Is Delayed Mental Health Treatment Detrimental to Employment?

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Abstract

Waiting times for mental health treatment have been increasing in many countries. Using administrative data on all inhabitants of the Netherlands and exploiting exogenous variation at the municipality level, I find that these waiting times have substantial repercussions on labor market outcomes for at least eight years after the start of treatment. A two-month (one standard deviation) increase in waiting time decreases the employment probability by four percentage points. Vulnerable groups with lower educational attainment or a migration background are especially affected given that the impact of waiting time is larger for them and their average waiting time is longer.

Keywords: Mental health, Labor supply, Disability Insurance

JEL: J08, I1, J22

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1 Introduction

Over the last several 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 (Hewlett & Moran, 2014). The onset of mental health problems has been found to have large negative effects on employment, with a corresponding decrease of 10 to 30 percentage points in the probability that an individual is employed (Frijters et al., 2014). Conversely, appropriate mental health treatment has been found to be effective in mitigating these negative impacts (Biasi et al., 2021; Shapiro, 2022).

Despite this, many countries struggle with providing sufficient mental healthcare capacity, leading to decreased access to treatment in the form of long waiting times. The Covid-19 pandemic has aggravated this issue, as emotional distress increased while access to treatment was reduced or even eliminated due to lockdowns. As a result, waiting times have been increasing in many countries, such as the UK, Australia, the US, and the Netherlands (Campbell, 2020; Kinsilla, 2021; Caron, 2021; n.d., 2021). Given the time it can now take before appropriate treatment can start, a crucial question is whether treatment remains effective in reducing the negative impact of mental health problems on employment if individuals have to wait several weeks or months before it can commence. While some correlational evidence now exists that increased waiting times are associated with worse mental health outcomes (Reichert & Jacobs, 2018), causal estimates of the impact on employment are yet to be documented. This knowledge gap leaves policymakers in the dark when it comes to quantifying the micro- and macro-level consequences of inadequate mental healthcare provision.

In this paper, I attempt to fill in this gap by investigating whether increased waiting times for specialized mental health treatment negatively affect labor market outcomes. Given that there exist large disparities in the propensity to receive mental health treatment between various demographic groups (Sentell et al., 2007), I additionally analyze whether certain groups are affected to a greater extent by these increased waiting times. To answer these questions, I used administrative data from the Netherlands regarding the usage of mental health treatments and the corresponding waiting times. Using anonymized citizen service numbers, I then merged this with data on labor market outcomes and demographic characteristics at an individual level. The main analysis focuses on waiting times for any kind of mental health problem. Given that the spectrum of mental health issues is broad, I additionally distinguish between treatments for the four main categories of mental health issues: personality disorders, mood disorders, anxiety disorders, and other disorders. The time window under consideration runs from 2012 to 2019.

To begin with, I introduce a benchmark for the potential effects of increased waiting times. This benchmark is estimated using an event-study specification comparing individuals starting mental health treatment to those who do not undergo treatment. Receiving treatment could be seen as an imperfect proxy of experiencing mental health problems, and the benchmark estimates should thus be interpreted as the net effect of the onset of mental health problems and the subsequent treatment of these problems. Due to potential reverse causality and time-varying confounders, the resulting estimated correlations should not be taken at face value, but serve instead as a point of comparison for the remaining analyses. With this in mind, the onset of mental health problems is associated with a nine percentage point reduction in the probability that a given individual is employed two years after the start of treatment. The majority of those whose employment was terminated subsequently made use of sickness/disability insurance (7 percentage points), or social assistance (4 percentage points).

Following this, I estimated the causal impact of increased waiting times on employment. This presents a methodological challenge: not only are waiting times likely endogenous with respect to the severity of a diagnosis, but individuals can also choose among providers based on expected waiting times. To account for this endogeneity, I instrumented individual waiting time using regional waiting time. This IV approach exploits plausibly exogenous regional variations in the congestion of the mental health system as measured through regional waiting time on a municipality level. I subsequently find that a two-month (equal to one standard deviation) increase in waiting time decreases the probability of employment by approximately four percentage points while also increasing the probability of receiving sickness/disability benefits by two percentage points. Heterogeneity in the effect of waiting time is limited with respect to the type of diagnosis and gender, but the impact of increased waiting time is noticeably higher for individuals with a migration background and those with lower educational attainment.

Given the negative effects that I find for delayed treatment –particularly for certain vulnerable groups– a crucial follow-up question is to what extent an individual's access to mental healthcare is impacted by their demographic characteristics. The final part of this paper, therefore, examines differences in waiting times based on gender, migration background, and educational attainment. As with the effects of delayed treatment, differences in waiting times based on gender are small, while those based on migration background and educational attainment are relatively large. Specifically, the average waiting time of individuals with a migration background is 7-11 days longer than that of individuals without a migration background. For less educated individuals, this gap is 3-13 days with respect to their higher-educated counterparts. These estimates are all on top of any differences in a rich set of observable characteristics, which include other demographics, job characteristics, provider fixed effects, and mental health diagnoses. It is important to stress that these differences in waiting time are therefore not caused by selection based on the municipality of residence, pre-treatment labor market status or differences in the severity of mental health problems.

To put these findings into perspective, the effects of increased waiting times are substantial relative to the changes in labor market status around the start of treatment. A two-month increase in waiting time results in a four percentage point reduction in the probability of employment, as compared to a "total" employment effect around the start of treatment of about nine percentage points. As just discussed, vulnerable groups experience both longer average waiting times and larger negative effects, meaning that the differential impact of reduced access to mental health treatment could be substantial. If policymakers wish to protect economically vulnerable individuals and combat inequality, my results suggest that greater availability of mental health resources could be a valuable tool in their arsenal.

The results contribute to several lines of research. First, there is extensive literature on the effects of mental health problems on employment. By their very nature, most mental health problems are interrelated, with a wide range of both observable and unobservable characteristics and events affecting mental health. To perform causal inference, early studies used cross-sectional data with instruments based on early-life events. Examples of these instruments are parental psychological problems (Ettner et al., 1997; Marcotte et al., 2000; Chatterji et al., 2011), degree of religiosity, perceived social support, and participation in physical activity (Alexandre & French, 2001; Hamilton et al., 1997; Ojeda et al., 2010) and past mental health issues (Ettner et al., 1997; Hamilton et al., 1997; Chatterji et al., 2007, 2011). The IV estimates of these studies point to a decrease in the probability of being employed by between 10 and 30 percentage points due to the onset of mental health problems. While these early-life events have a clear impact on mental health, they might also affect other aspects of an individual's life, such as their motivation or time preferences, potentially leading to biased IV estimates.

An exception in this strand of literature is a more recent study by Frijters et al. (2014) which uses panel data in which the death of a friend is used as an instrument for mental health. This instrument is less likely to violate the exclusion restriction, but the shock considered is specific and the impact on mental health is relatively small; the death of a close friend decreases mental health by on average 0.04 standard deviation. The authors' IV estimates indicate that a one standard deviation worsening of mental health decreases the probability of being employed by 30 percentage points.

Even more recently, attention has shifted to the effects of treatment for mental health problems on labor outcomes by using plausibly exogenous variation in the availability of pharmaceuticals. Biasi et al. (2021) show that the availability of lithium as a treatment for bipolar disorder reduced the earnings penalty of bipolar disorder by approximately one-third. Similarly, Shapiro (2022) finds that increases in the number of advertisements for antidepressants reduce workplace absenteeism significantly. This mitigating impact of treatment for mental disorders on employment suggests that there is a negative impact of mental health problems themselves on employment. I add to this literature in two ways. First, I use a much broader notion of treatment which includes both the use of pharmaceuticals and psychotherapy. Second, I do not examine variation in the availability of treatment, but variation in the time individuals have to wait before receiving it.

A small but growing strand of literature focuses on waiting times for various treatments. At the time of writing, the only study to investigate the effect of waiting times for mental health treatment finds moderate effects (Reichert & Jacobs, 2018). However, this study only examines correlations between waiting time and mental health itself and does not consider labor market outcomes. The impact of waiting time for other medical treatments has been examined using a similar estimation approach as used in this paper. Godøy et al. (2023) and Williams & Bretteville-Jensen (2022) estimate the causal impact of waiting times for orthopedic surgery and substance abuse treatment, respectively, on employment. Both studies use regional variation in waiting times as instruments to obtain causal estimates. Godøy et al. (2023) find no health effects, but strong employment effects of increased waiting time for orthopedic surgery. Williams & Bretteville-Jensen (2022) on the other hand, find both health and employment effects of increased waiting times for substance abuse treatment.

The effect of waiting times for non-medical treatment on employment has been considered by Autor et al. (2015) and Hauge & Markussen (2021). Autor et al. (2015) study increased processing times for disability insurance (DI) applications in the US and find that a 2.1-month (one standard deviation) increase in waiting time reduces the probability of employment 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. I add to this literature on waiting times by estimating the causal impact of waiting time for one of the most prevalent types of treatment: namely, treatment for mental health problems.

The last related strand of literature concerns inequality in both access to and use of mental healthcare. Previous research on this subject has mainly focused on the US context. There we see that 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 English proficiency, i.e., language barriers. However, little is known about differences in access conditional on seeking treatment. Furthermore, the differential impact of mental health problems on minority groups is also under-investigated. I fill these gaps in the literature by examining differences in waiting times conditional on seeking treatment, and by estimating differential impacts on various groups.

The remainder of this paper is organized as follows: the institutional setting and the data are described in Sections 2 and 3. Sections 4, 5 and 6 discuss the analyses on the onset of mental health problems, the exacerbating effects of waiting times, and unequal access to mental health treatment respectively. Section 7 concludes.

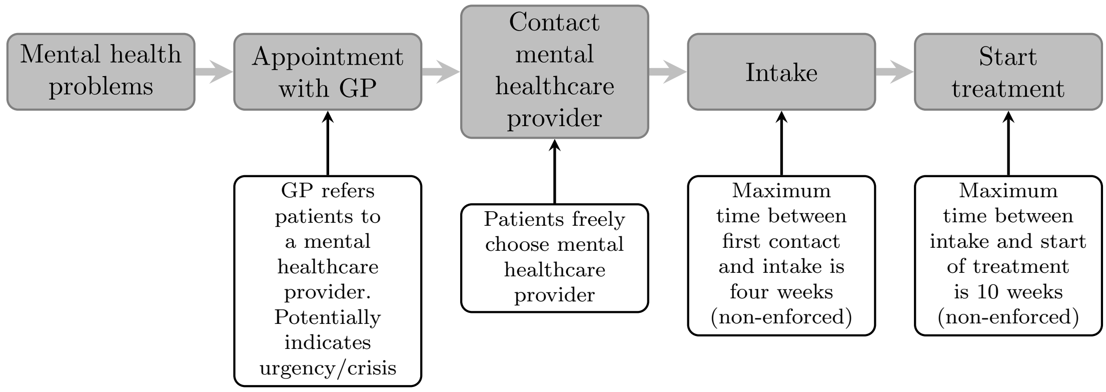
2 Mental healthcare in the Netherlands

Figure 1 illustrates the process individuals in the Netherlands go through from the moment they experience mental health problems, until the start of their treatment. Mental health problems as discussed in this paper range from mild depression to severe personality disorders. Treatment for all mental health problems is covered by universal health insurance. Individuals experiencing mental health problems first contact their general practitioner (GP). The GP is the gatekeeper of the mental healthcare system and makes the first assessment of the severity of mental health problems. In case of mild mental health problems, the GP can either decide to treat the individual within their GP practice or refer them to a provider of basic mental healthcare. If the problems are more severe, the GP will refer to specialized mental healthcare, which is the focus of this paper. Individuals can receive some form of treatment from their GP while waiting for specialized mental healthcare.

GPs can influence the waiting time by indicating the urgency of the case. In cases with high urgency, mental healthcare providers can schedule the intake sooner. In crisis situations, treatment starts as soon as possible (within a few 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.

After an individual has contacted a mental healthcare provider, the intake takes place. During the intake, a first assessment is made of the (severity of) the diagnosis, and a treatment plan is made. After the intake, treatment commences as soon as the provider

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



has the required capacity. In order to decrease the waiting time of patients, the Dutch Ministry of Health, Welfare and Sport has set norms for the maximum waiting times. Once an individual has contacted a mental healthcare provider, the intake should take place within four weeks and treatment should start within 10 weeks after the intake, implying a total waiting time of at most 14 weeks. Compliance with these norms is 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 the norms.

3 Data

To obtain individual time series on mental healthcare usage and a range of labor market outcomes, several administrative datasets provided by Statistics Netherlands covering the entire Dutch population are linked. These time series are complemented with data on both individual- and municipality-level characteristics. Linkage of datasets was done using anonymized citizen service numbers.

3.1 Data on (mental) healthcare

The mental healthcare data contains all treatment-related specialized mental healthcare events occurring between 2011 and 2019. Mental healthcare treatment is defined as having real-life or virtual contact with a mental healthcare provider. Treatment could be a combination of some form of therapy and pharmaceuticals, but the use of pharmaceuticals is not reported in the data. For all treatment-related events, I observe the date of the

Table 1: Sample selection steps

Inclusion criteria	Remaining sample
Start of mental health treatment 2012-2019[a]	1,537,153
Waiting time observed[b]	1,268,211
0 < Waiting time < 365 days[c]	1,062,563
Intake observed	1,016,127
18-65 years old during the first moment of contact	759,041
No mental healthcare spending in 3 years prior to treatment[d]	524,707

(a) Individuals showing up in the mental healthcare data in year t but not in year t-1; (b) Waiting time is observed if the first moment of contact is recorded and if there is at least one treatment activity; (c) Waiting times of more than one year are unlikely and could be caused by measurement error in the first moment of contact; (d) No mental healthcare spending in the 3 years before the first moment of contact.

event, the type of the event (first contact/intake/treatment/administrative, etc.), the number of contact minutes with a patient, the mental health diagnosis, the type of treatment provider (psychologist, psychiatrist or other) and anonymized identifiers for the patient and provider.

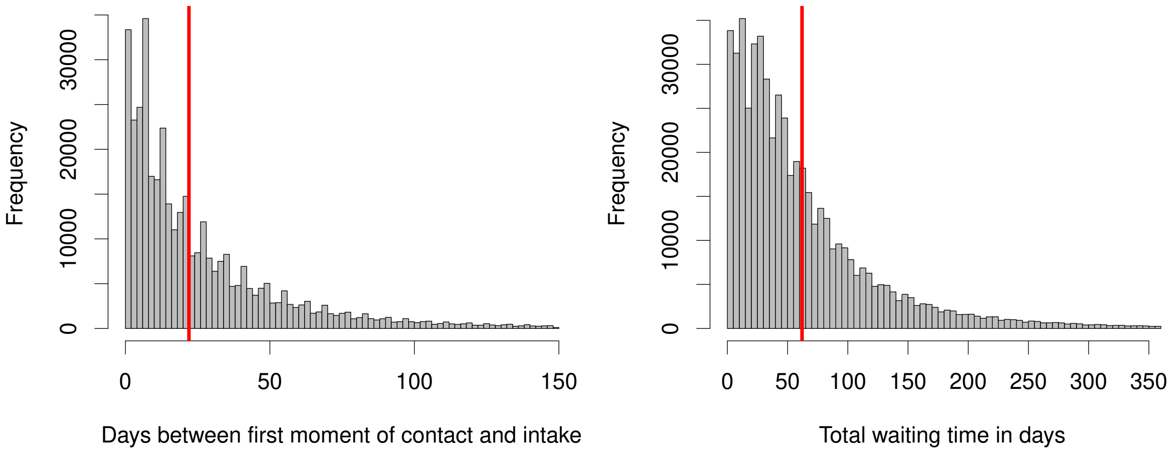
Table 1 shows the sample selection steps to obtain the final sample of individuals that started specialized mental health treatment and for whom waiting time is observed. Waiting times were calculated for all individuals who started mental health treatment between 2012 and 2019. Individuals receiving mental health treatment in 2011 are excluded, as it cannot be determined whether they started mental health treatment in 2011 or whether they were already being treated in 2010. Approximately one-and-a-half million individuals started mental health treatment in 2012-2019. Of these, waiting time is observed for 1,268,211 individuals. Excluding individuals with waiting times longer than one year or without an intake reduces the sample to 1,016,127 individuals. As this paper focuses on labor market outcomes, only individuals within the working-age range of 18 to 65 are included. Finally, to ensure that individuals are not merely continuing previous treatments, I exclude all individuals with mental healthcare spending in the three years prior to the start of treatment. The final sample comprises 524,707 individuals who started mental health treatment in the period under consideration.

Figure 2 shows the distributions of time until intake (left) and total waiting time (right) for the entire sample. Time until intake is defined as the number of days between the first moment of contact and the intake while waiting time equals the number of days

Figure 2: Distribution of time until intake (left) and waiting time (right) excluding observations with 0 days until intake. Mean values in red

(a) Intake time:
First contact until intake

(b) Waiting time:
First contact until treatment



between the first moment of contact and the start of treatment. Both time until intake and waiting time are right-skewed with an average time until intake of 22 days, and an average waiting time of 62 days (averages in red). The observed waiting times are likely to be under-reported given that there is considerable bunching at time until intake of 0 days 27.3% of all observations, not shown in Figure 2). IV estimation should account for potential measurement error bias caused by this under-reporting of waiting times.[1]

A secondary source of data on healthcare usage is obtained through the health insurance system. Statistics Netherlands provides the yearly healthcare expenditures covered by basic health insurance for the years 2009 through 2020. Given the compulsory nature of health insurance in the Netherlands and its broad coverage, the data covers the vast majority of all healthcare. Spending is reported in various subcategories, which allows the distinction between mental and non-mental healthcare expenditures and spending on pharmaceuticals.[2] Furthermore, the data on mental healthcare spending also contains spending on basic mental healthcare, which is not included in the primary data on specialized mental healthcare. Healthcare expenditures are used as additional outcome measures to determine whether waiting time also has an impact on healthcare usage.

[1]Zero days of time until intake implies that the day of first contact and intake are identical which is highly unlikely. Official statistics furthermore show slightly higher average waiting times (NZA, 2021). As a robustness test, I alternatively exclude entries with zero days until intake; this yielded similar results to the primary analysis. This implies that under-reporting of waiting times does not bias the results.

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

3.2 Data on labor market outcomes

The labor market outcomes of the sample include monthly measures of employment, labor earnings, working hours, and the receipt of unemployment benefits, sickness/disability benefits, and social assistance. The labor market panel spans the period from 2004 up until 2021. Data on monthly labor earnings and working hours are available from 2009 onward. For all analyses, the time series are converted to time relative to the first moment of contact with a mental healthcare provider. I follow individuals starting six years prior to treatment until eight years after the start of treatment (for an unbalanced panel).

The panel data on health and labor market outcomes are enriched with administrative records from Statistics Netherlands on the year of birth, gender, migration background, level of education, and the municipality of residence. For all 422 municipalities, I observe the distribution of income, the proportion of inhabitants receiving various social benefits, real-estate characteristics, population densities, the ethnic background of the population, and gender division.[3]

3.3 Descriptive statistics

The first column of Table 2 shows descriptive statistics of the individuals starting mental health treatment. For comparison, the second column shows 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 statistics of a sample matched one-to-one based on the propensity to start mental health treatment. The propensity score is estimated using only the demographic characteristics of the individuals. The matched sample will be used as a comparison group in the analysis of the effects of the onset of mental health problems. I discuss the matching procedure in detail in Section 4.

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 health problems for individuals aged 20 to 40. Furthermore, individuals receiving mental health treatment are more likely to be Dutch natives, and they tend to have completed a lower level of

[3]The population size of Dutch municipalities ranges from approximately 1,700 to one million inhabitants, with an average population size of approximately 44,000.

Table 2: Descriptive statistics of the sample of individuals starting mental health treatment in 2012-2019, a matched sample not receiving treatment and the general Dutch population not receiving mental health treatment

	Start MH treatment 2012-2019[a]	Matched sample[b]	No MH treatment 2010-2019[c]
Demographics[d]:			
Age	37.8	37.8	42.9
Female	54.0%	53.9%	53.8%
Dutch native	72.8%	73.1%	68.4%
Education unknown	20.9%	20.9%	47.5%
Education[e]:			
Low	22.9%	22.9%	18.7%
Middle	43.4%	43.1%	39.6%
High	33.7%	34.0%	41.8%
Annual healthcare expenditures[f]:			
Mental healthcare	€4,582,-	€28,-	€27,-
Physical healthcare	€2,082,-	€989,-	€1,026,-
Pharmaceuticals	€31,-	€16,-	€14,-
Mental healthcare treatment			
Main diagnosis:			
Mood	29.5%		
Anxiety	22.7%		
Personality	8.4%		
Other	39.5%		
Treatment provider:			
Psychologist[h]	43.2%		
Psychotherapist[h]	12.2%		
Psychiatrist[h]	20.1%		
Other[h]	24.5%		
Crisis	4.6%		
Treatment minutes[g]	117.2		
Number of individuals	524,707	524,707	14,674,592

(a) All individuals who start mental health treatment between 2012 and 2016 aged 18-65; (b) All individuals in the Dutch population who do not receive any mental health treatment between 2009 and 2019 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 healthcare provider; (g) Average number of treatment minutes in the first month of treatment; (h) Treated by a psychologist or psychiatrist during the first contact.

education.[4] By construction, the matched sample is almost identical to the treatment sample in terms of demographics. As expected, the treatment population has high mental healthcare spending, but their spending on both non-mental healthcare and pharmaceuti-

[4]The large percentage of unknown education level in the general population is due to the fact that the Dutch education registry started in the 1980s. The education level is unknown for most individuals in cohorts that graduated earlier. The difference in unknown education level between the sample with and without mental health treatment is mainly driven by the age difference.

cals is also almost twice as high as that of the other samples. This indicates the presence of co-morbidities and/or the interplay between mental and non-mental health.

To understand the impact of mental health problems and the delays in receiving treatment, it is instructive to examine 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 (29.5%) or anxiety disorders (22.7%), while personality disorders (8.4%) are less common. The remainder of the sample (39.5%) are diagnosed with some other disorder. The majority of all patients (43.2%) are treated by psychologists, while 12.2% and 20.1% are treated by psychotherapists and psychiatrists. Psychiatrists are allowed to prescribe medication and often treat more severe mental health problems, while psychotherapists and psychologists are not allowed to prescribe medication. Approximately one in twenty individuals that start treatment is reported to be in a crisis situation. These individuals are fast-tracked and treatment usually starts within days after the first moment of contact. In general, they receive more intensive treatment.

The intensity of monthly treatment decreases as treatment progress. The average number of treatment minutes is 117 in the first month and decreases to 37 and 19 minutes after one and two years respectively. The decrease in treatment minutes is mainly driven by a decrease in the number of individuals who continue treatment (extensive margin) and not by a decrease in the number of treatment minutes per treated individual.[5]

4 The association between onset and treatment of mental health problems and employment

As a benchmark for the effect of waiting times, I first provide a correlational measure of the net effect of mental health problems and their subsequent treatment on labor market outcomes. By their very nature, mental health problems are interrelated with a wide range of observable and unobservable characteristics and events. As discussed in

[5]See Appendix Figure A.1 for the distribution of treatment minutes at the start of treatment and after one and two years.

the introduction, previous literature has used early-life events as instruments for mental health. While these events have a clear impact on mental health, they also affect other aspects of an individual's life, such as motivation or time preferences, potentially leading to biased IV estimates.

Given the scarcity of convincing instruments for mental health, I used an event-study approach in which individuals undergoing mental healthcare treatment were compared to individuals not receiving treatment. This approach thus shows the net effect of both the onset of mental health problems and their treatment. By using an event-study setup, I am able to control and test for pre-treatment differences caused by unobserved confounders. However, the event-study setup does not control for reverse causality or time-varying unobserved confounders, and the resulting estimates should therefore not be interpreted as causal effects. Instead, the estimates will be used to benchmark the effects of waiting times for mental health treatment by indicating what effects would be expected given average waiting times.

4.1 Methodology

The event study compares individuals starting mental health treatment to a control group that does not undergo treatment. As shown in Table 2, individuals receiving mental health treatment are different from individuals not receiving treatment in terms of their age and gender. I, therefore, construct a control group using one-to-one matching on the propensity to start mental health treatment.[6] The propensity is estimated based on the municipality of residence, gender, age, migration background, and education level. The matched sample is very similar to the treatment sample in terms of these demographics but very different in terms of healthcare usage, as shown in Table 2. Comparisons to either the full population (no matching) or comparisons to the siblings of the patients, as proposed by Biasi et al. (2021), yield similar results.

To avoid comparisons between not-yet-treated and already-treated units, I use time

[6]Matching directly on all observable demographics yields similar results.

relative to the first moment of contact with a mental healthcare provider.[7] 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 on demographics, the baseline specification does not include these characteristics as control variables.[8] The time window ranges from 72 months prior to the first moment of contact until 96 months after the first moment of contact. The event-study specification looks as follows;

$$E_{it} = \alpha_t + \sum_{l=-71}^{96} \beta_l MH_i \, I_{t=l} + \varepsilon_{it} \tag{1}$$

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. β_l runs from 71 months prior to the first moment of contact until 96 months after the first moment of contact. The difference between those who do receive mental health treatment and those who do not is thus normalized to zero at month -72.

4.2 Results

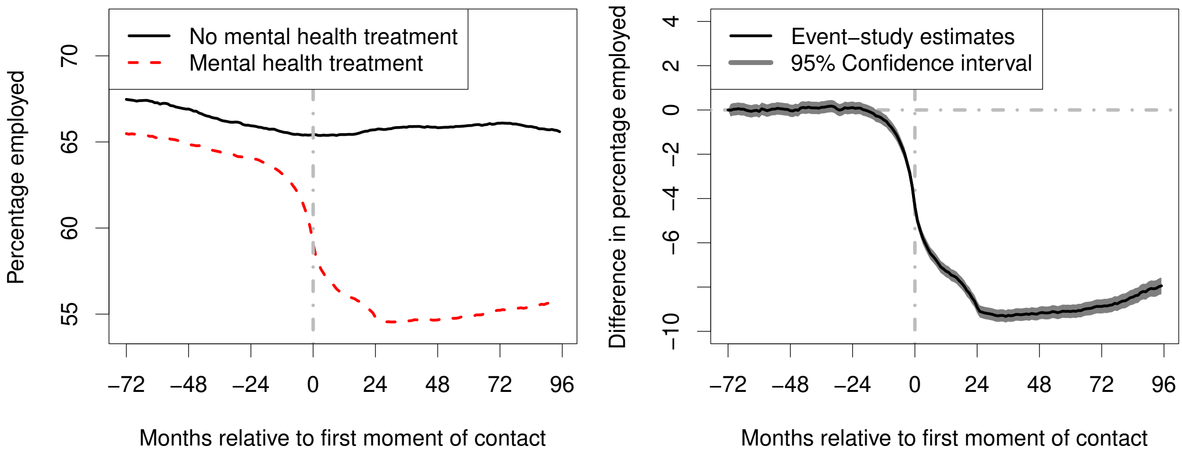
The left panel of Figure 3 shows the employment rates for the group who start mental health treatment, and the matched control group relative to the first moment of contact. The figure on the right shows the corresponding event-study estimate, i.e., the difference between the two groups. Figure 4 show similar estimates for the alternative labor market

[7] Recent literature has shown that using calendar time and a two-way fixed effects estimator can lead to biased results in cases of staggered treatment implementation or 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 starting mental health treatment) 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)).

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

Figure 3: Probability of employment (left) and corresponding event-study estimates (right) comparing individuals with and without mental health treatment

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



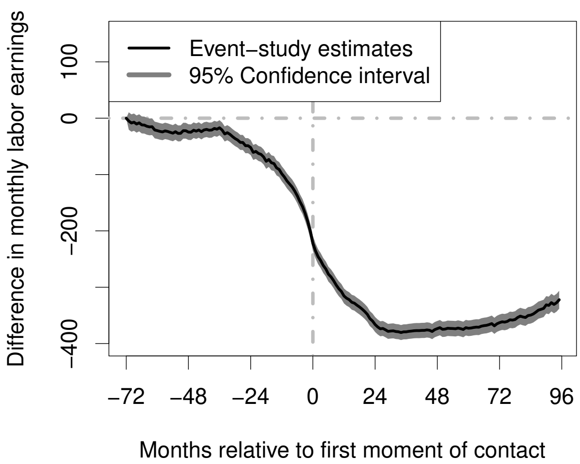
outcomes.[9] Despite matching based on propensity scores, the pre-treatment labor market status of individuals receiving mental health treatment is significantly different from the pre-treatment labor market status of individuals not receiving treatment. Six years prior to the first moment of contact, individuals in the treatment group are less likely to be employed but more likely to receive various social benefits. The trends furthermore show that most of these differences become larger in the years leading up to the first moment of contact.

The level difference between both groups points to differences in unobservable characteristics. Furthermore, the divergence of trends could be driven by a number of reasons. First of all, the onset of mental health problems happens prior to the start of treatment. The divergence could however also be driven by reverse causality: a deterioration of labor market status could have a negative effect on mental health. Additionally, there could be unobserved time-varying confounders affecting both mental health and employment. Reverse causality and unobserved confounders would bias the event-study estimates and these estimates should therefore not be interpreted as causal effects of the onset of mental health problems on labor market status. However, since these factors would most likely upwardly bias the estimates, the event-study estimates can be used to obtain the upper bounds of the causal effects.

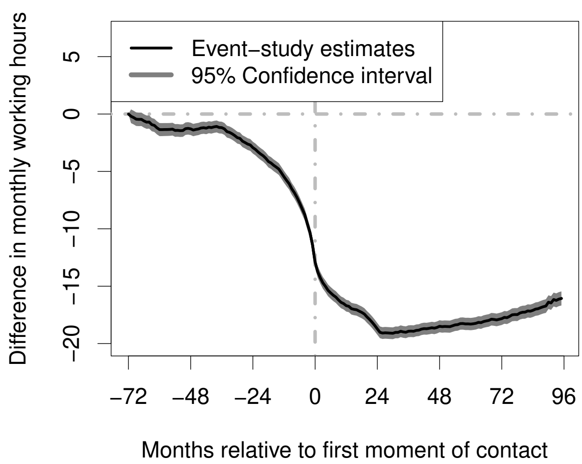
[9]Trends of these outcomes, equivalent to Figure 3 (a), can be found in Appendix Figure A.2.

Figure 4: Estimated event-study estimates and 95% CI comparing individuals with and without mental health treatment

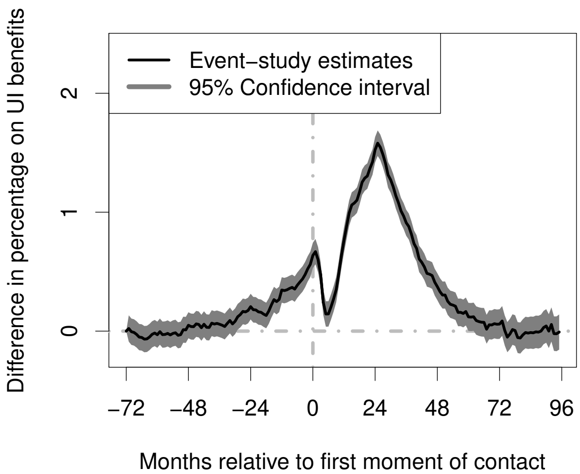
(a) Monthly labor earnings



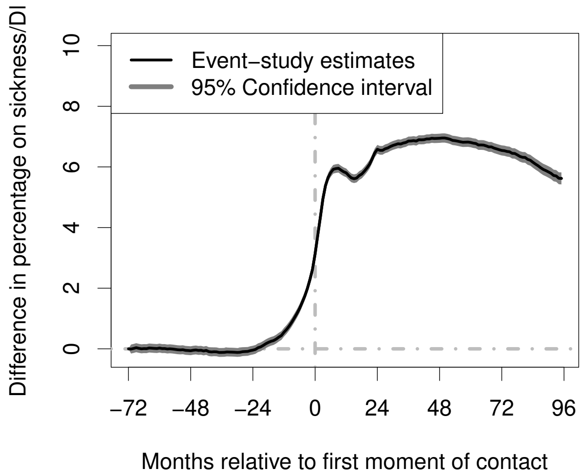
(b) Monthly working hours



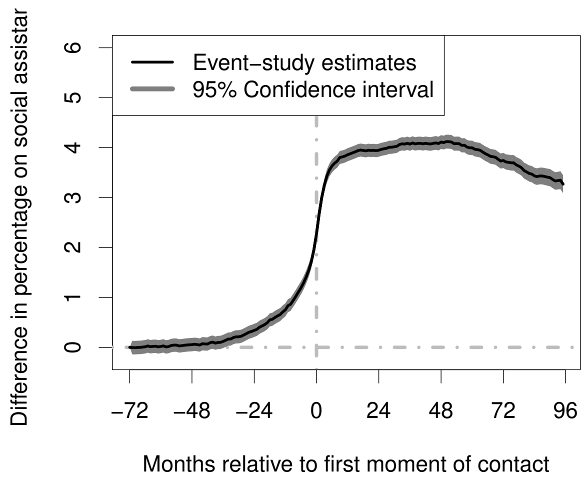
(c) UI benefits



(d) DI benefits



(e) Social assistance



I find that the onset of mental health problems and the treatment of these problems is associated with a 9 percentage point drop in employment. This estimate is close to the lower bound of estimates found in the IV studies, which range between 10 and 30 percentage points (Frijters et al., 2014; Ettner et al., 1997; Chatterji et al., 2011). The drop in employment rate corresponds to a drop in monthly labor earnings of approximately €400 and a 20-hour drop in the monthly number of hours worked (see Figure 4 (a) and (b)).

The drop in the employment rate is mirrored partly by an increase in the probability of receiving unemployment benefits of 1.5 percentage points (see Figure 4 (c)). The probability of receiving UI benefits drops shortly after the first moment of contact, caused by an inflow into sickness/DI benefits. The onset of mental health problems leads to a seven percentage point increase in the probability of receiving sickness and disability benefits (Figure 4 (d)). The increase in sickness and disability benefits is of a slightly smaller magnitude than the decrease in the employment rate. A similar pattern emerges for the probability of receiving social assistance, with an increase of approximately four percentage points (Figure 4 (e)).

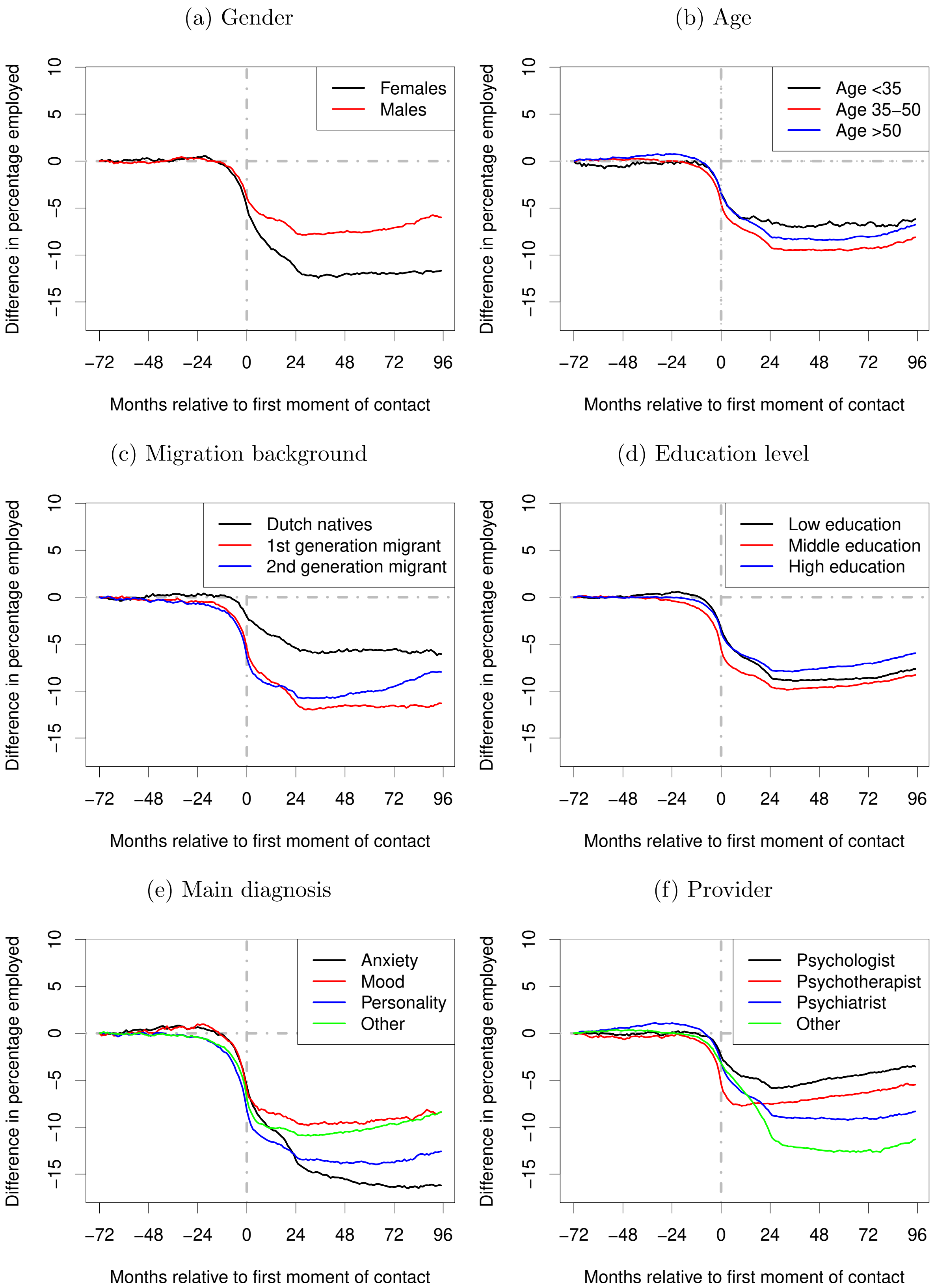
4.3 Heterogeneity analysis

The estimates reported above are based on all individuals that start some form of mental health treatment in the Netherlands. I now investigate whether the impact differs for different groups of the population and for different types of mental health problems. I re-estimated the event-study specification by gender, age, migration background, and education categories. I also examine differences based on the mental health diagnosis and the type of provider. Treatment can be provided by psychologists, psychotherapists, psychiatrists, and other providers. The type of provider might signal the severity of the underlying condition being treated.

Figure 5 shows the event study estimates of the impact of mental health problems on employment for the various subsamples.[10] Females and individuals with a migration background experience larger drops in employment around the first moment of contact with

[10]Figures including confidence intervals are available upon request. Given the large sample size, the estimated impacts are almost always significantly different for the various groups.

Figure 5: Heterogeneity of event-study estimates on employment comparing individuals with and without mental health treatment



a mental healthcare provider, while heterogeneity by age and education level is limited. Additionally, there exists significant heterogeneity by mental health status. Treatment for anxiety and personality disorders result in the largest drops in employment. Heterogeneity by treatment provider is as expected; individuals being treated by psychiatrists and other providers experience more severe employment drops, in accordance with the fact that these providers tend to treat individuals with more severe mental health problems than psychiatrists and psychotherapists.

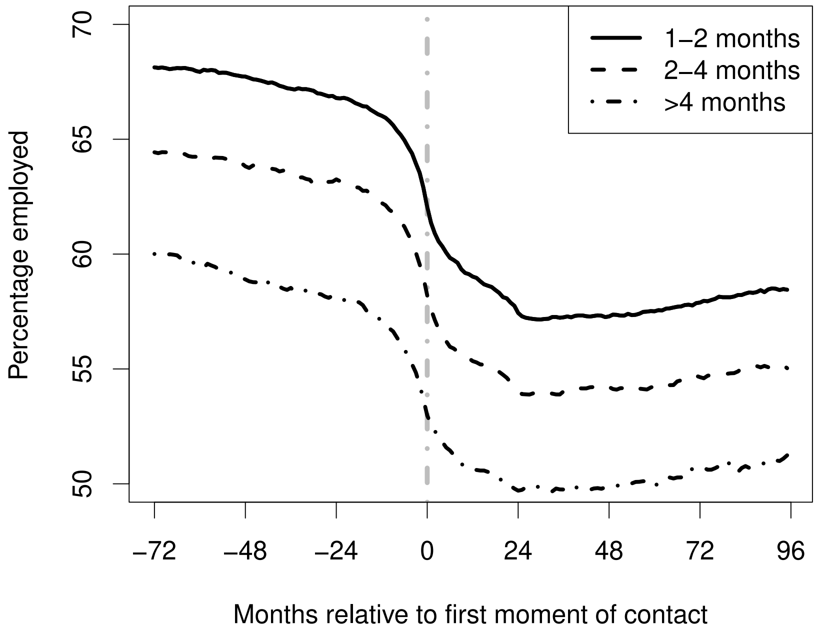
Summing up, the onset of mental health problems and subsequent treatment of these problems is associated with a decrease in employment of approximately nine percentage points and an increase in the probability to receive sickness/disability benefits and social assistance of approximately half that amount. Effects are larger for females than for males while individuals with a migration background are affected the most. As expected, being treated for more severe mental problems is associated with larger drops in employment.

5 The impact of increased waiting times for mental health problems

The negative impact of the onset of mental health problems on labor market status shown in the previous section is the impact averaged over the entire waiting time distribution. It encompasses individuals whose treatment started a week after the first moment of contact and those who had to wait several months. In what follows, I examine the causal impact of waiting time for mental health treatment.

Given the process between the onset of mental health problems and the start of treatment as described in Section 2, waiting times are likely to be endogenous due to a number of reasons. First of all, individuals can freely choose mental healthcare 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. Lastly, the severity of the mental health problems is partly determined during the intake. Based on the severity, individuals might have to wait longer or shorter until treatment starts.

Figure 6: Probability to be employed relative to the first moment of contact for three groups based on their individual waiting time



To illustrate the endogeneity of individual waiting times, Figure 6 shows the employment rate relative to the first moment of contact for three groups with different waiting times.[11] There is a 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 is similar for individuals with different waiting times but there is a level difference between the groups; individuals with longer individual waiting times have a lower probability to be employed, both prior to and after the first moment of contact. This holds when looking at raw averages (as in the figure), but also when controlling for a wide range of demographics. Individual waiting time thus correlates with both observable and unobservable characteristics, which also correlate with the probability to be employed. This implies that OLS estimates are biased and should not be interpreted as causal. Hence, IV estimation is required.

[11]Similar figures showing the trends in the receipt of UI benefits, DI benefits and social assistance are shown in Appendix Figure A.3

5.1 Methodology

To estimate the causal impact of waiting times, regional waiting time is used as an instrumental variable for individual 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.[12] Longer regional waiting times should therefore result in longer individual waiting times, without being correlated to –for example– the severity of the individual's mental health problems. The IV approach exploits plausibly exogenous variations in the congestion of the mental healthcare system, as measured through regional waiting time at the municipality level. The first and second stage of the IV model looks as follows:

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

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

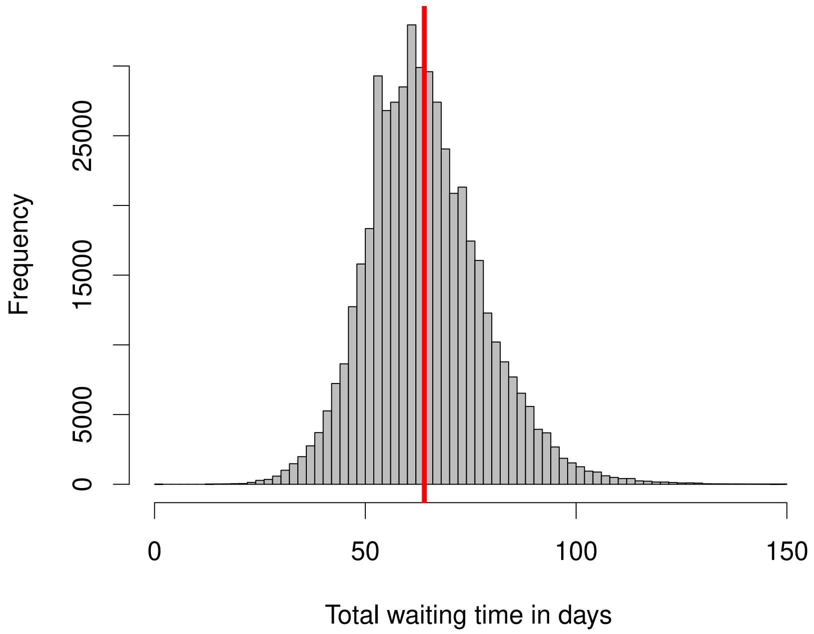
with IW_i and RW_i individual and regional waiting times, X_i individual characteristics, R_i regional characteristics (or regional fixed effects) and E_i the outcome of interest.[13] The following six labor market outcomes will be used; (1) Employment, (2) Monthly labor earnings, (3) Monthly number of working hours (4) Sickness/DI benefits, (5) UI benefits, (6) Social assistance. 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 six years prior to the first moment of contact and ends eight years after the first moment of contact. The IV estimates prior to the first moment of contact can be used as placebo tests for the exclusion restriction. Given that treatment has not commenced yet, waiting time should not have any effect on employment and the estimates should be close to zero.

The average waiting time of a region is computed using the leave-one-out principle. The regional waiting time of an individual is the average waiting time of all individuals

[12]Individuals choosing mental healthcare providers in a different region weakens the first stage of IV, but do not bias the second-stage estimates.

[13]See Appendix Table A.2 for a list of all control variables.

Figure 7: Distribution of leave-one-out regional waiting time. Mean value in red



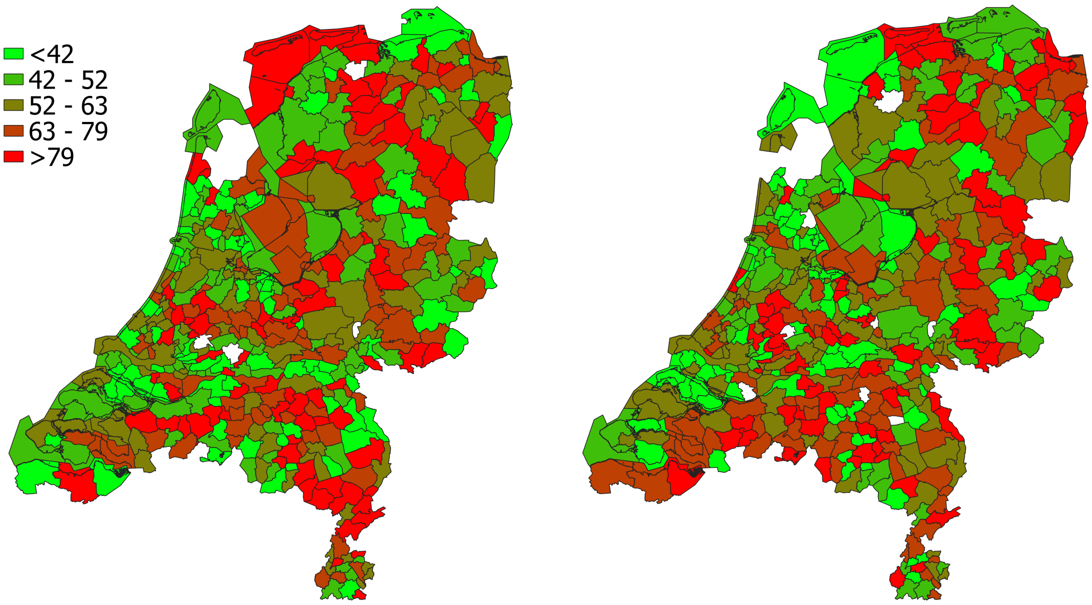
in that region who contacted a mental healthcare provider in the previous three months, excluding the individual under consideration.[14] Regions are defined at the municipality level, resulting in a total of 422 regions. The distribution of the leave-one-out regional waiting times is shown in Figure 7. Regional waiting time is almost symmetrically distributed, with a mean regional waiting time of 62 days and a standard deviation of 14 days. Further analyses show that variation between and within regions is mainly caused by variation in the number of individuals who terminated treatment in the preceding months. An increase in the number of individuals who stop treatment creates room for new treatments to start, reducing waiting times.

The IV approach exploits variation in regional waiting time between regions, and/or variation within the same region over time. To illustrate that there is indeed variation in both dimensions (time and region), Figure 8 shows a heatmap of the regional waiting time for all Dutch municipalities. Panel (a) shows a snapshot of January 2012, while panel (b) shows regional waiting times in February 2012.[15] Coloring is based on 5 quantiles of regional waiting time. Bright red indicates a region has an average regional waiting time in the highest quantile (long waiting times), while bright green indicates a region with a

[14]Using regional waiting time using a time window of one, two or four months gives similar results.
[15]A timelapse of regional waiting time between 2012-2019 can be found on rogerprudon.com/research.

Figure 8: Regional waiting time in days in January (left) and February (right) 2012

(a) January 2012 (b) February 2012



regional waiting time in the lowest quantile (short waiting times). As can be seen in the figure, there is indeed variation in time and variation between regions.

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.4 shows non-parametric estimates of the association between employment, as measured 12 months after the first moment of contact, and waiting time. For waiting times up to approximately 200 days (28 weeks), a linear specification seems valid.

To be able to interpret the obtained estimates as causal, regional waiting time should only influence labor market outcomes through individual waiting times. The next subsection discusses potential violations of this exclusion restriction and presents various tests. The estimates of the impact of waiting time are presented in the subsequent subsections.

5.2 Potential violations of the exclusion restriction

A potential concern with using regional waiting times as an instrument is that regions with longer waiting times could be different from 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 were used. The first specification controls for a wide range of regional characteristics. 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 fixed effects 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. Including regional fixed effects instead of regional controls increases the standard errors significantly as it only uses variation in waiting times within regions. At the same time, however, it eliminates any potential endogeneity based on unobserved differences between regions. Given their respective advantages and disadvantages, both specifications are used.

A second potential concern with 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. (2023) and Williams & Bretteville-Jensen (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, Appendix Table A.3 shows the estimated impact of the (lagged) (un)employment rate in a region on the regional waiting time in that region. The (un)employment rate in a region is not significantly associated with the regional waiting time. Including more lags (or leads) of the (un)employment rate gives similar results. 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.

Additionally, the exclusion restriction would also be violated if regional waiting time acts as a gatekeeper for the mental healthcare system. Longer waiting times might deter relatively healthy individuals from seeking treatment, resulting in differences in the composition of patients flowing into the mental healthcare system. The first way of testing this is by assessing whether the probability of actually starting treatment, conditional on contacting a mental healthcare provider, is affected by regional waiting time. If regional waiting time were to act as a gatekeeper, one might expect that –in regions with longer waiting times– more individuals would flow out of the mental healthcare system before starting treatment, increasing the fraction of patients who contact the mental healthcare provider without starting treatment. The insignificant estimated impact of regional waiting time on the probability to seek treatment outside of one municipality of residence shows that this is no concern (see Appendix Table A.4).

A second, more direct way of testing whether increased waiting time acts as a gatekeeping mechanism is by examining the composition of patients that contact mental healthcare providers. If, for example, long waiting times would deter relatively healthy individuals from starting mental health treatment, then the average health of those individuals who did start treatment would be worse. The second panel of Appendix Table A.4 shows only small correlations between regional waiting time and the composition of patients starting treatment, both in terms of demographics and in terms of the type of mental health diagnosis/treatment provider.

A final potential problem is that regional waiting time might affect the extent to which individuals try to reduce their waiting time. If this would be the case, the monotonicity assumption could be violated. The most straightforward way to reduce the waiting time would be to search for a provider with a shorter waiting time. Unfortunately, it cannot be inferred which provider individuals would go to if they would not try to cut the line. However, if individuals would broaden their search for providers with shorter waiting times, the probability of going to a provider outside of one's municipality of residence should increase. This provides a testable assumption of the monotonicity assumption. Regressing regional waiting time on an indicator for seeking care outside of one's municipality of residence shows that this is not the case (see Appendix Table A.4).

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

To assess the strength of regional waiting time as an instrument, Table 3 shows the first-stage estimates. A one-day increase in regional waiting time, on average, increases individual waiting time by 0.4 days. The inclusion of regional fixed effects instead of re-

Table 3: First-stage results of the impact of regional waiting time on individual waiting time using regional controls or regional fixed effects

	Individual waiting time	Individual waiting time
Regional waiting time	0.396**	0.289**
	(0.011)	(0.012)
F-statistic	1200	531
Regional controls	X	
Regional fixed effect		X

Standard errors shown in parentheses; *significant at a 10% significance level; **significant at a 5% significance level; The reported F-statistic compares models with and without the instrument.

gional controls does significantly decrease the estimate. However, even after the inclusion of regional fixed effects, 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.

5.4 Second stage: The impact of waiting time on employment and healthcare usage

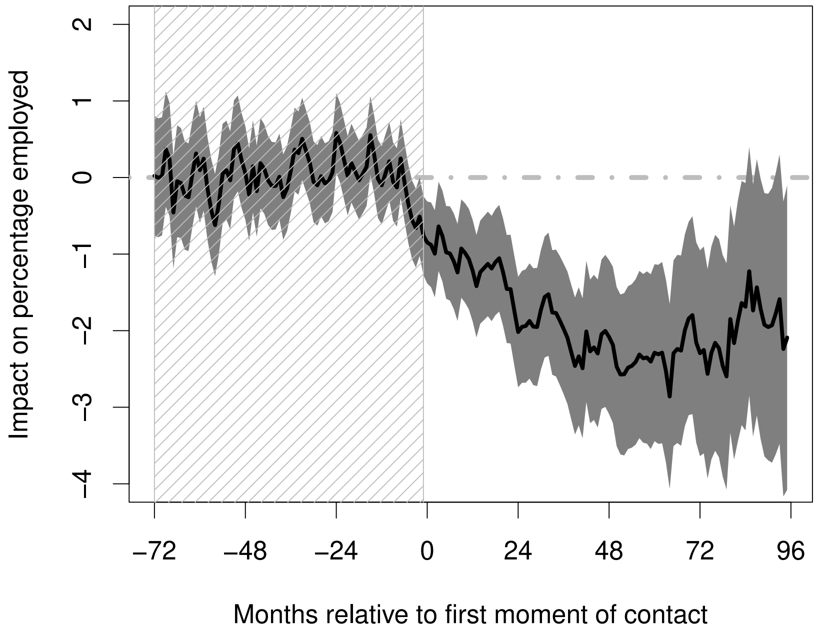
Turning to the causal impact of increased waiting time, Figure 9 shows the IV estimates and the corresponding 95% confidence intervals of one additional month of waiting time on employment. Note that the estimates are not event-study estimates, but instead obtained through repeated IV-estimation. The estimate at time t is obtained through regressing instrumented individual waiting time on the employment status at time t.

The estimates for the six years prior to the first moment of contact, highlighted in grey, are placebo estimates; the outcome is measured prior to the first moment of contact, and waiting time should therefore not have any effect. As discussed, OLS estimation does yield significant placebo estimates, signifying the correlation between pre-treatment labor market status and individual waiting time as shown in Figure 6.[16]. In contrast, the IV placebo estimates do not differ significantly from zero, increasing the credibility of the IV approach.

The impact of waiting time starts to show in the four months prior to the first moment

[16]The OLS estimates are shown in Appendix Figure A.5

Figure 9: Estimated impact and 95% CI of one additional month of waiting time on probability to be employed



of contact, but this is likely due to measurement error. As discussed in Section 3.1, for a considerable share of the sample the moment of intake is also the first moment of contact. Given that it is impossible to have an intake on the day in which individuals contact a mental healthcare providers, the actual first moment of contact is likely to be earlier. Measurement error in the first moment of contact implies that some individuals are already waiting in the months prior to $t = 0$, potentially explaining the observed effects in the months preceding the observed first moment of contact.

After the first moment of contact, increased waiting time has a negative and significant effect on the probability of being employed. A one-month increase in waiting time reduces the probability of employment by approximately two percentage points.[17]. The effects persist for at least eight years. OLS estimation points to a significant, but smaller negative effect of waiting time of approximately 0.3 percentage points (see Appendix Figure A.5). OLS thus underestimates the negative effect of waiting time, as it does not take into account that individuals with more severe mental problems, and hence worse labor market outcomes, are more likely to receive treatment quicker.

[17]Estimation using time until intake instead of total waiting time yields larger estimates, as shown in Appendix Figure A.6. If time until intake increases, all individuals are affected whereas mental healthcare providers are able to allocate increased waiting time to less severe cases if total waiting time increases. This potentially explains the larger effects of time until intake.

Using regional fixed effects instead of regional controls yields similar point estimates, but slightly larger confidence intervals given that less variation is used (See Appendix Figure A.7). 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.

Figure 10 shows the estimated impact on other labor market outcomes. The two percentage point reduction in the probability to be employed translates into a reduction in monthly labor earnings of approximately €100 (panel (a)), and the average number of working hours per month is reduced by approximately three (panel (b)). In relative terms, these impacts are comparable to the impact on the probability to be employed. This indicates that employment is mostly affected on the extensive margin. Panels (c)-(e) show that individuals whose employment is terminated flow into DI and social assistance, while the inflow into UI is unaffected. The effects persist for at least eight years.[18]

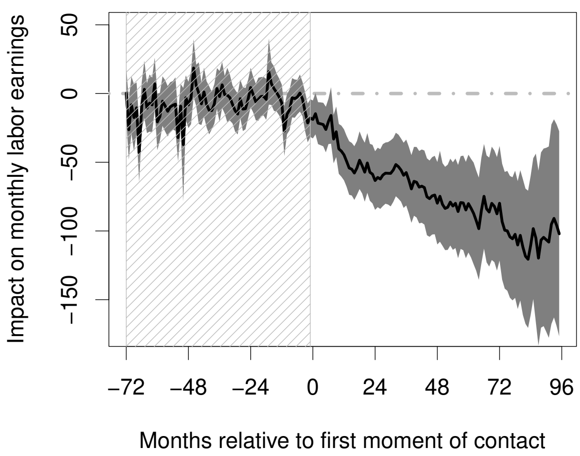
To interpret the magnitude of the causal impact of waiting time on labor market status, the effect sizes can be compared to the estimated effects of the onset of mental health problems from Section 4. The onset of mental health problems is associated with a drop in the probability of being employed of approximately nine percentage points, an increase in the probability to receive sickness/disability benefits of seven percentage points and an increase in the probability of receiving social assistance of four percentage points. A two-month (one standard deviation) increase in waiting time decreases the employment rate by four percentage points and increases the receipt of DI benefits by two percentage points and the receipt of social assistance by one percentage point. This is almost half of the average effect of the onset of mental health problems. While the receipt of unemployment benefits is also affected by the onset of mental health problems, increased waiting time does not affect the probability to receive these benefits.

There are various potential explanations for the negative impact of waiting time on labor market status, one being a deterioration of (mental) health. Unfortunately, objective measures of (mental) health are not available; that being said, I do observe the number of treatment minutes individuals receive on a monthly basis, and the amount

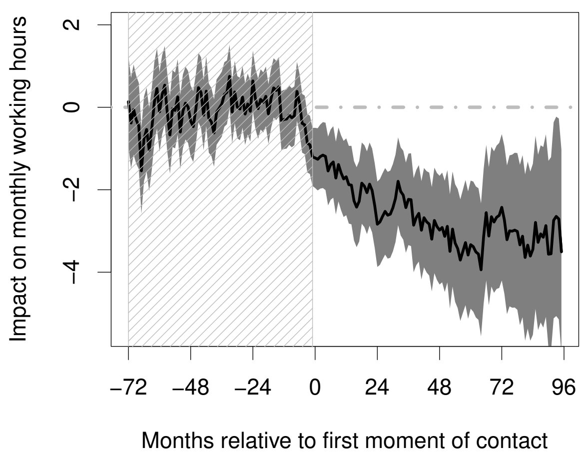
[18]In later years, the sample size decreases, which decreases the precision of the estimates.

Figure 10: Estimated impact and 95% CI of one additional month of waiting time on various labor market outcomes

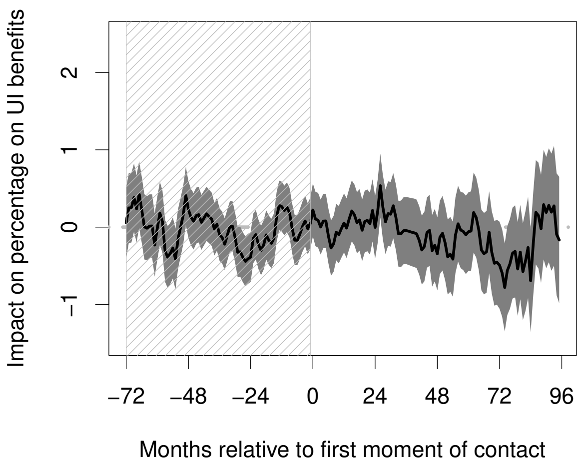
(a) Monthly labor earnings



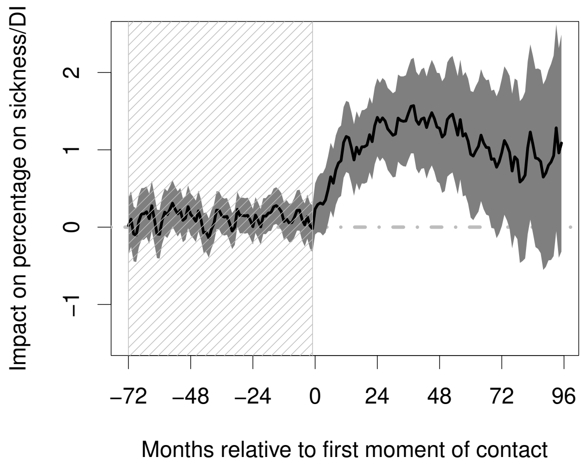
(b) Monthly working hours



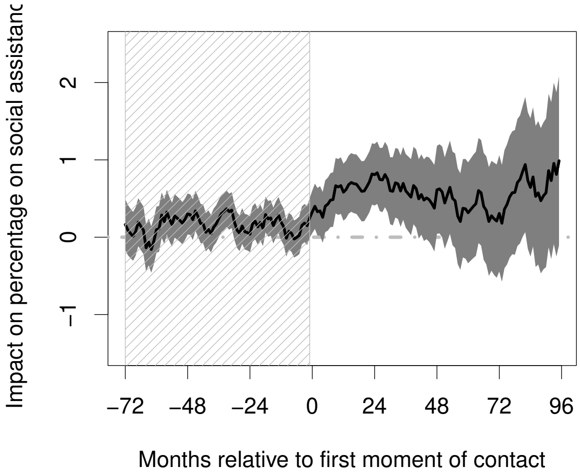
(c) UI benefits



(d) DI benefits



(e) Social assistance



of annual spending on mental healthcare, non-mental healthcare, and pharmaceuticals. One additional month of waiting time increases the cumulative amount of treatment minutes and mental healthcare spending significantly. In the first eight years after the first moment of treatment, the cumulative amount of treatment minutes increases by 150 and spending on mental healthcare increases by €875. Relative to average healthcare utilization of 1650 minutes and €7574, this corresponds to an increase of nine and eleven percent in healthcare utilization. Estimates for spending on non-mental healthcare, and pharmaceuticals are insignificant (See Appendix Figure A.8 for all results). Based on these impacts on observed healthcare utilization, increased waiting time for treatment seems to have an effect on (mental) health itself. The negative effects observed on labor market status might be driven by this impact on mental health, or by other mechanisms, such as increased distance to the labor market.

5.5 Heterogeneity analysis

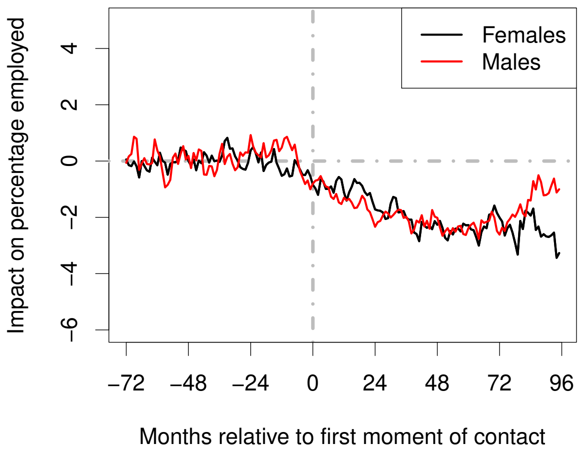
To investigate heterogeneous impacts, I split the sample based on various demographic characteristics and types of mental health problems. This is done both for the first stage and second stage of the IV estimation. Heterogeneity of the first-stage estimates indicates which groups are compliers in the IV setup as it shows which groups have to wait longer when regional waiting time increases. The heterogeneity of the second-stage estimates indicates a differential impact of increased waiting time on labor market status.

Heterogeneity in the first stage is very limited (see Appendix Table A.5), indicating that all subgroups are affected to a similar degree by increased regional waiting time. Figure 11 shows heterogeneity of the impact of waiting time on employment by gender, age, migration background, education level, and mental health status.[19] Heterogeneity based on gender and age is limited whereas heterogeneity by migration background and education level is more pronounced. First of all, individuals with a migration background suffer more in the long run, while the negative effects for Dutch natives fade out over time. Lower-educated individuals on the other hand suffer more in the short term, while higher-educated individuals suffer more in the long term.

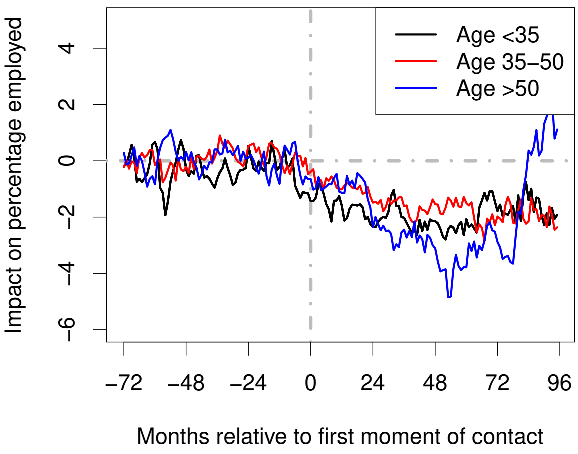
[19] Estimates including confidence intervals are available on request. Given the smaller sample sizes of the subgroups, the estimates are not significantly different from each other.

Figure 11: Heterogeneity of the impact of one additional month of waiting time on employment

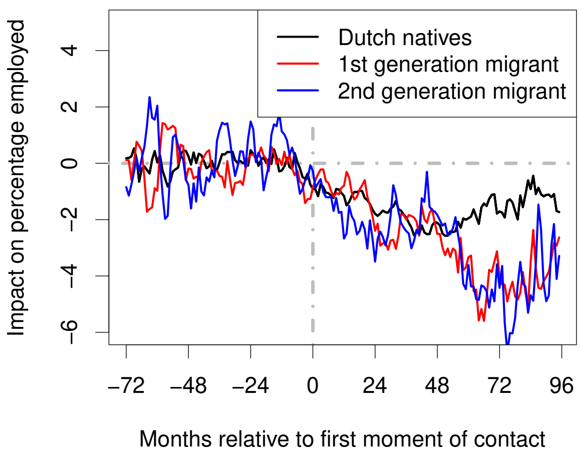
(a) Gender



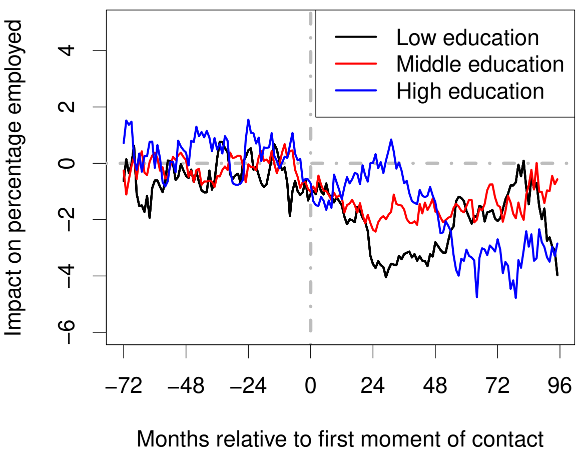
(b) Age



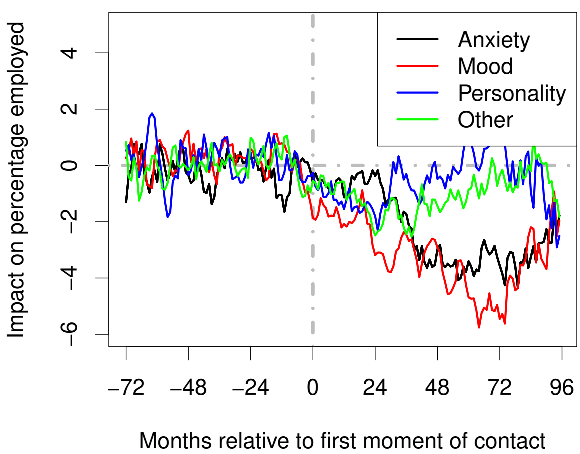
(c) Migration background



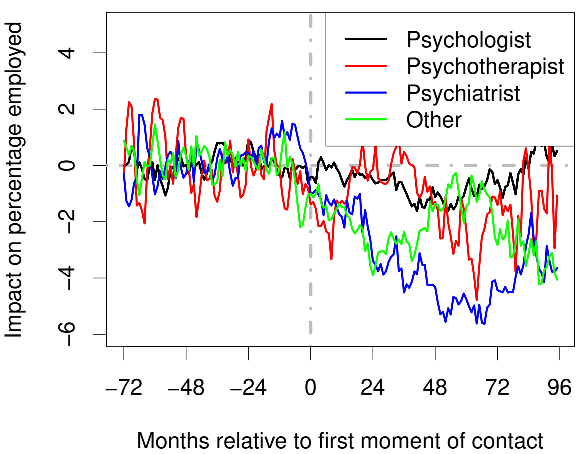
(d) Education level



(e) Main diagnosis



(f) Provider



Heterogeneity with respect to an individual's mental health diagnosis and type of provider is shown in panels (e) and (f). The impact of increased waiting time is the largest for anxiety and mood disorders and for treatment by psychiatrists. This is largely in line with the results of the previous section, which showed that individuals being treated for anxiety disorders and by psychiatrists experienced the largest drops in employment.

5.6 Regional waiting time as continuous treatment in an event study

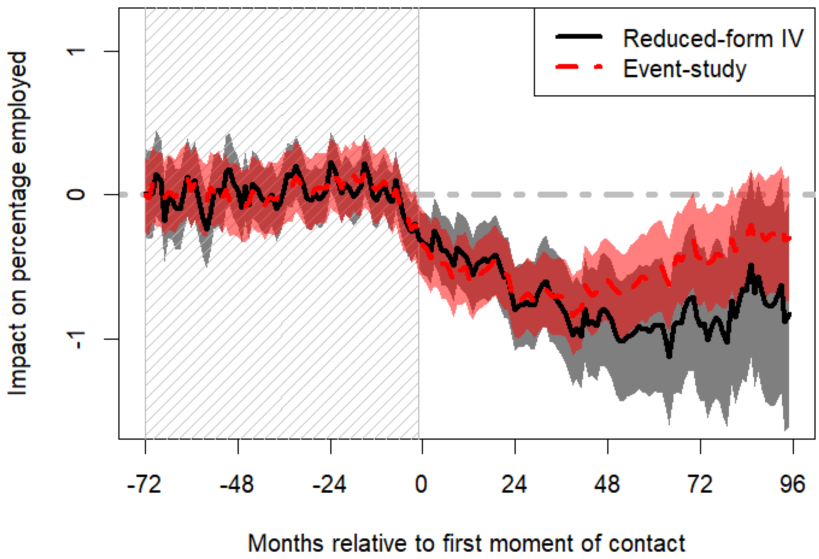
The IV estimation compares individuals in regions with long waiting times to individuals in regions with short waiting times. An alternative estimation approach is a difference-in-differences setup in which regional waiting time is a continuous treatment variable. Given that individuals who do not receive treatment are very different from those who do receive treatment, the setup does not use untreated individuals as a control group. Instead, individuals contacting a treatment provider in a region with a short regional waiting time are used as counterfactual for individuals who contact a treatment provider in a region with a long regional waiting time.

Estimation relies on the so-called strong parallel trends assumption, which implies that the employment trajectories of individuals in a region with a high regional waiting time would otherwise have been the same as the trajectories of individuals in regions with low regional waiting times if they had lived in the latter region(s) (Callaway et al., 2021). Whereas the IV strategy assumes that regional waiting time does not affect employment status prior to the first moment of contact, the DiD strategy does allow for differences prior to the first moment of contact, as long as these differences remain constant over time. As the DiD estimation relies on different assumptions, it can be used as a robustness test. The event-study specification looks as follows:

$$E_{it} = \tau_t + \sum_{l=-71}^{96} \beta_l RW_i + \alpha X_i + \varepsilon_{it} \tag{4}$$

with τ_t time fixed effects and X_i individual control variables. β_l are the parameters of interest and show the impact over time of regional waiting time. The impact of regional

Figure 12: Estimated impact of one additional month of regional waiting time on the probability of employment using reduced form IV with regional controls (black) and event-study estimation (red)



waiting time is normalized to zero at t=72, and the first 71 β_l coefficients are the placebo estimates prior to the first moment of contact.

Given that the event-study estimates correspond to increases in regional waiting time, they should be compared to the reduced form estimates of IV. Figure 12 shows these reduced form IV estimates (a re-scaled version of the estimates in Figure 9) and the event-study estimates of the effect of a one-month increase in regional waiting time on the probability of employment. For both estimation strategies, the placebo estimates are similar, thus indicating that the trends of individuals in regions with shorter and longer regional waiting times are parallel and equal. After the first moment of contact, the event-study estimates are similar to the IV estimates, but the event-study estimates appear to fade out over time. This could indicate that time-varying characteristics have an impact on employment. The IV specification controls for some of these time-varying characteristics whereas the event study does not.

To conclude, increased waiting time for mental health treatment has large effects both on the probability of being employed and the probability of receiving sickness/disability benefits. Heterogeneity of the impact of increased waiting time is significant, with individuals with a migration background and less educated individuals experiencing larger negative effects.

6 Unequal access to mental health treatment

Given the negative effects of waiting time and the heterogeneity of these effects, a crucial unanswered question is whether access to mental health is also heterogeneous. In this section, I investigate whether average waiting times differ between groups. The groups considered are the same groups as used in the heterogeneity analysis above; (1) gender, (2) migration background, and (3) education level. In addition, I explore four mechanisms that may drive differences in access to mental healthcare. First, sorting towards regions with short waiting times. Second, differences in pre-treatment labor market status. Third, differences in the propensity to contact a mental healthcare provider, resulting in differences in the severity of mental health problems at the first moment of contact. And fourth, the selection towards specific types of mental healthcare providers. I estimate how individual waiting time depends on individual characteristics using the following regression model:

$$IW_i = \alpha + \beta X_i + \delta Z_i + \varepsilon_i \tag{5}$$

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 added.

Table 4 show the differences in average waiting times. The average waiting time is 62.3 days. The raw differences in waiting time between the various groups (column (1)) show a small difference based on gender but larger differences based on migration background and education level. First-generation migrants and less educated individuals have to wait more than one week longer on average than their respective counterparts. To control for spatial sorting, column (2) includes regional fixed effects. The resulting estimates are similar, implying that spatial sorting does not explain the differences in waiting times. Differences in pre-treatment employment status do partly explain the observed difference in waiting times based on education level as shown in column (3). When comparing

Table 4: Differences in average waiting time by gender, migration background and education level

	Waiting time in days				
	(1)	(2)	(3)	(4)	(5)
Gender[a]**:**					
Female	1.4**	1.3**	2.0**	1.4**	-0.2
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
Migration background[b]**:**					
1^{st} generation[c]	7.9**	9.3**	7.1**	10.9**	7.1**
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
2^{nd} generation[d]	2.4**	3.3**	2.8**	4.4**	3.1**
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Education level[e]**:**					
Low	12.9**	11.8**	8.0**	10.0**	3.2**
	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
Middle	6.9**	6.0**	4.1**	5.0**	0.7**
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)
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
Mean waiting time	62.3	62.3	62.3	62.3	62.3
Sample size	524,707	524,707	524,707	524,707	524,707

Standard errors shown in parenthesis; *significant at a 5% significance level; **significant at a 1% significance level; (a) Baseline gender is male; (b) Baseline migration background is native, (c) Individuals who migrated to the Netherlands, (d) Children of first-generation migrants (e) Baseline education level is high

individuals seeking treatment for a similar diagnosis, the difference in waiting time is actually larger (column (4)).[20] Finally, column (5) includes provider fixed effects, hence comparing individuals with similar pre-treatment employment, seeking treatment for a similar mental health diagnosis at the same provider. The small difference based on gender disappears, while differences based on migration background and education level decrease as well. However, first-generation migrants and less educated individuals on average still have to wait seven and three days longer respectively.

The differences in waiting times based on migration background and education level can have various explanations. These individuals might be less aware of their options for finding providers with shorter waiting times, or resource constraints might force them to

[20]When zooming into individuals with a depression of the same severity, the conclusion remains unchanged as shown in Appendix Table A.6

choose the closest provider geographically. Additionally or alternatively, these individuals might be less capable of explaining their problems, for example, due to language barriers. The heterogeneity analysis of Section 5 indicated relatively large effects of waiting times for individuals with a migration background and individuals with a lower 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 migration background are strongly linked to socioeconomic status, these differences in waiting times might therefore further increase inequality in society.

7 Conclusion

The combination of increasingly prevalent mental health problems and limited corresponding treatment capacity has resulted in long waiting times in many OECD countries. Delays in accessing some other forms of care have been shown to negatively impact employment (Godøy et al., 2023; Williams & Bretteville-Jensen, 2022), yet little is known about the microeconomic impact of waiting times for mental healthcare specifically. Using administrative data for the Netherlands on mental health treatments and labor market outcomes, I estimated the causal impact of waiting times for treatment on employment.

As a benchmark, I first showed that the onset of mental health problems and the subsequent start of treatment is associated with a nine percentage point drop in an individual's employment probability, along with an increased inflow into both sickness/disability insurance and social assistance. Next, I conducted causal analyses on the effects of waiting times using regional waiting times as instruments. I showed that an increase in waiting time of one month (0.5 SD) decreases the probability of employment by two percentage points and increases the probability of receiving sickness/disability benefits by one percentage point for at least eight years. Differential impacts of waiting time on employment are substantial, with less educated individuals and those with a migration background experiencing the largest negative effects. These two groups also have to wait longer on average before receiving treatment. The burden of increased waiting time is therefore especially large for vulnerable groups, potentially increasing inequality in health and labor outcomes.

The obtained estimates of the effects of waiting time for mental health treatment have both similarities and differences with the estimates of waiting time for orthopedic surgeries as examined by Godøy et al. (2023) and for substance abuse treatment as examined by Williams & Bretteville-Jensen (2022). Comparable to the estimates in this paper, a one-month increase in waiting time increases the probability of receiving disability benefits by one percentage point for orthopedic surgery and it decreases the probability to be employed by three percentage points for substance abuse treatment. Godøy et al. (2023) also find disproportionately large effects on less educated individuals. However, there are marked differences in the extensive-margin effects of waiting time. While Godøy et al. (2023) find limited extensive-margin effects, both the present study and that of Williams & Bretteville-Jensen (2022) actually find employment to mostly be affected on the extensive margin. Another difference lies in the impact of delays on healthcare utilization. Waiting time for orthopedic surgery has a limited impact on the utilization of care while waiting time for mental health and for substance abuse treatment increases the utilization of care substantially. Nevertheless, waiting times for all three types of care have large and negative effects, which underscores the need to ensure timely access to a variety of healthcare services.

In the context of mental health treatment, waiting times can be reduced by either reducing the demand for treatment through prevention or by increasing the supply of treatment. The Dutch government has expressed a strong interest in prevention, as it is seen as a cost-effective intervention as compared to increased treatment capacity (Rijksoverheid, 2022). Conversely, however, a back-of-the-envelope calculation does indicate that the costs of increased provision would be dominated by savings on other government expenditures.[21] Reducing the waiting time in the Netherlands by one month for one year would yield a reduction in employment loss of approximately 2,000 individuals, with associated savings of almost €380 million. To achieve such a reduction in waiting time, an additional 50 psychiatrists/psychologists would be needed for one year, with a labor cost of approximately €5 million. These calculations are clearly an oversimplification,

[21] See Appendix Section A.5 for a back-of-the-envelope calculation of cost savings.

but they nevertheless show that the economic gains from reduced waiting times can be substantial. These findings have some notable policy implications. For instance, in the Netherlands, there are many students studying psychology, but only a relatively small share of them work as psychologists after graduation. Given the degree to which the social benefits of increased supply of mental healthcare could exceed the costs, it stands to reason that better compensation for mental health professionals could be in everyone's best interest if higher pay attracts more workers to the field.

Alongside such efforts to reduce waiting times, the differential effects of delayed treatment on vulnerable groups suggest that gains can be made by focusing on individuals with a migration background and those with lower educational attainment. Not only do these groups wait longer for mental healthcare on average, but the effect of waiting times on their employment status is also greater. Increased access to mental health treatment in neighborhoods with low socioeconomic status, along with targeted mental health interventions for (unemployed) vulnerable groups, might alleviate some of the additional burden these individuals face.

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A Appendix

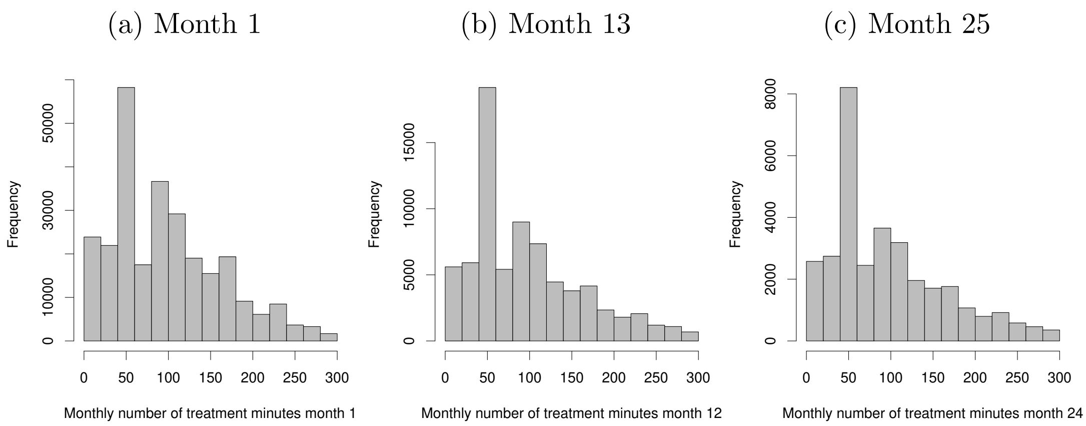
A.1 Additional Data

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

Mental healthcare	Non-mental healthcare	Pharmaceuticals
First-line psychological healthcare	General practitioner	Pharmacy
Mental healthcare	Hospital healthcare	
Basic-mental healthcare	Paramedical healthcare	
Specialist mental healthcare	Nursing without stay	
Geriatric rehabilitation healthcare		

Note: Several expenditure categories, such as healthcare abroad and other costs, as used by Statistics Netherlands are excluded from all categories as it is not clear to which category they belong.

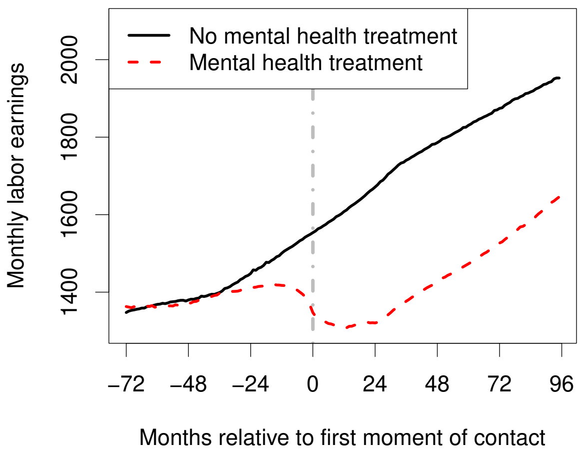
Figure A.1: The distribution of treatment minutes in the 1st, 13th and 25th month of treatment



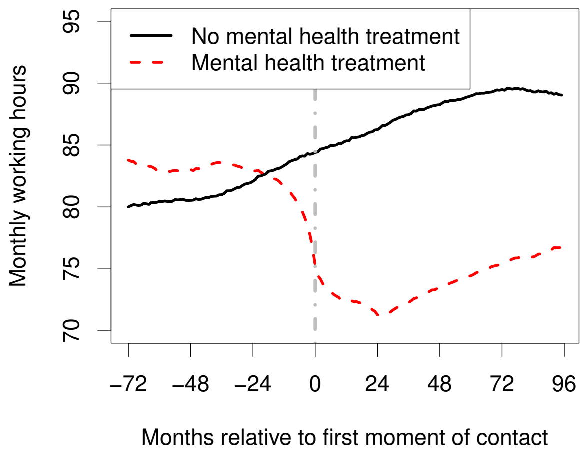
A.2 Additional results: onset of mental health problems

Figure A.2: Trends in labor market outcomes for individuals with and without mental health treatment relative to the first moment of contact

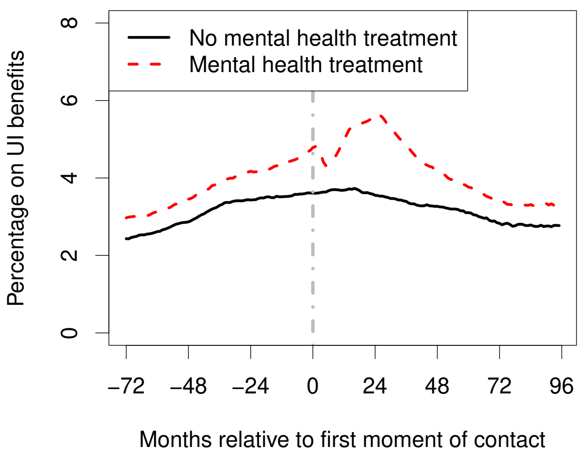
(a) Monthly labor earnings



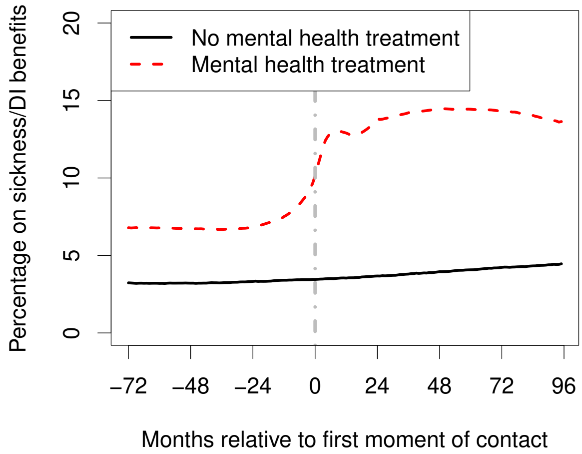
(b) Monthly working hours



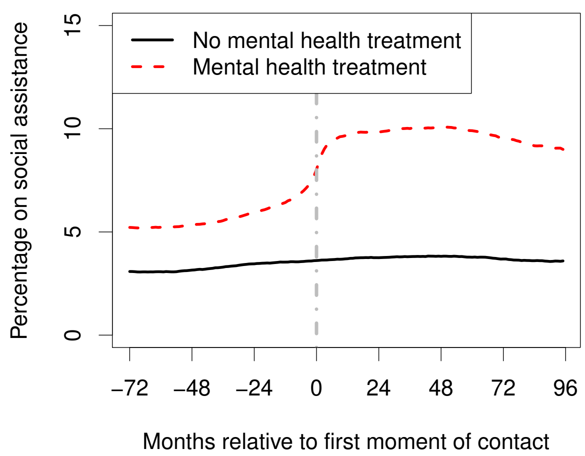
(c) UI benefits



(d) DI benefits



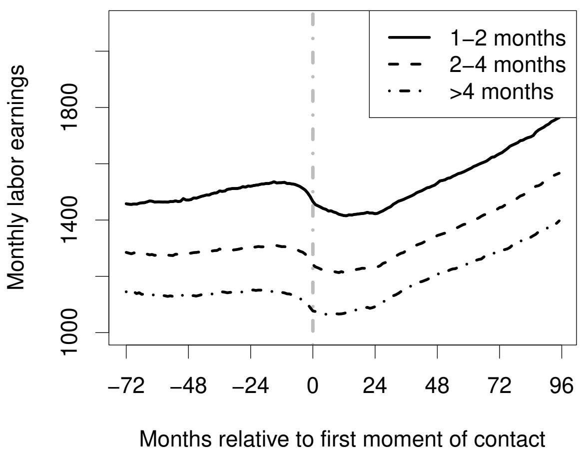
(e) Social assistance



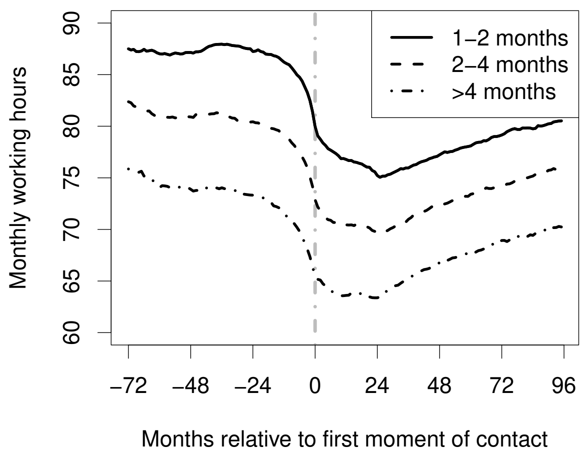
A.3 Additional results: impact of waiting time

Figure A.3: Trends in labor market outcomes relative to the first moment of contact for groups based on their individual waiting time

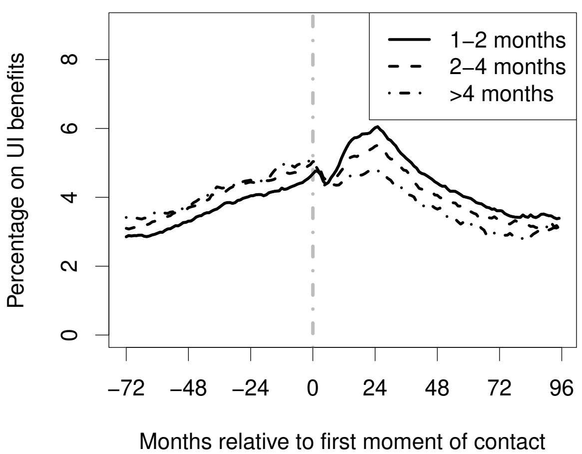
(a) Monthly labor earnings



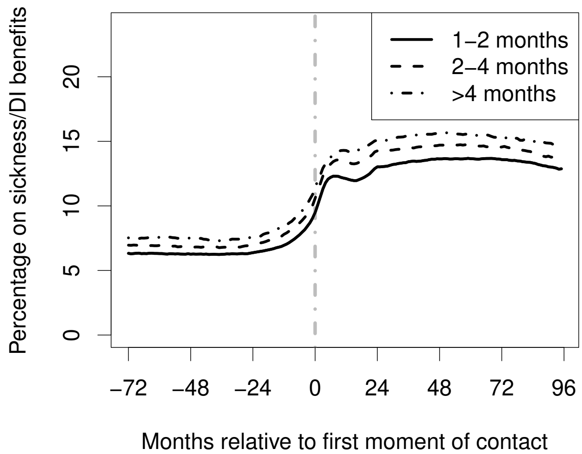
(b) Monthly working hours



(c) UI benefits



(d) DI benefits



(e) Social assistance

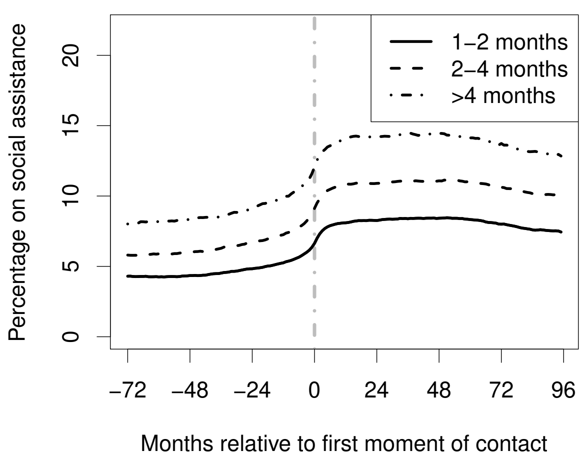


Table A.2: All control variables X_i used in the IV specification

Control variable	Values
Demographics:	
Gender	Male or Female
Age	Dummies for 5-year age groups
Migration status	Native, first or second generation migrant
Education level	Low, middle, high or unknown
Calendar-month of first contact	Year-month fixed effects (60 dummies)
Mental health status:	
Mental health diagnosis	DSM-IV classification
Crisis	Indicator for crisis admission
Zero days until intake	Indicator for days until intake equal to zero
Pre-treatment employment[a]**:**	
Employment	Indicator for being employed
UI	Indicator for receiving UI
Social assistance	Indicator for receiving social assistance
Sickness/DI	Indicator for receiving sickness/DI benefits
Municipality characteristics[b]**:**	
Percentage Caucasian	Dummy for decile
Percentage of Moroccan migrants	Dummy for decile
Percentage of Turkish migrants	Dummy for decile
Average house valuation	Dummy for decile
Percentage of owner-occupied houses	Dummy for decile
Percentage of housing-corporation-occupied houses	Dummy for decile
Percentage of houses build prior to the year 2000	Dummy for decile
Average income per inhabitant	Dummy for decile
Share below 40th percentile in income distribution	Dummy for decile
Share above 20th percentile in income distribution	Dummy for decile
Share with income below social minimum	Dummy for decile
Percentage of individuals receiving UI benefits	Dummy for decile
Percentage of individuals receiving DI benefits	Dummy for decile
Population density	Dummy for decile

(a) Pre-treatment employment outcomes are measured 24 months prior to treatment, or 24 months prior to outcome in case of placebo outcomes; (b) Value of municipality characteristics is the decile in which the municipality falls in the distribution over all municipalities

Figure A.4: Non-parametric estimates of the association between waiting time (grouped by week) and probability to be employed 12 months after the first moment of contact

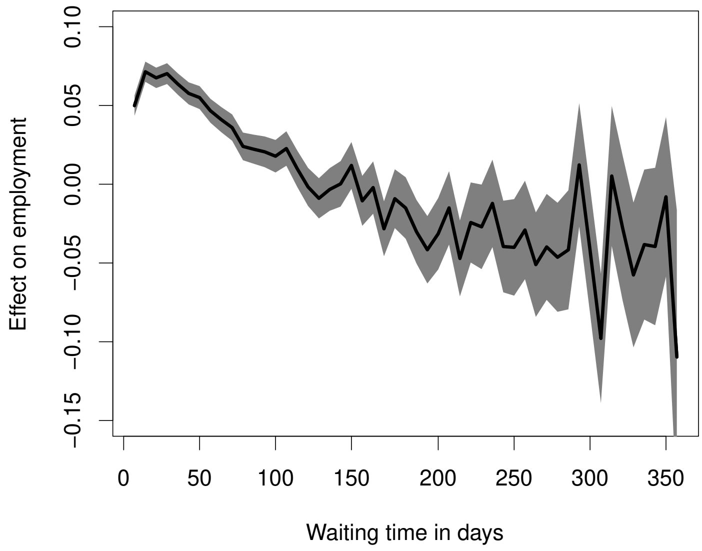


Table A.3: Impact of (lagged) regional unemployment rate on the regional waiting time

	Regional waiting time
Unemployment rate t	0.51
	(2.40)
Unemployment rate t-1	2.43
	(3.64)
Unemployment rate t-2	-0.49
	(3.60)
Unemployment rate t-3	1.48
	(2.31)
Employment rate t	-0.04
	(0.38)
Employment rate t-1	-0.01
	(0.54)
Employment rate t-2	-0.05
	(0.54)
Employment rate t-3	0.40
	(0.38)

Standard errors shown in parentheses; *significant at a 10% significance level; **significant at a 5% significance level

Table A.4: Impact of one additional month of regional waiting time on probability to start treatment or seek treatment in other municipality and on the composition of patients contacting mental healthcare providers

Impact on probability to:	
Start treatment	0.08%
	(0.12)
Seek treatment in other municipality	0.10%
	(0.14)
Impact on composition of patients	
Demographics:	
Female	0.18%
	(0.20)
Age	-0.12**
	(0.05)
Dutch Native	-0.33%
	(0.17)
Low education level	0.20%
	(0.18)
Middle education level	-0.37%
	(0.22)
High education level	0.18%
	(0.21)
Mental health diagnosis:	
Mood disorder	-0.52%**
	(0.18)
Personality disorder	0.66%**
	(0.11)
Anxiety disorder	-0.09%
	(0.17)
Other disorder	-0.05%
	(0.19)
Mental health provider:	
Psychologist	0.11%
	(0.20)
Psychotherapist	-0.22%
	(0.13)
Psychiatrist	0.00%
	(0.16)

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

Table A.5: Heterogeneity of first-stage estimates of the impact of regional waiting time on individual waiting time

Gender:	Male	Female		
	0.42** (0.01)	0.40** (0.01)		
Age:	<35	35-50	>50	
	0.47** (0.01)	0.41** (0.01)	0.32** (0.01)	
Migration background:	Native	1^{st} generation	2^{nd} generation	
	0.39** (0.01)	0.48** (0.02)	0.50** (0.02)	
Education level:	Low	Middle	High	
	0.48** (0.02)	0.46** (0.01)	0.36** (0.01)	
Diagnosis:	Anxiety	Mood	Personality	Other
	0.44** (0.01)	0.33** (0.01)	0.62** (0.03)	0.36** (0.01)
Provider:	Psychologist	Psychotherapist	Psychiatrist	Other
	0.47** (0.01)	0.32** (0.02)	0.32** (0.02)	0.39** (0.01)

Standard errors shown in parentheses; *significant at a 10% significance level; **significant at a 5% significance level

Figure A.5: Estimated impact and 95% CI of one additional month of waiting time on probability to be employed using IV with regional controls (black) and OLS (red)

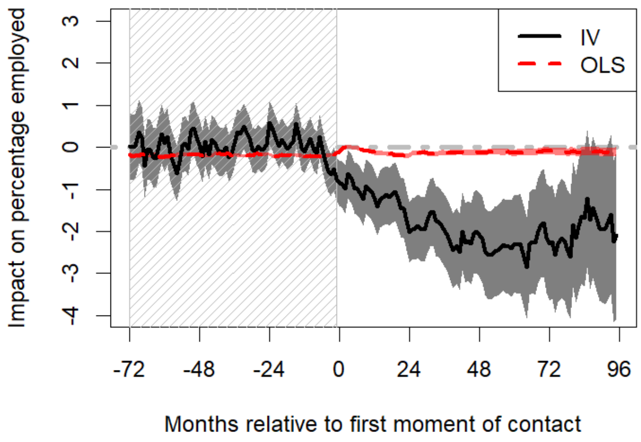


Figure A.6: Estimated impact and 95% CI of one additional month of total waiting time (black) and time until intake (red) on probability to be employed

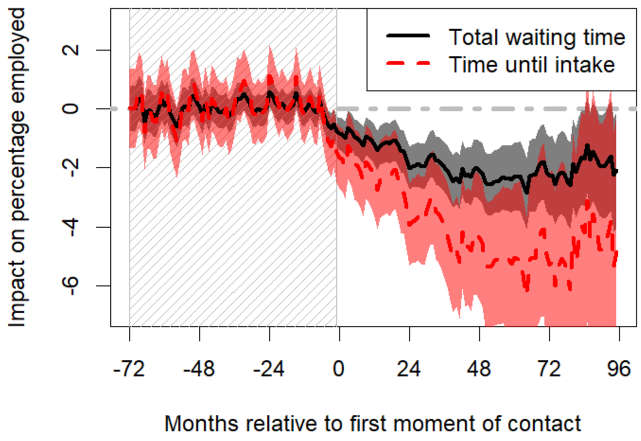


Figure A.7: Estimated impact and 95% CI of one additional month of waiting time on probability to be employed using regional controls (black) and regional fixed effects (red)

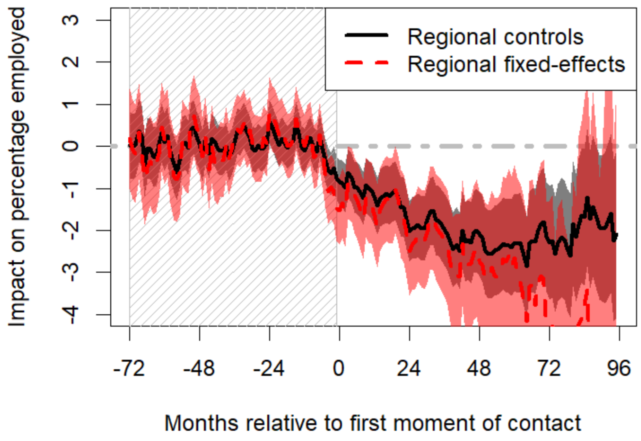
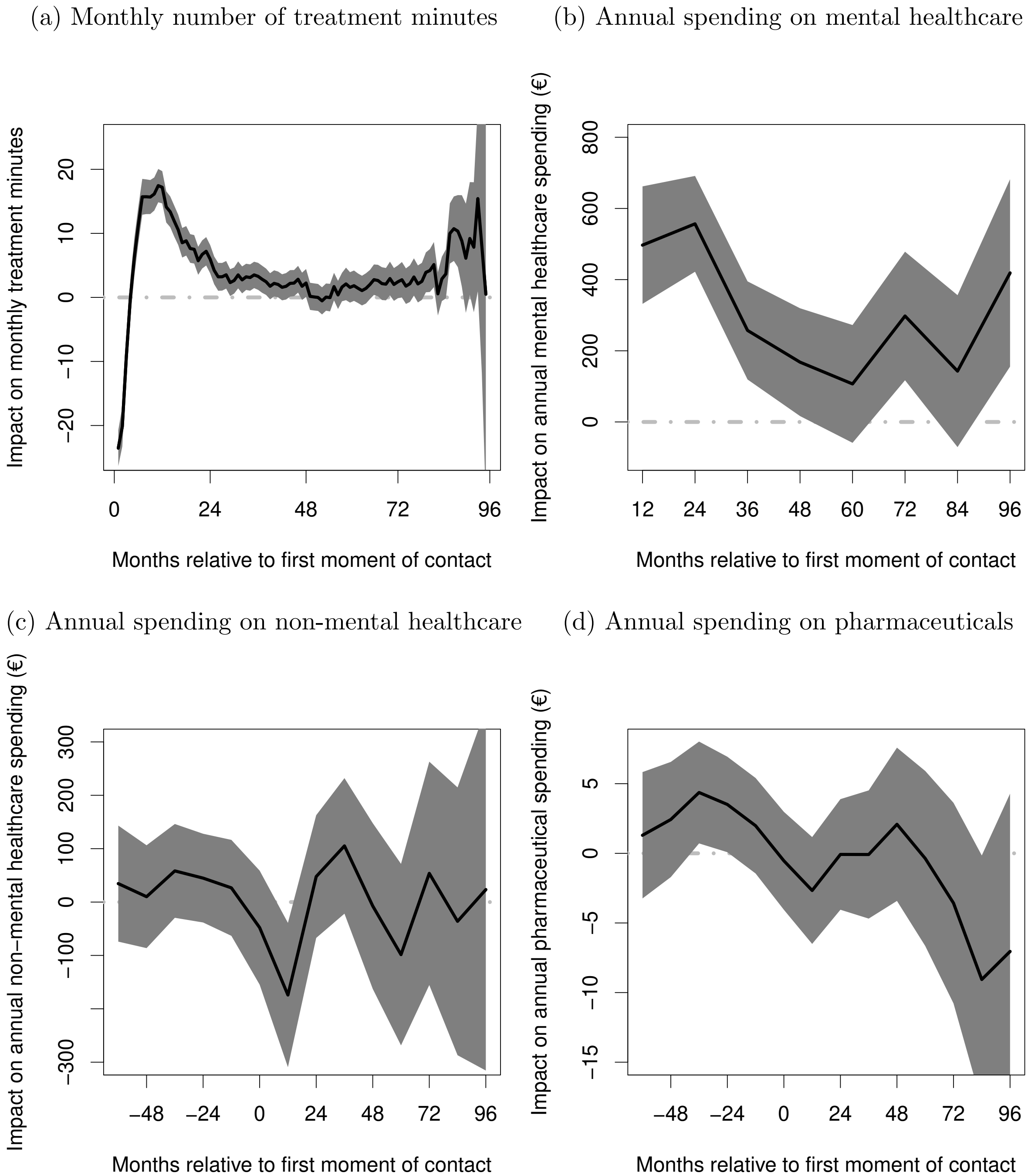


Figure A.8: Estimated impact and 95% CI of one additional month of waiting time on healthcare usage



A.4 Additional results: differences in average waiting time

Table A.6: Differences in waiting time for individuals with depression of given severity

	Low severity	Mild severity	High severity
Gender[a]:			
Female	-0.2	0.0	0.3
	(1.5)	(0.8)	(1.4)
Migration background[b]:			
1^{st} generation[c]	19.3**	13.2**	7.8**
	(2.1)	(1.1)	(1.7)
2^{nd} generation[d]	7.8**	5.0**	9.9**
	(2.3)	(1.2)	(2.0)
Education level[e]:			
Low	6.9**	6.7**	5.4**
	(2.2)	(1.2)	(1.9)
Middle	1.9	1.0	-2.1
	(1.7)	(1.0)	(1.7)
Demographic controls	X	X	X
Regional fixed effects			
Pre-treatment employment	X	X	X
Mental health diagnosis	X	X	X
Provider fixed effects	X	X	X
Mean waiting time	53.4	53.7	44.3
Sample size	5,980	19,094	6,746

Standard errors shown in parenthesis; *significant at a 5% level; **significant at a 1% significance level; (a) Baseline gender is male; (b) Baseline migration background is native, (c) Individuals who migrated to the Netherlands, (d) Children of first-generation migrants (e) Baseline education level is high

A.5 Back-of-the-envelope cost savings calculation

In the Netherlands, a one-month reduction in waiting time for one year would affect at least 100.000 individuals starting treatment per year. According to the IV estimates on employment, this would lead to a reduction in employment loss of approximately 2.000 individuals for at least eight years. The average cost to society of someone without employment has been estimated to be approximately €24.000,- according to the audit office of the Dutch government. A reduction in employment loss of 2.000 individuals thus translates into a cost savings of almost €380 million.