, (7) London, (8) South East, (9) South West, (10) Wales, (11) Scotland, (12) Northern Ireland.

Appendix III

Supplementary Table 2 Covariate balancing before and after matching

Covariates		Mean Treated	Mean Control	% Bias
Highest qualification level (Ref.: Degree)				
Other higher degree	Before	.12	.14	-5.6
	After	.12	.12	-0.1*
A-level	Before	.23	.22	1.8*
	After	.23	.23	-0.2*
GCSE	Before	.25	.20	12.2
	After	.24	.24	0.7*
Other qualification	Before	.09	.06	13.5
	After	.10	.09	0.3*
No qualification	Before	.04	.03	7.7
	After	.04	.04	1.2*
Government Office Region (Ref.: North East)				
North West	Before	.11	.10	2.6*
	After	.11	.11	0.2*
Yorkshire and the Humber	Before	.09	.08	1.8*
	After	.09	.08	0.7*
East Midlands	Before	.08	.08	-0.3*
	After	.08	.07	0.3*
West Midlands	Before	.09	.08	4.0
	After	.09	.09	0.1*
East of England	Before	.07	.09	-5.6
	After	.07	.07	-0.4*
London	Before	.13	.10	8.5
	After	.13	.13	-0.7*
South East	Before	.11	.12	-2.7*
	After	.11	.11	0.2*
South West	Before	.07	.08	-5.9
	After	.07	.07	-0.8*
Wales	Before	.06	.07	-2.0*
	After	.06	.06	-0.0*
Scotland	Before	.08	.10	-4.2
	After	.08	.08	0.2*
Northern Ireland	Before	.07	.06	2.0*
	After	.07	.07	0.2*

Notes: All covariates are measured before treatment; “Ref.” = reference group.; % bias expresses percentage standardized bias (Caliendo & Kopeinig, 2008); *%bias<3
Source: Understanding society, 2009-2019