Is Delayed Mental Health Treatment Detrimental for Employment?

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Abstract

Increasing prevalence of mental health problems and limited capacity of treatment have resulted in long waiting lists for mental health treatment. Little is known about the exacerbating effects of these increased waiting times. Using administrative data on mental health treatment and labor market status for all inhabitants of the Netherlands, I estimate the causal impact of increased waiting times on labor market status up to eight years after the onset of mental health problems. Individual waiting times are instrumented using regional waiting times to account for endogeneity. I find large and significant effects on employment and the receipt of sickness/disability benefits and social assistance. An increase in waiting time of two months (one standard deviation), results in a four percentage points decrease in employment. Furthermore, I show that vulnerable groups with a low education level or migration background are especially affected given that their average waiting time is up to 20 days longer.

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1 Introduction

In the last decades, the prevalence of mental health problems has been high and increasing in most OECD countries. Approximately half of all individuals suffer from mental health issues at some point in their lifetime (OECD, 2014). The increasing need for mental health treatment is often not matched by the provision of treatment, leading to decreased access to treatment in the form of increasing waiting times. The Covid-19 pandemic has aggravated this issue, as emotional distress increased while mental health treatment was decreased or completely halted due to lock-downs. As a result, waiting times have been increasing in many countries (for example in the UK (Campbell, 2020), in Australia (Kinsilla, 2021) and in the US (Caron, 2021)).

While the impact of a worsening of mental health on employment has been thoroughly investigated, little is known about the extent to which delayed treatment exacerbates the impact of mental health problems. The onset of mental health problems is associated with a drop in employment rate ranging between 10 and 30 percentage points (Frijters et al., 2014).[1] While Reichert & Jacobs (2018) do find that increased waiting time for mental health treatment is associated with worse mental health outcomes, the impact on labor market outcomes is unknown.[2] If waiting times indeed affect the relationship between mental health and employment, a pertaining question is whether specific groups are especially vulnerable to decreasing access of mental health treatment.[3]

This paper therefore investigates the following two research questions; (1) Do increased waiting times for mental health treatment worsen the impact of mental health problems on labor market outcomes, and (2) Is access to mental health treatment distributed unequally across the population. To answer these questions, I use administrative data for the Netherlands on the use of and wait-

[1]See Section 3 for a discussion on the general literature on the relationship between employment and mental health.

[2]See Section 4 for a more detailed discussion on the literature on the impact of waiting times.

[3]See Section 5 for a discussion on the literature on access to healthcare.

ing times for all mental health treatments, together with data on labor market outcomes and background characteristics. Both the treatment data and labor market outcomes are measured on a daily basis, allowing for detailed analyses on exact waiting times and the timing of changes of employment outcomes.

To provide a reference point for the potential effects of increased waiting times of mental health problems, I first estimate the effect of the onset of mental health problems by using an event-study specification which compares individuals with and without mental health problems. Given the potential presence of reverse causality and time-varying confounders, the obtained estimates should not be given a causal interpretation but are merely used as a benchmark for the effects of increased waiting times. The onset of mental health problems is associated with an eight percentage points decrease in the probability to be employed. Individuals of whom employment is terminated flow into sickness/disability insurance (seven percentage points) and social assistance (five percentage points).

As a second step, I estimate the causal impact of increased waiting times on employment. Individual waiting times can be endogenous as priority can be given to individuals with more (or less) severe mental health problems. At the same time, individuals may choose mental health providers based on (expected) waiting times. To account for the endogeneity of individual waiting times, instrumental variable (IV) estimation is used in which individual waiting times are instrumented using regional waiting times. The IV approach thus exploits plausibly exogenous variations in the congestion of the mental health system, as measured through regional waiting time. Using placebo regressions, I show that the effect of regional waiting times runs exclusively through changes in individual waiting times. Increased waiting time decreases the probability to be employed, while it increases the probability to receive sickness/disability benefits and social assistance for atleast five years after the start of treatment. A two month (i.e. one standard deviation) increase in waiting time decreases the probability to be employed by approximately four percentage points while it increases the probability to receive sickness/disability benefits by the same magnitude. The probability to receive social assistance increases by approximately one percentage point. The impact of increased waiting time on benefit receipt is slightly larger for individuals with a migration background and/or a low education level.

Given the negative effects of delayed treatment, a crucial question is whether access to mental health is equally distributed across various groups of the population. The final part of this paper therefor analyses differences in the access to mental healthcare based on gender, age, education level and ethnicity. Differences in waiting time based on gender and age are small, while difference based on ethnicity and education level are relatively large. Specifically, the average waiting time of migrants is 10-20 days longer than those of natives and lower-educated people have to wait 10-15 days longer than higher educated people, conditional on all other observable characteristics. It is important to stress that these differences in waiting time are thus not caused by selection based on municipality of residence, pre-treatment labor market status, or differences in the severity of mental health problems.

Putting these findings into perspective, the effects of increased waiting times are substantial. Specifically, a two-month increase in waiting time results in a decrease in employment of four percentage points, as compared to a 'total' employment effect of the onset of mental health problems of about eight percentage points. Furthermore, vulnerable groups appear to experience larger negative effects of increased waiting time, and are more likely to have longer waiting times as well. Decreasing access to mental health treatment might therefor increase inequality.

The remainder of this paper is organized as follows; The institutional setting and the data are illustrated in Section 2. Sections 3, 4 and 5 discuss the analyses on the effect of the onset of mental health problems, the exacerbating effects of waiting times, and unequal access to mental health treatment respectively. Section 6 concludes.

2 Mental healthcare in the Netherlands

Figure 1 illustrates the process individuals go through from the moment they experience mental health problems, until the start of their treatment. Mental healthcare is covered by mandatory health insurance but individuals experiencing mental health problems have to be referred by their general practitioner (GP). GPs can influence the waiting time by indicating whether there is high urgency, or whether it concerns a ”crisis” situation. In case of high urgency, mental health providers can plan the intake sooner. In case of crisis, treatment starts as soon as possible (within days). A GP can refer to a specific care-provider, but individuals are free to choose a different provider. To help individuals choose an appropriate mental healthcare provider, the government publishes general information about every provider, including average waiting times.

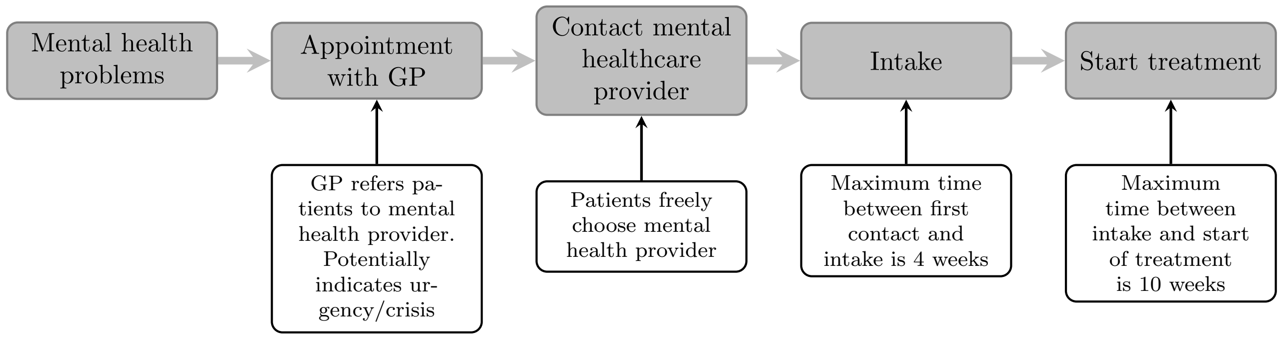


Figure 1: Timeline from start of mental health problems to the start of treatment

After an individual has contacted a mental health provider, the intake takes place. During the intake, a first assessment is made of the severity of the mental health problems, and a treatment plan is made. After the intake, actual treatment commences. In order to decrease the waiting time of patients, the Dutch government has set norms for the maximum waiting times (these norms are called “Treek-normen”). Once an individual has contacted a mental healthcare provider, the intake should take place within 4 weeks and actual treatment should start within 10 weeks after the intake implying a total waiting time of at most 14 weeks. Compliance with these norms is however limited, as no immediate action is taken once the norms are exceeded. As shown in the next subsection, individual waiting times can be significantly longer than these norms.

2.1 Data

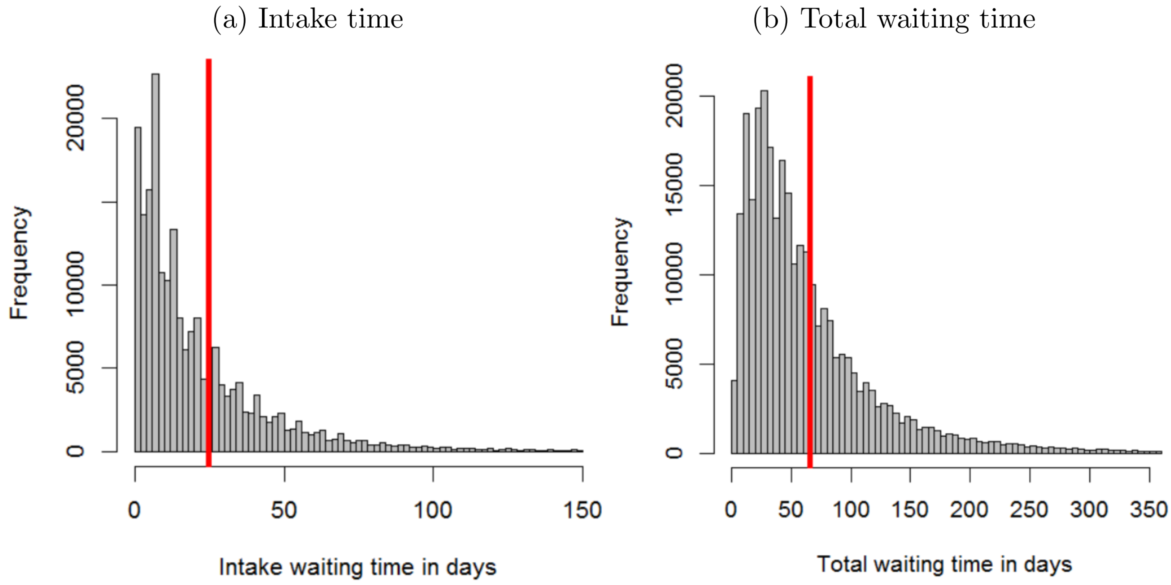
Several administrative datasets (provided by Statistics Netherlands) covering the entire Dutch population are linked to obtain individual time series on mental healthcare usage and a range of labor market outcomes. These time series are complemented with a dataset on individual and municipality characteristics.

Data on (mental) healthcare

The mental healthcare data contains all treatment-related mental healthcare events between 2011 and 2016. For these events, I observe the date of the event, the type of the event (first contact/intake/treatment/administrative etc.), the amount of contact minutes with a patient, the mental health diagnosis and (anonymized) identifiers for the patient and healthcare provider. Waiting times are calculated for all individuals who start mental health treatment between 2012 and 2016. Individuals receiving mental health treatment in 2011 are excluded, as it cannot be determined whether they have started mental health treatment in 2011 or whether they were already being treated in 2010. The amount of days between the first moment of contact and the intake is used as the "intake time" whereas the amount of days between the first moment of contact and the start of actual treatment is used as the "total waiting time". Total waiting time is observed for a total of 282,944 individuals in the time period under consideration.

Figure 2 shows the distributions of intake time (left) and total waiting time (right) for the entire sample. Both intake time and total waiting waiting time are right-skewed with an average intake time of 24 days, and an average total waiting time of 66 days (averages in red). There is considerable bunching at intake times equal to zero days (28% of all observations, excluded from the figure) implying that the first moment of contact and the intake occur on the same day. This is most likely due to measurement error of the first moment of contact; the first

Figure 2: Distribution of individual intake time (left) and individual total waiting time (right)



moment of contact is not properly recorded, and instead, the intake is reported as the moment of first contact. This implies that the observed intake times and total waiting times are an underestimation of the actual waiting times. IV estimation should account for bias through measurement error. To test whether this is the case, entries with intake times equal to zero days will also be omitted from the analysis as a robustness test.

A secondary source of data on healthcare usage is obtained through the healthcare insurance system. Statistics Netherlands provides the yearly healthcare expenditures covered by basic health insurance for the years 2009 until 2019. Given the compulsory nature of health insurance in the Netherlands, and the fullness of insurance, the dataset covers the vast majority of all healthcare. Spending is reported in various subcategories, which allows the distinction between mental and non-mental health expenditures and spending on pharmaceuticals.[4]

[4]See Appendix Section A.1 for classification of healthcare spending categories.

Data on labor market outcomes

The labor market outcomes include employment and the receipt of unemployment benefits, disability benefits, social assistance, or other social benefits. The labor market panel spans the period 2004 up until 2019. For most analyses, the time series are converted to time relative to the first moment of contact with a mental healthcare provider. Therefore, I am able to follow individuals from at most 12 years before mental health treatment (those starting treatment in 2016) until 8 years after the start of treatment (those starting treatment in 2012).

The timeseries data on health and labor market outcomes are enriched with administrative records from Statistics Netherlands on the year of birth, gender, nationality, level of education and municipality of residence. For all municipalities, a wide range of municipality characteristics are matched to the individual data. Municipality characteristics include gender, income and ethnicity distributions of the residents, the proportion of inhabitants receiving various social benefits, real-estate characteristics and population densities.

Descriptive statistics

Table 1 shows the descriptive statistics of all individuals who start mental health (MH) treatment between 2012 and 2016 aged 18-65 at the start of their treatment. The analyses focuses on individuals aged 18-65 as these are most likely to belong to the working population. The total sample is comprised of 282,944 individuals. For comparison, the first column shows the descriptive statistics of the full Dutch population aged between 18 and 65 who do not receive any mental health treatment between 2009 and 2019 and the third column shows the descriptive statistics of a sample matched one-to-one based on the propensity to start mental health treatment. The matched sample will be used as a control group in the analysis on the effects of the onset of mental health problems.[5]

Individuals receiving mental health treatment are on average younger than the rest of the population, which is mainly caused by a high prevalence of mental

[5] See Section 3 for a detailed discussion on the matching procedure.

Table 1: Descriptive statistics of sample of individuals starting mental health treatment in 2012-2016, and samples without mental health treatment

	No MH treatment 2010-2019[a]	Start MH treatment 2012-2016[b]	Matched sample[c]
Demographics[d]:			
Age	42.9	40.2	40.2
Female	53.8%	46.8%	47.1%
Dutch native	68.4%	72.2%	72.1%
Education unknown	47.5%	24.1%	24.8%
Education[e]:			
Low	18.7%	22.2%	22.7%
Middle	39.6%	41.1%	42.5%
High	41.8%	36.6%	34.8%
Annual health expenditures[f]:			
Mental healthcare	0	3,425	0
Physical healthcare	1026	1,684	1033
Number of individuals	14,674,592	282,944	282,944

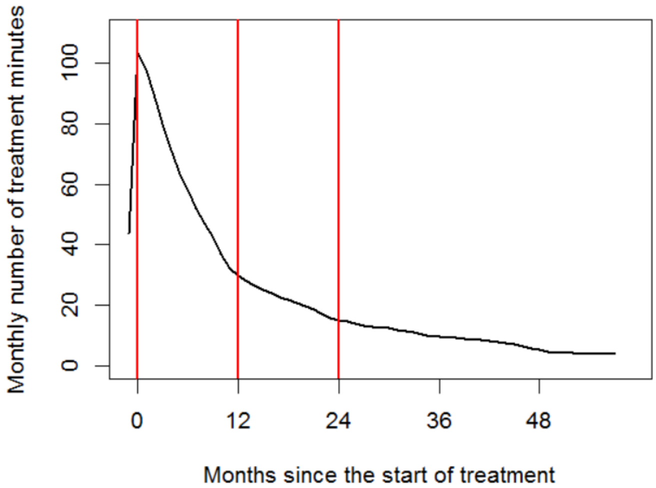
(a) All individuals in the Dutch population who do not receive any mental health treatment between 2009 and 2019 aged 18-65, (b) All individuals who start mental health treatment between 2012 and 2016 aged 18-65, (c) Sample of the Dutch population who do not receive mental health treatment between 2012 and 2016, matched one-to-one on the propensity to follow treatment with the mental treatment sample, (d) Demographics on January 2014,(e) Education level if known, (f) Yearly healthcare expenditures in the year of first contact with a mental health provider

health problems for individuals between the ages of 20 and 40. Furthermore, individuals receiving mental health treatment are more likely to be male and Dutch native, and they tend have completed a lower level of education.[6] The matched sample is almost identical to the treatment sample in terms of demographics. By construction, the treatment population has high mental healthcare spending but their non-mental healthcare expenditures are also almost twice as high as those of both other samples. This indicates the presence of co-morbidities and/or the interplay between mental and non-mental health.

To understand the impact of treatment and the delay of treatment, it is important to illustrate which mental health problems individuals face, and what treatment entails for them. The sample of individuals starting mental health treatment covers the full spectrum of mental health problems. The majority of them are diagnosed with mood disorders (30.7%) or anxiety disorders (22.7%),

[6]The difference in unknown education level is caused by the age differences. Education level for older cohorts has low coverage.

Figure 3: Average number of treatment minutes relative to the start of treatment



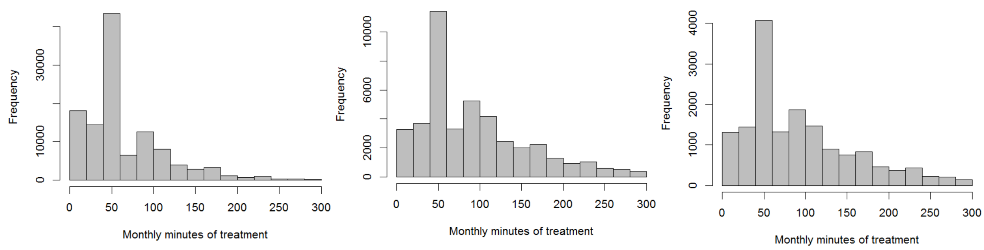
while personality disorders (8.0%) and substance-related mental health problems (7.7%) are less common. The remainder of the sample (30.9%) are diagnosed with some other disorder not belonging to these 4 main groups. The average amount of treatment minutes individuals receive decreases as time since the start of treatment increases (see Figure 3). The average amount of treatment minutes in the first month of treatment equals approximately 100, while this number decreases to 35 and 20 after respectively 1 and 2 years after the start of treatment.

The decrease in treatment minutes is mainly caused by a decrease in the amount of people who continue treatment (extensive margin) and not by a decrease in the number of treatment minutes per treated individuals. To illustrate, Figure 4 shows the distributions of treatment minutes after 1, 12 and 24 months. The distributions remain similar over time, but the amount of people receiving treatment decreases. The distributions furthermore show that median treatment is approximately one hour per month, but treatment intensity can range anywhere from 0 to more than 300 minutes per month.[7]

[7]The distributions shown in Figure 4 are truncated at 300 minutes. Treatment intensity can go upto as much as 15000 minutes per month in case individuals are institutionalized in a mental-healthcare facility.

Figure 4: The distribution of treatment minutes in the first, 12th and 24th month of treatment

(a) Month 1 (b) Month 12 (c) Month 24



3 The impact of mental health problems on employment

In order to interpret the effects of waiting times for mental health treatment, one should know what the impact of the onset of mental health problems is. By their very nature, most mental health problems are interrelated with a wide range of observable and unobservable characteristics and events. Hence, correlations between mental health and employment should not be interpret as causal. To make causal inference, recent literature has used instrumental variable estimation.

Early studies have used cross-sectional data with instruments based on early-life events. Examples of these instruments are parental psychological problems (See Ettner et al. (1997); Marcotte et al. (2000); Chatterji et al. (2011)), degree of religiosity, perceived social support and participation in physical activity (See Alexandre & French (2001); Hamilton et al. (1997); Ojeda et al. (2010)) and past mental health issues (See Ettner et al. (1997); Hamilton et al. (1997); Chatterji et al. (2007, 2011)). These IV estimates suggest that the onset of a mental health disorder causes a decrease in employment rate of 10 to 30 percentage points. However, it is debatable whether or not the exclusion restriction holds for the various instruments used. Many instrument are based upon early-life events. While these aspects have a clear impact on mental health, they might also affect other aspects of an individual's life, such as an individual's motivation or time preferences, potentially leading to biased IV estimates.

A recent study by Frijters et al. (2014), uses a panel in which the death of a friend is used as instrument for mental health, and finds that a one-standard deviation worsening in mental health, decreases the employment probability by 30 percentage points. This instrument is less likely to violate the exclusion restriction, as the authors also prove that the death of a close friend is not associated with other changes (such as bequests). However, the shock considered is very specific, and the impact on mental health is relatively small; the death of a close friend decrease mental health by on average 0.04 standard deviation.

Given the scarcity of convincing instruments, and their limitations, I will exploit an event-study approach in which I compare individuals undergoing mental healthcare treatment, to individuals who do not undergo treatment. By using an event-study setup, I control and test for pre-treatment differences caused by unobserved confounders. However, the event-study setup does not control for reverse causality and time-varying unobserved confounders and the resulting estimates should thus not be interpreted as causal effects. Instead, the estimates will be used to benchmark the effects of waiting times for mental health treatment.

3.1 Methodology

The event-study compares individuals undergoing mental health treatment, to a control group who does not undergo treatment. As already shown in Table 1, individuals receiving mental health treatment are very different than individuals not receiving mental health treatment. I therefore construct a control group using one-to-one matching on the propensity to start mental health treatment.[8] The propensity is estimated based on municipality of residence, gender, age, ethnicity and education level. The matched sample is very similar to the treatment sample in terms of these demographics, as shown in Table 1. Using siblings as an alternative control group, as proposed by Biasi et al. (2021), yields similar results.

[8]Matching on all observable characteristics yields similar results

To avoid potentially biased estimates due to comparisons between not-yet treated and already treated units, I consider time relative to the first moment of contact with a mental health provider.[9] For individuals in the control group, the counterfactual first moment of contact is not observed. I therefore use the first moment of contact of the matched treatment individual. Given that individuals are matched based on all observable characteristics, the baseline event-study specification does not include these characteristics as control variables.[10] The event-study specification is;

$$E_{it} = \alpha_{MH} + \alpha_t + \sum_{l=-T+1}^{-1} \beta_l MH_i \, I_{t=l} + \sum_{l=0}^{T} \beta_l MH_i \, I_{t=l} + \varepsilon_{it} \tag{1}$$

in which i subscripts the individual and t denotes the time relative to the first moment of contact (with $t = 0$ being the month of the first moment of contact). E_{it} is a labor market status outcome, MH_i is an indicator for receiving mental health treatment and $I_{t=l}$ indicates whether an observation is in month l relative to the first moment of contact. α_t captures the evolution over time for individuals who do not receive mental health treatment while β_l, the parameters of interest, capture deviations over time for individuals who do receive mental health treatment prior to and after the first moment of contact.

3.2 Results

Figures 5-11 show the proportions of individuals with a certain labor market status, and the corresponding event-study estimates. Despite matching based on propensity scores, the pre-treatment labor market status of individuals receiving mental health treatment is significantly different from the pre-treatment labor

[9] Recent literature has shown that using calendar time and a two-way fixed effects estimator can lead to biased results in case of staggered treatment implementation and dynamic treatment effects Goodman-Bacon (2021); Callaway & Sant'Anna (2021); Borusyak et al. (2021). By using time relative to the first moment of contact, a single treatment group (those experiencing the onset of mental health problems) is compared to a single control group that is never treated (those never receiving mental health treatment) and thus these concerns do not apply (see for example Baker et al. (2021)).

[10] Including observable characteristics as control does not affect the β_l estimates as the control variables do not change over time.

market status of individuals not receiving treatment. Six years prior to the first moment of contact, individuals in the treatment group are less likely to be employed, but more likely to receive various social benefits. The trends in Figures 5-11 furthermore show that most of these differences become larger in the years leading up to the first moment of contact.

Divergence of trends could be driven by a number of reasons. First of all, the onset of mental health problems happens prior to the moment individuals actually call a mental health provider. The time between the onset and the first moment of contact is unknown but could potentially be several months. Divergence due to the time difference between the onset of mental health problems and the first moment of contact, would be part of the causal effects of the onset of mental health problems. Divergence could however also be driven by reverse causality; a deterioration of labor market status could have a negative effect on mental health, biasing the event-study estimates. The event-study estimates should therefore not be interpreted as causal effects of the onset of mental health problems on labor market status. However, since reverse causality would upward bias the estimates, the event-study estimates can be used to obtain upper bounds of the causal effects.[11]

The employment rate drops by approximately eight percentage points in a two year interval around the first moment of contact relative to the employment rate of individuals without mental health problems. This estimate is close to the lower bound of estimates found in the IV studies discussed in the beginning of this section (IV estimates range between 10 and 30 percentage points). The drop in employment rate corresponds to a drop in monthly labor earnings of approximately €300,-, and a 15 hour drop in monthly number of working hours.

The drop in employment rate is mirrored partly by an increase in unemployment benefit receipt, with a divergence of at most 2.5 percentage points. The probability to receive UI benefits drops shortly after the first moment of contact, caused by a (temporary) inflow into sickness/DI benefits. The onset of mental

[11] Measurement error could bias the estimates towards zero. However, given the administrative and objective nature of the data, measurement error should be limited.

health problems leads to a large increase in sickness and disability benefit receipt. The increase in sickness and disability benefit receipt (seven percentage points) is of slightly smaller magnitude than the decrease in employment rate. A similar pattern emerges for social assistance receipt with an increase of approximately five percentage points. Inflow into other social benefit schemes is smaller, at approximately one percentage point.

Figure 5: Employment rates (left) and event-study estimates (right) for individuals with and without mental health treatment

(a) Employment rates (b) Event-study estimates

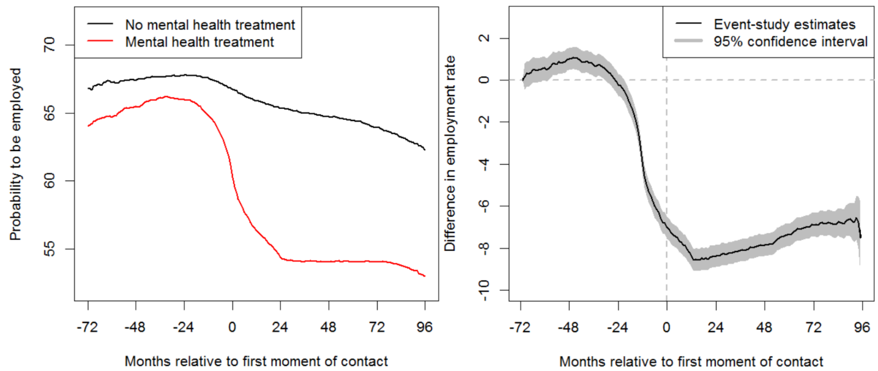


Figure 6: Monthly labor earnings (left) and event-study estimates (right) for individuals with and without mental health treatment

(a) Monthly labor earnings (b) Event-study estimates

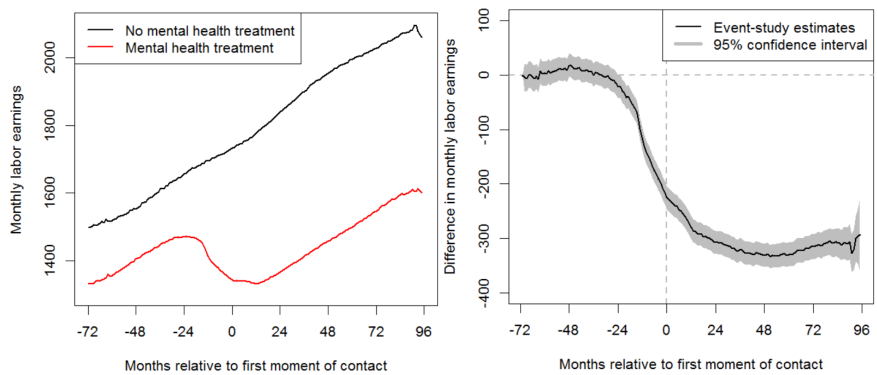


Figure 7: Monthly number of working hours (left) and event-study estimates (right) for individuals with and without mental health treatment

(a) Monthly number of working hours

(b) Event-study estimates

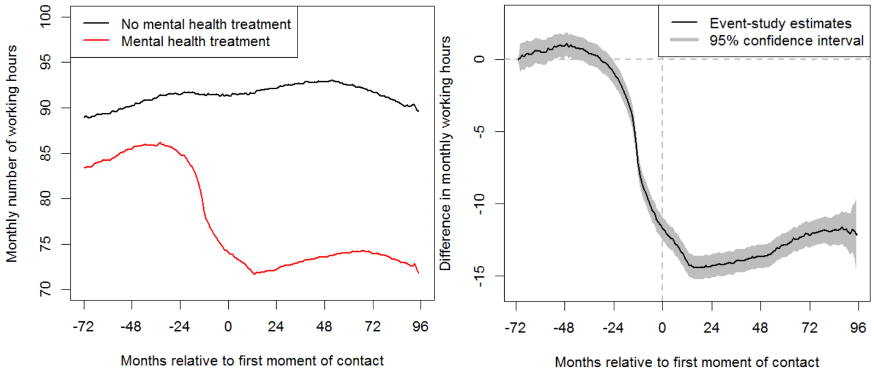


Figure 8: Unemployment benefit receipt (left) and event-study estimates (right) for individuals with and without mental health treatment

(a) Unemployment benefit receipt

(b) Event-study estimates

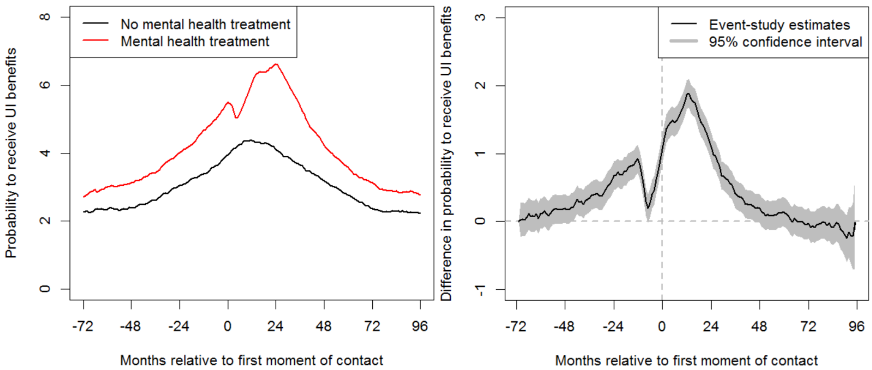


Figure 9: Sickness/Disability benefit receipt (left) and event-study estimates (right) for individuals with and without mental health treatment

(a) Sickness/Disability benefit receipt

(b) Event-study estimates

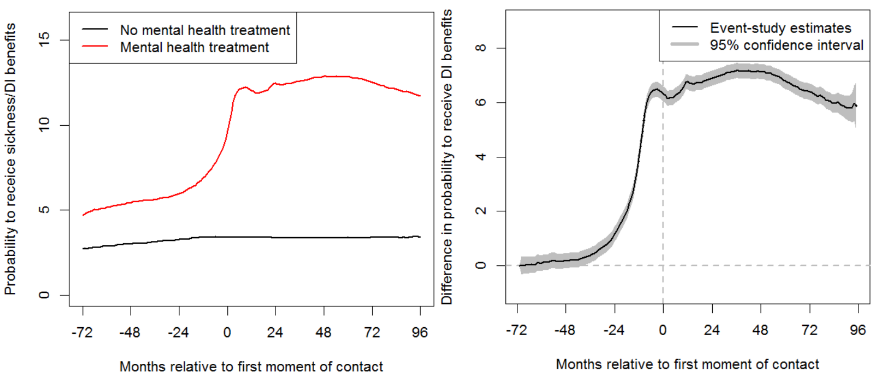


Figure 10: Social assistance receipt (left) and event-study estimates (right) for individuals with and without mental health treatment

(a) Social assistance receipt (b) Event-study estimates

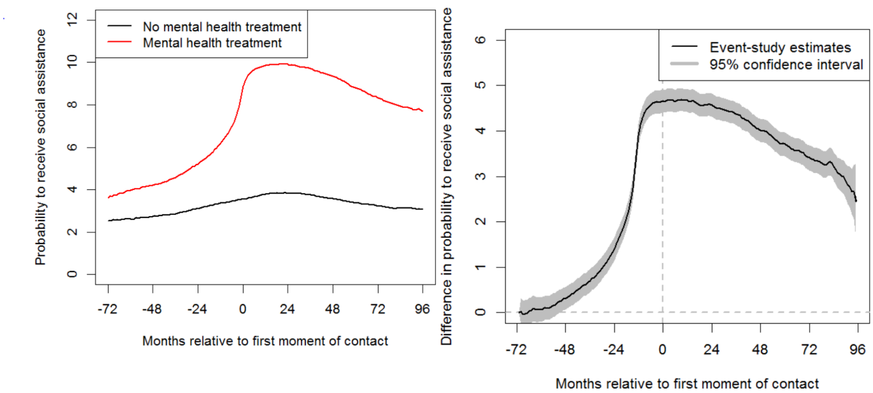
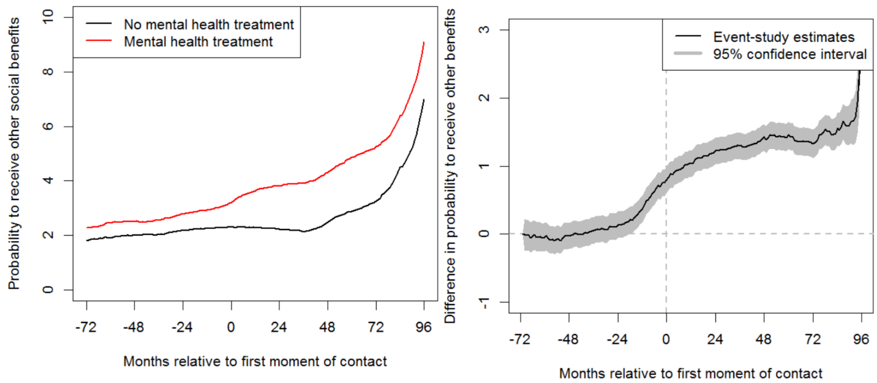


Figure 11: Receipt of other social benefits (left) and event-study estimates (right) for individuals with and without mental health treatment

(a) Receipt of other social benefits (b) Event-study estimates



Summing up, the onset of mental health problems decreases the employment rate by approximately eight percentage points, relative to the employment rate of individuals without mental health problems. Individuals that exit employment flow into sickness/disability insurance (seven percentage points) and/or social assistance insurance (five percentage points). Receipt of unemployment benefits (2.5 percentage points) and other social benefits (1 percentage point) are affected to a lesser extent. Given divergence of pre-trends and the potential of reverse causality, these estimates should however not be interpreted as causal impacts.

4 Increased waiting times for mental health problems

The negative impact of the onset of mental health problems on labor market status as illustrated in the previous section, is the impact averaged over the entire waiting time distribution. It thus encompasses individuals who's treatment commenced a week after the first moment of contact, and individuals who had to wait for months. Treatment itself has been found to be very effective in reducing the impact of mental health problems on employment (see for example (Biasi et al., 2021) and (Shapiro, 2020)) but little is known about whether increased waiting time for treatment worsens the impact of mental health problems or reduces the effectiveness of treatment. The only study which investigates the effect of waiting times for mental health treatment finds moderate effects (Reichert & Jacobs, 2018). However, this study only examines the effects on mental health itself and does not consider labor market outcomes. Furthermore, the authors use linear regressions and hence the estimates might be biased due to endogeneity of individual waiting time.

The impact of reducing waiting time for other medical treatments has been examined using (natural) experiments. Godøy et al. (2019) and Williams et al. (2022) estimate the causal impact of waiting time for respectively orthopedic surgery and substance abuse treatment on employment. Both studies use regional variation in waiting times to obtain causal estimates. Godøy et al. (2019) find no health effects, but strong employment effects of increased waiting time for orthopedic surgery. Williams et al. (2022) on the other hand finds both health and employment effects of increased waiting time for substance abuse treatment.

Waiting time for other types of "treatment" has been considered by Maestas et al. (2015) and Hauge & Markussen (2021). Maestas et al. (2015) consider increased processing time for DI applications in the US and find that a 2.1 month (one standard deviation) increase in waiting time reduces the probability to be employed by 3.5%. In contrast, Hauge & Markussen (2021) consider reduced waiting times for vocational rehabilitation programs for individuals on temporary DI in Norway, and find no significant effects of reduced waiting times. It is important to note that both of these studies focus on individuals who are (temporarily) outside the labor force, and increased waiting time thus potentially increases distance to the labor market. Waiting time for mental health treatment is potentially different as some individuals waiting for treatment can continue to work. These studies do however indicate that waiting times can affect labor market outcomes in some, but not all settings.

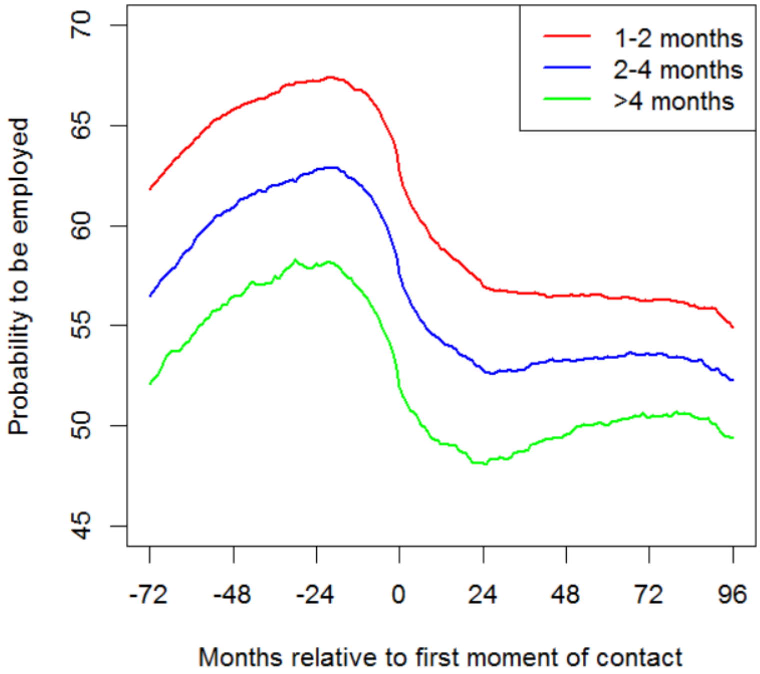
4.1 Methodology

Given the process between the onset of mental health problems and the start of actual treatment as described in Section 2, waiting times are likely to be endogenous due a number of reasons. First of all, individuals can freely choose mental health providers and some individuals might base their decision on reported average waiting times. Furthermore, GPs can indicate crisis or urgency on the referral, fast-tracking patients with more severe mental health issues. Crisis is observed in the data and can hence be controlled for, but urgency is not observed. Lastly, the severity of the mental health problems is partly determined during the intake, and based on the severity, individuals might have to wait longer or shorter until actual treatment starts.

To illustrate endogeneity of individual waiting times, Figure 12 shows the employment rate relative to the first moment of contact for three groups, based on their individual waiting time.[12] There is a clear drop in the employment rate around the first moment of contact, corresponding to the impact of mental health on employment as discussed in the previous section. The drop in employment rate appears to be similar for individuals with different total waiting times. However, there is a clear level difference between the three groups; individuals with longer individual waiting times have a lower probability to be employed, both prior to

[12] Similar figures showing the trends in the receipt of UI benefits, DI benefits, social assistance and other benefits are shown in Appendix Figure A.2

Figure 12: Employment rate relative to the first moment of contact for groups based on their individual waiting time



the first moment of contact and after the first moment of contact. This highlights the endogeneity of individual waiting time. As individuals are, by construction, not waiting prior to the first moment of contact, waiting time cannot have a causal impact on their employment rate prior to the first moment of contact. OLS estimates are thus biased and should not be interpreted as causal. Hence, IV estimation is required.[13]

In the IV estimation, individual waiting time is instrumented using regional waiting time. The intuition behind this instrument is that even though individuals can potentially choose mental healthcare providers based on expected waiting times, they are likely to choose providers within their region. Regions with longer average waiting times should thus result in longer individual waiting times, without being correlated to for example the severity of the mental health problems. The IV approach exploits plausibly exogenous variations in the congestion of the mental health system, as measured through regional waiting time.

[13]OLS estimates will be compared with IV estimates in the results section.

The first and second stage of the IV model look as follows;[14]

$$IW_i = \alpha_1 + \alpha_2 RW_i + \alpha_3 X_i + \alpha_4 R_i + \varepsilon_i \tag{2}$$

$$E_i = \beta_1 + \beta_2 \widehat{IW}_i + \beta_3 X_i + \beta_4 R_i + \mu_i \tag{3}$$

with IW_i and RW_i individual and regional waiting times, X_i individual characteristics, R_i regional characteristics (or regional dummies) and E_i the outcome of interest.[15] The following 5 labor market outcomes will be used; (1) Employment, (2) Sickness/DI benefits, (3) UI benefits, (4) Social assistance, (5) Other social benefits. Furthermore, I will also estimate the impact of waiting time on several measures of healthcare usage. The outcome of interest is measured at a specific point in time relative to the first moment of contact. The time window used, starts 6 years prior to the first moment of contact and ends 8 years after the first moment of contact. The IV estimates prior to the first moment of contact are placebo regressions which test the exclusion restriction. Given that treatment has not commenced yet, waiting time should not have any effect on employment and the estimates should thus be insignificantly different from zero.

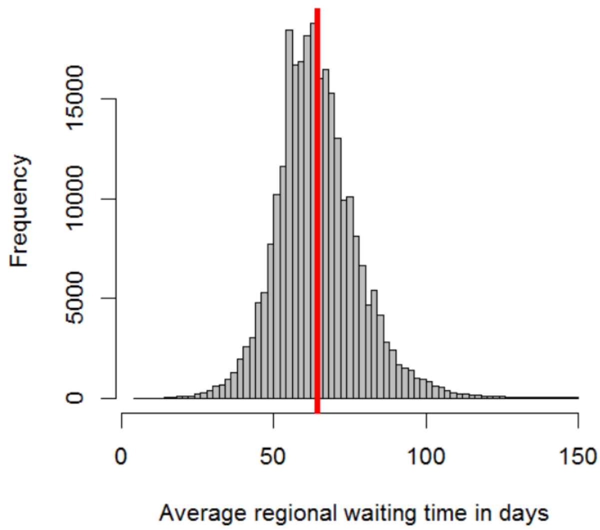
Average waiting time of a region is computed as the average waiting time of all individuals in that region, that contacted a mental health provider in the last 3 months, excluding the individual under consideration. Regions are defined on a municipality level, resulting in a total of 422 regions. The distribution of regional waiting times is shown in Figure 13. Regional waiting time is almost symmetrically distributed with mean regional waiting time of 66 days and standard deviation of 14 days.

To interpret the obtained IV estimates as causal impact, regional waiting time

[14]The IV specification assumes a linear relationship between waiting time and labor market status outcomes. To determine whether a linear relationship is likely, Appendix Figure A.1 shows non-parametric estimates of the association between employment, 12 months after the first moment of contact, and total waiting time. For waiting times up to approximately 200 days (28 weeks), a linear specification seems valid.

[15]As discussed, both the time until intake and the total waiting time is observed. Estimation will be performed using both waiting times.

Figure 13: Distribution of regional waiting time



should only influence labor market outcomes through individual waiting times. The next subsection discussion potential violations of this exclusion restriction, and presents various tests of the exclusion restriction. The first and second stage IV estimates are shown in the subsequent subsections.

Potential violations of the exclusion restriction

A potential concern with using regional waiting times as instrument is that regions with longer waiting times could be different than regions with shorter waiting times. The regions might have different living- and labor-market conditions, potentially violating the exclusion restriction. To account for differences between regions, two different specifications are used. The first specification controls for a wide range of regional characteristics (income, age, education and nationality distributions). By doing so, similar individuals in similar regions are compared, while exploiting variation both between regions and within regions over time. In the second specification, regional dummies are included instead of regional controls. By doing so, similar individuals in the same region at a different point in time are compared to each other, solely exploiting variation over time.[16] Including regional dummies, instead of regional controls, increases the standard

[16]For completeness, specifications without individual controls are shown in the Appendix.

Table 2: Impact of (lagged) regional unemployment rate on the regional waiting time

	Unemployment rate in month:			
	t	t-1	t-2	t-3
Regional waiting time	0.031	-0.012	-0.008	0.009
	(0.041)	(0.043)	(0.039)	(0.040)

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

errors significantly as it only uses variation in waiting times within regions but at the same time it eliminates any potential endogeneity based on unobserved differences between regions. Given their pros and cons, the final analysis uses both specifications.

A second potential concern with using regional waiting time is that changes in regional waiting time might be driven by local labor market shocks. If these shocks directly affect the mental health of the population, IV estimates will be biased. This issue is specific to mental health, and less relevant for the treatments discussed by Godøy et al. (2019) and Williams et al. (2022) as the underlying health issues are less likely to be caused by employment shocks. To test whether local labor market shocks affect regional waiting time, Table 2 show the estimated impact of the (lagged) unemployment rate in a region on the regional waiting time in that region. The unemployment rate does not influence the regional waiting time. To further rule out that estimated effects are driven by local labor market shocks, current and lagged regional employment rates are included as controls in the IV regressions. The inclusion of these controls does not affect the IV estimates, confirming that the results are not driven by local labor market shocks.

Lastly, the exclusion restriction would also be violated if regional waiting time would act as a gatekeeper for the mental healthcare system. Longer waiting times might deter relatively healthier individuals from starting treatment, resulting in differences in the composition of patients flowing into the mental healthcare system based on regional waiting time. A first way of testing whether this is the

Table 3: Impact of regional waiting time on probability to reach intake/start treatment

	Regional waiting time
Reach intake	-0.003
	(0.034)
Start treatment	0.007
	(0.041)

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

case, is assessing whether the probability to have an intake and/or actually start treatment, conditional on contacting a mental health provider, is affected by the regional waiting time. If regional waiting time would act as a gatekeeper, one might except that in regions with longer waiting times, more people would flow out of the mental healthcare system before starting treatment, hence increasing the fraction of patients who contact the mental health provider without starting treatment. To test whether this is the case, Table 3 shows the impact of regional waiting time on the probability to reach either the intake or start actual treatment, conditional on contacting a mental health provider. Regional waiting time has no significant effect on either of these measures.

A second more direct way of testing whether increased waiting time acts as a gatekeeping mechanisms, is through examining the composition of patients that contact mental health providers. If long waiting times would for example deter relatively healthy individuals from starting mental health treatment, the average health of those individuals who do start treatment would be worse. Table 4 shows the impact of (lagged) regional waiting time on the composition of patients starting treatment. The results indicate that regional waiting time has no significant impact on the composition of patients starting treatment, both in terms of demographic characteristics, and in terms of the type of mental health diagnosis they have. These results thus indicate that the composition of patients starting treatment, is not affected by changes in regional waiting time.

Table 4: Impact of regional waiting time on composition of patients starting mental health treatment

	Regional waiting time
Demographics:	
Age	0.039
	(0.033)
Female	0.003
	(0.005)
Dutch Native	-0.006
	(0.008)
Education unknown	0.012
	(0.034)
Low education level	0.008
	(0.031)
Middle education level	-0.003
	(0.033)
High education level	-0.011
	(0.033)
Mental health:	
Mood disorder	0.003
	(0.005)
Personality disorder	0.001
	(0.005)
Anxiety disorder	-0.004
	(0.005)
Other disorder	0.000
	(0.005)

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

First stage IV: The impact of regional waiting time on individual waiting time

Given that the exclusion restriction seems plausible, the second major assumption of the IV estimation concerns the strength of the instrument. To assess the strength, Table 5 show the first stage estimates using total waiting time.[17] As expected, longer regional waiting time increases individual waiting time. A 1 day

[17]The first stage IV results using waiting time until intake are shown in Appendix Table A.2.

Table 5: First stage IV results using total waiting time

	Regional controls	Regional dummies
Regional waiting time	0.405**	0.308**
	(0.010)	(0.011)
R^2	0.114	0.117
F-statistic	1565	734

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

increase in regional waiting time, on average increases individual waiting time by 0.4 days. Inclusion of regional dummies instead of regional controls does significantly decrease the estimate. This implies that individual waiting times differ between regions. However, even after the inclusion of regional dummies, regional waiting time still has a large and significant effect on individual waiting time. This is also reflected in the large F-statistics for both first stage estimates.[18]

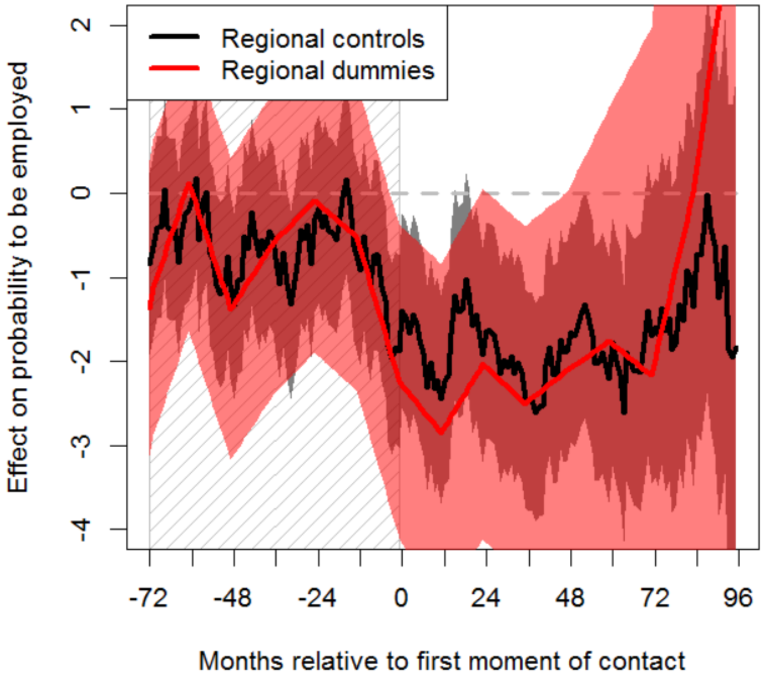
Second stage IV: The impact of waiting time on employment

Turning to the actual causal impact of increased waiting time on employment, Figure 14 shows the IV estimates of one additional month of total waiting time on employment. Estimates using regional controls are shown in black, while estimates using regional dummies are shown in red. The estimates for the 6 years prior to the first moment of contact, highlighted in gray, are placebo estimates; the outcome is measured prior to the first moment of contact and waiting time should therefore not have any effect.[19] As already briefly discussed, OLS estimation does yield significant placebo estimates, corresponding to the correlation between pre-treatment labor market status and individual waiting time as shown in Figure 12. In contrast, the IV placebo estimates are insignificantly different from zero, increasing the credibility of the IV approach. Furthermore, using regional dummies instead of regional controls yield similar point estimates, but

[18]The F-statistic compares models with and without the instrument.

[19]Placebo estimates using IV specifications without individual controls are shown in Appendix Table A.4

Figure 14: Estimated impact of one additional month of total waiting time on employment rate using regional controls (black) and regional dummies (red)



larger confidence intervals as less variation is used.[20] The similarity between the point estimates of the two specifications implies that the estimated impacts using regional controls, are not driven by unobserved differences between regions.

After the first moment of contact, increased waiting time has a negative and significant effect on the employment rate. A one month increase in total waiting time, reduces the probability to be employed by approximately 2 p.p.. The effects persist for approximately 5 years. Figure 15 shows the estimated impact on the other labor market outcomes. The 2 p.p. reduction in the probability to be employed , translates into a reduction in monthly labor market earnings of approximately €100,- (panel (a)), and the average number of working hours is reduces by approximately 3 hours (panel (b)). Panels (c)-(f) show that individuals of whom employment is terminated, flow into DI benefits and social assistance, while the inflow into UI and other benefits is unaffected by increased

[20]This also holds for all other labor market outcomes, as shown in Appendix Figure X.

waiting time.[21] The effects persist for atleast 5 years.[22]

To interpret the magnitude of the causal impact of waiting time on labor market status, the effect sizes can be compared to the estimated effects of the onset of mental health problems of Section 3. The onset of mental health problems is associated with a drop in the probability to be employed of approximately eight percentage points, an increase in the probability to receive sickness/disability benefits of seven percentage points and an increase in the probability to receive social assistance of five percentage point. A two months (one standard deviation) increase in total waiting time decreases the employment rate by four percentage points and increases the receipt of DI benefits by a similar magnitude. This is approximately halve of the average effect of the onset of mental health problems. The relative effect of increased waiting time on social benefit receipt is smaller, at approximately a quarter of the effects observed at the onset of mental health problems. While the receipt of unemployment benefits and other benefits is also affected by the onset of mental health problems, increased waiting time does not affect the probability to receive these benefits.

Heterogeneity analysis

To determine whether the effects of increased waiting times are heterogeneous, IV estimation is performed on subsamples based on gender, age, education level and nationality. Given that the largest effects are found approximately 1 year after the first moment of contact, the heterogeneity analyses is performed on the impact after one year.

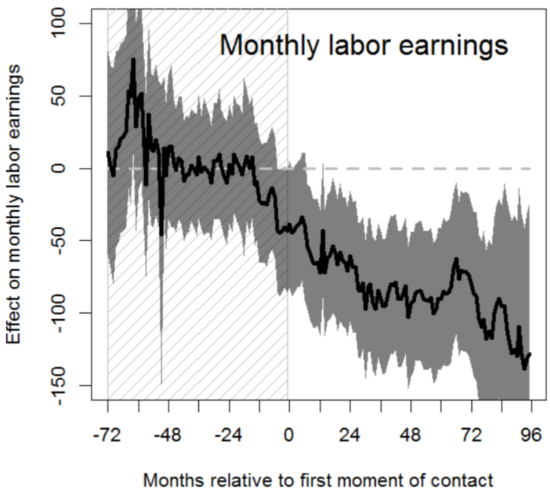
Table 6 show the impact for the full sample, and for samples split by gender. Differences in the impact of waiting times based on gender are limited with

[21] Results using waiting time until intake are shown in Appendix Figures X. The impact of waiting time until intake is generally larger. One potential reason for the larger magnitude, is that increased intake time affects all patients equally. In contrast, increases in total waiting time can be distributed by mental health providers based on severity. If total waiting times increase, providers can allocate more of the increase to less severe cases, potentially limiting the impact of increased waiting times. From a policy perspective, this also implies that intake times should be kept as short as possible.

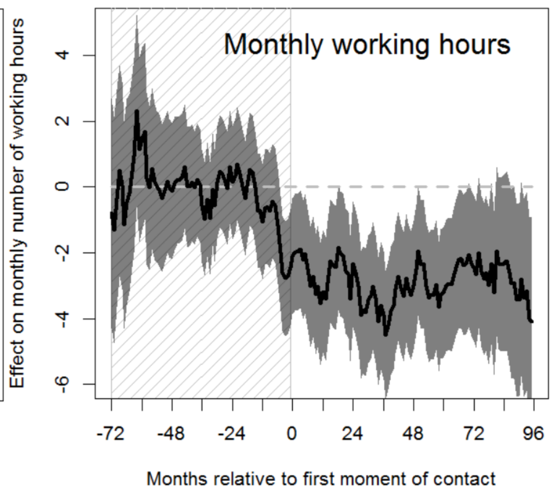
[22] After 5 years, the sample size decreases as individuals starting mental health treatment in 2016 can no longer be followed. This decreases the precision of the obtained estimates.

Figure 15: Impact of one additional month of total waiting time on labor market outcomes

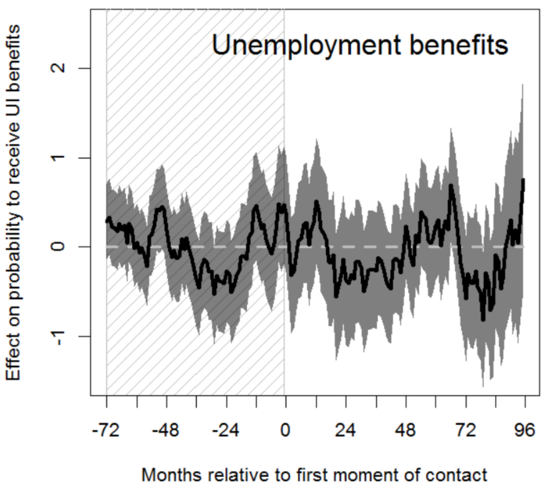
(a) Monthly labor earnings



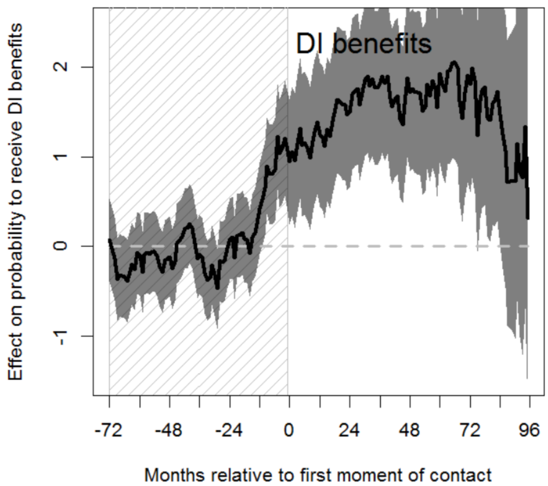
(b) Monthly working hours



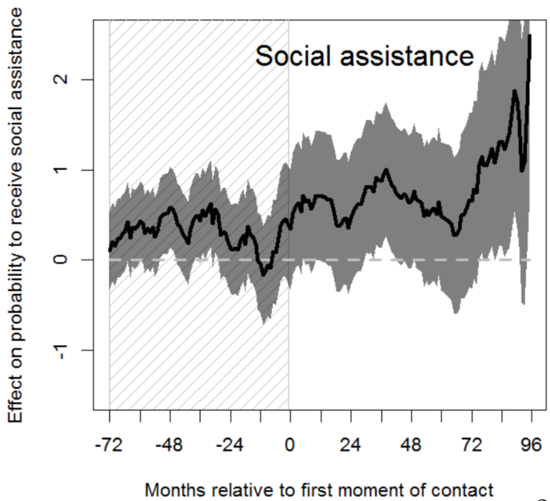
(c) UI benefits



(d) DI benefits



(e) Social assistance



(f) Other benefits

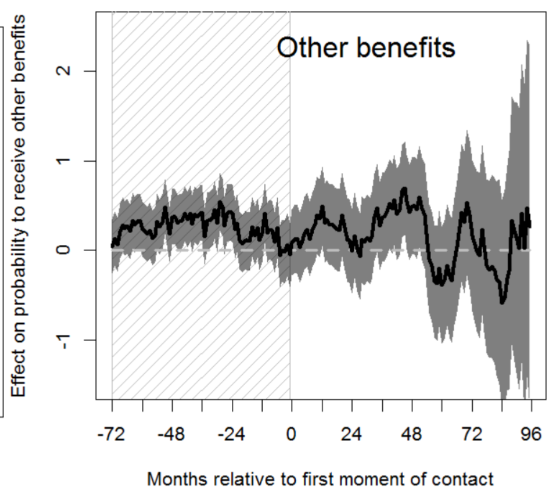


Table 6: Heterogeneity of the impact of waiting time by gender

	Full	Gender	
	Sample	Female	Male
Employment	-2.331**	-2.373**	-2.170**
	(0.582)	(0.810)	(0.835)
UI benefits	0.050	-0.372	0.437
	(0.330)	(0.449)	(0.486)
DI benefits	1.414**	1.571**	1.276*
	(0.380)	(0.529)	(0.543)
Social assistance	0.340	0.095	0.517
	(0.323)	(0.439)	(0.477)
Other benefits	0.628**	0.814**	0.420
	(0.207)	(0.263)	(0.323)
Sample size	282,944	151,148	131,796

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

females slightly more likely to receive various social benefit. Differences by age, as shown in Appendix Table A.5 are also relatively small, with no apparent age gradient. Differences based on ethnicity and education level, as shown in Table 7 are larger, with second generation immigrants being more likely to become unemployed, and both first and second generation immigrants being more likely to receive sickness/DI benefits. When looking at differences based on education level, a different picture emerges with individuals with a low education level less likely to receive DI benefits but mote likely to receive social assistance and other social benefits.

Summing up, increased waiting time for mental health treatment has large effects on the probability to be employed, receive sickness/disability benefits and other social benefits. Heterogeneity of the impact of increased waiting time is limited. However, individuals with a migration background are more likely to flow into sickness/DI benefits, and lower educated individuals are more likely to flow into social assistance.

Table 7: Heterogeneity of the impact of waiting time by ethnicity and education level

	Ethnicity			Education		
	Native	1^e	2^f	Low	Middle	High
Employment	-2.399**	-1.287	-4.743**	0.531	-3.065**	-3.496*
	(0.684)	(1.476)	(1.802)	(1.529)	(0.927)	(1.478)
UI benefits	0.257	-1.178	-0.587	0.210	0.602	-0.922
	(0.389)	(0.893)	(0.937)	(0.946)	(0.571)	(0.853)
DI benefits	1.114**	3.111**	2.158*	0.555	1.890**	0.930
	(0.419)	(1.209)	(1.156)	(1.228)	(0.622)	(0.754)
Social assistance	0.447	-0.166	0.540	1.622	-0.204	0.436
	(0.331)	(1.123)	(1.133)	(1.270)	(0.536)	(0.529)
Other benefits	0.534*	0.667	0.313	0.731	0.689*	0.283
	(0.247)	(0.468)	(0.636)	(0.728)	(0.308)	(0.389)
Sample size	205,033	46,352	31,559	38,516	92,432	77,774

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

5 Unequal access to mental health treatment

Given the negative effects of waiting time on labor market outcomes, and the heterogeneity of these effects, a crucial unanswered question is whether access to mental health is also heterogeneous, and if so, what causes potential differences in access.

Previous research on unequal access to mental healthcare has mainly focused on differences in the usage of healthcare in the US context. Large differences exist, with minority groups being up to 80% less likely to use mental healthcare (Sentell et al., 2007; Cook et al., 2017). Sentell et al. (2007) find that one of the main reasons for this reduced access is limited proficiency in English, i.e. language barriers. These studies indicate that, in the US context, differences in access to mental healthcare are large. However, no research has been done on differences in access in European countries. Furthermore, previous studies have focused on differences in the propensity to use mental healthcare, while this paper focuses on differences in waiting times conditional on using mental healthcare.

In this section, I will therefore investigate whether average waiting times differ between groups based on observable characteristics. The groups considered are the same groups as used in the heterogeneity analysis above; (1) by gender, (2) by age, (3) by ethnicity and (4) by education level. Several mechanisms might potentially cause differences in access to mental health. In this section, I consider the following four mechanisms; (a) sorting towards regions with short waiting times, (b) differences in pre-treatment labor market status which explain differences in waiting times, (c) different in the propensity to contact a mental health provider, which results in differences in the severity of mental health problems at the first moment of contact, and (d) selection towards specific mental health providers.

5.1 Methodology

To determine whether there is unequal access to mental health treatment, I estimate differences in waiting times for the various groups considered. The regression equation of interest is the following:

$$IW_i = \alpha + \beta X_i + \delta Z_i + \varepsilon_i \tag{4}$$

With IW_i individual waiting time, X_i indicators for the various groups considered, and Z_i other control variables. In the baseline specification, no control variables (Z_i) are included. I thus estimate the total difference in waiting times between the various groups. To determine which mechanisms cause the observed differences in waiting time, various control variables are sequentially included.

First of all, I include regional waiting times and regional dummies to determine whether differences are caused by spatial sorting into regions with shorter waiting times. Next, pre-treatment labor market status is included to determine whether differences in waiting times are caused by differences in labor market status of the various groups. As a third step, I investigate whether differences in waiting time are caused by differences in the type or severity of mental health problems. To do so, I use two different approaches. First of all, I control for the diagnosis as assessed during the intake, thus comparing individuals with similar mental health problems. As severity might still be different within the same diagnosis, I next focus on a subsample of individuals with depressions. For these individuals, the severity of the depression is determined during the intake. Hence, for individuals with the same severity, differences in the propensity to contact a mental health provider should not affect their waiting times. Lastly, to test whether within regions, there is also selection towards certain mental health providers, I include mental healthcare provider fixed effects.

5.2 Results

Table A.6 show the differences in average waiting times. Average waiting time is 64.4 days. There is a clear age gradient, with young individuals having to wait up to 2 weeks longer than older individuals. These differences are not caused by spatial sorting or labor market status, but they are caused to a large extend by differences in mental health diagnosis. When controlling for diagnosis, differences in waiting times reduce by more 50%. The inclusion of mental health provider fixed effects reduces the gradient in age even further. The raw difference in waiting time between males and females are very small (3 days), and remains small in all specifications. The inclusion of mental health diagnosis and provider fixed effects reduces the difference to almost zero days.

Table 8: Differences in waiting time by age-group, gender, nationality and education level

	(1)	(2)	(3)	(4)	(5)
Mean waiting time	64.4	64.4	64.4	64.4	64.4
Age^a:					
20-25	-2.4	-2.2	-1.8	0.0	1.3
25-30	-5.4	-5.2	-3.4	0.0	2.7
30-35	-8.2	-8.0	-4.9	-1.0	2.2
35-40	-8.1	-7.8	-4.4	-0.2	3.3
40-45	-9.6	-9.2	-5.7	-0.9	3.1
45-50	-10.6	-9.8	-6.4	-0.9	3.3
50-55	-12.7	-12.3	-8.9	-2.3	2.3
55-60	-14.1	-13.8	-10.7	-3.3	1.4
60+	-16.6	-16.2	-14.4	-6.6	-2.2
Gender^b:					
Female	3.4	3.0	3.8	1.8	0.2
Ethnicity^c:					
1^{st} generation^d	8.6	10.2	8.8	12.3	8.0
2^{nd} generation^e	1.7	3.1	2.6	4.0	3.0
Education level^f:					
Low	14.6	13.0	9.3	10.5	4.5
Middle	6.7	5.7	4.4	4.7	0.9
Demographic controls	X	X	X	X	X
Regional fixed-effects		X	X	X	
Pre-treatment employment			X	X	X
Mental health diagnosis				X	X
Provider fixed-effects					X

All estimates in the table are significant at a 1% significance level; (a) Baseline age is 18-20 years old, (b) Baseline gender is male; (c) Baseline ethnicity is native, (d) Individuals who migrated to the Netherlands, (e) Children of migrants, born in the Netherlands (f) Baseline education level is high

When examining differences based on ethnicity and education level, the results are somewhat different. First generation migrants have to wait approximately 1 week longer than natives. However, the difference in waiting time becomes larger when controlling for spatial sorting, pre-treatment labor market status and mental health diagnosis. For second generation migrants (children of first generation migrants), differences in waiting times are much smaller. Similarly, individuals with a low education level have average waiting times of one to two weeks more than individuals with a high education level. These differences are partly caused by differences in pre-treatment labor market status, but even after controlling for all observable characteristics, a difference of more than one week remains.

Table 9 show the difference in waiting times while zooming into individuals with a depression of a given severity. The estimated differences confirm the results obtained for the full population; differences in waiting times based on gender and age are small, while differences based on ethnicity or education level are significant. Migrants, which the same age, gender, education level and mental health diagnosis, who live in the same region and go to the same mental health provider than their native counterpart, have to wait up to 20 days for treatment. For individuals with a low education level, the difference is approximately 7 days compared to individuals with a high education level.

The differences in waiting times based on ethnicity and education level can have various explanations. These individuals might be less aware of the available options to search for providers with shorter waiting lists or resource constraints might force them choose the geographically closest provider. Additionally or alternatively, these individuals might be less capable of explaining their issues, either due to cognitive limitations or language barriers. However, from a cost-benefit perspective, waiting times should not depend on these characteristics. Furthermore, the heterogeneity analysis of Section 4 pointed at relatively large effects of waiting times for individuals with a migration background and individuals with a low education level. Hence, the cost of increased waiting time appears to be larger for these groups, and they tend to have longer waiting times. Given that education level and ethnicity is strongly linked to social economic status, these differences in waiting times might thus further increase inequality in society.

Table 9: Differences in waiting time for individuals with depression of given severity

	Low severity	Mild severity	High severity
Mean waiting time	55.2	57.3	49.4
Age^{a}**:**			
20-25	1.5	2.2	5.7
25-30	3.4	3.0	6.5
30-35	1.4	2.2	7.5
35-40	5.9	2.0	7.2
40-45	5.3	3.5	3.8
45-50	5.5	2.8	6.6
50-55	5.6	3.8	6.4
55-60	0.9	2.0	8.1
60+	2.2	-0.4	4.4
Gender^{b}**:**			
Female	-0.3	1.1	0.6
Ethnicity^{c}**:**			
1^{st} generation^{d}	19.7	14.0	9.4
2^{nd} generation^{e}	8.6	5.2	7.8
Education level^{f}**:**			
Low	6.6	6.7	8.1
Middle	1.5	0.6	0.4
Demographic controls	X	X	X
Regional fixed-effects	X	X	X
Pre-treatment employment	X	X	X
Provider fixed-effects	X	X	X

All estimates in the table are significant at a 1% significance level; (a) Baseline age is 18-20 years old, (b) Baseline gender is male; (c) Baseline ethnicity is native, (d) Individuals who migrated to the Netherlands, (e) Children of migrants, born in the Netherlands (f) Baseline education level is high

6 Conclusion

The increased prevalence of mental health problems, paired with limited capacity of treatment, has resulted in long waiting lists in many OECD countries. While the impact of a worsening of mental health on employment has been thoroughly investigated, little is known about the extent to which delayed treatment exacerbates the impact of mental health problems. In light of these considerations, this paper investigates the following two research questions: (1) Do increased waiting times for mental health treatment worsen the impact of mental health problems on labor market outcomes, and (2) Is access to mental health treatment distributed unequally across the population? To answer these questions, I use large-scale linked administrative data for the Netherlands on the use and waiting times of mental health treatments and labor market outcomes of individuals.

To put the potential effects of increased waiting times in perspective, I first estimate the impact of the onset of mental health problems using an event-study approach which compares individuals with mental health problems to individuals without mental health problems who are matched one-to-one based on the propensity to start mental health treatment. This yields a negative employment effect of eight percentage point. Individuals of whom employment is terminated enter into sickness/disability insurance and/or into social assistance. It should be noted that the event-study approach does not control for potential reverse causality and time-varying unobservable confounders. The estimates are thus upper bounds but can be used as a benchmark for the impact of increased waiting times.

I next show that individual waiting times for mental health treatment are endogenous, but can be instrumented using regional waiting times. Increased waiting time negatively affects the probability to be employed. An increase in total waiting time of two months (1 standard deviation) decreases the probability to be employed by approximately four percentage points and increases the probability to receive sickness/disability benefits by a similar magnitude. The probability to receive social assistance increases by approximately percentage point. The effects persist for atleast 5 years. When examining heterogeneity of these impacts based on gender, age, ethnicity and education level, slightly larger effects are found on benefit receipt for individuals with a low education level and individuals with a migration background.

As a final step, I show that there are systematic differences in waiting times across demographic groups. This raises important equity questions. The negative impact of increased waiting seems to affect vulnerable groups – as defined by ethnicity and education level – to a larger extent than other groups, since on average they have to wait longer. Specifically, the average waiting time of immigrants is 10-20 days longer than those of non-immigrants and the average waiting time of lower-educated individuals is 10-15 days longer than those of higher-educated individuals. These differences in waiting times are not caused by selection based on municipality of residence, pre-treatment labor market status, or differences in the severity of mental health problems. At the same time, I showed that the impact of increased waiting time is relatively large for these groups. The burden of decreasing access to mental health treatment is thus especially large for vulnerable groups, potentially increasing inequality.

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A Appendix

A.1 Classification of healthcare cost

Table A.1: Construction of mental healthcare expenditures and physical healthcare expenditures based on expenditure categories used by Statistics Netherlands

Expenditure category[a]	Mental healthcare	Non-mental healthcare	Pharmaceuticals
General practitioner		X	
Pharmacy			X
Dental healthcare			
Hospital healthcare		X	
Paramedical healthcare		X	
Apparatus			
Hospital transportation			
Birth care			
Health care abroad			
Other cost			
First-line psychological healthcare	X		
Mental healthcare	X		
Basic-mental healthcare	X		
Specialist mental healthcare	X		
Geriatric rehabilitation healthcare	X		
Nursing without stay		X	
Sensory disability healthcare			

Note: (a) Expenditure categories as used by Statistics Netherlands

Table A.2: First stage IV results using waiting time until intake

	Regional controls	Regional dummies
Regional waiting time	0.136**	0.114**
	(0.005)	(0.006)
R^2	0.052	0.059
F-statistic	724	417

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

A.2 Additional results

Figure A.1: Non-parametric estimates of the association between total waiting time (grouped by week) and employment 12 months after the first moment of contact

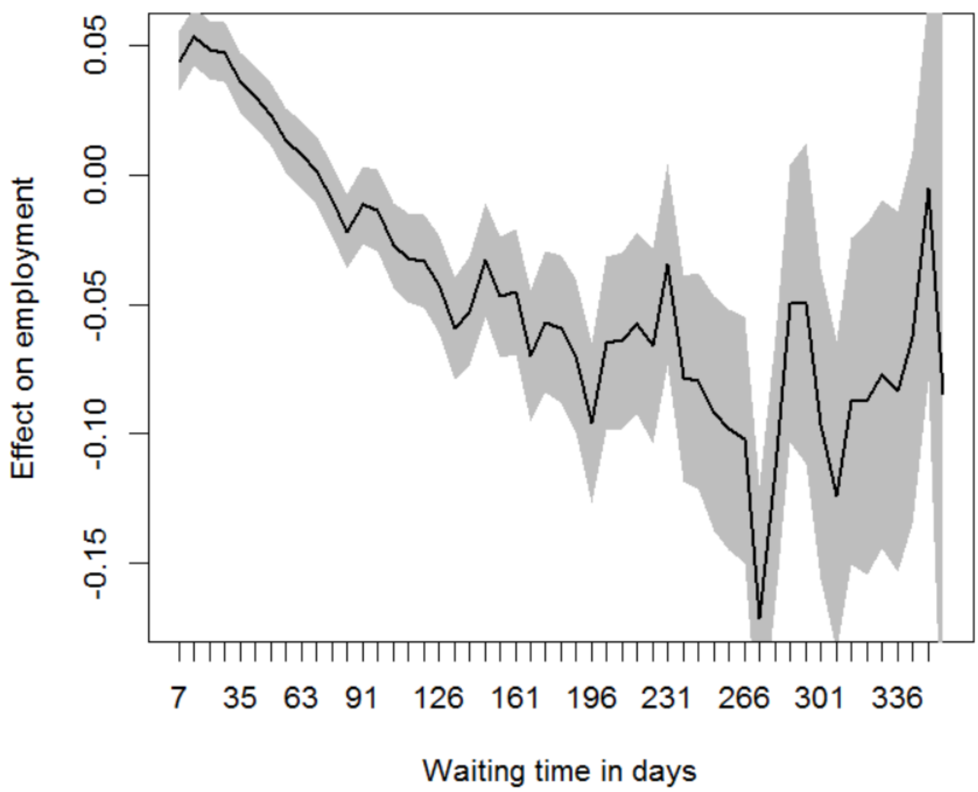
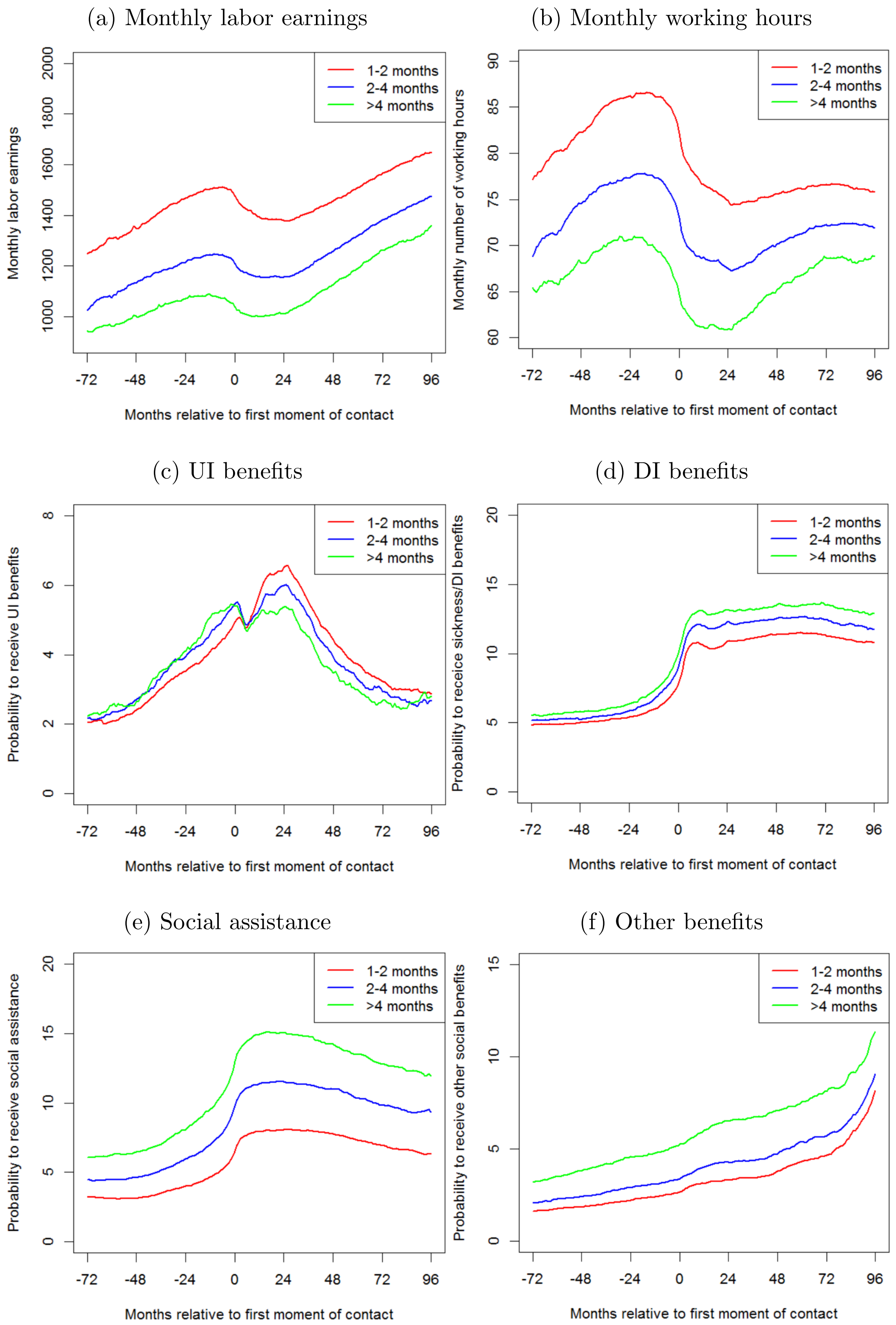


Table A.3: First stage IV results including specifications with fewer controls

	First stage IV estimates									
	Intake time					Total waiting time				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Regional waiting time	0.150**	0.169**	0.167**	0.136**	0.114**	0.517**	0.507**	0.501**	0.405**	0.308**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)	(0.010)	(0.011)
R^2	0.006	0.037	0.040	0.052	0.059	0.015	0.105	0.112	0.114	0.117
F-statistic	1533	1678	1589	724	417	4170	3684	3519	1565	734
Individual controls		X	X	X	X		X	X	X	X
Prior labor market status			X	X	X			X	X	X
Regional controls				X					X	
Regional dummies					X					X

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

Figure A.2: Trends in labor market outcomes relative to the first moment of contact for groups based on their individual waiting time



(a) Monthly labor earnings

(b) Monthly working hours

(c) UI benefits

(d) DI benefits

(e) Social assistance

(f) Other benefits

Table A.4: Placebo estimation results on the effect of waiting times on employment one year before inflow

	Placebo estimates											
	Intake time						Total waiting time					
	OLS	(1)	(2)	(3)	(4)	(5)	OLS	(1)	(2)	(3)	(4)	(5)
Employment[a]	-0.497**	8.945**	0.241	0.581	-2.146	-1.182	-1.251**	2.593**	0.080	0.193	-0.719	-0.438
	(0.073)	(1.407)	(1.275)	(0.952)	(1.418)	(1.873)	(0.048)	(0.404)	(0.425)	(0.317)	(0.475)	(0.694)
UI benefits	0.222**	-0.121	2.161**	1.812**	1.781*	1.517	0.175**	-0.035	0.721**	0.603**	0.597*	0.562
	(0.043)	(0.593)	(0.568)	(0.562)	(0.836)	(1.105)	(0.021)	(0.172)	(0.189)	(0.186)	(0.280)	(0.409)
Sickness/DI benefits	0.177**	4.910**	4.688**	1.389**	0.455	-0.082	0.433**	1.423**	1.563**	0.462**	0.152	-0.030
	(0.033)	(0.715)	(0.672)	(0.427)	(0.635)	(0.840)	(0.025)	(0.205)	(0.222)	(0.142)	(0.213)	(0.311)
Social assistance	0.275**	-1.238	1.138	0.339	-0.192	-0.587	0.632**	-0.359	0.379	0.113	-0.064	-0.217
	(0.032)	(0.675)	(0.618)	(0.421)	(0.626)	(0.829)	(0.023)	(0.195)	(0.206)	(0.140)	(0.210)	(0.307)
Other social benefits	0.119**	5.649**	3.136**	0.577*	0.403	0.402	0.277**	1.638**	1.045**	0.192**	0.135	0.149
	(0.021)	(0.492)	(0.458)	(0.274)	(0.408)	(0.540)	(0.017)	(0.139)	(0.152)	(0.091)	(0.137)	(0.200)
Outside labor force	-0.160**	-13.091**	-7.318**	-3.090**	-0.403	-0.719	-0.023	-3.795**	-2.440**	-1.028**	-0.135	-0.266
	(0.063)	(1.221)	(1.112)	(0.817)	(1.211)	(1.601)	(0.041)	(0.346)	(0.368)	(0.271)	(0.406)	(0.593)
Individual controls	X		X	X	X	X	X		X	X	X	X
Labor market status	X			X	X	X	X			X	X	X
Regional controls					X						X	
Regional dummies	X					X	X					X

[a] Effect on probability to be employed; Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

Table A.5: Heterogeneity by age of the impact of waiting times 1 year after the onset of mental health problems

	18-20	20-25	25-30	30-35	35-40	40-45	45-50	50-55	55-60	60-65
Employment	-2.773	-1.039	-3.152*	-3.244	-4.464**	-1.848	-1.149	-3.344	-2.676	-2.304
	(2.250)	(1.549)	(1.489)	(1.749)	(1.694)	(1.736)	(1.622)	(1.811)	(2.570)	(2.851)
UI benefits	0.417	-0.200	-1.180	1.504	1.425	-1.223	0.586	0.029	-0.697	-1.278
	(0.454)	(0.603)	(0.856)	(1.115)	(1.088)	(1.172)	(1.108)	(1.243)	(1.725)	(1.666)
Sickness/DI benefits	1.241*	-0.186	2.216*	-0.388	0.029	2.423	1.650	2.242	4.405*	4.146
	(0.491)	(0.709)	(0.959)	(1.187)	(1.181)	(1.266)	(1.224)	(1.464)	(2.149)	(2.584)
Social assistance	0.392	1.535	0.102	-0.934	0.341	-0.130	-1.169	2.651**	0.504	0.715
	(0.800)	(0.884)	(0.949)	(1.100)	(1.003)	(1.001)	(0.936)	(0.998)	(1.092)	(1.224)
Other social benefits	1.370	0.718	0.478	0.352	-0.623	1.486*	0.141	0.027	1.077	1.282
	(0.970)	(0.574)	(0.489)	(0.518)	(0.475)	(0.549)	(0.518)	(0.676)	(1.127)	(1.344)
Outside labor force	1.075	-0.060	1.322	1.292	2.920*	-0.266	-1.366	-2.410	-0.237	-4.330
	(2.197)	(1.364)	(1.124)	(1.260)	(1.229)	(1.124)	(1.161)	(1.262)	(1.807)	(3.199)
Sample size	19,917	37,977	36,536	33,333	31,634	33,092	30,619	26,681	19,892	13,263

Standard errors shown in parentheses; *significant at a 5% significance level; **significant at a 1% significance level

Table A.6: Differences in time until intake by age-group, gender, nationality and education level

	(1)	(2)	(3)	(4)	(5)
Mean waiting time	23.5	23.5	23.5	23.5	23.5
Age[a]:					
20-25	-1.2	-1.2	-1.5	-0.7	0.0
25-30	-1.9	-1.8	-2.1	-0.8	0.4
30-35	-2.7	-2.5	-2.4	-1.0	0.3
35-40	-2.6	-2.4	-2.2	-0.7	0.6
40-45	-3.3	-3.0	-2.7	-1.1	0.4
45-50	-3.2	-2.9	-2.6	-0.9	0.7
50-55	-3.9	-3.6	-3.4	-1.5	0.4
55-60	-4.3	-4.1	-4.0	-1.9	-0.1
60+	-4.9	-4.7	-5.0	-2.7	-1.2
Gender[b]:					
Female	0.8	0.8	1.0	0.4	-0.3
Ethnicity[c]:					
1^{st} generation[d]	4.0	4.7	4.2	4.8	3.8
2^{nd} generation[e]	0.8	1.3	1.2	1.4	0.8
Education level[f]:					
Low	6.8	6.6	5.0	4.9	2.6
Middle	3.0	2.8	2.2	2.1	0.6
Demographic controls	X	X	X	X	X
Regional fixed-effects		X	X	X	
Pre-treatment employment			X	X	X
Mental health diagnosis				X	X
Provider fixed-effects					X

All estimates in the table are significant at a 1% significance level; (a) Baseline age is 18-20 years old, (b) Baseline gender is male; (c ethnicity is native, (d) Individuals who migrated to the Netherlands, (e) Children of migrants, born in the Netherlands (f) Baseline level is high