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IZA DP No. 15083

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ABSTRACT

What's Another Day? The Effects of Wait Time for Substance Abuse Treatment on Health-Care Utilization, Employment and Crime*

This research provides the first evidence on the impacts of waiting times for treatment for a substance use disorder (SUD). Using rich linked administrative information from Norway, we study the impact of waiting time on health-care utilization, employment and crime for patients who enter outpatient treatment for cannabis use disorder. Confounding due to unobserved severity of illness is addressed using an instrumental variables strategy that exploits plausibly exogenous variation in congestion in Norway's health-care system. We find that waiting to access treatment increases the use of health-care services at both the extensive and intensive margins, measured by the duration of a treatment episode and the number of consultations within a treatment episode, respectively. Waiting time also has spill-over effects, reducing employment after entering treatment and increasing crime both before and after treatment begins. Together, these findings suggest that waiting times to access treatment for a SUD imposes significant costs on patients, health-care systems, and on society more broadly.

JEL Classification: I12, J22, K42

Keywords: waiting times, cannabis, substance use treatment, employment, crime

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1 Introduction

The US opioid crisis has brought renewed focus and attention to the high cost of substance abuse.[1] Substance abuse not only impacts the health, productivity, and social wellbeing of substance abusers, it also effects the communities in which they live, and is an important contributor to the global burden of disease (GBD 2016 Alcohol and Drug Use Collaborators, 2018). As recognized in the Biden-Harris Administration's $4 billion policy response to the US addiction epidemic, key to addressing the impacts of substance abuse is timely access to evidence-based treatment.[2] Despite this, waiting times for treatment for substance use disorders (SUDs) are common, especially in countries with universal health-care systems in which patients pay no or low out of pocket costs for treatment (Martin & Smith, 1999).[3] And in an environment in which many jurisdictions are moving to liberalise their drug policies, and demand for SUD treatment continues to grow, it is of critical importance to understand the consequences of waiting times to access to treatment, for SUD patients, for health-care systems, and for society more broadly (EMCDDA, 2021; UNODC, 2021).

This research provides the first evidence on the impacts of waiting times for treatment for a SUD. It does so by seeking answers to three key questions. First, we investigate whether delaying access to treatment for a SUD results in the disease progressing, necessitating more extensive treatment interventions. Concerns regarding the impacts of waiting times on patient health and health-care use are not new (Cullis *et al.*, 2000; Koopmanschap *et al.*, 2005; Lindsay & Feigenbaum, 1984). To date, however, the empirical evidence has been largely based on studies using hospital administrative data to examine the impact of waiting for inpatient procedures, such as knee or hip replacements, or other orthopaedic surgeries, on outcomes such as the length of hospital stay and in-hospital mortality (Gødoy *et al.*, 2019; Hamilton & Bramley-Harker, 1999; Nikolova *et al.*, 2016; Siciliani & Iverson, 2011). This literature finds that waiting times do not lead to greater post-surgery health-care utilization or mortality, suggesting that patient health is unaffected by waiting times for the procedures studied. Whether these findings can be generalized to the treatment of SUDs is, however, questionable. A notable difference between SUD patients and those

[1] In the US, one in five individuals aged 12 and older are estimated to be living with a SUD (US Department of Health and Human Services, 2016).

[2] Funds appropriated under the American Rescue Plan will enable expanded access to treatment services. See `https://www.whitehouse.gov/wp-content/uploads/2021/03/BidenHarris-Statement-of-Drug-Policy-Priorities-April-1.pdf`. The role of treatment for SUDs is also recognised in the United Nation's 2030 Agenda for Sustainable Development, which targets the strengthening of treatment of substance under the goal of healthy lives and promoting well-being for all at all ages.

[3] Substance use disorders are medical illnesses characterized by clinically significant impairments in health, social function, and impaired control over substance use. They are diagnosed through assessing cognitive, behavioural, and psychological symptoms (American Psychiatric Association, 2013). Wait times are also a major impediment to treatment in the US (Corredor-Waldron & Currie, 2021).

previously studied is that SUD patients are typically more socially marginalized and economically disadvantaged, making them more vulnerable to adverse health impacts of delayed treatment.

The second question this research seeks to address is whether the effects of waiting to enter treatment for a SUD spill-over into non-health domains. Spill-over effects are particularly salient in the context of SUD treatment because substance abusers tend to have weaker attachments to work and a greater tendency for crime than found in the general population (Hen, 2011; White, 2016). As a consequence, delaying access to treatment risks exacerbating or prolonging substance abusers joblessness and crime. The third key question this research seeks to address is whether the impacts of waiting times vary in magnitude or sign depending on patients' social and economic disadvantage. For example, waiting times might have larger negative employment effects for substance users with a high degree of disadvantage because this group requires significant support and assistance to re-enter the labor market. Or it could be that the adverse employment effects are larger for less disadvantaged patients because this group could have maintained their employment had they received timely treatment. Understanding the health, health-care utilization, and spill-over effects of waiting times, and whether these effects vary with patient disadvantage, is critical to inform policies around prioritization, and for improving the design and targeting of treatment programs. It is in providing new evidence on how, and for whom, waiting time matters that we seek to make a contribution.

Establishing the impacts of waiting times to access treatment for a SUD poses a number of challenges. First and foremost is the availability of suitable data. Unlike inpatient procedures, which occur in hospitals that collect and collate information related to the patient, the procedure, and post-surgery health-care use, treatment for a SUD typically occurs in a decentralized outpatient setting, with services delivered by a variety of health-care professionals, often outside of mainstream health-care systems. This makes it difficult to obtain information on waiting times and health-care use, or other measures of wellbeing, for a representative sample of individuals seeking treatment for a SUD. We overcome these data challenges by using administrative data from the Norwegian Patient Registry on individuals entering treatment with a primary diagnosis of cannabis use disorder (CUD). This patient group is particularly salient for examining the impacts of waiting to access treatment. Globally, CUD it is second only to opioid use disorder in prevalence among illicit substance use disorders (GBD 2016 Alcohol and Drug Use Collaborators, 2018) and in Europe, cannabis is now the most frequently reported problem drug among new patients entering drug treatment, accounting for half of all first time admissions (EMCDDA, 2019). And because the NPR has been linked to employment and crime registries, we are able to the study of impacts of waiting time for CUD patients in the domains of socio-economic functioning measured by employment and crime, in addition to its impact on health-care utilization.

Even with the benefit of rich, linked administrative data, establishing the impacts of wait time is complicated by the fact that it is not randomly assigned to patients. In Norway, waiting time is determined by a combination of prioritization based on severity of illness and supply side factors that we collectively refer to as congestion. While congestion is plausibly exogenous with respect to the time a patient waits for treatment, the severity of illness, and hence prioritization, is likely to be endogenous. Further, severity of illness (and prioritization) is unobserved in the administrative data we use. This is an issue for establishing the causal impacts of wait time because, in addition to impacting the length of time a patient waits for treatment, the severity of a patient's illness is likely to impact on the outcomes we study. For example, more severely ill patients tend to wait a shorter time to enter treatment and they tend to experience a longer duration of treatment. Estimates of the impact of waiting times that fail to account for severity of illness will confound the two effects, leading to an under-statement of the true impact of wait times on the duration of treatment.

We use an instrumental variables (IV) strategy to disentangle the confounding effects of severity of illness from the impacts of waiting to access treatment. Our approach exploits plausibly exogenous variation in wait times due to geographic and temporal variation in health-care congestion, and is closely related to the approach used by Gødoy *et al.* (2019).[4] Congestion faced by a patient entering treatment in a specific geographic region, called a health trust, at a specific point in time, is measured by the average wait time of individuals who enter treatment in neighbouring health trusts around the same date as the index patient. Essentially, we leverage differences in wait times between patients due to the effect of differences in local congestion. With this strategy, we to address the issue of negative selection into wait times, and estimate effects for those at the margin of wait times for whom congestion matters. We provide evidence in support of our strategy, demonstrating that our instrument, congestion, is uncorrelated with patient characteristics (conditional on health trust by year, and month of entry fixed effects), consistent with random assignment, and is relevant in explaining waiting times of patients. We also provide evidence that congestion satisfies monotonicity and explore a potential violation of the exclusion restriction. We interpret our IV estimates as informative about local average treatment effects (LATE) of waiting time.

Our empirical findings contributes three main insights. First, longer waiting times to access treatment for CUD leads to greater use of health-care services. Relative to patients whose treatment was not delayed, those who experienced the (sample) average wait time are 12% less likely to have completed a treatment episode within 12 months of starting, and are 6% less likely to have completed treatment within 24 months of starting. In addition, patients who experienced the average wait

[4] Our IV is also similar to the Hausman type instrument introduced by Nevo (2001).

time attend 45% more treatment consultations 24 months after entering treatment compared to a patient who accessed treatment without waiting. This increased utilization of health-care services points to a deterioration in health of those whose access to treatment is delayed.

We also find significant evidence that waiting time to access treatment adversely impacts on economic and social functioning. In terms of employment, we find that relative to patients whose treatment was not delayed, patients who experienced the average wait time are 30% less likely to have been employed at any time in the 24 months following the start of a treatment episode, and are 25% less likely to have been employed 36 months following the start of treatment. Our third main finding relates to the impact of wait time on crime. We find that waiting to access treatment increases the probability of being charged with a crime before entering treatment by 45% (evaluated at the average wait time). And relative to those who do not wait to start treatment, waiting the sample average wait time increases the total number of charges by 41%, and the number of drug-related charges by 70%, in the 12 month period following the start of treatment. Twenty four months after starting treatment, the number of drug related charges remains 44% higher for those who waited the average wait time. These findings are robust to a battery of sensitivity tests that attempt to account for severity of illness, that exclude potentially influential subsamples, and that examine functional form assumptions.

In order to explore whether the impacts of wait times differ for those who are more economically and socially disadvantaged, we undertake a heterogeneity analysis in which we defined patients as disadvantaged on the basis of either (1) their prior criminal involvement or, (2) a lack of attachment to school or work. This analysis reveals significant evidence of differential impacts of waiting time on employment outcomes but not on health-care utilization or crime related outcomes. In particular, we find that waiting time to access treatment reduces employment among individuals who had prior attachment to school or work, and among those who did not have prior criminal charges. Employment of individuals without a prior attachment to work or school, and among those with prior criminal charges, is not significantly affected by waiting times to access treatment. This suggests that the negative employment effects of waiting times are larger for those who are less disadvantaged, and highlights the complex interactions between waiting times for substance abuse treatment and disadvantage.

This research makes a contribution to several distinct literatures. First, it contributes to the literature examining the consequences of waiting time. As discussed above, this literature, which is largely based on studies of inpatient treatments such as hip, knee and orthopaedic surgeries, finds no evidence that waiting for treatment adversely impacts on post-surgery health-care use. This suggests that waiting times do not adversely impact on patients' health (Gødoy *et al.*, 2019; Hamilton & Bramley-Harker, 1999; Moscelli *et al.*, 2016).[5] In contrast, we find that waiting for treatment for CUD increases both the duration and the intensity of treatment, suggesting a deterioration in patients' health.

This research also contributes to the nascent literature examining the consequences of barriers to accessing treatment for SUDs. As noted by Corredor-Waldron & Currie (2021), a lack of large scale administrative data containing information on patients undertaking substance use treatment, the care they receive, and their outcomes has lead to a paucity of research in this area. Previous studies on barriers to accessing treatment for a SUD use county level data on the location of treatment facilities, finding that improved access to treatment reduces emergency room visits (Corredor-Waldron & Currie, 2021) and local crime (Bondurant *et al.*, 2018). Our study complements and builds this literature by studying wait times as a barrier to treatment, and by using large scale administrative data on individuals. In doing so, we extend the documented adverse impacts of barriers to treatment beyond those borne by communities, to include those borne by substance abuse patients.

Finally, our research relates to the literature on the impacts of cannabis use. While there is much evidence of a positive association between cannabis use and crime, whether the association represents a causal relationship is less clear. For example, Adda *et al.* (2014) find that although depenalising cannabis possession in a borough of London increases cannabis related offences, it decreases non-drug related crime. Similarly, studies reviewed by Anderson & Rees (2021) find no evidence of an increase in crime, and some reductions in crime, especially violent crime, in US states the have legalized the medical use of cannabis.[6] Our finding that delaying access to treatment for CUD increases offending is in contrast with these previous studies. It is, however, in line with Bondurant *et al.* (2018) who find that the presence of substance abuse treatment facilities reduces crime, and suggests that substance abuse, and not substance use, leads to crime. Finally, this research also contributes to the literature studying the labour market impacts of cannabis use. As discussed in a recent review of this literature, both negative and null effects of cannabis use on employment have been reported (Van Ours & Williams, 2015). Our finding that waiting to access treatment reduces employment is consistent with studies that find cannabis use decreases employment. In sum, our findings highlight the importance of timely access to treatment for reducing offending and increasing employment among individuals with CUD.

[5] Gødoy *et al.* (2019) expands the sets of outcomes considered to include employment and labor market attachment. Reichert & Jacobs (2018) estimates the association between wait times to enter an early intervention treatment for psychosis on a summary measure of patient well-being.

[6] Studies reviewed by Anderson & Rees (2021) that investigate openings of dispensaries also found reductions in crime, while studies on dispensary closings found an increase in crime. However, as noted by the authors, the latter is unlikely to represent a causal effect as restaurant closings are also found to be associated with an increase in crime.

The rest of this paper is laid out as follows. The next section provides background information on context and institutions relevant to our study. Section 3 describes our instrumental variable approach to identifying the impacts of waiting times. This is followed by a description of the data in section 4 and an evaluation of our instrumental variable in section 5. We present our results in Section 6 and conclude with a discussion of our findings and their implications in Section 7.

2 Institutional Setting

2.1 Cannabis in Norway

Cannabis use, possession, production and sale is illegal in Norway. Nonetheless, around 22% of Norwegians aged 16-64 report having used cannabis at some point in their life, and 9% of 16-34 year olds report having used it in the last year (Sandøy, 2020). And while the prevalence of annual use has been stable since 2010, Norway has seen a 34% increase in the number of patients per 1000 in the population entering specialist treatment for CUD between 2010 and 2019.[7] Over the same period, the THC content of cannabis products seized in Norway rose from around 9% to 29% (The National Criminal Investigation Service, 2020) and this increase in potency provides the most credible explanation for growing admissions into treatment, with several studies finding positive associations between high THC content and cannabis dependence, worse mental health and first time cannabis treatment admissions (Di Forti et al. 2015; Freeman and Winstock, 2015; Meier, 2017; Freeman et al. 2020).[8]

2.2 The Norwegian health-care system

Norway has a universal public health-care system that provides publicly funded health-care services to all Norwegians at zero or low cost.[9] Treatment services for SUD are the responsibility of the specialist care sector. While policy priorities and budgets for specialist care are determined nationally by the Ministry of Health and Care Services, the administration and provision of services is decentralized, with four Regional Health Authorities overseeing the administration of 20 health

[7]Authors calculations based on Andreas (2021) for the number of patients seeking specialist care in 2010 and 2019 and Statistics Norway, Population Table, `https://www.ssb.no/en/statbank/list/folkemengde` for the population of Norway in 2010 and 2019.

[8]Norway's experience is not unique, with Germany, Spain and the UK also recording rising cannabis related treatment admissions despite stable or decreasing rates of use (UNODC, 2016).

[9]Patients' out of pocket payments are limited by a cost-sharing ceiling which is set by the parliament each year. When the ceiling has been reached, an exemption card for health-care services is issued, which entitles the holder to free treatment and benefits for the remainder of the calendar year The cost-sharing ceiling was set at NKr 1980 (€265) in 2012 Ringard *et al.* (2013).

trusts that deliver health services.[10] In addition, each of the RHAs contracts with the private and not-for-profit sectors for the public provision of health services. To ensure that the provision of specialist services is aligned with national priorities, the Ministry of Health and Care Services issues the RHAs letters of instruction (containing operational directives on general goals to be achieved) each year, along with their annual budgets (Ringard *et al.*, 2016).[11] In turn, the RHAs issue each of the health trusts under their control letters of instruction along with annual budgets to ensure that the national priorities are addressed.

2.3 Substance Abuse Treatment in the Specialist Care Sector

In Norway, as in Europe more generally, treatment for CUD typically occurs in an outpatient setting (EMCDDA, 2015). Over the period 2010-2018, 81% of patients who entered specialised care for CUD in Norway received outpatient treatment and 82% of outpatient services for CUD patients were provided by health trusts, with the balance of publicly funded services provided by specialists in the non-profit and the private sectors.[12] There are no pharmacotherapies approved for the treatment of CUD. Treatment is based on psychosocial interventions, such as Cognitive Behavioral Therapy and Motivational Interviewing (EMCDDA, 2015).

Prior to 2004, addiction treatment was provided by the counties under the system of social services. The 2004 Substance Treatment Reform shifted responsibility for all substance abuse treatment and rehabilitation services to the state via the RHAs, and made substance abuse treatment a part of specialized mental care services.[13] At the same time, treatment services for substance abuse became known as "interdisciplinary specialized services for substance abusers" (TSB), in reference to the expertise from medicine, psychology, and social work that comprised the treatment teams.[14] TSB services are offered at local hospitals or substance abuse treatment centers, through psychiatric units at local hospitals, and through privately practising specialists and non-profit organisations

[10]RHAs are state-owned corporations that report to the Ministry of Health and Care Services. The four RHAs are the Northern Norway Regional Health Authority, the Central Norway Regional Health Authority, the Western Norway Regional Health Authority and the and South-Eastern Norway Regional Health Authorities. The Northern, Central and Western Norway RHAs oversee four health trusts, and the South-Eastern RHA oversees eight health trusts.

[11]The annual budgets of RHAs consist of block grants and activity based components, with the size of RHAs block grants depending on factors such as the number of inhabitants living in the region and the demographics of the population.

[12]Information on the number of CUD patients in inpatient an outpatient specialised health care can be found here: `https://www.fhi.no/nettpub/narkotikainorge/tiltak-og-behandling/behandling-for-narkotikaproblemer-i-spesialisthelsetjenesten/?term=&h=1`. Information on the number of CUD outpatients receiving treatment in health trusts and the private sector in 2014 is reported in Table 2.2 of Pedersen *et al.* (2016).

[13]The Administrative Alcohol and Drug Reform of 2004 stipulates that Norway's four regional health authorities shall provide outpatient and inpatient interdisciplinary specialised treatment, either through their own health trusts or through private contractors.

[14]TSB and covers provision of inpatient and outpatient treatment, detoxification and emergency care.

contracted to provide publicly funded specialist treatment.

In moving responsibility for treatment into the specialised care sector, the Substance Treatment Reform gave substance users the same rights to treatment services as other patient groups.[15] In the three years following the reform, referrals for TSB treatment increased at a rate that outstripped the increase in resources allocated to it, resulting in lengthening wait times for treatment (Nesvaag and Lie, 2010).[16] The state responded with a National Action Plan on Alcohol and Drugs (2008-2012) which included targets to increase capacity, in terms of number of staff and the number of treatment places, in order to reduce waiting times (Norwegian National Action Plan on Alcohol and Drugs, 2008). As a consequence of the of marked increase in resources allocated to TSB under the National Action Plan, waiting times to access treatment for SUD fell substantially over the period on which our analysis is based.

2.4 Patients' Rights Act of 1999

An important feature of Norway's health system is that patients have rights and entitlements that are legally protected under the Patients' Rights Act of 1999. Of particular relevance to this study are the right of equal access to health-care services, and the right to individualised treatment.

The right to equal access implies that patients presenting similarly from a clinical perspective should receive similar prioritization and therefore wait a similar amount of time for treatment, irrespective of where they live and any other (non-clinical) characteristics. In practice, accessing treatment involves a letter of referral being sent to the priority setting unit of the patient's local health trust, and the priority setting unit sending the referral to (one of) its discipline specific assessment panel(s).[17] The assessment panel determines whether the referred patient is entitled to specialised health treatment (based on the criteria of expected costs relative to benefits of receiving health-care), and prioritizes patients according to their health need (i.e. according to the severity of their medical condition). Assessments do not depend upon the patient's gender, ethnicity, socioeconomic status, past harmful behaviour, or productivity. Nor do assessments depend on,

[15] SUD patients' referrals for treatment are undertaken by interdisciplinary panels comprised of specialists in medicine and psychology and a trained social worker. Each health trust has at least one assessment panel for SUD treatment referrals. Some have as many as nine assessment panels (Rollag *et al.*, 2020). In assessing the right to specialised treatment for SUD patients, the health trust assessment panels evaluate cost effectiveness of the available treatment as well as the severity of the illness. Cost-effectiveness is used not only to decide which patients should have access to specialized services, but also the kind of services they should have access to, and for how long it is cost-effective to provide specialized services to each specific patient.

[16] Substance abuse treatment is mainly financed though block grants (accounting for around 3% of block grant funding) and earmarked funding. Block grant funding is also used by the RHAs to finance the provision of substance abuse treatment services by the health trusts and drug treatment centers.

[17] For practical reasons, patients seeking outpatient treatment tend to seek it close to where they live. Research showing that proximity to treatment facility is an important determinant of retention in treatment for SUDs (Beardsley *et al.*, 2003).

or take into account, the capacity or availability of the relevant treatment at the facility chosen by the patient, or in the specialist care sector more broadly. And while equal access for equal need is a protected right, it is important to note that the assessment and prioritization process is decentralized, and variation in the interpretation and application of guidelines across the health trust specific assessment panels can result in differences in the prioritization of patients who appear to present similarly from a clinical perspective (Rollag *et al.*, 2020).[18] We account for the potential for health trust specific idiosyncracies in prioritizing patients in the construction of our measure of local health-care congestion.

The right to individualised treatment implies that, unlike in many health-care systems with pre-determined or time limited treatment plans, in Norway the type, length and intensity of treatment varies across patients according to their needs and their response to treatment.[19] It is important in the context of our study for two main reasons. First, it implies that while supply side resource constraints may impact on how long a patient waits to receive treatment, it should not impact on the treatment received, either at the extensive or intensive margins. And second, it is a source of exogenous variation in congestion across health trusts and time, due to the idiosyncratic nature of the durations of incumbent patients' treatment, which impacts on the waiting time of patients yet to enter treatment.

In the following section we develop an instrumental variables strategy that leverages geographic and temporal variation in waiting time due to health system congestion that is unrelated to an individual patient's severity of illness. We use this variation to identify the causal impact of waiting times to enter treatment on outcomes related to health care utilization, work and crime.

3 Empirical Approach

To evaluate the impact of wait time for specialist outpatient treatment, we start by specifying the following model

$$y_{i,j,t+s} = \delta_s wait_{i,j,t} + {\beta_s}' X_{i,j,t+s} + \nu_{i,j,t+s} \tag{1}$$

where $y_{i,j,t+s}$ is the outcome of interest for individual i, who enters treatment at health trust j on date t t, measured s periods after entering treatment ; $wait_{i,j,t}$ is the number of days individual i

[18] Also see `https://docplayer.me/24506753-Ny-prioriteringsveileder-for-tsb.html`

[19] For outpatient care, for example, treatment lasting more than 3 months is reviewed every 8 weeks in the first year and every 8 to 12 weeks in subsequent years of treatment. For information on timing of evaluation points, see `https://www.helsedirektoratet.no/pakkeforlop/rusbehandling-tsb/behandling-og-oppfolging-rusbehandling-tsb-pakkeforlop/evalueringspunkter`

waits to enter treatment at health trust j, on date of entry into treatment t, $X_{i,j,t+s}$ is a vector of control variables, and δ_s is the parameter of interest, capturing the impact of wait time s periods after starting treatment. The outcomes of interest are: completed episode of treatment; number of specialist consultations in the episode of treatment; ever employed; number of days employed; ever charged with a crime; number of criminal charges. These outcomes are measured s months after entering treatment, $s = 3, ..., 36$.

Obtaining causal estimates of the parameters in this model is complicated by the fact that waiting time is not randomly assigned. All else being equal, and to the extent that patients access to treatment is prioritized on the basis of severity of illness, a shorter waiting time reflects a greater severity of illness at the time of assessment. This is an issue because severity of illness is not observed and, in addition to being associated with a shorter waiting time, a more severe illness may also be associated with worse outcomes, such as a greater duration or intensity of treatment, a lower probability of being employed, and a higher probability of being charged with a crime. As a consequence, OLS estimates will confound the impact of unobserved severity with the impact of wait time to access treatment.

Our research design addresses this concern using an Instrumental Variables (IV) strategy. Our strategy seeks to separate the endogenous determinants of wait time to enter treatment, due to a patient's severity of illness or other individual specific unobserved characteristics, from exogenous determinants of wait time that arise due to congestion in local health-care markets. Essentially, we compare outcomes, such as duration of treatment, for patients who face different levels of local health-care market congestion and interpret any difference as the causal effect of the change in waiting time due to the difference in congestion.

We measure local health-care market congestion faced by a patient entering treatment in a health trust on a specific date using the average wait time of patients entering treatment in neighbouring health trusts around the same point in time. Specifically, the instrument for the waiting time of patient i entering treatment at health trust j, in time period t , $Z_{j(i),t}$, is defined as the average wait time of patients entering into treatment at health trusts neighbouring health trust j in the time interval $\pm d$ days from the date patient i enters treatment. We define the set of health trusts neighbouring health trust j as all health trusts that share a border with health trust j, and we set $d = 31$, so we average over the interval spanning 31 days before through to 31 days after the index patient enters treatment. We note that an alternative approach would be to construct the measure of local congestion using the leave-out mean of wait times of patients entering into treatment in the same health trust, rather than neighbouring health trusts, as the index patient. We do not follow this approach because health trust specific idiosyncracies in interpretation and application of prioritization guidelines may induce a correlation between patients' unobserved severity of illness and the measure of congestion based on patients entering into treatment at the same health trust.

In order to implement our Two Stage Least Squares approach, we write the first stage as:

$$wait_{i,j,t} = \alpha Z_{j(i),t} + \gamma' X_{i,j,t+s} + \epsilon_{i,j,t} \tag{2}$$

Because congestion depends on health trust resources, which are determined by annual budgets and seasonal patterns, our vector on control variable always include health trust by year fixed effects (to account for changes in annual budgets) and month fixed effects (to account for the impact of seasonal patterns in demand). The identifying assumption is that, controlling for health trust by year fixed effects, month fixed effects and observed individual characteristics, time varying health trust specific shocks to congestion are independent across neighbouring health trusts.

2SLS provides consistent estimates of the causal parameter of interest in equation (1) if (a) the instrumental variable is relevant in explaining the time patient i waits for treatment in health trust j (relevance), (2) conditional on health trust by year fixed effects and month of entry fixed effects, the instrument is as good as randomly assigned (random assignment) , and (3) the instrument only impacts on the outcomes of interest through its impact on the time patient i waits to receive treatment (excludability). Further, under heterogeneous treatment effects, a Local Average Treatment Effects (LATE) interpretation requires (4) that the instrument satisfies monotonicity. In our application, this means that the time patient i waits for treatment is monotonically increasing in the local health-care congestion around the time that patient i enters treatment. If these assumptions are met, our empirical design identifies the causal impact of wait time for specialist treatment for CUD on the outcomes of interest for individuals who would have had a shorter wait if they experienced less congestion. This is the Local Average Treatment Effect (LATE). We assess random assignment, relevance and monotonicity of the instrument in section 5. We discuss the exclusion restriction in section 6.4, after presenting our results on the impacts of wait time on health-care utilization, employment and crime.

4 Data

4.1 Data sources

The starting point for building our data set is the Norwegian Patient Registry (NPR), which covers all patients in the specialist care system in Norway. All entities that offer treatment for substance use have been required to report to the NPR since 1 January 2009. The NPR data used in this study are for a cohort of individuals who were admitted into specialist care treatment between 1 January 2009 and 31 December 2010 with an ICD-10 cannabis related disorder as their a primary diagnosis. For this cohort of patients, the registry data provides information on the date of each assessment, the type of treatment the patient was assessed as eligible for (outpatient or inpatient), the date of each consultation within each treatment episode in specialist care, and dates that the patients entered and exited treatment in specialist care for all treatment episodes through to 31 December 2013.

The NPR patient sample has been linked by Statistics Norway (using unique individual identifiers) to the Norwegian Employment Registry, which contains the start and end date of each job held, the Norwegian Crime Registry, which records the date on which all criminal charges were laid, and the Norwegian Population Registry which contains demographic and socioeconomic information.[20]

4.2 Sample

The sample used to construct the instrumental variable consists of all episodes of specialised care that (1) were provided as outpatient treatment; (2) has an ICD-10 cannabis related disorder as the primary diagnosis; and (3) had a start date occurring between 1 January 2009 and 31 December 2010. We follow the convention of excluding waiting times in excess of two years as they are likely to reflect data entry errors (Askildsen *et al.*, 2011; Gødoy *et al.*, 2019). This sample is comprised of 2893 individuals and 5413 episodes of outpatient treatment.

The sample used to estimate our empirical model further restricts the above sample to patients who are at least 20 years old at the time they entered treatment and whose first observed episode of treatment is for outpatient treatment. We restrict the estimation sample to those aged at least 20 to ensures that sample members are old enough to have completed high school by the date they enter into treatment.[21] We exclude patients for whom the first observed of episode is for inpatient treatment because the duty of care for inpatient facilities extends beyond the conclusion of episodes of inpatient treatment, and this is likely to impact wait times for subsequent episodes of outpatient as well as inpatient treatment. These additional restrictions results in an estimation sample comprised of 2386 individuals who were admitted into specialist care for a total of 3630 episodes of outpatient treatment between 1 January 2009 and 31 December 2010.

[20] A person is charged if he or she is deemed an alleged offender at the time the crime investigation is completed by the police, i.e. is regarded a perpetrator by the police and the prosecuting authorities, irrespective of subsequent sanctions.

[21] The information on enrolment in education is limited to enrolment status on 1 January 2009-2013. The coarseness of the enrolment data is not well suited to our analysis and for this reason we are unable to study the impact of waiting for treatment on school enrolment.

We also have a random sample drawn from the general Norwegian population, matched on age (in 2010) and gender to the patient sample. This general population sample has also been linked to the NPR, the Employment Registry, the Crime Registry, and the Norwegian Population Registry. The general population sample allows us to characterise the patient sample relative to general population of Norway in terms of their mental ill health (including addiction), their labour market and criminal offending behaviours, and their demographic and socioeconomic profile. The matched sample from the general population is comprised of 6752 individuals.

4.3 Comparing CUD Patients and the general population

Table 1 reports descriptive statistics for the patient sample and the matched sample from the general population. The patient sample (and therefore the match sample from the general population) are overwhelmingly male (78%) and have an average age of 28.[22] Table 1 shows that above and beyond their substance use, the patient sample is characterised by significant mental ill health compared to the general population sample, with 45% of the CUD patients having a diagnosis of a mental health disorder (other than a SUD) over the period 2009-2013 compared to 7% in the general population sample. The patient group are six times more likely to enter treatment with a primary or secondary diagnosis of anxiety or depression compared to the general population sample. Diagnoses of personality and childhood disorders are 10 – 11 times more prevalent in the patient sample.

The lower panel of Table 1 shows that the patient group differ from the general population along dimensions beyond substance use and mental ill health. For example, patients are more likely to be single and less likely to be in a couple with children compared to the general population. While patients are less likely to be an immigrant from a non-OECD country, they are more likely to come from a low SES background, as measured by having parents with no more than the compulsory level of education. As shown in Table 1, only 51% of patients were employed, and just 14% were in school at any time in the 12 month period ending 24 months prior to assessment for treatment. By contrast, 72% of the general population sample were employed and 23% were in school over a comparable period.[23] The patient sample are also more criminally active, with 28% charged at least once in the 12 month period ending 24 months before their assessment date compared to just 5% of the general population over a comparable 12 month period. This suggests that the disadvantage of the patient group was established well before they enter treatment.

[22]This is the average age of those entering treatment for CUD in 2009 or 2010 conditional on being older than 19. The average age at entry into treatment for cannabis users in Europe is 26 years old (EMCDDA, 2015).

[23]The comparison period is the 12 month period ending 1 January 2008. This period is chosen for the comparison as its ending date is 24 months before 1 January 2010, the midpoint of the date of entry into treatment for the patient sample.

The early disadvantage of the patient group is confirmed in Figure 1, which shows the evolution of the patient and general population samples' work and criminal behaviour. The left panel of Figure 1 graphs the proportion of the patient group who are employed at any point in 6 month intervals starting 36 months before and extending to 36 after being assessed for specialized care for CUD. For the general population sample, we graph the proportion in work for the 6 year period centered on 1 January 2010. The important points to take away from this figure are that (1) patients are substantially less engaged in work than the general population but their participation rate appears to be follow the same upward trend as the general population until about a year before they are assessed; (2) patients participation in work starts to decline from a year before they are assessed and does not recover in the three years after their assessment; (3) participation in work in the general population sample has an upward trend over the entire 6 year period centered on 1 January 2010. The latter point is of particular interest given that the patients are entering treatment over the period 2009-2010, and there may be some concern that their employment outcomes could be adversely affected by macroeconomic shocks related to the Great Recession. Figure 1 suggests this is unlikely to be a concern, with an upward trend in participation in employment for the general population sample over the six year period spanning 1 January 2007 to 1 January 2013. This accords with previous research that finds that Norway was not much affected by the Great Recession (Berg & Eitrheim, 2013).

The right panel of Figure 1 graphs the proportion of the patients and general population samples who are charged with a crime one or more times in six monthly intervals spanning the six year period starting from three years before patients assessment date and out to three years after their assessment date. For the general population sample, the six year period is centred on January 1 2010. This figure shows that, in the patient sample, offending increases up to the date of assessment and declines there after. Three years after the assessment date, the proportion of patients offending in the previous six months is the same as in the six month period ending 30 months before the assessment date. The figure also shows that there is a very low (around 3%), but consistent level of offending in the general population sample in the six year period spanning 1 January 2007- 1 January 2013.

4.4 Patients sample: Descriptive statistics on key variables

The outcomes we study relate to health-care utilization, measured using indicators for completed treatment episode s months after entry into treatment, and by the number of specialist consultations recorded within the treatment episode s months after entry into treatment; employment, measured by indicators for any registered employment s months after entry into treatment, and by the number of days employed s months after entry into treatment; and crime, as measured by indicators for any charges s months after entry into treatment, and by the number of charges s months after entry into treatment.[24] In our empirical analysis, we study the impact of wait time on the outcomes of interest before entering treatment in addition to its impacts after entering treatment. This distinction is reflected in Table 2 which reports descriptive statistics on outcomes of interest while waiting to start treatment (measured from the date of assessment to the day before entering treatment) in the first panel, and three years after starting treatment (measured from the date of entry into treatment to 36 months after entering treatment) in the second panel of Table 2.

As shown in Table 2, 25% of the sample of patients were employed at the date they were assessed as entitled to necessary treatment and 22% were employed at the date that their treatment began. While waiting for treatment, 15% of the patient sample were charged with a crime, and amongst those charged, the average number of charges is 2.94.

The second panel of Table 2 reports on outcomes measured at 36 months after starting treatment. It shows that, on average, patients have 12.22 treatment consultations per episode of treatment, and that the average duration of treatment is 280 days, with 94% of patients completing an episode of treatment three years after treatment began. Conditioning on having completed treatment, the average duration of treatment is 207 days. Weak attachment to the labour market and criminal offending continues to characterise the patient sample after they start treatment, with 46% of the patient sample having any registered employment and 52% being charged with a crime in the three years after entering treatment. Conditional on any employment in this three year period, the average number of days employed is 403 (this includes weekends, as it is calculated using start an end dates for each job). Among those charged with a crime, the average number of times they were charged is 7.3.

As shown in the top panel of Table 2, the average number of days that patients in our sample wait to enter treatment is 99 (we re-scale wait time to days per 100 days). Figure 2 shows that there is significant variation in wait times across health trusts and across calendar time, with wait times lower for patients entering into treatment in 2010 compared with those entering in 2009. This reflects the efforts to reduce wait times for TSB under the 2008-2012 plan. As with waiting time, there is also substantial variation across health trusts and over time in both the duration of treatment and the number of specialist consultations within the index episode of treatment, as shown in Appendix Figure A.1 and Appendix Figure A.2. These figures also show that, along with the reduction in waiting times, there have been reductions in the duration of treatment and the number of specialist consultations within an episode for those entering into treatment in 2010

[24] The Employment Registry records start and end date for all jobs. The Crime Registry records months and year of all charges.

compared to those entering in 2009. In terms of our IV, local health-care market congestion, Table 2 shows that the sample average for the IV is 93 days. In the following section we conduct an extensive investigation of the instrument, providing evidence that it meets the necessary assumptions for our IV strategy to identify causal treatment effects.

5 Evaluating the Instrument

Our instrumental variable is intended to measure local health-care system congestion for outpatient treatment for CUD. It is similar to the approach used by Gødoy *et al.* (2019) who study the impact of wait time in the context of orthopaedic surgery.[25] In this section, we provide evidence that our instrument meets the identifying assumptions underlying our empirical approach. Evidence on conditional independence and relevance of the instrument is provided in Sections 5.1 and 5.2, respectively. Monotonicity is investigated in Section 5.3. We reserve discussion of the exclusion restriction until Section 6.4, following the presentation of our baseline results.

5.1 Conditional Independence

Columns 1 and 2 of Table 3 examine whether the instrumental variable meets the assumptions of conditional independence. Column 1 of Table 3 shows estimates from regressing the number of days (per 100 days) spent waiting to enter treatment on the full set of control variables, including health trust by year and month of entry into treatment fixed effects. It reveals that, conditional on health trust by year of entry fixed effects and month of entry fixed effects, the control variables are jointly correlated with the time patients wait to enter treatment (F-$stat$=16.25, $p - value = 0.00$), with demographic characteristics, past work or school enrolment history and past criminal charges individually significantly correlated with the time patients wait to enter treatment.

Column 2 of Table 3 examines whether our congestion variable is correlated with the same set of control variables, conditional on interacted health trust and year of entry fixed effects and month of entry fixed effects. We find some evidence that gender is correlated with local congestion, with females facing an additional 1.9 days per 100 (or 2%) more congestion than males. Nonetheless, as shown in the bottom of Table 3, conditional on health trust by year and month of entry fixed effects, the set of control variables are not jointly significant in explaining congestion, (F-$stat$=1.28, $p - value = 0.29$). Given that patients' observed characteristics are jointly uncorrelated with our instrument, it seems reasonable to infer that their unobserved characteristics are also uncorrelated with the instrument, as required for conditional independence. To the extent that a correlation

[25] The instrument used by Gødoy *et al.* (2019) is the (leave-out) average wait time of patients who receive treatment at same hospital as the index patient.

between gender and congestion is a concern, this is addressed in estimation by including gender in the full set of control variables.

5.2 Relevance

Columns 3 and 4 of Table 3 provide evidence on instrument relevance. Column 3 reports the first stage estimates for a specification that controls for health trust by year of entry fixed effects and month of entry fixed effects only (basic controls). In column 4, the first stage specification includes the full set of individual controls (all controls). As can be seen from Table 3, our instrument is a highly significant predictor of the time a patient waits to start treatment irrespective of whether only basic or all controls are included. We find that a one standard deviation increase in the instrument increases the wait time to enter treatment by 43 days (0.63 X 0.69=0.43). Table 3 also reports the *F-statistic* for testing the null hypothesis that the coefficient on the instrument in the first stage is zero. This test suggests that weak instruments is not a concern.

Overall, Table 3 provides confidence that our instrument satisfies the assumptions of relevance and conditional independence, and that it is not subject to concerns related to having a weak instrument.

5.3 Monotonicity

Monotonicity implies that a patient who waits a longer time to enter treatment when (or where) congestion is lower will also wait a longer time when (or where) congestion is higher. If monotonicity is satisfied, then our estimates uncover the impact of waiting time among the group of patients who would have waited fewer days for treatment had they faced less congestion. While we cannot directly test whether monotonicity holds in our sample, we follow previous studies and examine the implication that the instrument for wait time should be non-negative for any subsample. To examine this, we construct the instrumental variable using the full sample, but estimate the first stage on subsamples defined by gender, age, parents education, household type, treatment facility type, offending history, employment and schooling history and municipality size. As shown in Table 4, we find the instrument to have a positive coefficient in the first stage regressions for all subsamples. Further, the instrument is statistically significant for all subsamples, with the single exception being the subsample who were charged with a crime 2 years before their assessment. Overall, this evidence is consistent with monotonicity being satisfied in our sample of patients.

6 Results

6.1 The impact of waiting time on health care utilization

A general concern with the use of waiting time as a rationing system for accessing treatment is that patients' illness is likely to become more severe if treatment is delayed. If this occurs, the health of patients will be worse at entry into treatment compared to when they sought treatment and as a result (and in the absence of limits to treatment), we expect this will result in a lengthier time in treatment and a greater number of treatment consultations within an episode of treatment. In this section, we empirically examine whether this is the case.

The first panel of Figure 3 graphs the results from IV estimation of the impact of wait time on the cumulative probability of completing treatment evaluated at 3, 6, 9 through to 36 months after treatment begins. The graph displays the IV coefficient estimate on wait time along with the 90% confidence band. The graph shows that each additional day spent waiting to enter treatment reduces the probability of completing treatment (compared to a patient who did not wait) up to 24 months after entering treatment. The magnitude of the impact of wait time is greatest at 6 months after treatment begins. Evaluated at the sample average wait time of 99 days our estimate indicates a 29% (12 percentage point) decrease in the probability of completing treatment within 6 months relative to the sample average of 41.4 percent. Table 5 shows that the impact of waiting time falls to a 12% (9 percentage points) reduction in the probability of completing treatment 12 months after it begins, and a 6% (5 percentage point) reduction 24 months after entering treatment (evaluated at the sample average wait time of 99 days and compared to not having to wait to receive treatment). As shown in Figure 3, the adverse impact of waiting times on completing treatment do not extend beyond 24 months after treatment begins.

Table 5 also shows that the OLS estimates under-estimate the magnitude of the impact of waiting for treatment. This likely reflects the confounding effect of unobserved severity of illness at assessment, which is expected to be negatively correlated with waiting time. The final column of Table 5 provides estimates of the impact of wait time on the duration of treatment measured in days.[26] Although not significant at conventional levels (p-value of 0.126), the estimates suggest that the sample average wait of 99 days days spent waiting for treatment adds an additional 60 days to the length of treatment.

The second panel of Figure 3 graphs the IV estimate of the coefficient on wait time for the outcome cumulative number of consultations within the treatment episode, along with the 90% confidence band, evaluated at 3, 6, 9 through to 36 months after treatment begins. The graph

[26] These estimates ignore the censoring of duration of treatment for the 6% of patients who do not complete within three years of starting treatment, and therefore may be downward biased.

shows that each additional day spent waiting to enter treatment increases the number of specialist consultations in the episode of treatment for 36 months after entering treatment. Table 5 shows that, evaluated at the sample average wait time of 99 days our estimate indicates a 35% increase in the number of consultations (3 additional specialist consultations) 12 months after entering treatment relative to the sample average of 9 consultations. The impact of waiting time rises to a 45% increase in the number of consultations within the treatment episode 24 months after starting treatment, and a 39% increase 36 months after starting treatment (evaluated at the sample average wait time of 99 days and compared to not having to wait to receive treatment). Table 5 also shows that the OLS estimates under-estimate the magnitude of the impact of waiting for treatment. This is consistent with the confounding effects of a lower unobserved severity of illness at assessment amongst those who wait longer to start treatment.

The finding of increased use of treatment services at the extensive and intensive margin as a result of waiting to access treatment is consistent with deteriorating patient psychological health, and hence a greater severity of illness upon entry into treatment. In the context we study, this indicates that not only does the use of waiting time for CUD treatment increase the burden on the health-care system, it imposes significant costs on patients, whose health deteriorates while waiting for treatment.

6.2 Employment

Problematic substance use is associated with lower employment and this raises the question of whether waiting to access treatment for CUD has spill-over effects on employment. In order to answer this question, we use our IV framework to estimate the impact of waiting to access treatment on the probability of being employed and on the number of days employed.

Figure 4 displays the IV coefficient estimates of the impact of waiting to enter treatment on the probability of being employed (left hand side) and on the number of days employed (right hand side figure) at the time of entering treatment, and at cumulative 3 monthly increments from the date of entry into treatment through to 36 months after entering treatment. The graph for being employed shows that an additional day spent waiting to enter treatment reduces the probability that a patient has been employed at any point in time over the full follow-up period of 36 months after entering treatment. The impact is statistically significant from 12 months after entering treatment and remains so at 36 months after entering treatment. As shown in the top panel of Table 6 (which reports OLS, reduced form and IV coefficient estimates), the IV estimate indicates that the average wait time to enter treatment reduced the probability of employment by 30% at 12 months and at 24 months after entry into treatment, and by 25% 36 months after entering treatment (relative to not having to wait for treatment).

The right hand side panel of Figure 4 graphs the impact of waiting to start treatment on the intensive margin of employment, measured by the number of days employed since the date that treatment begins, measured at 3 monthly increments. The graph shows that the coefficient estimates on waiting time becomes larger in magnitude the longer is the elapsed time since entering treatment. As shown in the lower panel of Table 6, our IV estimates imply that the evaluated at the average wait time of 99 days, the reduction in the cumulative number of days worked is 20% 12 months after entering treatment, 30% 24 months after entering treatment and is 25% at 36 months after entering treatment (relative to not having to wait for treatment). We note, however, that the coefficient estimates of the impact of wait time on the cumulative number of days worked are quite noisey and are not statistically significant at conventional levels.

Table 6 also reports OLS estimates of the association between waiting time to enter treatment and the probability to being employed (top panel) and the number of days employed (bottom panel). Comparing the OLS and IV estimates, it is clear that even after controlling for a large number of characteristics of the patients, including whether they were employed or in school in the 12 month period ending two years before being assessed for the index treatment episode, OLS is still subject to significant confounding. In particular, OLS under-estimates the magnitude of the reduction in employment and the number of days employed due to waiting to enter treatment. This is expected given that the confounding likely reflects severity of illness at the time of referral, and previous research suggests that the more severe cases are less likely to be employed.

Overall, these results point to significant and persistent employment reductions (particularly at the extensive margins) from delaying patients receipt of treatment for CUD. This represents a further cost, in an addition to the costs of worsened mental health of the patients and the resulting longer durations and intensity of treatment, caused by waiting to access treatment.

6.3 Crime

Our patient sample is highly engaged in crime (relative to the sample from the general population), and their involvement in crime peaks around the time they are assessed for treatment. This may suggest that their criminal behaviour could be a precipitating factor in them seeking treatment. How then, does a delay in accessing treatment due to waiting times impact on their offending behaviour? In order to answer this question, we use our IV model to estimate the impact of waiting to access treatment on the probability of being charged with a crime and on the number of times patients are charged with a crime.

Figure 5 graphs the results from IV estimation of the impact of waiting to enter treatment on the probability of being charged with a crime (left hand side) and the cumulative number of charges (right hand side). The graph plots the coefficient on wait time at 0, 3, 6, through to 36 months after entering specialist treatment. Note that"0 months after entering treatment" refers to the outcome of being charged with a crime while waiting for treatment to begin (left hand side) and the number of times charged with a crime while waiting for treatment to begin (right hand side), respectively. The left hand side graph shows that waiting to access treatment (statistically significantly) increases the probability of being charged with a crime before entry into treatment but does not have a significant impact after entry into treatment. As shown in Table 7, the coefficient estimates imply that patients who wait the average wait time of 99 days to access treatment are 45% more likely to be charged with a crime before entering treatment than individuals who do not wait.

The right hand side graph in Figure 5 shows that although waiting for treatment may not impact on crime at the extensive margin after entering treatment, it does increase crime at the intensive margin. In particular, waiting time is shown to increase the number of charges up to 12 months after entering treatment (at the 10% level of significance). As shown in Table 7, 12 months after starting treatment, patients who experience the average wait time are expected to experience 41% more criminal charges, which equates to around 0.6 charges.

It is interesting to contrast these IV estimates with the OLS estimates of the relationship between waiting time and offending. Table 7 shows that the OLS estimates suggest that longer waiting times is associated with (statistically significantly) less crime (at both the extensive and intensive margins), even after controlling for involvement in crime in the 12 month period ending two years before the patients are assessed for the index diagnosis, and a large number of individual characteristics. In contrast to the OLS estimates, the IV estimates of the impact of wait time on crime are positive, suggesting that longer wait times are associated with more offending. This indicates that patients with a greater severity of illness at assessment, and who are therefore prioritised for shorter waiting times, are more criminally involved. These results highlight the importance of addressing the issue of confounding due to omitted severity of illness at assessment.

We also investigate the impact of waiting time on drug related charges and non-drug related charges separately. The IV coefficient estimates are graphed in Appendix Figure A.3 (any drug related charges, cumulative number of drug related charges) and Appendix Figure A.4 (any non-drug related charges, cumulative number of non-drug related charges). These results confirm that, for both drug related and non-drug related charges, waiting time to enter treatment increases crime at the intensive margin. Specifically, we find positive and statistically significant impacts on the cumulative number of charges out to 24 months after entering treatment for drug related charges, and out to 12 months for non-drug related charges. As shown in Table 8 and 9, patients who experience the average wait time experience 69% more drug charges (0.4 charges) and 35% more non-drug related charges (0.3 charges) 12 months after entering treatment. Twenty four months after entering treatment, patients who waited the average time to access treatment are charged with 44% (0.43 drug charges) more drug offences compared to a patient who did not wait to enter treatment.

In summary, these results point to significant impacts on criminal behaviour of delaying access to treatment for CUD patients. Specifically, we find delaying access to treatment increases the probability that a patient is involved in criminal activity while waiting to start treatment. We also find significant impacts of wait time on the intensive margin after entry into treatment that persist up to 24 months for drug related crimes and up to 12 months for non-drug related crimes. This greater involvement in crime represents a further cost caused by waiting to access treatment.

6.4 Examining the exclusion restriction

When using instrumental variable estimation to study the impact of wait time on employment or crime, there may be concern that the exclusion restriction is violated. This could occur if duration of treatment impacts on employment, for example, and assessment panels determine duration of treatment as well as patient prioritization. In principle, this is unlikely to be an issue because the role of the assessment panels is to determine whether patients are entitled to treatment and if they are prioritize them on the basis of their severity of illness. Assessment panels do not make treatment decisions. Nonetheless, we explore whether this is an issue in practice by constructing an instrumental variable for the duration of treatment in the same way as we constructed the instrument for waiting time.[27]

In exploring the first stage for the duration of treatment, we find that after controlling for health trust by year fixed effects, month of entry fixed effects, characteristics of the patient and the local health-care market congestion, the IV for duration of treatment (neighbouring health trusts' average duration of treatment) is not relevant (p-value=0.90).[28] This suggests that assessment panel prioritizations have no direct impact on the duration of treatment patients receive. This is consistent with assessment panels playing no role in treatment decisions and is compatible with the patient protected right to received treatment according to their needs. Overall, we conclude that we find no evidence that the exclusion restriction is violated by assessment panels determining

[27] That is, we construct the average of the duration of treatment for patients entering treatment at neighbouring health trusts around the same date as the index patient.

[28] Additionally, we find no evidence that the average duration of treatment received by patients entering neighbouring health trusts around the same time as the index patient directly impacts employment and crime outcomes.

durations of treatment.

6.5 Robustness

We explore the sensitivity of the results to using additional information to account for patients severity of illness; we investigate whether the results are driven by particular groups, such as those living in Oslo (the capital of Norway, and the city with the largest drug market), or those who experienced the longest wait times; and we examine functional form assumptions. We conduct this analysis on outcomes measured 24 months after patients enter treatment. The results are reported in Appendix Table A1 for outcomes related to treatment (duration of treatment and number of consultations within the treatment episode). The results related to employment, all crime and drug crimes are reported in Appendix Table A2, A3 ad A4, respectively. Column 1 of these tables repeats baseline IV estimates reported in Table 5 (specialist health-care utilization for the episode of treatment), Table 6 (employment), Table 7 (crime) and Table 8 (drug crime).

Columns 2 and 3 in Appendix Tables A.1, A.2, A.3 and A.4 report IV estimates from specifications that investigate the robustness of the findings to including additional (and potentially endogenous) variables related to patients' severity of illness. The specification reported in column 2 accounts for mental illnesses identified in the referral for the episode of treatment by including an indicator for any (non-SUD) ICD-10 codes related to any mental illness or disorders as a primary or secondary diagnosis in their referral. The specification in column 3 adds a set of indicators for specific mental health disorders (schizophrenia, anxiety disorders, mood disorders, childhood disorders, ADHD, mental disorders, personality disorders, developmental disorders, other mental health disorders) diagnosed at any time over the observation period (ending 31 December 2013). Each indicator is set equal to one if the patient has been diagnosed with the specific disorder (as a primary or secondary diagnosis) in any referral for the full observation period and is otherwise equal to zero. As can be seen from the tables, adding a control for mental illnesses diagnosed in the index referral (column 2) or a set of controls for types of mental illnesses diagnosed in any referrals (column 3) has very little impact on the magnitude of our IV coefficient estimates, and has no qualitative impact on the findings regarding the impact of wait times on the outcomes we study.

Column 4, 5 and 6 of Appendix Tables A.1 (health-care utilization), A.2 (employment), A.3 (any crime) and A.4 (drug crime) investigate whether our findings are being driven by specific groups. One may be concerned, for example, that substance use, and by extension, waiting for treatment for substance use is a larger issue in Oslo than elsewhere in Norway. Column 4 examines whether this is the case by reporting on results from estimation when residents of Oslo are excluded from the sample. They show that the coefficient estimates are unaffected by excluding patients who live in Oslo. In columns 5 and 6 we examine the extent to which our findings are being driven by patients who wait a very long time. To do so, we remove from our estimation sample patients whose wait time falls in the top 1% (column 5) and the top 5% (column 6). As can be seen from the estimates in the Appendix Tables A.1, A.2, A.3 and A.4, removing the largest 1% of wait times, or the largest 5% of wait times, has no qualitative impact on our findings.

Column 7 of Appendix Tables A.1, A.2, A.3 and A.4 investigates whether our results are sensitive to functional form assumptions. We do so by replacing waiting time and continuous outcomes that are measured in levels (number of treatments, number of days worked, number of times charged with a crime) with their inverse hyperbolic sine transformation. Note that we the use the inverse hyperbolic sine (IHS) transformation rather than the log transformation because the former is defined for observations for that take on a value of zero, and except for very small values, can be interpreted in the same way as logged variables. As can be seen from the tables, estimates using the IHS transformed variables are qualitatively similar to those based on the variables measured in levels.

6.6 Heterogeneity

Knowing for whom the impacts of waiting to access treatment are the greatest can be useful for policy-makers seeking to mitigate or reduce the associated costs. In this section, we examine whether the impact on waiting time differs for patients who are socially or economically vulnerable before they sought treatment. To do this, we conduct a heterogeneity analysis in which we split the sample of patients by whether they were in work or school, and by whether they had been charged with one or more crimes, in the 12 month period ending two years before their assessment. We evaluate these impacts over the 24 month period after entering treatment.

6.6.1 Heterogeneity in specialised care utilisation

Appendix Tables A.5 contains the results of the heterogeneity analysis for outcomes related to utilization of specialised outpatient treatment services for CUD. Column 1 and 2 report results for the subsample of patients who were neither in school nor work (column 1) and who were either in school or work (column 2) at any point in the 12 month period ending two years before they were assessed. Column 3 reports results for those who were not charged with a crime and column 4 reports results for those who were charged with a crime in the 12 month period ending two years before they were assessed. Panel A reports results for the outcome completing treatment within 24 months of entering treatment, and panel B reports results for the outcome number of treatment consultations during the first 24 months of treatment. As shown in the table, we find no evidence of differential impacts of waiting to access treatment on either completing treatment or the number of treatments between those who were engaged in school and work and those who were not, nor between those who were charged with a crime and those who were not, 2 years before being assessed for treatment for CUD.

6.6.2 Heterogeneity in work and crime

Table A.6 contains the results of the heterogeneity analysis for outcomes related to employment (in panels A and B), any criminal charges (panel C and D) and drug related charges (panel E and F). As with Table A.5, Column 1 and column 2 report results for the subsample of patients who were neither in school nor work, and who were either in school or work, in the 12 month period ending two years before they were assessed, respectively. And columns 3 and 4 report results for those who were not charged with a crime and those who were charged with a crime in the 12 month period ending two years before they were assessed, respectively.

Starting with panel A, we find statistically different impacts of wait time on the employment outcomes for those with and without previous engagement in school or work, and for those with and without criminal charges. Specifically, the estimates in panel A show that waiting to access treatment reduces the probability of being employed at any time in the 24 months after entering treatment for patients who were previously engaged in work or school (column 2), but waiting time has no impact for those who were not previously engaged in school or work (column 1). Similarly, the estimates in columns 3 and 4 of panel A show that waiting to access treatment reduces the probability of being employed at any time in the 24 months after entering treatment for patients without criminal charges (column 3), but waiting time has no impact on employment for those with criminal charges in the two years before being assessed for treatment (column 4).

The results in panel B, for the outcome number of days worked are quite noisey, making it difficult to infer where the differences across groups found for employment at the extensive margin also occur at the intensive margin. Similarly, the results for criminal behaviour reported in panels C (any charges within two years of starting treatment, D (number of charges within two years of starting treatment), E (any drug charges within two years of starting treatment) and F (number of drug charges within two years of starting treatment) are quite noisey. This is especially the case for the subsample of patients who were charged two years before assessment, for which the sample size is quite small. We do find (weak) evidence that waiting to access treatment may increase the number of drug charges for those with a previous attachment to school or work, but not those without this attachment. However, the 95% confidence intervals on these point estimates are overlapping, suggesting a lack of precision in the estimates (especially in the smaller sample of those without a previous attachment to school or work) rather than differential effects is driving this finding.

7 Discussion

This paper studies the impact of waiting time to access outpatient treatment for a substance use disorder (SUD). The specific context we study is treatment for cannabis use disorder (CUD), a health issue for which treatment is increasingly being sought, and for which treatment most often occurs in an outpatient setting. Globally, CUD is second only to opioid use disorder in prevalence amongst illicit substance use disorders and given the policy shifts that have occurred and that are underway in many OECD countries, the demand for treatment for CUD is likely to continue to grow. The substantial and growing demand for its treatment, combined with the marginalisation and disadvantage characterising this patient group, makes CUD an important and salient case study for assessing the impacts of waiting time for treatment.

We measure the impacts of waiting for treatment for CUD across the domains of health-care utilization, employment and crime. To do so, our analyses draws on rich linked administrative data on individuals from Norway, that allows the study of the impacts of waiting time out to a time horizon of three years after entering into treatment. A challenge for establishing the causal impact of waiting times is that severity of illness is used to prioritize patients in Norway, and because severity of illness is unobserved, it is a potential source of confounding in our analysis. We address this issue using an instrumental variables strategy that exploits variation in waiting time generated by congestion in Norway's health-care system.

Our analysis reveals significant and long lasting impacts from waiting time to access treatment for CUD. In terms of health care-utilization, delaying access to treatment by the sample average wait time reduces the likelihood of completing an episode of treatment by 6% and increases the number of specialist consultations by 45%, two years after entering treatment. This indicates a worsening of patient's health upon entry into treatment relative to when they were assessed. We also find adverse impacts of delaying access to CUD treatment on employment. We estimate that delaying access to CUD treatment by the average waiting time reduces the probability of any employment by 30% two years of entering treatment, and by 25% three years after entering treatment. Furthermore, the employment impacts of waiting for treatment are driven by patients with prior attachment to school or work and without prior criminal charges (measured over a 12 month period that ends two years before patients are assessed for treatment). Finally, we find that waiting time to access treatment increases the risk of being charged with a crime before entry into treatment by 45%, and increases the number of non-drug related charges and drug related charges a year after starting treatment by 35% and 69% respectively, and increases the number of drug related charges two years after entering treatment by 44% (evaluated at the average wait time).

Our finding offer several policy insights. First and foremost, our findings speak to decisions regarding the allocation of resources within and to the health sector. They show that using wait time as a means of rationing access to outpatient treatment for CUD imposes significant costs to patients, the health-care sector, and society more broadly through worsened health that requires increased utilization of health services, reduced employment and increased criminal behaviour. Our findings also offer insights that may be useful at the operational level. Specifically, they raise the question of whether the prioritization of SUD patients should take into account factors beyond health, such as disadvantage. And they suggest an opportunity to integrate programs that seek to reduce criminal behaviour and promote training and employment within SUD treatment programs.

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Table 1: Comparing the patient sample with the Norwegian population: 2009-2013

variable	pateints	controls	patient/control
female	0.22	0.23	0.96
age	28.30	28.58	0.99
Any Treatment	1.00	0.09	10.82
Primary: alcohol or drugs	1.00	0.02	65.55
Secondary: alcohol or drugs	0.54	0.02	35.40
Any Mental health disorders	0.45	0.07	6.03
Any schizophrenia	0.05	0.01	9.93
Any anxiety	0.20	0.04	5.70
Any mood	0.20	0.03	5.80
Any childhood	0.10	0.01	10.72
Any personality	0.10	0.01	10.08
Any developmental	0.01	0.00	2.70
single	0.51	0.27	1.87
couple with children < 18	0.13	0.32	0.40
single with children < 18	0.06	0.04	1.36
couple or single with adult children	0.22	0.26	0.86
couple with no children	0.07	0.10	0.68
non-european immigrant	0.07	0.08	0.88
father: compulsary educ only	0.33	0.22	1.50
mother: compulsary educ only	0.42	0.27	1.56
mental health condition at index	0.11	–	
employed 24-36 mths before assess [b]	0.51	0.72	0.71
in school 24-36 mths before assess [b]	0.14	0.23	0.62
in school or emply 24-36 mths before assess [b]	0.57	0.79	0.72
charged 24-26 mths before assess [b]	0.28	0.05	5.61
TSB facility	0.56	0.01	56.00
Psychiatric facility	0.44	0.09	4.89

N=2386 for patients and N=6752 for controls from the Norwegian population. Socioeconomic and demographic characteristics are measured in January 2010. a.Facility type refers to index episode for patients and any treatment for controls. b.Evaluated at 1 January 2010 (rather than assessment date) for controls.

Table 2: Descriptive Statistics

	mean	standard deviation
Wait time until start treatment (100 days)	0.99	1.46
IV: Average wait (100 days)	0.93	0.63
while waiting to start treatment		
	mean	**standard deviation**
Employed at assessment	0.25	0.43
Employed at start of treatment	0.22	0.42
Charged with crime	0.15	0.18
Number of times charged	0.43	1.86
Number of times charged | charged	2.94	4.00
3 years after starting treatment		
	mean	**standard deviation**
Number of Consultations	12.22	19.12
Duration of treatment (days)	279.99	379.27
Completed treatment	0.94	0.24
Duration of treatment | completed treatment	207.37	255.11
Days employed	185.23	288.71
Ever employed	0.46	0.50
Days employed | ever employed	403.35	305.82
Number of times charged with a crime	3.79	8.15
Ever charged with a crime	0.52	0.50
Number of times charged with a crime | ever charged	7.3	10.11

Sample consists of 3630 observations on 2386 unique individuals.

Table 3: Investigating Instrument Validity and Relevance

	Conditional Independence		First stage	
	Depedent variable		Controls	
	wait	average wait	Basic	All
gender is female	0.152**	0.019**		0.139**
	(0.060)	(0.009)		(0.060)
age	0.044*	-0.002		0.046*
	(0.024)	(0.004)		(0.024)
age2	-0.001	0.000		-0.001
	(0.000)	(0.000)		(0.000)
father: compulsary educ only	-0.042	-0.009		-0.036
	(0.041)	(0.010)		(0.040)
mother: compulsary educ only	0.038	-0.007		0.043
	(0.038)	(0.007)		(0.040)
noneurop imm	-0.025	-0.009		-0.019
	(0.058)	(0.015)		(0.058)
couple with kids ¡18	-0.069	-0.010		-0.062
	(0.061)	(0.013)		(0.060)
single with kids¡18	0.029	-0.013		0.038
	(0.117)	(0.013)		(0.120)
couple or single with adult kids	0.024	-0.008		0.029
	(0.047)	(0.016)		(0.042)
couple with no kids	-0.072	-0.003		-0.069
	(0.083)	(0.021)		(0.083)
psychiatric hopsital	0.022	0.003		0.020
	(0.128)	(0.013)		(0.125)
charged 24-36 mths before assess	-0.219***	0.008		-0.224***
	(0.034)	(0.012)		(0.037)
in school or work 24-36 mths before assess	-0.153***	0.002		-0.154***
	(0.048)	(0.008)		(0.047)
IV: avwait			0.689***	0.690***
			(0.161)	(0.167)
Includes health trust by year FE	Y	Y	Y	Y
Include month FE	Y	Y	Y	Y
F-stat for joint test (p-value)	16.25 (0.00)	1.28 (0.29)		
First stage F-stat (p-value)			18.28 (0.00)	17.15 (0.00)

3630 Observation on 2386 unique individuals. Standard errors clustered on individual and hospital trust in parentheses. The F-statistic is the test statistic for the null that the coefficients on the control variables (other than Health Trust by year fixed effects, and month of entering treatment fixed effects) are jointly zero in columns 1 and 2; in columns 3 and 4 the F-statistic is for the null hypothesis that the IV is not statistically significant. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Examining Monotonicity

Gender	Female	Male
average wait	0.840**	0.630***
	(0.387)	(0.145)
Observations	841	2,784
Age	**Age<27**	**Age>26**
average wait	0.554***	0.806***
	(0.169)	(0.198)
Observations	1,922	1,707
Both Parents education more than Compulsary	**Yes**	**No**
average wait	1.208***	0.625***
	(0.239)	(0.159)
Observations	677	2,949
Household Type	**Single person**	**Not single person**
average wait	0.737***	0.668734***
	(0.151)	(0.233936)
Observations	1,863	1,765
Facility type	**TSB**	**Psychiatric**
average wait	0.783***	0.509***
	(0.265)	(0.133)
Observations	1,882	1,747
Crime 24-36 months before assess	**Yes**	**No**
average wait	0.256	0.871***
	(0.207)	(0.184)
Observations	1,074	2,553
School of Employed 24-36 months before assess	**Yes**	**No**
average wait	0.575***	0.854***
	(0.160)	(0.217)
Observations	2,038	1,589

Standard errors clustered on individual and hospital trust in brackets. The table reports the first–stage estimate of the coefficient on the instrumental variable, where the IV is constructed using the full sample and estimation of the first stage is over the subsample defined by the column headings. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: The impact of wait time on completing treatment episode and number of treatments

	Dependent Variable			
	Completed treatment			Treatment length
	0-12 months	0-24 months	0-36 months	number of days
OLS: wait time				
no controls	-0.040***	-0.019***	-0.010***	35.181***
	(0.008)	(0.005)	(0.004)	(8.024)
all controls	-0.038***	-0.017***	-0.009**	33.013***
	(0.009)	(0.006)	(0.004)	(8.830)
RF: avwait				
all controls	-0.061**	-0.038*	0.015	42.138*
	(0.023)	(0.018)	(0.017)	(22.960)
IV: wait time				
all controls	-0.089**	-0.055*	0.022	61.0311
	(0.043)	(0.033)	(0.023)	(39.8838)
impact (%)	-11.94	-6.17	2.32	21.58
dependent var mean	0.738	0.882	0.938	279.99

	Dependent Variable			
	Number of Treatments			Number of Treatments
	0-12 months	0-24 months	0-36 months	by end of episode
OLS: wait time				
no controls	0.725***	1.202***	1.468***	1.255***
	(0.164)	(0.259)	(0.338)	(0.432)
all controls	0.690***	1.130***	1.375***	1.150**
	(0.186)	(0.288)	(0.374)	(0.483)
RF: avwait				
all controls	2.184***	3.476***	3.357***	2.201
	(0.532)	(0.878)	(1.133)	(1.604)
IV: wait time				
all controls	3.16***	5.04***	4.86**	3.19
	(0.99)	(1.64)	(1.99)	(2.41)
impact (%)	35.40	44.67	39.37	21.08
dependent var mean	8.84	11.17	12.22	14.98

Standard errors clustered on individual and hospital trust in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Top panel: Dependent variable is an indicator equal to 1 if patient has not completed treatment x months after entering treatment. Bottom panel: Dependent variable is the number of treatment consultations within the episode of treatment x months after entering treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins.

Table 6: The impact of wait time to access treatment on employment and days employed

	Dependent Variable			
	Any Employment			
	At entry to treatment	0-12 months	0-24 months	0-36 months
OLS: wait time				
no controls	-0.005	-0.005	-0.013*	-0.014**
	(0.006)	(0.007)	(0.007)	(0.007)
all controls	-0.004	-0.003	-0.009	-0.009
	(0.006)	(0.006)	(0.007)	(0.008)
RF: avwait				
all controls	-0.033	-0.066**	-0.083**	-0.079**
	(0.028)	(0.031)	(0.030)	(0.033)
IV: wait time				
all controls	-0.048	-0.097**	-0.122***	-0.116**
	(0.038)	(0.048)	(0.043)	(0.049)
impact (%)	-21.31	-29.82	-30.19	-25.02
dependent var mean	0.223	0.322	0.4	0.459

	Dependent Variable			
	Number days employed			
	At entry to treatment	0-12 months	0-24 months	0-36 months
OLS: wait time				
no controls	-0.005	-1.289	-1.724	-2.703
	(0.006)	(1.408)	(2.514)	(3.514)
all controls	-0.004	-0.927	-0.585	-0.933
	(0.006)	(1.414)	(2.616)	(3.716)
RF: avwait				
all controls	-0.033	-7.532	-15.930	-31.241
	(0.028)	(7.120)	(15.649)	(22.172)
IV: wait time				
all controls	-0.048	-10.993	-23.250	-45.598
	(0.038)	(10.628)	(23.064)	(32.118)
impact (%)	-21.31	-19.90	-20.09	-24.37
dependent var mean	0.223	54.693	114.548	185.231

Standard errors clustered on individual and hospital trust in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Top panel: Dependent variable is an indicator for the respondent ever being employed x months after starting treatment. Bottom panel: Dependent variable is the cumulative total number of days worked x months after starting treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins.

Table 7: The impact of wait time to access treatment on charges and number of times charged

	Dependent Variable			
	Any Charges			
	Before treatment	0-12 months	0-24 months	0-36 months
OLS: wait time				
no controls	0.046***	-0.026***	-0.024***	-0.026***
	(0.005)	(0.008)	(0.007)	(0.007)
all controls	0.052***	-0.016**	-0.013**	-0.015**
	(0.005)	(0.007)	(0.006)	(0.006)
RF: avwait				
all controls	0.047*	0.027	0.028	0.014
	(0.024)	(0.041)	(0.037)	(0.034)
IV: wait time				
all controls	0.069**	0.039	0.041	0.020
	(0.029)	(0.057)	(0.048)	(0.047)
impact (%)	45.54	11.36	9.02	3.81
dependent var mean	0.15	0.34	0.45	0.52

	Dependent Variable			
	Number of times charged			
	Before treatment	0-12 months	0-24 months	0-36 months
OLS: wait time				
no controls	0.242***	-0.193**	-0.329***	-0.501***
	(0.030)	(0.072)	(0.103)	(0.133)
all controls	0.261***	-0.138**	-0.226**	-0.358***
	(0.030)	(0.060)	(0.083)	(0.101)
RF: avwait				
all controls	0.043	0.436	0.480	0.536
	(0.096)	(0.262)	(0.453)	(0.560)
IV: wait time				
all controls	0.063	0.631*	0.695	0.777
	(0.126)	(0.342)	(0.625)	(0.795)
impact (%)	14.50	41.10	24.66	20.30
dependent var mean	0.43	1.52	2.79	3.79

Standard errors clustered on individual and hospital trust in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Top panel: Dependent variable is an indicator for the respondent ever being charged with a crime x months after starting treatment. Bottom panel: dependent variable the number of times charged with a crime x months after starting treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins.

Table 8: The impact of wait time to access treatment on drug charges and number of drug charges

	Dependent Variable			
	Any Drug Charges			
	Before treatment	0-12 months	0-24 months	0-36 months
OLS: wait time				
no controls	0.100***	-0.021**	-0.017*	-0.023***
	(0.014)	(0.008)	(0.008)	(0.007)
all controls	0.105***	-0.014**	-0.008	-0.013**
	(0.014)	(0.006)	(0.007)	(0.006)
RF: avwait				
all controls	0.027	0.019	0.011	-0.012
	(0.042)	(0.036)	(0.034)	(0.038)
IV: wait time				
all controls	0.039	0.028	0.015	-0.017
	(0.055)	(0.049)	(0.046)	(0.055)
impact (%)	44.35	12.87	4.60	-4.30
dependent var mean	0.09	0.22	0.32	0.39
	Dependent Variable			
	Number of Drug charges			
	Before treatment	0-12 months	0-24 months	0-36 months
OLS: wait time				
no controls	0.100***	-0.060*	-0.093**	-0.151***
	(0.014)	(0.029)	(0.040)	(0.053)
all controls	0.105***	-0.042	-0.057*	-0.099**
	(0.014)	(0.026)	(0.032)	(0.040)
RF: avwait				
all controls	0.027	0.272**	0.332*	0.304
	(0.042)	(0.127)	(0.180)	(0.242)
IV: wait time				
all controls	0.039	0.394**	0.480*	0.440
	(0.055)	(0.176)	(0.264)	(0.349)
impact (%)	21.46	69.51	44.03	28.53
dependent var mean	0.18	0.56	1.08	1.53

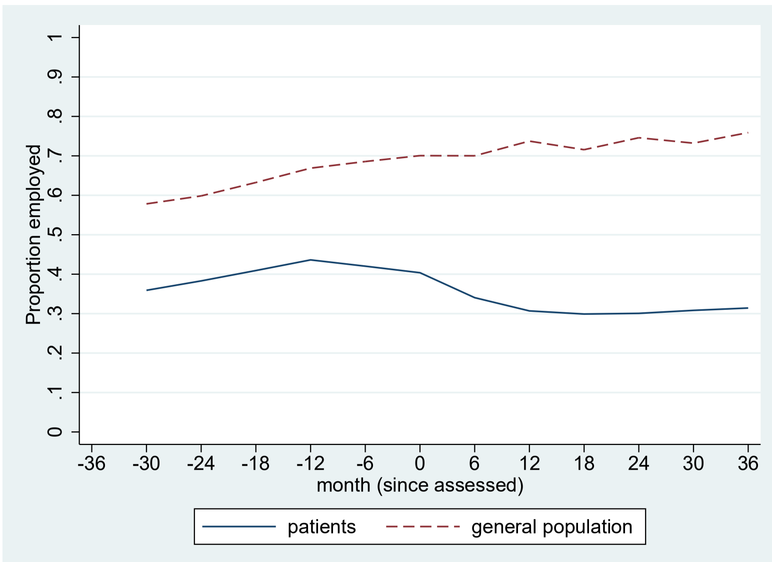
Standard errors clustered on individual and hospital trust in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Top panel: Dependent variable is an indicator for the respondent ever being charged with a crime x months after starting treatment. Bottom panel: dependent variable the number of times charged with a crime x months after starting treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins.

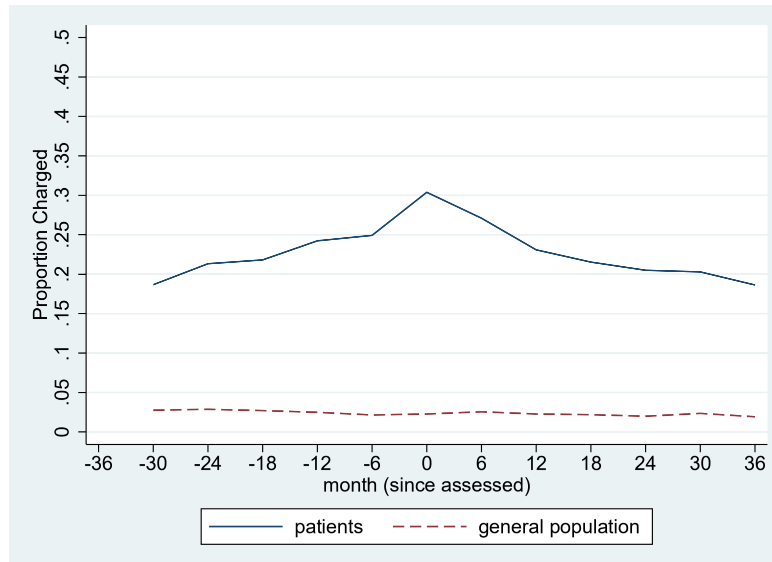
Table 9: The impact of wait time to access treatment on non-drug charges and number of non-drug charges

	Dependent Variable			
	Any Non-Drug Charges			
	Before treatment	0-12 months	0-24 months	0-36 months
OLS: wait time				
no controls	0.142***	-0.020***	-0.027***	-0.028***
	(0.029)	(0.007)	(0.006)	(0.007)
all controls	0.156***	-0.012*	-0.016***	-0.018***
	(0.029)	(0.006)	(0.005)	(0.006)
RF: avwait				
all controls	0.017	0.016	0.017	0.032
	(0.070)	(0.036)	(0.032)	(0.031)
IV: wait time				
all controls	0.024	0.023	0.024	0.046
	(0.095)	(0.052)	(0.045)	(0.044)
impact (%)	22.94	10.02	7.33	11.71
dependent var mean	0.10	0.23	0.32	0.39
	Dependent Variable			
	Number of Non-Drug charges			
	Before treatment	0-12 months	0-24 months	0-36 months
OLS: wait time				
no controls	0.151***	-0.086**	-0.170***	-0.269***
	(0.030)	(0.038)	(0.056)	(0.074)
all controls	0.156***	-0.074**	-0.147***	-0.237***
	(0.029)	(0.033)	(0.052)	(0.066)
RF: avwait				
all controls	0.017	0.203	0.187	0.271
	(0.070)	(0.130)	(0.268)	(0.332)
IV: wait time				
all controls	0.024	0.293*	0.271	0.393
	(0.095)	(0.173)	(0.372)	(0.474)
impact (%)	9.30	35.24	17.04	18.28
dependent var mean	0.26	0.82	1.57	2.13

Standard errors clustered on individual and hospital trust in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Top panel: Dependent variable is an indicator for the respondent ever being charged with a crime x months after starting treatment. Bottom panel: dependent variable the number of times charged with a crime x months after starting treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins.

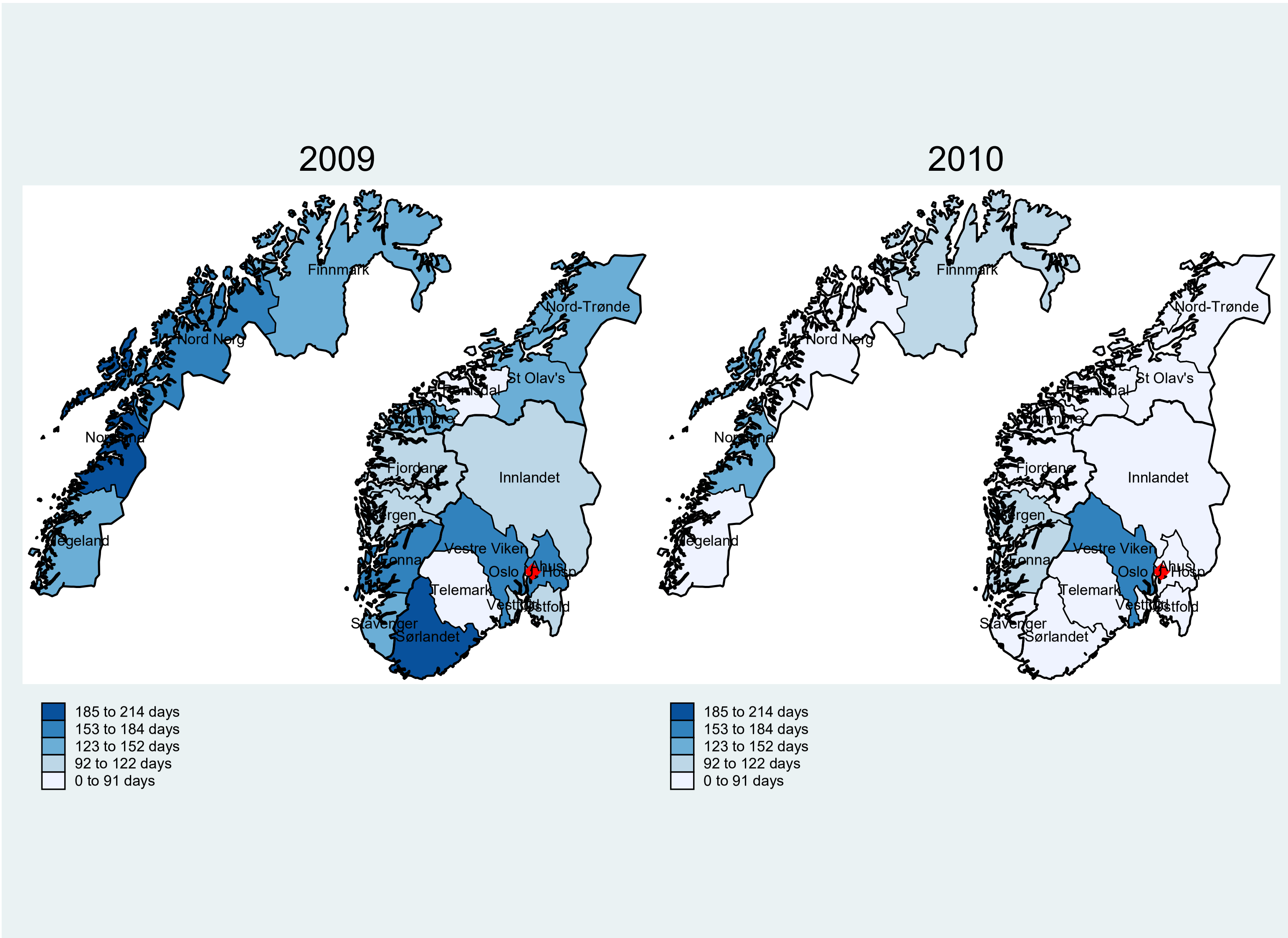
Figure 1: Evolution of participation in work and crime: Before and after assessment





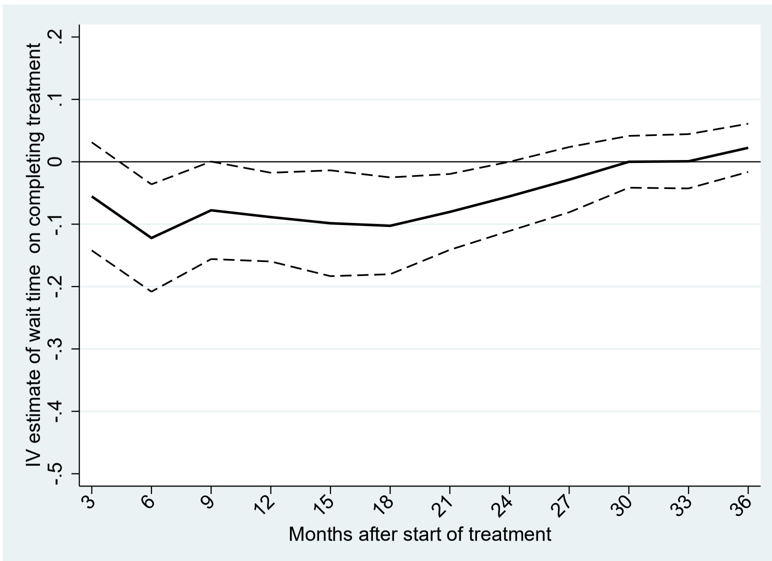
Patient sample consists of 2386 outpatients who were over the age of 19 at the time of entering treatment. The general population sample consists of 7302 individuals from Norway's general population matched on gender and age to the patient sample. Month is normalized on the month of entry into treatment for the patient sample and on January 2010 (the midpoint of period over which patients enter into treatment) for the general population sample.

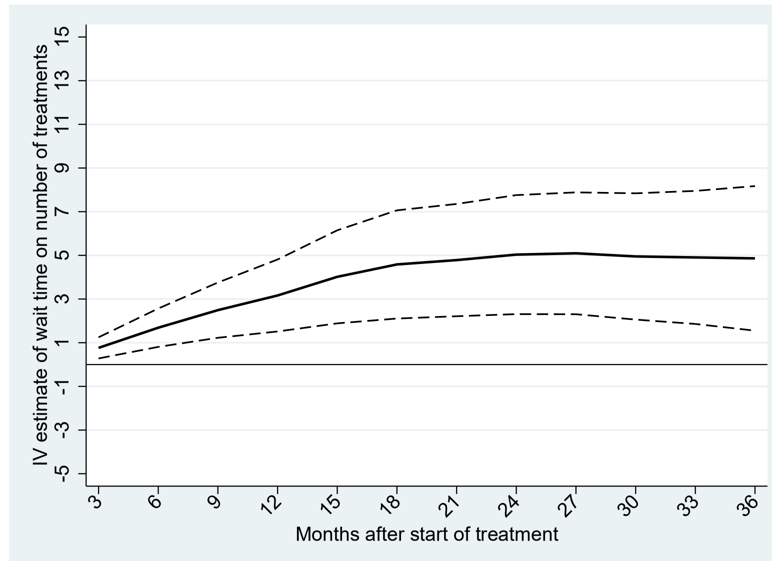
Figure 2: Variation in Wait Time



Sample consists of 3630 outpatients who were over the age of 19 at the time of entering treatment. Left panel: Average wait time (measured in 100s of days) to enter treatment in each health trust in 2009. Right panel: Average wait time to enter treatment in each health trust in 2010.

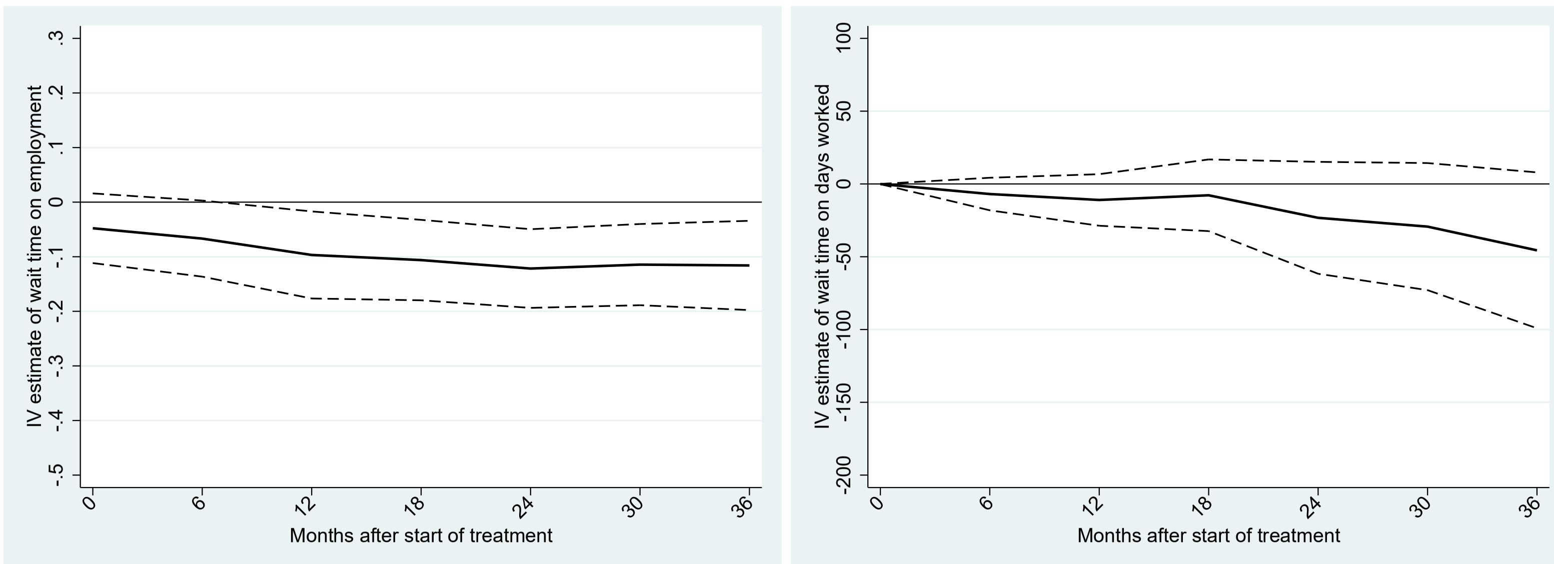
Figure 3: IV estimates of the impact of waiting time: Completion of treatment and number of consultations





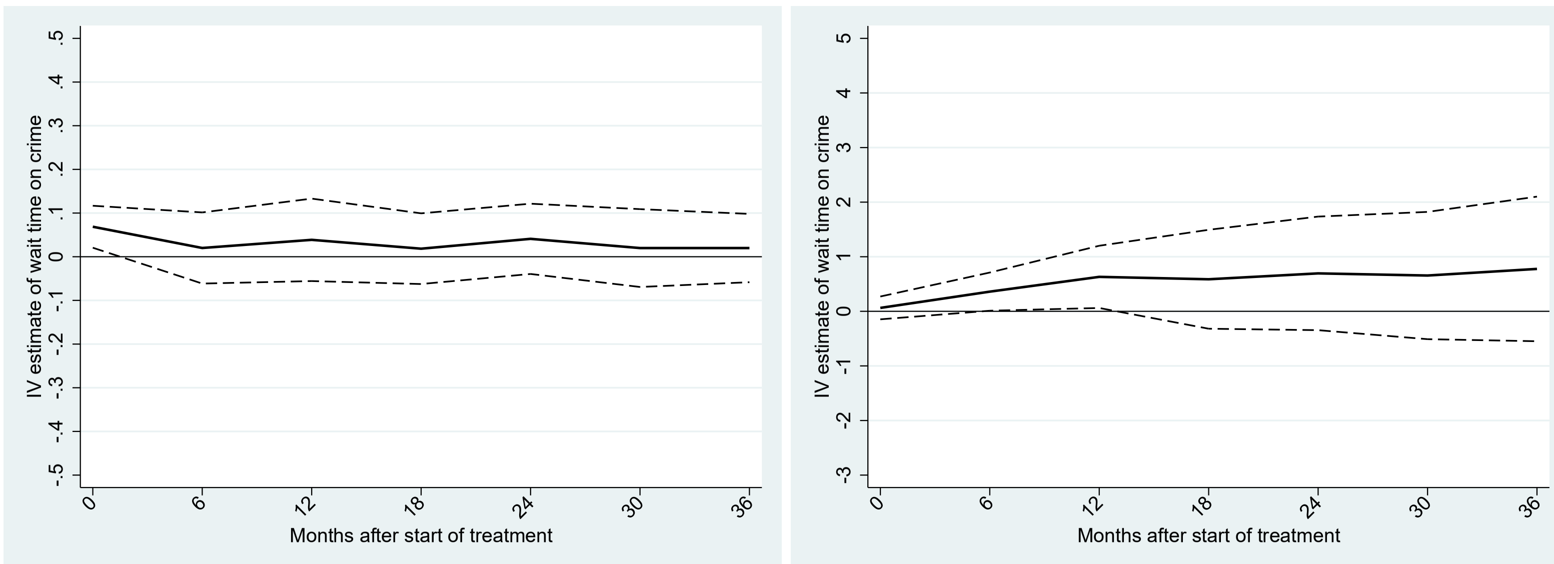
Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Panel a: Dependent variable is an indicator equal to 1 if completed treatment x months after entering treatment. Panel b: Dependent variable is the cumulative number of treatment sessions x months after entering treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins. Solid lines show IV coefficient estimates. Dashed lines show 90% confidence interval based on robust standard errors.

Figure 4: IV estimates of the impact of waiting time on employment and days employed



Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Left panel: dependent variable is an indicator for the respondent ever being employed x months after starting treatment, except at 0, where the outcome is an indicator for being employed at the date of entering treatment. Right panel: dependent variable is the cumulative total number of days worked x months after starting treatment except at 0, where the outcome is an indicator for being employed at the date of entering treatment. Waiting time is measured as the number of days from assessment date until treatment begins. Solid lines show IV coefficient estimates. Dashed lines show 90% confidence interval based on clustered (on individual and health trust) standard errors.

Figure 5: IV estimates of the impact of waiting time on being charged with a crime and the number of charges



Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Left panel: dependent variable is an indicator for the respondent ever being charged with a crime x months after starting treatment, except at 0, where the outcome is an indicator for being charged with a crime while waiting to enter treatment. Right panel: dependent variable the number of times charged with a crime x months after starting treatment except at 0, where the outcome is an indicator for number of charges while waiting to enter treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins. Solid lines show IV coefficient estimates. Dashed lines show 90% confidence interval based on clustered (on individual and hospital trust) standard errors.

Appendix

Table A.1: Robustness: Index Specialist Care Episode

	Baseline	Mental Health	All MH	No Oslo	Drop top 1%	Drop top5%	ihs wait
	Dependent variable: In treatment after 24 months						
wait	0.056*	0.057*	0.054	0.076*	0.067*	0.097*	
	(0.033)	(0.034)	(0.033)	(0.040)	(0.039)	(0.057)	
ihs wait							0.099
							(0.063)
Observations	3,630	3,630	3,630	3,122	3,592	3,447	3,630
	Dependent variable: number of treatments						
wait	5.035***	5.029***	4.829***	6.369***	5.914***	10.320***	
	(1.636)	(1.625)	(1.679)	(2.196)	(2.189)	(3.662)	
ihs_wait							0.834***
ihs wait							(0.262)
Observations	3,630	3,630	3,630	3,122	3,592	3,447	3,630

Clustered (on individual and health trust) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column 2 adds an indicator for a primary or secondary ICD10 (non-substance use) mental illness diagnosis at the index episode; Column 3 adds a set of indicators for a primary or secondary ICD10 diagnosis of schizophrenia, anxiety disorders, mood disorders, childhood disorders, ADHD, mental disorders, personality disorders, developmental disorders, other mental health conditions at the index or subsequent treatment episodes; Column 3 excludes observations on patients who live in Oslo; column 4 removes observations on the highest 1% of wait times; column 5 removes observations on the highest 1% of wait times; column 6 replaces wait time with the inverse hyperbolic sine of wait times.

Table A.2: Robustness: Employment

	Baseline	Index MH	All MH	No Oslo	Drop top1%	Drop top5%	HIS wait
	Dependent variable: ever worked 24 months post						
wait	-0.120***	-0.118***	-0.132***	-0.108***	-0.137***	-0.220**	
	(0.040)	(0.040)	(0.036)	(0.041)	(0.053)	(0.099)	
his wait							-0.205***
							(0.078)
Observations	3,630	3,630	3,630	3,122	3,592	3,447	3,630
	Dependent variable: days worked 24 months post						
wait	-22.612	-21.846	-26.272	-21.380	-24.096	-33.726	
	(21.856)	(21.445)	(20.835)	(21.773)	(26.774)	(44.199)	
his wait							-1.154**
							(0.525)
Observations	3,630	3,630	3,630	3,122	3,592	3,447	3,630

Clustered (on individual and health trust) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column 2 adds an indicator for a primary or secondary ICD10 (non-substance use) mental illness diagnosis at the index episode; Column 3 adds a set of indicators for a primary or secondary ICD10 diagnosis of schizophrenia, anxiety disorders, mood disorders, childhood disorders, ADHD, mental disorders, personality disorders, developmental disorders, other mental health conditions at the index or subsequent treatment episodes; Column 3 excludes observations on patients who live in Oslo; column 4 removes observations on the highest 1% of wait times; column 5 removes observations on the highest 1% of wait times; column 6 replaces wait time with the inverse hyperbolic sine of wait times.

Table A.3: Robustness: Crime

	Baseline	Index MH	All MH	No Oslo	Drop top1%	Drop top5%	ihs wait
	Dependent variable: ever charged 24 months post						
wait	0.041	0.040	0.048	0.067	0.039	0.077	
	(0.048)	(0.049)	(0.047)	(0.048)	(0.055)	(0.094)	
ihs wait							0.066
							(0.097)
Observations	3,630	3,630	3,630	3,122	3,592	3,447	3,630
	Dependent variable: number of times charged 24 months post						
wait	0.695	0.682	0.754	0.834	0.741	1.148	
	(0.625)	(0.623)	(0.587)	(0.707)	(0.731)	(1.193)	
ihs wait							0.159
							(0.276)
Observations	3,630	3,630	3,630	3,122	3,592	3,447	3,630

Clustered (on individual and health trust) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column 2 adds an indicator for a primary or secondary ICD10 (non-substance use) mental illness diagnosis at the index episode; Column 3 adds a set of indicators for a primary or secondary ICD10 diagnosis of schizophrenia, anxiety disorders, mood disorders, childhood disorders, ADHD, mental disorders, personality disorders, developmental disorders, other mental health conditions at the index or subsequent treatment episodes; Column 3 excludes observations on patients who live in Oslo; column 4 removes observations on the highest 1% of wait times; column 5 removes observations on the highest 1% of wait times; column 6 replaces wait time with the inverse hyperbolic sine of wait times.

Table A.4: Robustness: Drug Crime

	Baseline	Index MH	All MH	No Oslo	Drop top1%	Drop top5%	ihs wait
	Dependent variable: any drug charge 24 months post						
wait	0.015	0.014	0.024	0.023	0.016	0.027	
	(0.046)	(0.047)	(0.043)	(0.052)	(0.054)	(0.096)	
ihs wait							0.025
							(0.091)
Observations	3,630	3,630	3,630	3,122	3,592	3,447	3,630
	Dependent variable: number of times charged 24 months post						
wait	0.480*	0.470*	0.521**	0.498	0.546*	0.921*	
	(0.264)	(0.262)	(0.233)	(0.305)	(0.330)	(0.555)	
ihs wait							0.332***
							(0.050)
Observations	3,630	3,630	3,630	3,122	3,592	3,447	3,630

Clustered (on individual and health trust) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Column 2 adds an indicator for a primary or secondary ICD10 (non-substance use) mental illness diagnosis at the index episode; Column 3 adds a set of indicators for a primary or secondary ICD10 diagnosis of schizophrenia, anxiety disorders, mood disorders, childhood disorders, ADHD, mental disorders, personality disorders, developmental disorders, other mental health conditions at the index or subsequent treatment episodes; Column 3 excludes observations on patients who live in Oslo; column 4 removes observations on the highest 1% of wait times; column 5 removes observations on the highest 1% of wait times; column 6 replaces wait time with the inverse hyperbolic sine of wait times.

Table A.5: Heterogeneity Analysis: Specialist Treatment

Panel A	Dependent Variable: Completed treatment			
IV: wait time	-0.057	-0.057	-0.035	-0.199
	(0.047)	(0.043)	(0.033)	(0.204)
Obs	1,590	2,040	2,553	1,077
Panel B	**Dependent Variable: Number of treatments**			
IV: wait time	4.388**	5.563**	5.224***	5.045
	(2.159)	(2.208)	(1.638)	(8.121)
Obs	1,590	2,040	2,553	1,077
In school of work 24 months before assess	N	Y	–	–
Any charges 24 months before assess	–	–	N	Y

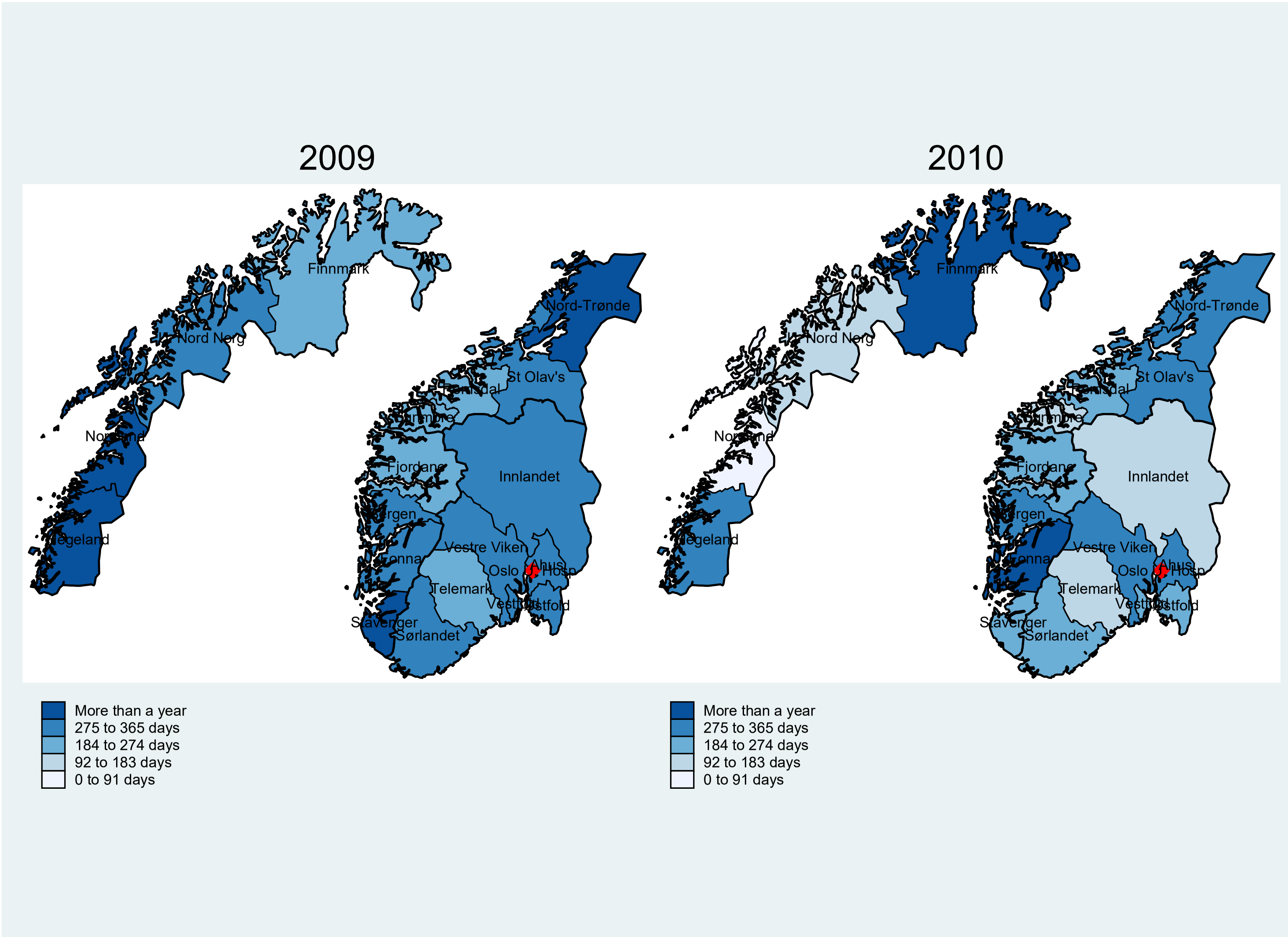
Clustered (on individual and health trust) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample consists of 3630 Observation on 2386 unique individuals. Panel A: Dependent variable is an indicator for completing treatment 24 months after starting treatment. Panel B: Dependent variable is the number of treatment consultations within the first 24 months of starting treatment. Waiting time is measured as the number of days from assessment date until treatment begins.

Table A.6: Heterogeneity Analysis: Work and Crime

Panel A	Dependent Variable: Employed			
IV: wait time	0.031	-0.277***	-0.082***	-0.374
	(0.048)	(0.066)	(0.032)	(0.366)
Obs	1,590	2,040	2,553	1,077
Panel B	**Dependent Variable: Days employed**			
IV: wait time	5.091	-51.010	-3.221	-159.183
	(13.217)	(34.409)	(17.426)	(152.966)
Obs	1,590	2,040	2,553	1,077
Panel C	**Dependent Variable: Charged with a crime**			
IV: wait time	0.002	0.070	0.022	0.254
	(0.062)	(0.048)	(0.051)	(0.316)
Obs	1,590	2,040	2,553	1,077
Panel D	**Dependent Variable: Number of charges**			
IV: wait time	0.480	0.798	0.372	3.603
	(0.934)	(0.690)	(0.512)	(3.611)
Obs	1,590	2,040	2,553	1,077
Panel E	**Dependent Variable: Charged with a drug crime**			
IV: wait time	0.022	-0.004	0.012	0.071
	(0.047)	(0.062)	(0.050)	(0.265)
Obs	1,590	2,040	2,553	1,077
Panel F	**Dependent Variable: Number of drug charges**			
IV: wait time	0.333	0.503*	0.159	2.918
	(0.366)	(0.264)	(0.178)	(2.320)
Obs	1,590	2,040	2,553	1,077
In school of work 24 months before assess	N	Y	–	–
Any charges 24 months before assess	–	–	N	Y

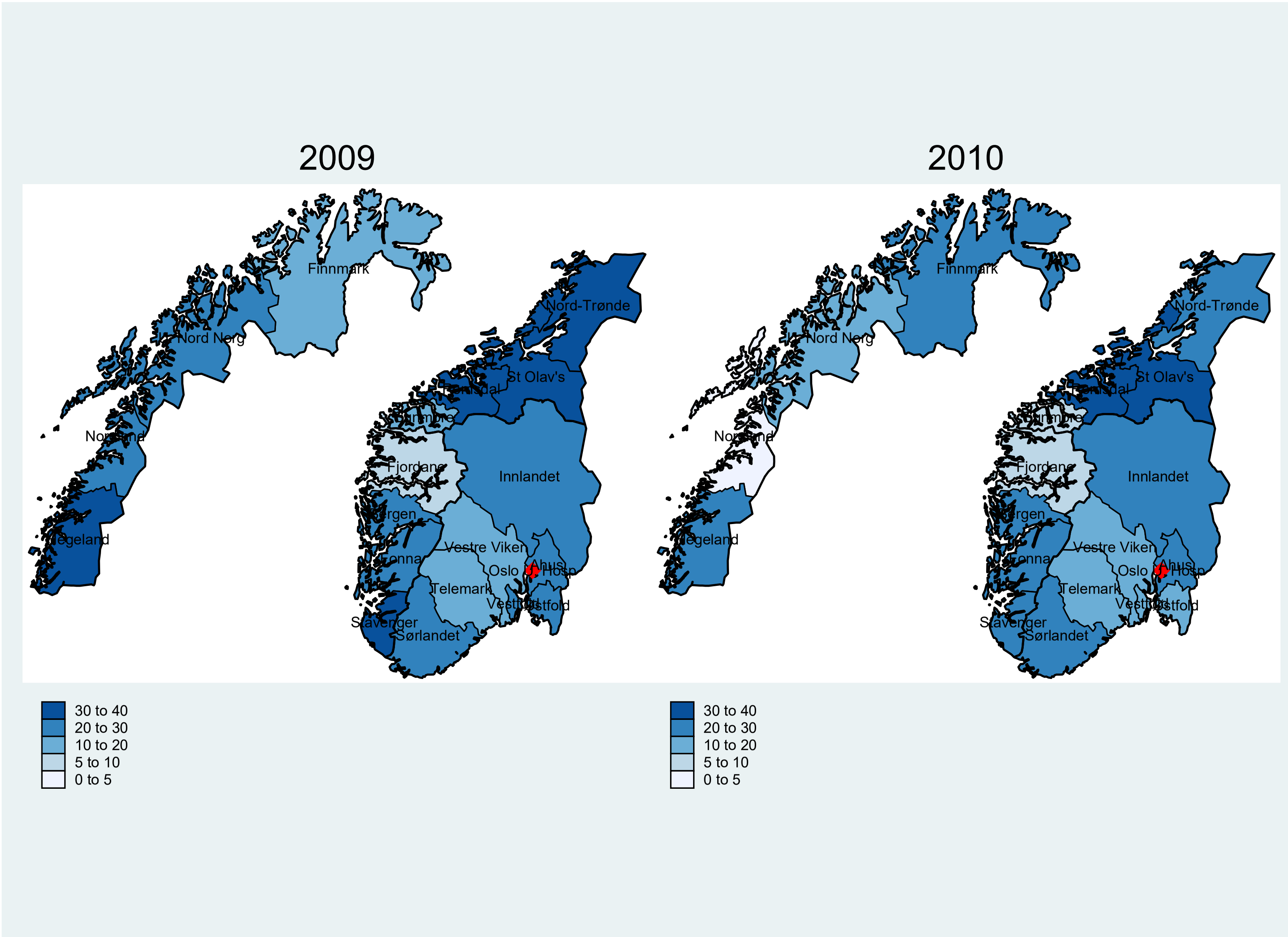
Clustered (on individual and health trust) standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Sample consists of 3630 Observation on 2386 unique individuals. Panel A: Dependent variable is an indicator for being employed any time within 24 months of starting treatment. Panel B: Dependent variable is the number of days employed within 24 months of starting treatment. Panel C: Dependent variable is an indicator for being charged with a crime any time within 24 months of starting treatment. Panel B: Dependent variable is the number of times charged with a crime within 24 months of starting treatment. Waiting time is measured as the number of days from assessment date until treatment begins.

Figure A.1: Variation in the duration of treatment



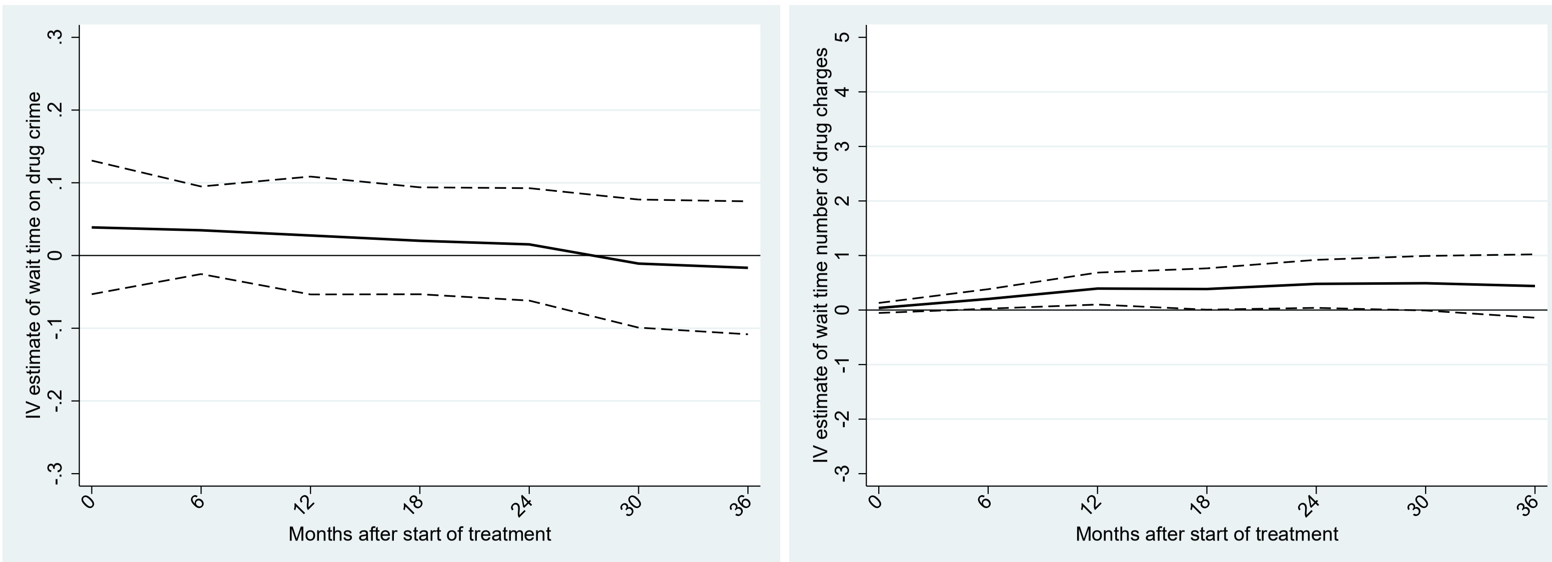
Sample consists of 3630 Observation on 2386 unique individuals. Left panel: Average duration of treatment in each health trust in 2009. Right panel: Average duration of treatment in each health trust in 2010.

Figure A.2: Variation in the number of consultations in the index treatment episode



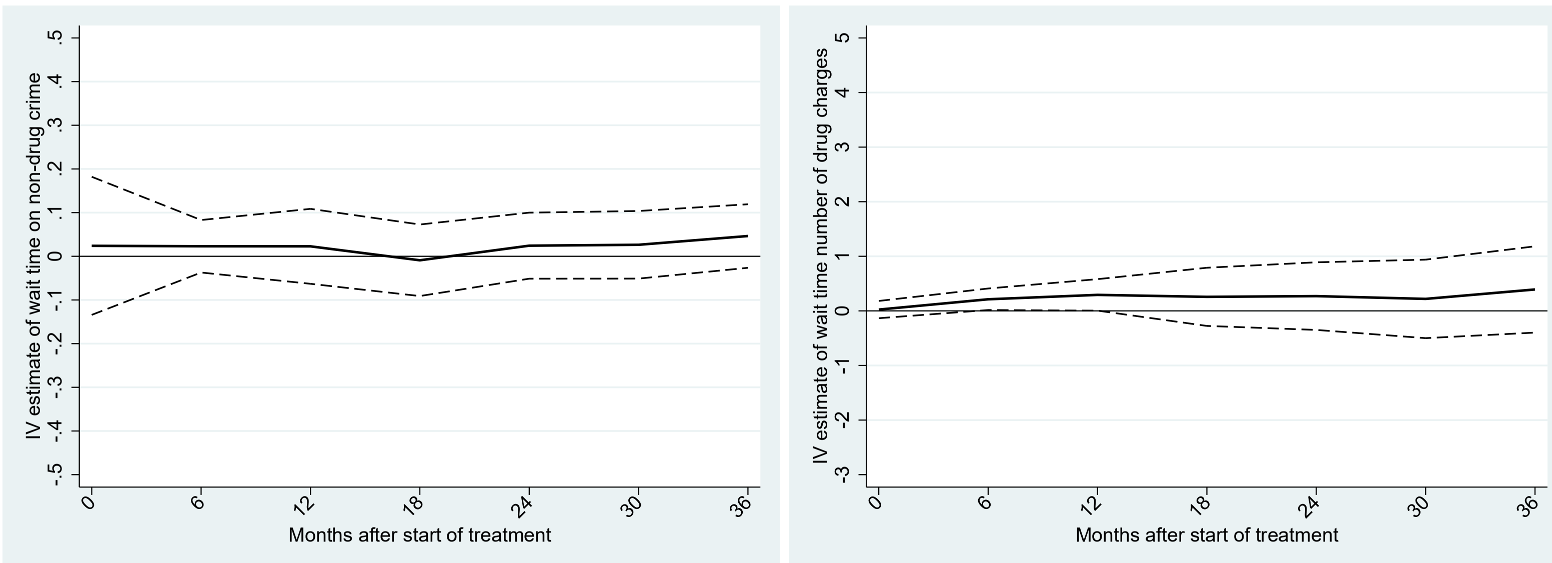
Sample consists of 3630 Observation on 2386 unique individuals. Left panel: Average number of consultations in the index treatment episode in each health trust in 2009. Right panel: Average number of consultations in the index treatment episode in each health trust in 2010.

Figure A.3: IV estimates of the impact of waiting time on being charged with a drug crime and the number of drug crime charges



Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Left panel: Dependent variable is an indicator for the respondent ever being charged with a drug crime x months after starting treatment, except at 0, where the outcome is an indicator for being charged with a drug crime while waiting to enter treatment. Right panel: Dependent variable is the number of times charged with a drug crime x months after starting treatment except at 0, where the outcome is the number of drug crime charges while waiting to enter treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins. Dashed lines show 90% confidence interval based on clustered (on individual and health trust) standard errors.

Figure A.4: IV estimates of the impact of waiting time on being charged with a non-drug related crime and the number of drug crime charges



Estimation sample consists of 3630 observations on 2386 outpatients who were over the age of 19 at the time of entering treatment. Left panel: Dependent variable is an indicator for the respondent ever being charged with a non-drug related crime x months after starting treatment, except at 0, where the outcome is an indicator for being charged with a non-drug crime while waiting to enter treatment. Right panel: Dependent variable the number of charges for non-drug related crimes x months after starting treatment except at 0, where the outcome is number of non-drug crime charges while waiting to enter treatment. Waiting time is measured as the number of 100 days from assessment date until treatment begins. Solid lines show IV coefficient estimates. Dashed lines show 90% confidence interval based on clustered (on individual and health trust) standard errors.