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Talking therapy: Impacts of a nationwide mental health service in England

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Abstract
Mental health problems impose significant costs, yet healthcare systems of-ten overlook them. We provide the first causal evidence on the effectiveness of a nationwide-scaled mental health service in England for treating depression and anxiety using non-experimental data and methods. We exploit over-subscription and resulting exogenous variation in waiting times across areas and time for identification, based on a novel dataset of over one million patients. We find that treatment improves mental health and reduces impairment in work and social life. We provide suggestive evidence that it enhances employment. Impacts vary across patients and services. Nevertheless, the programme is highly cost-effective.

Keywords: mental health, psychological therapies, quasi-natural experiment, policy evaluation, machine learning, cost-benefit analysis
JEL Codes: I18; D04; D61

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1 Introduction

Nearly one billion people globally live with a mental health disorder (WHO, 2022). The economic burden of mental ill health is estimated to reach $5 trillion, representing between 4% and 8% of GDP across different regions (Arias et al., 2022). Poor mental health is linked to worse labour market outcomes (Banerjee et al., 2017; Chatterji et al., 2011; Frijters et al., 2014) and educational attainment (J. M. Fletcher, 2010), with spillovers to families amplifying societal costs (J. Fletcher, 2009). Allocating resources to cost-effective mental health policies is important, as improvements in mental health enhance human capital leading to long-term economic benefits (Layard, 2016).

Despite the burden imposed by mental ill health, evidence on the effectiveness of population-wide mental health policies is scarce. While randomised controlled trials (RCTs) provide strong evidence for the effectiveness of psychological therapies in controlled settings (Lambert, 2013; Nathan & Gorman, 2015; A. Roth & Fonagy, 2005), there are no guarantees that scaling these interventions to national levels will produce similar outcomes (List, 2022). This is due to larger scale, access to more diverse population groups, and the fact that patients choose to get treatment rather than being allocated to it.[1]

This paper is the first to estimate the causal effects of a population-wide mental health policy.[2] We study its overall effect as well as heterogeneous effects across patients, services, and areas. Our results serve as a guide and benchmark for implementing similar policies worldwide, as countries increasingly recognise the growing economic burden of mental ill health.

We study the *Improving Access to Psychological Therapies (IAPT)* programme, which is a nationwide mental health service in England that provides evidence-based psychological therapies for depression and anxiety.[3] The programme is the largest in the world: to date, it has deployed over 10,500 new therapists and treated over seven million patients (more than 13% of the English population), primarily via

[1] See Cronin et al. (2024) for a discussion on the importance of the latter in the context of public policy.

[2] Although only for patients aged 18 to 38, Serena (2022) is an important contribution closest in spirit to ours. It examines the impacts of expanding partial health insurance coverage of psychological therapy in Denmark, allowing patients access to private practice psychologists, on health service use, labour market outcomes and suicide attempts as an extreme outcome of mental ill health. We examine the direct mental health impacts on all patients accessing clinicians trained within the programme and adhering to its guidelines.

[3] The programme has recently been renamed *NHS Talking Therapies for Anxiety and Depression*.

cognitive behavioural therapies (CBT). IAPT therapists are specifically trained to provide treatments recommended by the *National Institute for Health and Care Excellence (NICE)* in the UK and, hence, supported by an extensive body of causal evidence on their effectiveness. All therapists who work in the programme adhere to the same national guidelines. IAPT services are free of charge to patients.

We use data on over one million patients from a novel dataset comprised of all individuals who started their treatment between April 2016 and December 2018.[4] Our main outcomes are binary indicators for *reliable recovery*, *reliable improvement*, and *reliable deterioration*, which are based on validated measures of depression (PHQ-9 scores) and anxiety (GAD-7 scores) reported by patients before each session.[5] We also study self-reported work and social functioning as well as employment. Our dataset is of an exceptionally high quality with outcomes recorded for 98% of patients. The patients in our sample attended, on average, 7.7 sessions. We combine these comprehensive session-by-session patient-level data with regional data on service characteristics from NHS Digital as well as socio-economic characteristics of local areas from the Office for National Statistics (ONS) in the UK.

We estimate the causal effects of being treated within the IAPT programme using a quasi-experimental approach. Based on institutional knowledge,[6] we rely on oversubscription of patients to the programme for identification, which creates exogenous variation in waiting times across services (and, thereby, geographical areas) *and* over time, as more patients are referred to therapies than can be instantly treated.[7] In essence, we compare the changes in mental health of patients who were waiting for the start of treatment to those of patients who completed treatment during the same period of time. Waiting time is defined as the period from initial

[4]The rollout started in 2008, and by 2016 the programme's operations and current outcome monitoring system were fully established.

[5]Reliable improvement is one if a patient's PHQ-9 and/or GAD-7 scores decreased, i.e. symptoms improved, and neither score increased; reliable deterioration is one if PHQ-9 and/or GAD-7 scores increased and neither decreased; reliable recovery is one if a patient reliably improved and both PHQ-9 and GAD-7 score are below the clinical cut-of at the end of treatment. All changes should be larger than a reliable amount, i.e. larger than measurement error, which is defined by the scale. Section 3 provides more details on how our outcomes are constructed.

[6]We have benefited greatly from discussions with Richard Layard and David Clark, the founders of the IAPT programme, whose insights into the programme's key features and how it operates helped inform our identification strategy.

[7]The use of waitlists to identify treatment effects in economics is not new. An early contribution is found in Berger and Black (1992). The idea has also been implemented in experimental settings (cf. Finkelstein et al., 2019; Jacob & Ludwig, 2012; Jacob et al., 2015). More recent works, like ours, exploit naturally occurring waitlists due to oversubscription or excess demand (Beam & Quimbo, 2023; Dague et al., 2017; Dinerstein et al., 2022; Hoe, 2023; Robles et al., 2021).

assessment (which has little to no therapeutic content) to the first clinical session, meaning that outcomes are measured at the same time for both treatment and control group.

Our identification strategy is supported by the fact that treatment in the programme, which is part of the public healthcare system aiming to treat patients fairly, is allocated strictly on a first-come first-serve protocol. We provide empirical evidence that waiting times are not systematically related to the number of sessions, treatment duration, or the severity of depression or anxiety symptoms at the start or end of treatment.[8] Differences in waiting times stem from variation in demand for treatment and the availability of therapists across areas and over time, due to staff recruitment and turnover, therapists undergoing training, and regional differences in the balance between high-intensity and low-intensity treatment provision.[9]

Our empirical analysis, which consists of three steps, leads to six key findings. We first estimate the overall treatment effects of the IAPT programme. Findings (i) to (iii) detail the programme's positive causal effects on mental health as well as work and social life outcomes of patients. We then use a nonparametric matching method to estimate heterogeneous treatment effects conditional on covariates commonly used in correlational studies. We find significant heterogeneity and discuss its sources in (iv). Finally, using state-of-the-art machine-learning (ML) techniques (generalised random forests), we explore the data further for factors that drive heterogeneity in treatment outcomes and might have been ignored in earlier correlational studies. Two factors emerge: employment and self-referral, and they are discussed (v) and (vi). Our key findings are:

(i) We find that the programme causally improves the mental health of patients. Relative to waitlisted patients in our quasi-experimental control group, treated patients' mental health is significantly more likely to have *reliably improved* at the end of the treatment, with a *reliably recovery* rate from mental ill health of about 43%.[10]

[8]The latter finding differs from Prudon (2024), who found that delaying treatment lowers its effectiveness in improving employment outcomes. The difference may be explained by the fact that the dataset in Prudon (2024) includes more severe cases than treated by IAPT and a different mix of diagnoses, particularly personality disorders.

[9]Patients are allocated to high- or low-intensity treatment based on diagnosis and symptoms severity at initial assessment, with the possibility of being reassigned to a different intensity level during their treatment. Different intensities include different therapeutic approaches. Each therapist may be trained to deliver low- or high-intensity therapy, or both. All our analyses are conditional on treatment intensity.

[10]Our dataset is unique in that it allows a straightforward comparison of average treatment effects

Being treated in the programme reduces the symptoms of depression, as measured by PHQ-9 scores, by 5.1 points, and of anxiety, as measured by GAD-7 scores, by 4.8 points. Our session-by-session patient-level outcome data show that there is a steady session value added from the first to the last clinical session.

(ii) We detect positive short-term ripple effects on work and social life. Amongst those who were initially unemployed or on long-term sick leave, treated patients are significantly more likely to report being employed at the end of treatment (an increase of about three percentage points) and significantly less likely to receive statutory sick pay (a decrease of about three percentage points). Being treated also reduces patients' perceived functional impairment due to mental ill health, with overall impairment being 65% SD lower at the end of treatment. Patients who undergo a course of treatment report to function better in all measured domains of life, including work, home management, leisure, and social relationships.

(iii) We find that treated patients are significantly less likely to experience mental health deterioration. The ability to observe mental health deterioration in a non-RCT context is unique to the IAPT programme due to its data collection protocol. This finding provides empirical evidence that addresses recent concerns that psychological interventions may inadvertently cause harm for some (see, for example, Harvey et al. (2023) on specific psychological therapies and their unintended consequences on youth).

(iv) We find substantial heterogeneity in the programme's effectiveness. Nevertheless, even groups that benefit the least experience positive and significant mental health improvements. Patients typically at risk of lower mental health outcomes, e.g. those who live with a disability, generally benefit less from the programme, whilst area deprivation is negatively and funding positively related to patient outcomes. The magnitudes of these heterogeneities differs from those in earlier correlational studies (Delgadillo et al., 2016; Moller et al., 2019). Specifically, we find that patients with long-term health conditions are approximately three percentage points less likely to reliably recover, which is significantly lower than the 14 percentage points difference estimated by Moller et al. (2019). This suggests that a

with earlier, smaller RCTs. In our data, 54% of patients in the treatment group reliably recovered by the end of treatment, compared to 9% who recovered naturally in the waitlist control group. The end-of-treatment recovery rate is similar to findings from RCTs of IAPT-style programmes in Norway (59%, Knapstad et al. (2020)) and Spain (50%, Cano-Vindel et al., 2022). However, unlike our study, these trials used treatment-as-usual control groups rather than waitlists, leading to higher recovery rates in control groups: 32% in Norway and 13% in Spain.

large part of the difference is due to natural recovery, underscoring the importance of using causal approaches to study heterogeneity. Similar to mental health improvement, there is substantial heterogeneity in mental health deterioration. Some groups do not show significant benefits, but they also do not experience harm.

(v) Moving from nonparametric heterogeneous treatment effects to our ML analysis, we show that unemployed patients, on average, respond less favourably to treatment than their employed counterparts. In particular, unemployed patients are 13.3 percentage points less likely to recover as a result of treatment, which represents 30% of the programme's average treatment effect. Additionally, they are 1.2 percentage points less likely to recover naturally while on the waitlist. Unemployed patients are also more likely to deteriorate, although this effect is rather small. This is an important consideration for any analysis of the effect of mental health policies on labour market outcomes.

(vi) Finally, we provide evidence that self-referrals – the possibility to access treatment without a GP as a gatekeeper, which is another unique feature of the IAPT programme – improves access to care: self-referred patients do so, on average, 364 days after the onset of symptoms, whilst patients who were referred via other pathways waited, on average, 461 days. We find that patients who self-referred are 3.8 percentage point more likely to recover as the result of treatment, which represents 8% of the average treatment effect. Self-referral emerges as an important source of heterogeneity not addressed by earlier literature, based on our ML analysis.

Our results are robust to different definitions of treatment and control group (varying cut-off waiting time durations to allocate patients into treatment and control), to controlling for clinical session spacing, and to repeat enrolment in the programme. They are also robust to different model specifications (using logit as opposed to linear probability models), estimation samples (excluding certain mental health problems), and outcomes (using changes in PHQ-9 and GAD-7 scores as well as changes in a composite mental health index as opposed to reliable recovery, improvement, and deterioration). To address potential concerns about selective dropout from the programme, we conduct a bounding analysis showing that the programme remains effective (though with lower effects sizes) even under the most extreme assumptions. Finally, to address concerns about treatment discontinuation being endogenous and potentially leading to selection on the outcome, we estimate treatment effects using data from the second-last and third-last clinical sessions. We also control for the total number of sessions and therapy duration to

ensure comparable selection on observables between treatment and control group. A conservative cost-benefit calculation suggests that the benefits of the programme are (at least) five times larger than its costs.

For the purpose of informing policies, our paper improves on existing evaluations that are either non-causal based on before-after comparisons (e.g. Clark et al. (2009, 2018), Delgadillo et al. (2018), and Gyani et al. (2013)) or small-scale based on RCTs (e.g. Cano-Vindel et al. (2022), Clark et al. (2022), Ehlers et al. (2023), Fonagy et al. (2019), Knapstad et al. (2020), Smith et al. (2024), Strauss et al. (2023), and Toffolutti et al. (2021)). Non-causal studies are confounded by natural recovery or deterioration. Specifically, our study finds natural recovery tends to be the prevailing factor that makes estimates from before-after comparisons generally larger than the actual treatment effects. We also show that different patient groups exhibit different natural recovery rates, implying that relying on correlational analysis can misrepresent the heterogeneous effects of the programme. On the other hand, while RCTs are considered the gold standard to estimate causal effects due to their controlled environment, they have only been applied to small samples that cannot be extrapolated to represent the effectiveness of the programme on the patient population at large. Moreover, the modest scale and scope of participant diversity in experiments do not allow exploring why treatment works well for some patients but not for others. For example, unemployed patients constitute less than ten percent of our sample, making it unlikely that we would have sufficient statistical power to credibly explore heterogeneities by employment status in an RCT-sized study.

Although mental ill health costs the taxpayer billions of dollars every year, the literature in economics more broadly has, so far, looked at mental health mostly as a by-product, for example of interventions aimed at making people move towards higher living standards (Fryer Jr. & Katz, 2013; Ludwig et al., 2013; Stillman et al., 2009), of policy changes in the areas of labour, health, or social protection (Avendano et al., 2020; Barnay & Juin, 2016; Chuard, 2023; Lang, 2013; Ortega, 2022), or wider socio-economic circumstances (Adhvaryu et al., 2019; Fruehwirth et al., 2019). Only recently have scholars started looking at interventions and policies aimed at *directly* improving mental health, for example via psychological therapy. Our work complements the recent and growing literature in economics that documents positive impacts of therapy on various health and human capital outcomes.[11]

[11] Examples include perinatal depression and subsequent female empowerment and investments into children's cognitive and socio-emotional skills (Baranov et al., 2020; Sevim et al., 2023a, 2023b);

Most of these studies find medium to strong impacts that are often lasting.[12] Almost all of the evidence comes from developing countries (a notable exception is Blattman et al. (2017), who study the impact of CBT on criminal arrests in Chicago) and relies exclusively on RCTs, mostly with small samples. The methodological difference between these papers and ours is that we take a quasi-experimental approach using data on the universe of beneficiaries, which can be useful for guiding counterfactual questions on scaling up smaller pilots to the policy level (cf. List, 2022).

2 The IAPT Programme

2.1 Institutional Context

In 2008, the UK Government launched the IAPT programme to make evidence-based psychological therapies more widely available within the National Health Service (NHS), its universal public healthcare system, focusing on the most common mental health problems: depression and anxiety disorders.[13] At its inception, the then Secretary of State for Health and Social Care, Alan Johnson, argued: "All too often in the recent past, people experiencing anxiety and depression received relatively little help from the NHS unless their condition was particularly severe: in 2000, only 9 per cent of people [...] received psychological therapy, despite clear evidence of its effectiveness. This is something we are determined to change" (Department for Health, 2008).

What followed was an unprecedented, nationwide rollout of a mental health service, covering all 135 public health service providers (so-called *Clinical Commissioning Groups (CCGs)*, or *services* for short) in England at the time. CCGs were independent, geographically distinct bodies accountable to the Secretary of State for Health and Social Care through NHS England, each reflecting local needs and

mental health of individuals living in poor households (Barker et al., 2022); anti-social and criminal behaviour amongst economically disadvantaged youth (Blattman et al., 2017; Heller et al., 2017) or violence amongst prisoners (Batistich et al., 2024); self-image (Ghosal et al., 2022); and overall psychological and economic wellbeing (Bossuroy et al., 2022; Haushofer et al., 2022). Angelucci and Bennett, 2023 look at antidepressants and livelihoods support, individually and jointly, detecting impacts on mental health (though not on economic outcomes) when combined.

[12] See also (Johnsen & Friborg, 2015) and (Cuijpers et al., 2010, 2016) for meta-analyses on the effectiveness of CBT in treating mental ill health.

[13] For a detailed overview of the IAPT programme, see Clark (2018).

responsible for commissioning public healthcare for, on average, a quarter of a million of people NHS (2021b).[14] Today, IAPT is the largest programme of its kind in the world. It is seen as a pioneering model for treating mental ill health at the general population level, and is being replicated in other countries, e.g. Norway, Spain, Sweden, and Australia.[15] By now, IAPT has treated over seven million patients, and the NHS has committed to further expand access (NHS, 2019).

The programme provides psychological therapies recommended by the *National Institute for Health and Care Excellence (NICE)* in the UK, an independent body mandated with reviewing evidence for treatments (not limited to mental health) and issuing clinical guidelines for how effective treatments should be implemented within the NHS. For depression and anxiety disorders, NICE strongly supports psychological therapies, in particular CBT, and advocates a stepped-care model with both low and high-intensity treatments.[16] To access the programme, patients can either be referred by their GPs or they can refer themselves (so-called *self-referral*). The latter feature was a new option at the time the programme was launched, whose goal was to make psychological therapies more accessible amongst underserved population groups. As there is universal public healthcare in England, accessing the programme is free of charge, without co-payment.

In their first session, patients undergo an initial assessment in which they are screened for the type of problem and the severity of symptoms. If patients are above the clinical caseness threshold for depression and/or anxiety, they are admitted and jointly agree with trained therapists on a course of treatment; if they are below this threshold or their problem is considered more appropriate for a different service, they are signposted elsewhere.[17] Note that the IAPT programme was launched precisely because there was a lack of treatment options for mild to moderate cases of mental disorders. Everybody who is admitted eventually gets treated. After the initial assessment, admitted patients are waitlisted and, after a while, start treatment in their second session, which constitutes the first clinical session. Those

[14] CCGs emerged from *Primary Care Trusts (PCTs)* in 2013. In 2022, they were replaced with *Integrated Care Systems (ICS)*.

[15] The Norwegian adaptation is named *Prompt Mental Health Care* (*RPH* in Norwegian, see Knapstad et al. (2020) for a clinical trial). In Spain, Psicofundación developed the PsicAP clinical trial, following the IAPT approach (see Cano-Vindel et al. (2022)). Australia's *New Access* programme for depression and anxiety is strongly influenced by IAPT (see Baigent et al. (2023)).

[16] See NICE Clinical Guideline 123 "Common mental health problems: identification and pathways to care" at www.nice.org.uk/guidance/CG123.

[17] For example, the IAPT programme does not treat particularly severe cases or cases with complex co-morbidities.

with mild to moderate symptoms start with low-intensity treatment (e.g. guided self-help, computerised CBT, or group-based physical activity programmes) and, if not responding, are upgraded to a higher intensity (usually weekly face-to-face one-to-one sessions); those with moderate to more severe symptoms, as well as with special forms of anxiety disorders such as post-traumatic stress disorder, start immediately with high-intensity treatment. While low-intensity treatment is often conducted online or over the phone, high-intensity treatment is conducted in-person, delivered locally where patients and therapists live, typically at local GP practices or community centres rented by CCGs specifically for this purpose. Note that therapists only treat patients in their geographical area. About 60% of patients entering the programme (over 560,000 patients per year) receive at least one clinical session. Of these, the vast majority receive treatments based on CBT, though other treatments are also available to preserve an element of choice. Overall, 30% receive low-intensity treatments based on CBT principles, 24% high-intensity CBT, 38% low-to-high-intensity stepped care (a change from low to high-intensity CBT), and 8% other forms of treatment (NHS, 2021a).[18]

CBT itself refers to a wide range of psychological therapies that reduce dysfunctional emotions and behaviours by changing behaviours, appraisals of situations and thinking patterns, or both (Beck, 2020). The basic idea is that symptomatic change follows from cognitive or behavioural change, brought about by, for example, analysing maladaptive thinking patters, teaching more adaptive self-talk, or implementing more adaptive behaviours (Brewin, 1996).[19] Therapists may prescribe medication additional to psychological therapy (which we are routinely controlling for in our analyses).

Specifically for the IAPT programme, the UK Department of Health and Social Care implemented a standardised training with dedicated national curricula for therapists covering a wide range of evidence-based CBT treatments.[20] New

[18] Other forms of treatment may include, for example, interpersonal psychotherapy, couples therapy, counselling, brief psychodynamic therapy, or mindfulness-based cognitive therapy, which are recommended for depression but not for anxiety disorders.

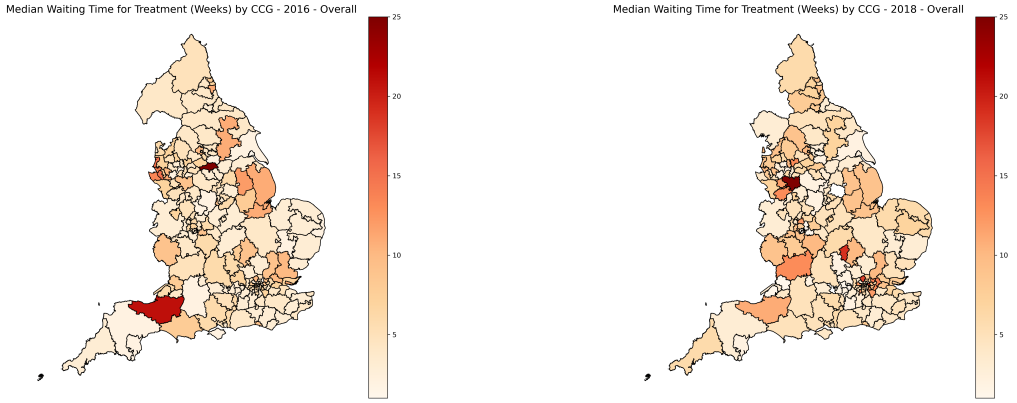
[19] Take a panic attack, for instance: a typical CBT treatment helps patients understand what a panic attack is and how it affects them: their feelings, e.g. "I am scared"; their thinking, e.g. "I am going to pass out"; their physical symptoms, e.g. "My heart is racing and I am sweating"; and their behaviours, e.g. "I am running away from the situation". It then teaches patients to plan, implement, and, after implementation, evaluate an adaptive behavioural response, while avoiding maladaptive responses such as running away from the situation, an avoidance behaviour that eventually leads to even more panic in the future (cf. C. Williams, 2013).

[20] These national curricula can be found at: https:\hee.nhs.uk. A competency framework, which

therapists working in the programme are required to learn at least two treatments for depression and one for each anxiety disorder. The training follows a joint university and on-the-job approach, whereby over a period of one year trainees attend university for several days per week to obtain an accredited postgraduate diploma (more days for trainees in high-intensity treatments, who are required to have prior experience in mental health services and are also paid more) and spend the rest of their time in on-the-job training. By 2019, about 10,500 newly trained therapists were deployed.

In 2018, the IAPT programme served about 17% of the community prevalence of depression and anxiety disorders. As a result, there was more demand for psychological therapies than there was supply. This oversubscription of patients to treatments yields substantial variation in waiting times between initial assessment and first clinical session, which varies across services (geographical areas) and over time, depending on supply-side constraints (e.g. shortages of trained therapists, and in particular, specific types of therapists, i.e. low- or high-intensity, depending on local needs) and demand-side characteristics (e.g. clusters of mental ill health in some areas). Figure 1 illustrates the differences in median waiting times across areas and between 2016 and 2018. The variation is further discussed in Section 4.1. This oversubscription and resulting exogenous variation in waiting times informs our identification strategy.

Figure 1: Median Waiting Times in Weeks for Treatment by Clinical Commissioning Groups (CCGs)



(a) 2016 (b) 2018

specifies the clinical training and skills to deliver these treatments, can be found at: https://www.ucl.ac.uk/pals/research/cehp/research_groups/core/competence-frameworks.

2.2 Earlier Evaluations

Earlier evaluations of the IAPT programme provide only correlational evidence based on the comparison of patients' states before and after treatment. The first empirical study by Clark et al. (2009) evaluated two demonstration sites. The authors found a recovery rate of about 56%, which was largely maintained in a follow-up about ten months later.[21] Gyani et al. (2013) estimated the pre-post recovery rate to be 40.3% at the early stages of national rollout. Later in the rollout, recovery rates exceeded the original target of 50% (Clark et al., 2018).[22]

Another stream of evidence supporting the effectiveness of the IAPT programme comes from small-scale, short-run RCTs, testing new therapeutic approaches[23] or isolated components of the overall system.[24] Two recent RCTs show the effectiveness of IAPT-style interventions in other countries. A Norwegian study by Knapstad et al. (2020) involving 681 patients suffering from moderate depression or anxiety shows significant recovery rates and symptom reductions. In a follow-up study, Smith et al. (2024) find that former patients exhibit significantly higher incomes three years post-treatment, with a resulting benefit-cost ratio of about 4. A Spanish study involving 1,691 patients demonstrates that adding an IAPT-style psychological treatment in primary care is more (cost-)effective than treatment-as-usual (Cano-Vindel et al., 2022).

3 Data

The IAPT programme adopted an elaborate session-by-session patient-level outcome monitoring system to ensure that post-treatment outcomes are available to therapists at all times, even if patients finish their therapy early. This is a useful design to avoid missing endline data, which could lead to an overestimation of the effectiveness of treatment. We define a course of treatment as including the initial assessment and at least two subsequent clinical sessions. As outcomes are asked *before* the start of each session (including the initial assessment) and the initial assessment has little therapeutic content, this definition allows us to track the mental

[21] See also Richards and Suckling (2009), who also evaluated one of these sites.

[22] See Delgadillo et al. (2018) for an area-level analysis.

[23] See Fonagy et al. (2019), Toffolutti et al. (2021), Clark et al. (2022), Ehlers et al. (2023), or Strauss et al. (2023), for example.

[24] See Richards et al. (2020) or Gruber et al. (2022), for example, andWakefield et al. (2020) for a meta-analysis of earlier RCTs.

health of patients from their initial assessment to at least after their first clinical session. In our sample, outcomes are available for 98% of patients who attended such a course of treatment.[25]

The IAPT protocol requires patients to complete the same clinically validated measures of depression and anxiety in each session (including the initial assessment). A therapist asks the patient to complete the measures in a neutral setting, on the day of the session and before the session starts, typically while patients are waiting for their appointment or earlier on the day.[26] Therapists then review these measures at the start of each session and use them for session planning. The outcome data are regularly reviewed by supervisors and service managers to ensure compliance with this protocol. While the protocol aims to avoid wasting valuable clinical time and to reduce issues related to the self-reporting of measures (e.g. priming or demand effects), it is also a key feature of our identification strategy as it enables us to observe the evolution of mental health between initial assessment and first clinical session without any actual treatment occurring.

Our dataset consists of the universe of patients ever treated, entering the programme during the 2016 to 2018 period.[27] We obtain the data from NHS Digital, which include patients' session-by-session outcomes as well as rich information on their psychological-therapy and individual characteristics. We complement these patient-level data with regional data on the characteristics of services (*Clinical Commissioning Groups, CCGs*) (e.g. number of staff) from NHS Digital as well as socio-economic characteristics of local areas (e.g. local deprivation) from the Office for National Statistics (ONS) in the UK.

Outcomes. Our measure for depression is the Patient Health Questionnaire 9 (PHQ-9), a routine instrument for assessing symptoms of depression amongst general and clinical populations (Kroenke et al., 2001).[28] It consists of nine, four-point items that are summed up to a total, whereby scores from zero to four imply no or

[25]This is in line with official statistics by NHS Digital, who report non-missing outcome data on 98.5% of patients (NHS, 2016).

[26]If treatment occurs online (e.g. via Zoom) or via phone, patients can enter their data online.

[27]This covers the entire period in which the outcome monitoring system was operational, up until Covid-19.

[28]The PHQ-9 asks patients about various aspects of their mood over the past two weeks and to report the frequency – ranging from "not at all" to "nearly every day" – of experiencing specific symptoms, such as how often they felt down, had little interest in doing things, felt tired, or had thoughts that they would be better off dead or of hurting themselves.

minimal, from five to nine mild, from ten to 14 moderate, from 15 to 19 moderately severe, and from 20 to 27 severe depressive symptoms. PHQ-9 scores equal to or greater than the clinical cut-off of ten indicate a clinical case. Our measure for anxiety is the Generalised Anxiety Disorder Questionnaire (GAD-7), likewise a routine instrument for measuring anxious affect and worry (Spitzer et al., 2006).[29] It consists of seven, four-point items that are also summed up, whereby scores from zero to four imply minimal, from five to nine mild, from ten to 14 moderate, and from 15 to 21 severe anxiety. GAD-7 scores equal to or greater than the cut-off of eight indicate a clinical case. Both measures are mandatory to collect, though therapists may also capture additional measures to assess more specific anxiety disorders.[30]

As depression and anxiety are highly co-morbid (cf. Kalin, 2020), the IAPT programme defines three main outcomes that take into account both PHQ-9 and GAD-7 scores:

1. *Reliable Improvement* is a binary indicator that is one if a patient's PHQ-9 and/or GAD-7 scores have decreased by a reliable amount and neither has shown a reliable increase.

2. *Reliable Deterioration* is, conversely, a binary indicator that is one if a patient's PHQ-9 and/or GAD-7 scores have increased by a reliable amount and neither has shown a reliable decrease.

3. *Reliable Recovery* is a binary indicator that takes on one if a patient has reliably improved *and* that patient's PHQ-9 and/or GAD-7 scores are above the clinical cut-off on either measure at the start of treatment and both are below the cut-off at the end of treatment.

IAPT uses the term *reliable* to mean a change in score that exceeds the measurement error of the scale, which for PHQ-9 is a change equal to or greater than six and for GAD-7 a change equal to or greater than four.

In defining our outcomes this way, we adopt a conservative approach that measures treatment outcomes irrespective of the specific clinical problem being treated,

[29]The GAD-7 asks patients about their anxiety levels over the past two weeks and to report their frequency, inquiring about symptoms such as feeling nervous, not being able to stop or control worrying, worrying too much about different things, trouble relaxing, being so restless that it is hard to sit still, becoming easily annoyed or irritable, and feeling afraid, as if something awful might happen.

[30]For social anxiety disorder, for example, the Social Phobia Inventory (SPIN) (Connor et al., 2000) is collected *in addition* to both PHQ-9 and GAD-7.

focusing on being free from mental ill health as the ultimate outcome of psychological therapy. As secondary outcomes on mental health, we also look at PHQ-9 and GAD-7 scores separately and at a mental health index, which is an average of both standardised scores.

We are also interested in the effect of treatment beyond measures of mental health. We look at the work and social life of patients using data from the *Work and Social Adjustment Scale* (Mundt et al., 2002), a clinically validated scale that measures patients' perceived functional impairment due to a particular health problem (here: mental ill health) overall as well as in different domains of life, including work, home management, social and private leisure, and close relationships.[31] Besides this scale, we use data on self-reported employment, in particular whether patients report to be employed as opposed to unemployed or long-term sick and whether patients report to receive statutory sick pay. As with our mental health outcomes, these are asked session-by-session. Appendix Table A.I shows summary statistics of our outcomes.

Covariates. Patients' psychological-therapy characteristics include their referral type (whether they were referred by their GP or via self-referral), the time between referral and initial assessment in weeks, treatment mode (in person or online), whether they where prescribed additional medication (e.g. antidepressants), their initial diagnosis (depression and/or anxiety, including its type), and their treatment intensity (low or high-intensity treatment, and whether they changed their intensity during the course of treatment). Patients' individual characteristics include their age, gender, ethnicity, religion, sexual orientation, whether they have a long-term health condition, their self-reported employment status, and whether they are a member of the armed forces. Finally, we obtain precise information on the locations and times of patients' initial assessment and all subsequent clinical sessions.

To capture supply-side constraints of the programme, the characteristics of services include the local number of staff, number of patients, and funding per patient. To capture demand-side characteristics, the socio-economic characteristics of local

[31] The scale consists of five, eight-point items that are summed up to a total, whereby scores below ten imply no or minimal impairment, from ten to 20 significant impairment but less severe clinical symptoms, and above 20 moderately severe or worse psychopathology. The item on work, for example, asks patients to rate: "Because of my [mental ill health], my ability to work is impaired. 0 means not at all impaired and 8 means very severely impaired to the point I can't work."

areas include the local unemployment rate and median wage as well as local deprivation (an index of multiple deprivation and sub-indices for deprivation in the areas of income, employment, education, health, crime, housing, and the environment). Appendix Table A.II shows summary statistics of our covariates.

Estimation Sample. Our raw sample includes all patients who started treatment between April 2016 and December 2018. We focus on this period because certain psychological-therapy characteristics (particularly, but not limited to, the initial diagnosis) were consistently recorded only from April 2016 onwards. Moreover, according to official statistics by NHS Digital, aggregate recovery rates reached a stable level from around the same time, suggesting that the programme had moved from an initial implementation and scale-up phase to a more steady state of operation (cf. Clark, 2018), which we are primarily interested in when estimating its causal policy effects. We remove courses of treatment that started in 2019 to not include patients that started in 2019 but did not finish by the time the Covid-19 pandemic disrupted data collection.

We restrict this sample to attended sessions with non-missing values for both PHQ-9 and GAD-7 (recall that these are available for 98% of our sample). Moreover, we limit ourselves to patients who were at caseness prior to treatment, i.e. those who meet the clinical threshold for a mental health condition according to their PHQ-9 or GAD-7 scores at initial assessment.[32] The IAPT programme was launched precisely to serve these patients, making them its primary focus. Finally, we limit ourselves to patients who completed at least three sessions (the initial assessment and at least two subsequent clinical sessions), a requirement of our research design. We primarily study the effect of the full course of treatment, but in Section 5.2, we also look at the relative impact and value added of separate sessions cumulatively over the course of treatment. Our estimation sample includes 1,246,792 patients who attended, on average, 7.7 sessions (standard deviation of 4.1).[33]

[32] In special circumstances, therapists might accept individuals who do not meet treatment thresholds based on mental health scores if clinical judgment suggests the need for intervention. We do not include these patients in our sample, as they would qualify as recovered from the start and inflate the programme's effect.

[33] When cross-validating the properties of our estimation sample with official statistics by NHS Digital, we find a very similar recovery rate: 55.5% in our sample vs. 49.3% (NHS, 2017). Recall that, given our research design, we calculate recovery rates from a course of treatment that includes at least three sessions. The NHS defines a course of treatment as including at least two sessions.

4 Empirical Strategy

4.1 Identification

Our aim is to estimate the causal effect of being treated within the IAPT programme. We use the potential outcomes framework by Rubin (1974), where the average treatment effect on the treated (ATT) can be written as the average difference in the outcomes between patients who receive treatment and those who do not.

Consider patient i who was assessed at time t and the duration of the (potential) treatment is w. For the moment, for the purpose of illustrating the main idea with lighter notation, take w as fixed and suppose we only consider a subset of the data for these patients. Let t_1 and t_2 respectively denote t and $t + w$. We introduce the following variables: D_i is a treatment dummy that takes value one for the treated; $Y_{it_j}(0)$ is the outcome for patient i at time t_j if they were to *not* receive treatment; $Y_{it_j}(1)$ is the outcome for patient i at time t_j if they were to receive treatment; and X_i is a vector of observed characteristics associated with patient i.

Our parameters of interest are ATT and CATT (conditional ATT) that we denote respectively by θ and $\theta(X_i)$. They are formally defined as:

$$\begin{aligned} \theta := &\quad E\left[Y_{it_2}(1) - Y_{it_2}(0) \,|D_i = 1\right], \\ \theta(X_i) := &\quad E\left[Y_{it_2}(1) - Y_{it_2}(0) \,|D_i = 1, X_i\right]. \end{aligned}$$

ATT and CATT are not identified without further assumptions since we only observe $Y_{it_j} := D_i Y_{it_j}(1) + (1 - D_i) Y_{it_j}(0)$, but never both $Y_{it_j}(1)$ and $Y_{it_j}(0)$. The identifying assumptions we make below are standard in the econometrics literature on difference-in-differences models when two time periods are available (e.g. see J. Roth et al. (2023)). In what follows, it is convenient to define $\Delta Y_i := Y_{it_2} - Y_{it_1}$ and $\Delta Y_i(d) := Y_{it_2}(d) - Y_{it_1}(d)$ for $d = 0, 1$. We assume the following assumptions hold throughout:

Assumption 1: Parallel trends. For all i**,**

$$E\left[\Delta Y_i(0) \,|D_i = 1, X_i\right] = E\left[\Delta Y_i(0) \,|D_i = 0, X_i\right] \text{ almost surely.}$$

Assumption 2: No anticipatory effects. For all i**,**

$$E\left[Y_i(0) \,|D_i = 1, X_i\right] = E\left[Y_i(1) \,|D_i = 1, X_i\right] \text{ almost surely.}$$

In our context, Assumption 1 states that the expected natural recovery for patients in the treatment and control group are the same without the IAPT programme. Assumption 2 states that the expected initial outcome, prior to any treatment, for patients in the treatment group is not affected by them being in the treatment group.

Under Assumptions 1 and 2, the observed change in expected outcomes for the treatment group can be decomposed into the treatment effect and the observed change in expected outcomes for the control group. That is, we can write ATT and CATT in difference-in-differences in terms of observables, namely:

$$\theta = E\left[\Delta Y_i | D_i = 1\right] - E\left[\Delta Y_i | D_i = 0\right], \tag{1}$$

$$\theta\left(X_i\right) = E\left[\Delta Y_i | D_i = 1, X_i\right] - E\left[\Delta Y_i | D_i = 0, X_i\right]. \tag{2}$$

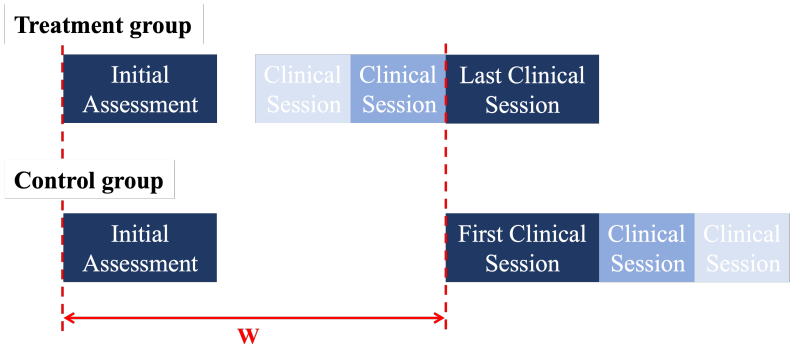
In Appendix B, we provide a proof that ATT and CATT can be written in terms of the distribution of observables, along with more detailed discussions.

We analyse our data through the lens of a two-period model, which is justified under the assumption that $\{(\Delta Y_i, D_i, X_i)\}_{i=1}^{n}$ is a random sample that, in turn, imposes the stable unit treatment value assumption and stationarity of the data generating process. This framework permits t_1 and t_2, hence $t_2 - t_1$, to vary across patients. Indeed, it is worth emphasising that our patients enter the programme at different times, so that our data are not suitable to be studied under a multi-period, cohort-wide adoption of a staggered treatment framework, which is the main focus in the survey by J. Roth et al. (2023).

A well-designed and carefully executed RCT can ensure that Assumptions 1 and 2 hold. However, the IAPT programme has not been implemented as an RCT. We thus take a quasi-experimental approach and argue that Assumptions 1 and 2 reasonably hold. We do so by exploiting the oversubscription of patients to the programme for identification, which creates exogenous variation in waiting times between initial assessment and the first clinical session across services (geographical areas) and over time. In particular, we create a quasi-experimental control group using patients who, after their initial assessment, are waiting for their first clinical session. We then compare the change in mental health outcomes for patients between their initial assessment and their last clinical session (our treatment group) with the change in mental health outcomes for patients between their initial assessment and their first clinical session (our control group). In doing so, we are comparing patients who reach respective sessions (the last clinical session for our

treatment group, the first for our control group) around the same time after initial assessment. Figure 2 illustrates our research design.

Figure 2: Research Design – Waitlist-Based Quasi-Randomisation



Note: Own illustration.

Given that X_i includes psychological-therapy, individual, and local-area characteristics, as well as service and time fixed effects, we argue that Assumptions 1 and 2 reasonably hold. Note that Assumption 1 is weaker than assuming that treatment assignment in our quasi-experiment is random conditional on X_i.

Before moving on to estimation, we discuss two aspects that are crucial to our identification strategy. The first is on variation and effect of waiting times, and the second is on selection related to Assumption 1 (parallel trends).

Waiting Times. As alluded in the Introduction, there are various reasons that contribute to substantial variation in waiting times between initial assessment and first clinical session across services (geographical areas) and over time. We illustrate the extent of this variation, which we exploit for identification, in Appendix Section C. Figure C.I shows histograms of waiting times for our entire estimation sample and for individual years, Figure C.II histograms for different treatment intensities across all years. Table C.I presents relevant summary statistics. Figure C.III shows a heat map of median waiting times, overall and by treatment intensity, across services for all years. Figures C.IV to C.VI replicate Figure C.III for each individual year.

There may be concern that waiting itself could have a negative impact and, thereby, introduce downward bias in natural recovery. We argue that this is unlikely to be an issue, for various reasons. First, waiting is to be expected by all patients. Criticisms on waiting times in the NHS have long been well-publicised, so

that having to wait is common knowledge. Moreover, the strict first-come first-serve protocol and associated waiting times are announced at initial assessment. Empirically, Appendix Figure C.VII plots our main outcomes – reliable recovery, improvement, and deterioration – as raw data for different waiting times. As seen, there is evidence for a slight natural recovery, which is, however, quantitatively minor. We find that waitlisted patients are, if anything, more likely to improve than to deteriorate. Hence, our identified treatment effects come from therapy being beneficial, rather than from waiting being detrimental.

In our baseline results, we allocate patients into treatment or control using the 50th percentile of waiting time (between 22 and 41 days, depending on the intensity of treatment) as a default threshold. However, we also conduct robustness checks using the 25th, 75th, and 90th percentile, which confirm our results.[34].

Selection. While controlling for psychological-therapy, individual, and local-area characteristics, as well as service and time fixed effects ensures that waiting times are conditionally independent from outcomes, there may be concern about residual selection.

When it comes to *within-sample selection*, there may be a concern that therapists could prioritise patients with worse mental health, or certain demographics. This is avoided due to the stepped-care protocol of the IAPT programme: after referral and subsequent initial assessment, therapists allocate patients to either low- or high-intensity treatment, in each of which they are processed. This allocation is done following a strict first-come first-serve protocol, based on fairness principles, which is rigorously followed.[35] In line with this, we observe only a weak, insignificant correlation between waiting time and either PHQ-9 or GAD-7 score.[36] Note that we routinely control for pre-treatment mental health by including our mental health index, as an average of both standardised PHQ-9 and GAD-7 scores, in all our models.

To empirically test that there is no prioritisation of patients based on severity

[34] See Section 5.2 for these robustness checks.

[35] If present, prioritisation would lead to a lower-bound estimate. Note that, given a general shortage of therapists, higher-need patients are not systematically send to more experienced therapists (within each treatment intensity), which would result in an upper bound. As discussed in Section 2.1, therapists receive a standardised training with dedicated national curricula. To the extent that the initial assessment itself has therapeutic value, this does not bias our results as it is balanced between groups.

[36] $r = 0.017$ for PHQ-9, $r = 0.016$ for GAD-7.

of symptoms, we regress waiting time on our mental health index, pre-treatment, controlling for psychological-therapy, individual, and local-area characteristics, as well as service and time fixed effects. Appendix Table E.XIII shows that a one standard deviation increase in our mental health index, pre-treatment, is associated with starting treatment less than one day later, on average. Although statistically significant due to the large sample size, this relationship is economically negligible (and, if anything, counter-intuitive in sign). Table E.XIII shows similar results by treatment intensity.

Appendix Table D.I shows balancing properties of covariates between our treatment and control group, which uses the 50th percentile of waiting time as a default threshold. Following Imbens and Rubin (2015), we calculate four scale-free overlap measures: normalised differences (which, unlike simple differences in means, are insensitive to the number of observations) and, to measure dispersion of covariates between groups, the logs of the ratios of standard deviations and the shares of the control (treated) units outside the 0.025 and 0.975 quantiles of the covariate distribution of the treated (control) units. As seen, almost none of the normalised differences exceeds 0.25, which Imbens and Wooldridge (2009) suggest as a threshold above which covariates can be considered unbalanced. The only noticeable imbalance is that a larger share of the treated are treated via phone (and, in turn, a smaller share face-to-face). Note that we routinely control for treatment mode in all our models. Moreover, there are almost no noticeable differences in dispersion of covariates between groups, as indicated by logs of the ratios of standard deviations that are below one and shares of the units outside the 0.025 and 0.975 quantiles of the counterpart covariate distribution that are close to zero. Our covariates are, therefore, well balanced between groups.

Next, Appendix Table D.II shows balancing properties of outcomes between our treatment and control group at the start of different sessions. As seen, neither at initial assessment nor at the start of the first or last clinical session does any of the normalised differences exceed the recommended threshold of 0.25 (Imbens & Wooldridge, 2009). There is little evidence for an unusual dispersion of outcomes between groups at any point in time either. Patients in treatment and control are, therefore, well comparable in terms of outcomes at the start of therapy and after therapy has ended, as well as when attending their first clinical session after waiting.

Finally, Appendix E demonstrates that waiting time has no meaningful association with the number of sessions, treatment duration, or the severity of depression

or anxiety symptoms (measured in terms of PHQ-9 and GAD-scores) at the start or end of treatment. We present these results on average and by treatment intensity, for the 50th percentile of waiting time as our default threshold to allocate patients into treatment and control as well as for the 25th, 75th, and 90th percentiles.

When it comes to *out-of-sample selection*, a potential issue may arise with patients discontinuing treatment. If attrition is selective – meaning that the probability of dropping out is correlated with the likelihood of recovery – it may introduce bias into our treatment effect estimates. For example, patients in our control group may naturally recover during the wait between initial assessment and their first clinical session and, therefore, drop out of the programme. To reduce this concern, in Appendix Section H, we establish bounds around our treatment effect estimates by imputing outcomes under various scenarios. We find that, even under the most extreme assumptions such that all those dropping out of the treatment group would experience deterioration and all those dropping out of the control group would experience recovery, our estimated treatment effects for both reliable recovery and reliable improvement remain significant and positive. Estimates under these assumptions are approximately half the magnitude of our baseline results. The programme continues to significantly reduce the likelihood of reliable deterioration, except in the most extreme scenario.

Similarly, individuals in our control group may, during the wait between initial assessment and their first clinical session, opt for an alternative treatment outside of the IAPT programme while still being part of the programme. This would introduce upward bias in natural recovery, suggesting that our estimated treatment effects can be interpreted as a lower bound. It is worth noting that the IAPT programme is run by the NHS, which is the monopolist provider of state-funded healthcare in England. It was launched precisely because patients had few other treatment options available.

4.2 Estimation

4.2.1 Average Treatment Effects

In Section 4.1, we only consider patients at time t that have w weeks as the duration of or waiting time for treatment. We now combine observations for different t's and w's and update our notation by letting $\Delta Y_i := D_i \Delta Y_i^{tr} + (1 - D_i) \Delta Y_i^c$, with $\Delta Y_i^{tr} := Y_{it_i+W_i}(1) - Y_{it_i}(1)$ and $\Delta Y_i^c := Y_{it_i+W_i}(0) - Y_{it_i}(0)$. That is, ΔY_i

is the change in the outcome of individual i, which is the change between initial assessment and the last clinical session if i belongs to our treatment group, ΔY_i^{tr}; and the change between initial assessment and the first clinical session if i belongs to our control group, ΔY_i^c, cf. Figure 2. Due to the importance of the duration of or waiting time for treatment in our model, we treat this separately from other covariates and denote it by W_i. W_i denotes the duration of treatment or waiting time respectively for a patient in the treatment or control group. D_i is the treatment dummy, which is one if i's first clinical session falls below a pre-defined threshold of waiting time. Our default threshold is the 50th percentile, which is between 22 and 41 days, depending on the intensity of treatment.[37] X_i contains all other relevant observables including psychological-therapy, individual, local-area characteristics, type of service and time.

We assume $\{(\Delta Y_i, D_i, W_i, X_i)\}_{i=1}^n$ to be i.i.d. and expand the conditioning set in Assumptions 1 and 2 to include W_i. While we can identify heterogeneous treatments under this assumption, in this subsection, we focus on a model with homogeneous treatment and suppose that the following holds:

$$E\left[\Delta Y_i | D_i, W_i, X_i\right] = \beta_0 + \beta_1 D_i + \beta_2^\top \widetilde{W}_i + \beta_3^\top \widetilde{X}_{it_i} + \mu_{r_i} + \nu_{t_i}. \tag{3}$$

Then, β_1 represents the ATT. Here, W_i is represented by a vector, $\widetilde{W}_i$, of binary variables indicating the weeks in which a patient completed either treatment or waiting so that $\beta_2^\top \widetilde{W}_i$ captures the possibly non-linear effect of natural recovery for patient i. X_i contains some variables that can vary with time for different patients, and it is decomposed into $\widetilde{X}_{it_i}$, which contains psychological-therapy, individual, service and local-area characteristics, and μ_{r_i} and ν_{t_i} are, respectively, service (i.e. 135 CCGs) and time fixed effects (i.e. day-of-week, month, and year). Including both service and time fixed effects implies that we are looking at variation across services (and, thereby, geographical areas) *and* over time. We also routinely control for waiting time and time lapsed between referral and initial assessment in weeks as well as for pre-treatment mental health (in form of our standardised mental health index) throughout.

We estimate the following model:

[37] The median threshold is 27 days for low and 22 days for high-intensity treatment, 35 days for stepped-up courses, 41 days for stepped-down courses, and 32 days if the treatment intensity is undefined (due to multiple changes).

$$\Delta Y_i = \beta_0 + \beta_1 D_i + \beta_2^\top \widetilde{W}_i + \beta_3^\top \widetilde{X}_{it_i} + \mu_{r_i} + \nu_{t_i} + u_i. \tag{4}$$

Note that the time-varying covariates net systematic differences between our treatment and control group at the psychological-therapy and individual level as well as at the service and local-area level (e.g. differences in local deprivation over time that may be directly related to our outcome and, indirectly via waiting time, to our treatment dummy), whereas the service and time fixed effects net out any remaining unobserved heterogeneity across services and over time. We estimate treatment effects in Equation 4 using OLS with robust standard errors clustered at the service level.[38]

4.2.2 Heterogeneous Treatment Effects

Under Equation 3, the treatment effect is assumed to be the same for all types of patients. To estimate how the effectiveness of the IAPT programme varies across patients, services, and areas with different characteristics, we take two approaches. First, we construct matching estimators using a pre-selected set of previously observed sources of heterogeneity, as found in earlier correlational literature based on reduced-form analysis of treatment outcomes. Second, we use a state-of-the-art machine learning (ML) technique and let the data tell us the most relevant sources of heterogeneity for the treatment effect. Specifically, for the latter, we use the *generalised random forest*, a data-driven way to identify the sources of heterogeneity amongst all available covariates. The validity of our estimators in terms of identifying the treatment effect follows under the same assumptions as outlined in Section 4.1.

ATT with pre-selected sources of heterogeneity. We are interested in whether the treatment effect differs for different patients, services, and areas, and if so, what characteristics are associated with better or worse outcomes. Using a similar notation as before, let our data be $\{(\Delta Y_i, D_i, W_i, Q_i)\}_{i=1}^n$. To facilitate matching, we dichotomise the covariates identified in earlier correlational studies as related to heterogeneity in treatment outcomes. Each combination of these dichotomised covariates defines a patient type, represented by Q_i, which replaces X_i as the type

[38] Given that ΔY_i is discrete for out main outcomes, in Section 5.2, we provide the results of logit model as a robustness check.

indicator for each patient. Our CATT is then indexed by (w, q), which corresponds to a particular treatment/waiting time duration and patient type. In this case, as alluded to earlier, our CATT is identified and can be written for each (w, q) as (cf. Equation 2),

$$\theta(w, q) := E[\Delta Y_i^{tr} | W_i = w, Q_i = q] - E[\Delta Y_i^{c} | W_i = w, Q_i = q]. \quad (5)$$

Since (W_i, Q_i) are discrete, there are finite combinations of (w, q). We can estimate $\theta(w, q)$ nonparametrically by calculating the difference between the average outcomes of the treated and the control patients whose $W_i = w$ and $Q_i = q$. We only include sub-populations that have a sufficient number of observations for both treatment and control group.[39] Sub-populations that have too few observations and those that do not have a treatment or control group counterpart are excluded from the analysis. This ensures that we only use the treated patients that have a close control-group counterpart, and *vice versa*.

Stacking the nonparametric estimators for $\theta(w, q)$ over (w, q) gives us a vector of CATTs that has an asymptotically normal distribution following from a standard central limit theorem. Furthermore, the asymptotic distribution of the vector of CATTs can be consistently bootstrapped using the standard resampling method with replacement since the empirical measure can be bootstrapped in this way (Gine & Zinn, 1990). Conveniently, however, the nonparametric estimator just described is numerically equivalent to the OLS estimator of $\{\theta(w, q)\}$ from this saturated model:

$$\begin{aligned} \Delta Y_i &= \sum_{w,q} \beta(w, q) \times \mathbf{1}\{Q_i = q, W_i = w\} \\ &\quad + \sum_{w,q} \theta(w, q) \times \mathbf{1}\{Q_i = q, W_i = w\} \times D_i + u_i. \end{aligned} \quad (6)$$

where $\mathbf{1}\{Q_i = q, W_i = w\}$ is a dummy which is one if the patient was either treated in or waited for w weeks and belongs to type q. We provide a proof of this equivalence in Appendix B. Thus, in practice, we use the above linear equation to estimate the CATTs by OLS, which provides a simple framework for inference on $\{\theta(w, q)\}$. For example, one can simply test the homogeneity hypothesis on the CATTs, where the null hypothesis states that all CATTs are equal, using a Wald test.

[39] The results are reported for a minimum of 100 observations per treatment and control group.

ATT with data-driven sources of heterogeneity. To further explore heterogeneities without constraining the analysis to a set of pre-selected sources, we use the *generalised random forest* (Athey et al., 2019).

The algorithm recursively splits the sample into two bins, with each bin subsequently split further. This process continues iteratively, creating a tree-like structure. Somewhat similar to our nonparametric approach, the bins share the same realisations of covariates. The difference is that the partitioning into bins does not rely on the researcher's choice of covariates but is done in a data-driven way to maximise heterogeneity in within-bin treatment effect estimates across bins. This partitioning process is repeated multiple times, generating several trees. The individual treatment effect estimates from these trees are then averaged to reduce variance, ultimately providing individual-level CATT estimates.[40]

To take it to a more familiar context, a forest can be thought of as a nearest-neighbour method, in that it performs the estimation using a weighted average of observations in the "neighbourhood". However, in contrast to classical methods, the neighbourhood is defined in a flexible data-driven way. By treating the forest as an adaptive nearest-neighbour estimator, Athey et al. (2019) show that the estimates of the generalised random forest are consistent and asymptotically normal.[41]

5 Results

5.1 Average Treatment Effects

Table 1 shows the average treatment effects on our main outcomes – reliable recovery, improvement, and deterioration – using our default control group (50th percentile of waiting time). Columns 1, 3, and 5 show models without controls, Columns 2, 4, and 6 report the results for models that control for psychological-

[40] In practice, the algorithm uses different subsamples for binning and treatment effect estimation. This is known as the *honest* approach that serves to avoid overfitting and biasing estimates. As a technical note, we assume that potential outcomes are independent of treatment assignment, conditional on the set of covariates. Our algorithm incorporates this conditioning by orthogonalising the treatment indicator and the outcomes and calculating the within-bin treatment effect estimate from regression residualised outcomes on residualised propensity scores. This technique is sometimes known as *double machine learning*, which is particularly important for our application given that we use observational rather than experimental data. For further details on double machine learning, see Chernozhukov et al. (2018).

[41] See Athey et al. (2019) and Wager and Athey (2018) for a detailed account of the algorithm and its corresponding asymptotic theory.

therapy, individual, service, and local-area characteristics as well as service and time fixed effects, which are our preferred models.

Table 1: Average Treatment Effects on Mental Health

	Reliable Recovery (0-1)		Reliable Improvement (0-1)		Reliable Deterioration (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.443***	0.431***	0.388***	0.377***	-0.085***	-0.084***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.001)
Therapy Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Service Controls	No	Yes	No	Yes	No	Yes
Local-Area Controls	No	Yes	No	Yes	No	Yes
Service Fixed Effects	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes
Number of Individuals	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792
Treatment Group	618,574	618,574	618,574	618,574	618,574	618,574
Control Group	628,218	628,218	628,218	628,218	628,218	628,218
R Squared	0.228	0.289	0.152	0.187	0.022	0.064

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

We find that being treated within the IAPT programme significantly improves patients' mental health outcomes. In particular, it increases the likelihood to reliably recover by about 43 and to reliably improve by about 38 percentage points, on average, while reducing the likelihood to deteriorate by about 8 percentage points.[42] The latter suggests, in particular, that the programme has, on average, no adverse effects, which is a contribution in its own right addressing recent concerns that well-intended psychological interventions can have unintended consequences (cf. Harvey et al., 2023). Point estimates and associated standard errors are remarkably similar regardless of whether we include covariates or not.

Treatment Intensity. Next, Table 2 presents the results of the main streams of the IAPT programme's stepped-care model, by splitting Table 1 into its different

[42] Overall, 53% of patients reliably recover at the end of the treatment, 74% reliably improve, and 5% reliably deteriorate.

treatment intensities. Panel A shows the average treatment effects for patients in the low-intensity treatment, Panel B for those in the high-intensity treatment, and Panel C for those who are stepped up from initially low to then high intensity. The full results, which include smaller streams (patients who are stepped down from initially high to then low intensity or patients for whom the intensity was not recorded), are presented in Appendix Table F.I.

Table 2: Average Treatment Effects on Mental Health by Treatment Intensity

	Reliable Recovery (0-1)		Reliable Improvement (0-1)		Reliable Deterioration (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low Intensity						
Treatment	0.440***	0.430***	0.368***	0.360***	-0.078***	-0.078***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Number of Individuals	491,942	491,942	491,942	491,942	491,942	491,942
Treatment Group	245,433	245,433	245,433	245,433	245,433	245,433
Control Group	246,509	246,509	246,509	246,509	246,509	246,509
R Squared	0.216	0.284	0.138	0.179	0.020	0.053
Panel B: High Intensity						
Treatment	0.439***	0.429***	0.404***	0.393***	-0.084***	-0.084***
	(0.008)	(0.008)	(0.007)	(0.006)	(0.003)	(0.002)
Number of Individuals	275,990	275,990	275,990	275,990	275990	275990
Treatment Group	136,379	136,379	136,379	136,379	136379	136379
Control Group	139,611	139,611	139,611	139,611	139611	139611
R Squared	0.234	0.298	0.164	0.198	0.021	0.069
Panel C: Step Up (Low to High Intensity)						
Treatment	0.449***	0.435***	0.404***	0.385***	-0.095***	-0.090***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Number of Individuals	388,136	388,136	388,136	388,136	388136	388136
Treatment Group	191,868	191,868	191,868	191,868	191868	191868
Control Group	196,268	196,268	196,268	196,268	196268	196268
R Squared	0.244	0.296	0.164	0.200	0.024	0.078
Therapy Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Service Controls	No	Yes	No	Yes	No	Yes
Local-Area Controls	No	Yes	No	Yes	No	Yes
Service Fixed Effects	No	Yes	No	Yes	No	Yes

Time Fixed Effects	No	Yes	No	Yes	No	Yes

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In line with our previous results, we find that treatment significantly increases the likelihood to reliably recover and improve while decreasing the likelihood to deteriorate in each treatment intensity, by about the same size. Similar impacts across treatment intensities suggest that the allocation of patients by trained therapists to different treatment intensities results in an appropriate patient-therapy fit.

The similarity of recovery across treatment intensities may tempt one to think that different intensities are redundant if these lead to similar outcomes. Note, however, that patients in different treatment intensities have different therapeutic needs. Appendix Table F.II replicates Table 2 by replacing our main outcomes – reliable recovery, improvement, and deterioration – with changes in underlying PHQ-9 and GAD-7 scores as well as changes in our mental health index. As seen, patients in the high-intensity treatment show much stronger symptom reductions in their PHQ-9 and GAD-7 scores as well as in our mental health index, and so do patients for whom treatment intensity is changed during their course of treatment. This suggests that therapists (re-)allocate patients to suitable treatments, if needed, and that different treatment intensities cater to different needs, which is also reflected in differences in underlying therapies and mechanisms, as outlined in Section 2.

Work and Social Life Outcomes. Finally, we look at ripple effects of improved mental health on patients' work and social life. We do so in two ways: first, we look at changes in the *Work and Social Adjustment Scale* (Mundt et al., 2002). Second, we look at changes in employment as a result of treatment. We are particularly interested in patients who report being unemployed, being long-term sick, or receiving statutory sick pay at the start of treatment, and hence look at the change from being unemployed to being employed, from being long-term sick to being employed, and from receiving statutory sick pay to not.

Appendix Table F.III shows our average treatment effects on the *Work and Social Adjustment Scale*. As seen, being treated within the IAPT programme significantly and strongly reduces patients' perceived functional impairment due to mental ill health, decreasing overall impairment by 5.7 points on a 0-to-40 scale (65% SD of

the pre-treatment score in the treatment group), driven in almost equal parts by reductions in each domain of life (each between one and 1.4 points on a 0-to-8 scale), including work (-1.1 points, 42% SD of the pre-treatment score). That is, patients who undergo psychological therapy report to function better in all domains of life afterwards.

Appendix Table F.IV shows our average treatment effects on employment as a result of treatment.[43] As seen, being treated within the IAPT programme has, overall, no or only negligible effects on employment. However, when restricting our sample to patients who were unemployed or long-term sick at the start of treatment, we find that being treated significantly increases their likelihood to be employed by three and two percentage points, respectively, while decreasing their likelihood to receive statutory sick pay by three percentage points. Although these effects are small, they are very short-term, as employment is last measured at the beginning of the last clinical session, and the typical course of treatment lasts between six to twenty weeks. That is, there is evidence for small, positive short-term impacts on employment of patients who undergo psychological therapy.

5.2 Robustness Checks

We conduct a wide range of robustness checks for our average treatment effects obtained from Equation 4.

Selection on Outcome and Session Value Added. So far, we restricted our estimation sample to patients who completed a course of treatment, consisting of initial assessment and at least two subsequent clinical sessions. There could be concern that the timing of the last clinical session may be endogenous, i.e. therapists may discard patients after they have reached a particular threshold of recovery, and patients then leave the programme). To check for selection on the outcome, we exploit our session-by-session patient-level outcome data to redefine the completion of treatment, to not pertain to the last but to the penultimate clinical session or

[43] Different from our previous analysis, we estimate treatment effects by regressing post-treatment employment on pre-treatment employment and our treatment dummy, all other things being the same. This is because patients can be either employed or not, respectively, at the start and at the end of treatment, which may, when switching from employed to not employed, result in a difference in our employment outcome of minus one, which cannot be estimated using a linear probability model. We circumvent this issue using a value-added model. Note that all of our previous results continue to hold when using this alternative model.

even to the one before. Arguably, the latter two sessions should not be susceptible to selection on the outcome. Appendix Table G.I shows that, for both redefinitions of treatment completion, we continue to detect strong, positive impacts of treatment on mental health. Naturally, impacts are somewhat reduced, as we omit clinical sessions with therapeutical contents, which are particularly relevant for courses of treatment with a lower number of total sessions. Note that the number of observations drops because we lose particularly short courses of treatment. A related concern regarding selection on the outcome could be that therapists may switch patients from, say, low to high intensity because their health may deteriorate. When grouping together low-intensity and step-up as well as high-intensity and step-down, here too we continue to detect strong, positive impacts of treatment on mental health (Appendix Table G.II).

To further address potential selection on the outcomes, i.e. the total number of sessions or treatment duration, we estimate a model with the same selection on outcomes for treatment and control groups. Appendix Table G.III additionally controls for the total number of clinical sessions and the total duration of treatment in weeks. As seen, our results remain robust. Note that we routinely control for a large set of pre-treatment characteristics including patients' psychological-therapy characteristics, including their referral type (whether they were referred by their GP or via self-referral), the time between referral and initial assessment in weeks, treatment mode (in person or online), whether they where prescribed additional medication (e.g. antidepressants), their initial diagnosis (depression and/or anxiety, including its type), and their treatment intensity (low or high-intensity treatment, and whether they changed their intensity during the course of treatment).

Our session-by-session patient-level outcome data also allow us to look at the relative impact and value added of separate sessions cumulatively over the course of treatment. Appendix Figure G.I shows reliable recovery for different bins of sessions, separately for patients who have a total of three, seven, nine, and 13 sessions, equivalent to the 25th, 50th, 75th, and 90th percentile in the overall session distribution. For example, *Sessions 5* for patients who have a total of nine sessions is the value added, in terms of reliable recovery, of having attended five out of the nine sessions, while *Sessions 9* is the value added of having attended all sessions. In each case, the control group is restricted to patients who have the same number of total sessions. We observe that the relative session value added is lower for patients who have a higher total number of sessions. For example, the value added of having at-

tended five sessions is only nine percentage points for patients who have a total of 13 sessions, yet 14 percentage points for those who have a total of nine and even 22 percentage points for those who have a total of seven sessions. That is, the rate of improvement from mental ill health is lower the higher the number of total sessions. Moreover, most of the session value added, in terms of reliable recovery, is generated during the last two sessions, regardless of the total number of sessions. Appendix Figures G.II and G.III replicate Figure G.I for reliable improvement and deterioration, showing a similar pattern.

Session Spacing. Typically, patients are meant to have one session per week, though the median number of weeks between sessions is 1.6 (mean of 2.0 and standard deviation of 1.6), depending on patients' availability. Appendix Table G.IV shows that our results are robust to additionally controlling for the average number weeks between sessions.

Appendix Table G.V then makes full use of our session-by-session patient-level outcome data to look at the spacing of sessions over the course of treatment, by re-estimating our average treatment effects by percentile of the number of weeks between sessions. We differentiate the lower 25th percentile (session spacing of 1.1 weeks) from the upper 25th (2.4 weeks) and the upper 10th percentile (3.5 weeks). As seen, reliable recovery and improvement are slightly higher the lower the number of weeks between sessions. Although the variation in session spacing is rather small, a caveat of this analysis is that session spacing may be partly endogenous, for example if reasons for rescheduling sessions are correlated with aspects of mental health.

Repeat Enrolment. Repeat enrolment may be a sign of poor mental health amongst dropouts. We observe that, in total, 187,148 patients (about 15%) enrol more than once in the IAPT programme. To check whether waitlisted patients in our default control group drop out and present again later, Appendix Table G.VI regresses the likelihood to enrol more than once in the programme on the weeks on the waitlist amongst control-group patients, with and without controls. As seen, the weeks on the waitlist have negligible predictive power for repeat enrolment. As patients who repeatedly enrol may be special in other ways too, Appendix Table G.VII excludes them altogether from our analysis. As seen, our results remain similar to before.

Selective Attrition. We address potential concerns about selective attrition in detail in Appendix Section H, where we show that the programme remains highly effective for reliable improvement and reliable recovery even under extreme assumptions on the outcomes of patients who discontinue treatment or drop out, though the magnitude of the effects varies under different assumptions. The programme also continues to significantly reduce the likelihood of reliable deterioration, except in the scenario with the most extreme assumptions, i.e. that all dropped-out respondents who would have been assigned to the treatment group experience deterioration and all those dropping out of the control group experience recovery.

Other Robustness Checks. Our results are robust to different definitions of treatment and control group when varying treatment and corresponding waiting time durations. In Section 4.1, we have shown that waiting times are not systematically related to the number of sessions, treatment duration, or the severity of depression or anxiety symptoms at the start or end of treatment. So far, we used the median waiting time as a cut-off to define treatment and control group. Appendix Table G.VIII now uses, instead of the 50th percentile of waiting time, the 25th, 75th, and 90th percentile, respectively, to allocate patients into treatment and control group. The estimates remain similar.

Our results are also robust to different models, samples, and outcomes. Appendix Table G.IX Column 1 estimates a logit instead of a linear probability model. Columns 2 and 3 selectively exclude certain mental health problems: Column 2 excludes patients who have substance abuse disorders as these exhibit different behaviours when on a waitlist than others (J. Williams & Bretterville-Jensen, 2022), whereas Column 3 focuses only on patients who have depression and anxiety disorders, the main target population of the IAPT programme and vast majority. Finally, Columns 4 to 6 replace our main outcomes – reliable recovery, improvement, and deterioration – with changes in PHQ-9 and GAD-7 scores as well as changes in our mental health index. In all cases, our results remain robust.

5.3 Heterogeneous Treatment Effects

We now focus on the CATT estimates of our main outcomes: reliable recovery, reliable improvement, and reliable deterioration. The CATT estimates presented here are based on our default control group based on the 50th percentile of waiting

time.

Results with pre-selected sources of heterogeneity. We selected potential sources of heterogeneity based on earlier findings on characteristics correlated with treatment outcomes and include treatment intensity, severity of the symptoms at the initial assessment, ethnicity, religion, presence of a long-term health condition, service size, service funding, and area deprivation.[44] [45] Figure 3 presents the histograms of our heterogeneous treatment effect estimates produced by the matching approach described in Section 4.2.2. The vertical dashed line represents the estimated average treatment effect.[46]

We find statistically significant heterogeneity in the treatment effect across sub-populations. By studying the sub-populations with the lowest and the highest treatment effects, we show that, although the programme increases the probability of recovery and improvement for all sub-populations of patients considered, there are some for whom the programme does *not* decrease the probability of deterioration.

[44]The covariates are selected based on the following earlier studies. Gyani et al. (2013): course intensity, a binary indicator for severity of symptoms above the median at initial assessment, and severity as a z-score constructed from PHQ-9 and GAD-7 scores at initial assessment; Moller et al. (2019): ethnicity, religion, and presence of a long-term health condition; Clark (2018) and Gyani et al. (2013): binary indicators for service size by number of staff and service funding per patient above the median; Delgadillo et al. (2016): a binary indicator for area deprivation above the median.

[45]After eliminating observations that do not have a match, we are left with 76% of the original sample or 947,457 observations spread over 1,171 matched sub-populations. The summary statistics of the outcomes and covariates in the original and the final sample are presented in Appendix Table I.I. The sub-populations are well-balanced in terms of the number of treated and control observations. The share of treated observations varies from 22% to 82% with an average of 49%.

[46]The estimators described in Section 4.2.2 can also be used to estimate the ATT by aggregating CATTs. These average effects, both from using pre-selected or data-driven observed heterogeneities, are in line with the results of the ATT estimates presented in Section 5.1. The nonparametric matching approach estimates the ATT of the programme to be 0.434 (0.001) for reliable recovery, 0.379 (0.001) for reliable improvement, and -0.086 (0.001) for reliable deterioration. In our ML analysis, the ATT is estimated to be 0.436 (0.001) for reliable recovery, 0.383 (0.001) for reliable improvement, and -0.089 (0.001) for reliable deterioration.

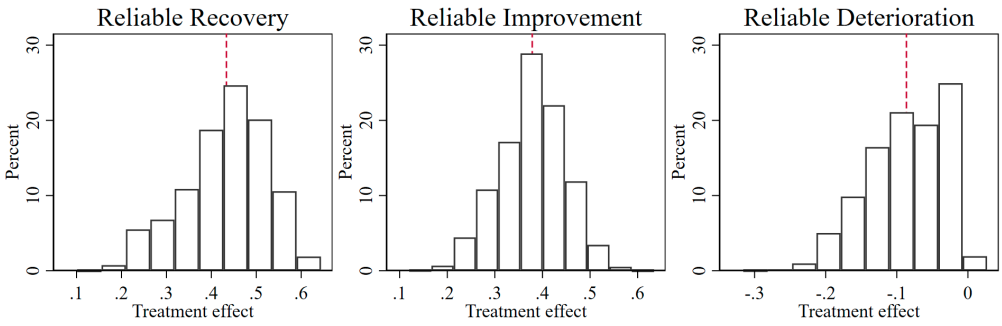


Figure 3: Conditional Average Treatment Effects – Matching Approach

Note: The histograms plot the distributions of conditional average treatment effects, which are estimated as a difference in average outcomes between treatment and control group observations in sub-populations formed by combinations of psychological-therapy, individual, service, and local area characteristics. The estimates are weighted by the number of treatment-group observations in each sub-population.

To understand in more detail which specific characteristics are systematically associated with better or worse treatment effects, we estimate the following model:

$$\begin{aligned} \Delta Y_i = \beta_0 + \beta_1 D_i + \sum_q \beta_q Q_i + \sum_w \beta_w W_i \\ + \sum_q \gamma_q Q_i D_i + \sum_w \gamma_w W_i D_i + u_i, \end{aligned} \tag{7}$$

where, to assess how the effect of the treatment differs for different sub-populations, the treatment dummy, D_i, is interacted with the psychological-therapy and individual as well as service and local-area characteristics, Q_i. γ_q in Equation 7 is informative on how treatment effects vary for different patients. Table 5.3 presents the estimates of the coefficients on the interaction between these characteristics and the treatment dummy. The full results are presented in Appendix Table I.II.

We find moderate heterogeneity in treatment effects across different intensities of treatment, with patients in high-intensity treatments being more likely to reliably improve and less likely to reliably deteriorate.

Table 3: Heterogeneous Treatment Effects on Mental Health: Pre-Defined Sources

	Reliable Recovery	Reliable Improvement	Reliable Deterioration

	(1)	(2)	(3)
*Reference Category: Course Intensity: Low Intensity * Treated*			
High Intensity * Treated	0.002	0.039***	-0.016***
	(0.002)	(0.003)	(0.002)
Step Down * Treated	0.003	0.017	0.001
	(0.010)	(0.012)	(0.007)
Step Up * Treated	-0.018***	0.021***	-0.019***
	(0.002)	(0.003)	(0.002)
Undefined * Treated	-0.036***	-0.066***	-0.011
	(0.012)	(0.013)	(0.008)
Severity above Median * Treated	-0.088***	-0.071***	0.096***
	(0.002)	(0.002)	(0.001)
Deprivation above Median * Treated	-0.027***	0.004**	-0.014***
	(0.002)	(0.002)	(0.001)
Long-Term Health Condition * Treated	-0.026***	0.003	-0.008***
	(0.003)	(0.003)	(0.002)
Service Size above Median (Number of	-0.004**	-0.006***	0.003**
Staff) * Treated	(0.002)	(0.002)	(0.001)
Service Funding per Patient above	0.021***	0.026***	-0.010***
Median * Treated	(0.002)	(0.002)	(0.001)
*Reference Category: Religion: Christian * Treated*			
Not Religious * Treated	-0.025***	-0.013***	0.007***
	(0.003)	(0.003)	(0.002)
Other Religion and Missing * Treated	-0.030***	-0.021***	0.006***
	(0.003)	(0.004)	(0.002)
*Reference Category: Ethnicity: White British * Treated*			
Other * Treated	-0.018**	0.000	-0.016***
	(0.007)	(0.008)	(0.005)
Missing * Treated	-0.055***	-0.030***	0.002
	(0.003)	(0.003)	(0.002)
Number of Individuals	947,547	947,547	947,547
R Squared	0.26	0.16	0.05

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. The full results are presented in Appendix Table I.II. *** p<0.01, ** p<0.05, * p<0.1.

We also find that patients with higher severity at the beginning of treatment are less likely to reliably recover. This is perhaps not surprising, given that patients with more severe symptoms need to show considerably more improvement to be classified as reliably recovered. We see that patients with higher severity are also less likely to reliably improve and more likely to deteriorate.

In terms of heterogeneity by patient characteristics, patients with long-term

health conditions are around three percentage points less likely to reliably recover. The direction of the gap confirms findings by Moller et al. (2019) for the difference in treatment outcomes. However, the difference in outcomes found by Moller et al. (2019) is significantly higher in magnitude, at 14 percentage points. This likely indicates that a large part of the difference estimated by Moller et al. (2019) is due to the difference in natural recovery rates. We also find that non-White-British patients, or those whose ethnicity is not recorded, perhaps reflecting the data collection quality, are less likely to reliably recover. Non-religious patients are less likely to reliably recover or improve and more likely to deteriorate.

For area characteristics, patients in more deprived areas are less likely to reliably recover, which is in line with the findings of Delgadillo et al. (2016). The effect size is similar to having a long-term health condition. However, these patients are moderately less likely to deteriorate. For service characteristics, patients in larger services are slightly less likely to reliably recover or improve and more likely to deteriorate. Patients in services with higher funding are more likely to reliably recover or improve and less likely to deteriorate.

In sum, the categories of patients that typically have lower mental health outcomes, e.g. living with a disability, also benefit less from the programme. Area deprivation is related negatively to patient outcomes, whilst funding of the services is positively related.

Results with data-driven sources of heterogeneity. Figure 4 presents the histograms of our heterogeneous treatment effect estimates produced by the generalised random forest described in Section 4.2.2.[47] The vertical dashed line again represents the estimated average treatment effect. The algorithm identifies some heterogeneity in treatment effects for all three outcomes. As in the previous approach, the distributions of treatment effects for reliable recovery and improvement are bounded away from zero, whilst reliable deterioration is not.

[47]The forest includes 1,000 trees. Each tree is built using 10% of the sample. The minimum bin size is 500 observations. To improve the performance of the algorithm, some smaller covariate groups were merged together.

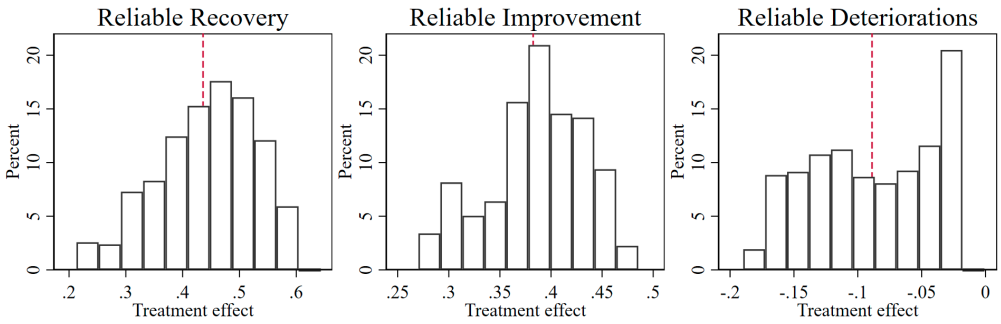


Figure 4: Conditional Average Treatment Effects – Generalised Random Forest

Note: The histograms plot the distributions of conditional average treatment effects estimated with generalised random forest.

To understand which sup-populations benefit most and least from treatment, we study the average levels of psychological-therapy, individual, service and local-area characteristics in sup-populations formed by quartiles of the estimated treatment effect distribution. The first quartile includes individuals whose estimated treatment effects were in the bottom 25% of all estimated individual treatment effects, the second to fourth quartiles are formed accordingly. Appendix Tables I.III, I.IV, and I.V report the results for all covariates. Here, we discuss covariates that show substantial difference across quartiles.

First, the results of the data-driven approach support the findings from the previous section. Patients who are less likely to recover tend to exhibit more severe symptoms at the start of treatment. They are also more likely to live in deprived areas, attend larger services as indicated by the number of patients, or have their gender, ethnicity, sexual orientation, or disability status not recorded. These patterns largely hold for reliable improvement, where, in addition, patients who are less likely to improve attend services that, on average, have lower funding. Patients for whom the programme is less effective in terms of reducing deterioration are more likely to experience more severe symptoms at the start of treatment and to live in more deprived areas.

Second, the ML algorithm provides two new insights: patients who recover less are more likely to be unemployed at the start of treatment, whilst patients who recover more are more likely to self-refer. To study these sources in a more systematic way, we estimate a modification of Equation 4, where the treatment dummy is now interacted with each of the two newly identified sources. Table 5.3 reports the results for reliable recovery, reliable improvement, and reliable deterioration.

Table 4: Heterogeneous Treatment Effects on Mental Health: Sources Identified in the ML Algorithm

	Reliable Recovery (1)	Reliable Improvement (2)	Reliable Deterioration (3)
Unemployed vs. Employed			
Treated	0.468***	0.387***	-0.085***
	(0.004)	(0.004)	(0.001)
Unemployed	-0.012***	-0.083***	0.029***
	(0.001)	(0.003)	(0.002)
Unemployed * Treated	-0.133***	-0.042***	0.009***
	(0.004)	(0.004)	(0.002)
Number of Individuals	828,356	828,356	828,356
R Squared	0.30	0.19	0.06
Self Referral vs. Non-Self Referral			
Treated	0.404***	0.373***	-0.089***
	(0.005)	(0.004)	(0.002)
Self Referral	0.016***	0.043***	-0.022***
	(0.006)	(0.006)	(0.004)
Self Referral * Treated	0.038***	0.006	0.007***
	(0.005)	(0.004)	(0.002)
Number of Individuals	1,246,792	1,246,792	1,246,792
R Squared	0.29	0.19	0.06
Therapy Controls	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Service Controls	Yes	Yes	Yes
Local-Area Controls	Yes	Yes	Yes
Service Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Unemployment emerges as a significant source of heterogeneity for both patients awaiting treatment and those undergoing it, even after controlling for a rich set of covariates, including the severity of symptoms. The first panel of Table 5.3 presents the results of the comparison of employed and unemployed patients.[48] Unemployed patients are 1.2 percentage points less likely to recover naturally while

[48]The number of observations is lower than in other specifications because we exclude individuals with other employment statuses.

on the waitlist. Additionally, they are 13.3 percentage points less likely to recover as a result of treatment, which represents 30% of the programme's average treatment effect. Unemployed individuals are also less likely to reliably improve and more likely to deteriorate, thought the magnitude of the estimate for the latter is small. Earlier studies generally agree that unemployment negatively affects mental health (Cygan-Rehm et al., 2017), highlighting the need for public policy to prioritise early prevention of mental health issues amongst the unemployed. We provide suggestive evidence that unemployed patients, on average, respond to treatment less favourably than their employed counterparts.

Self-referral is an unusual and possibly controversial feature of the IAPT programme.[49] The possibility to self-referral contrasts with other healthcare in the UK as well as with healthcare provision in other countries, such as Denmark or the Netherlands. Hence, the IAPT dataset provides a unique opportunity to study how these patients respond to treatment.[50]

The second panel of Table 5.3 presents the results of the comparison of treatment effects for self-referred patients with those who accessed treatment via other pathways. We find that patients who self-referred are 1.6 percentage points more likely to recover while on the waitlist and 3.8 percentage point more likely to recover as the result of treatment, which represents 8% of the average treatment effect. Self-referred patients are also more likely to reliably improve and less likely to reliably deteriorate while on the waitlist, though these effects are similar to non-self-referral patients.These findings underline the importance of using causal methods for treatment effect estimation: more favourable outcomes would appear in a correlational analysis from differences in natural recovery rates rather than a difference in treatment effect estimates.

In sum, this is suggestive evidence that the option of self-referrals improves access to mental healthcare. Self-referred patients did so, on average, 364 days after the onset of symptoms, whilst patients who were referred via other pathways

[49] See Brown et al. (2010) for a discussion of advantages, e.g. improved access, and disadvantages, e.g. system overload due to relatively minor cases, of self-referrals.

[50] Anecdotal evidence suggests that some patients who self-referred to the programme did so at the recommendation of their GP. Since participation in the programme demands a certain level of commitment, clinicians might use self-referral as a way to ensure that patients are more likely to remain engaged if they choose to join independently. In our data, we cannot differentiate between those who were informally referred by their GP and those who discovered the programme on their own, so we analyse these groups together. 71.5% of all patients in our sample self-referred. All patients are assessed in the same way, regardless of the referral type.

waited, on average, 461 days.[51]

5.4 Cost-Benefit Calculation

We perform a simple and conservative cost-benefit calculation. In doing so, we compare being treated within the IAPT programme to business-as-usual prior to IAPT, which in most cases was no treatment at all.[52] Note that we routinely control for medication usage in treatment and control, as pharmacology could be a complement (or substitute) to IAPT.[53]

We appraise benefits and costs over a three-year period. Looking at benefits first, we found that treatment significantly decreases PHQ-9 scores by about five points, on average (cf. Table G.IX). A five-point decrease in PHQ-9 scores, in turn, corresponds to an increase in the *EuroQol-5 Dimensions (EQ-5D)* index of about 0.03 points (Furukawa et al., 2021).[54] UK Government values 1.0 QALYs at £70,000 (in 2019 prices) (Treasury, 2022). For simplicity, let us assume that benefits accrue linearly over the course of treatment, which typically takes two months (corresponding to, on average, eight sessions, with one session per week). Unfortunately, the IAPT data do not include a long-run follow-up, so we cannot say something about relapse rates. However, the literature suggests that relapse rates after CBT are generally quite low (compared to alternative forms of treatment), typically only around 40% six years after the end of treatment (cf. Fava et al., 2004). To be conservative, let us assume that relapse is instantaneous. With these considerations in mind, we obtain monetised benefits of (((0.00 + 0.03) / 2) * 2 months + (0.03 * 0.6) * 10 months) / 12 months + 0.03 * 0.6 * 2 years * £70,000 = £3,745 per patient over a three-year period. Next, we look at costs. Clark (2018) calculates fixed costs per patient of £680 if one divides the total investment into IAPT in 2015–2016 (the start of our

[51] We observe a self-reported date of symptom onset for approximately a third of the total sample. We remove observations where the date of onset was recorded after the referral date.

[52] Recall that the IAPT programme was launched precisely because there was a lack of treatment options for mild to moderate common mental health problems in the UK. Besides IAPT, there were (and are) community mental health services in the UK, but these are targeting primarily severe cases. To our knowledge, there exists no systematic evaluation of these services.

[53] We do not find that being treated within the IAPT programme reduces medication usage, if used (results available upon request).

[54] The EQ-5D is a routine instrument for the economic valuation of health-related quality of life, and its index is equivalent to a *Quality-Adjusted Life-Year (QALY)*, defined as one year in perfect mental and physical health. The index typically ranges from zero (representing death or a state equivalent to death, the worst possible health state) to one (representing full health, the best possible state). For more information on the instrument, see https://euroqol.org/.

observation period, after which the programme reached its stable 50% target recovery rate) by the total number of courses of treatment during that period. Hence, we obtain net benefits of £3,745 - £680 = £3,065 per patient three years after the end of treatment, or a benefit-cost ratio of 5.5.[55]

This is likely to be a conservative ratio, for several reasons. When it comes to benefits, it is unlikely that relapse is instantaneous (in fact, Fava et al. (2004) show that relapse in the first twelve months after treatment is only about 15%). Moreover, we only looked at mental health, our main outcome. It is well-documented that improvements in mental health can lead to improvements in physical health later on (cf. Cho et al., 2010). We did not include ripple effects either, for example spillovers on significant others (such as partners, children, or the wider community). Reichman et al. (2015) show that being out of depression can lead to significant improvements in relationships. It is likely that these additional benefits are substantial. Most importantly, when it comes to costs, we only included direct programme costs, neglecting public savings to the treasury in form of additional tax income and reduced (disability) benefits, nor did we include other savings to the healthcare system, which for the physically ill with co-morbid mental ill health can be substantial (Chiles et al., 1999; Clark & Layard, 2014). In a Norwegian RCT study of an IAPT-style intervention, Smith et al. (2024) find that income (and hence taxes) increase significantly two to three years after the end of therapy. This has also been found in a Spanish context (Munoz-Navarro et al., 2024).[56] This has led some authors to argue that public savings in terms of taxes and benefits alone would turn net public costs negative, making the programme pay for itself (Layard, 2016). As we observe patients only from start to end of therapy, we remain conservative and focus only on benefits in terms of mental health, which by themselves already suggest that the programme is worth it.

[55] An alternative way to look at benefits is to use *Wellbeing-Years (WELLBYs)* (Frijters & Krekel, 2021; Frijters et al., 2020). Noting that an increase in the EQ-5D-5L index of 0.03 points translates into an increase in WELLBYs of 0.11 (using a conversion factor of 1 EQ-5D-5L = 3.79 WELLBYs, see Frijters and Krekel, 2021 Table 3A.4), and that 1.0 WELLBYs is valued by HM Treasury at £13,000 (Treasury, 2021), we obtain monetised benefits of (((0.00 + 0.11) / 2) * 2 months + (0.11 * 0.6) * 10 months) / 12 months + 0.11 * 0.6 * 2 years * £13,000 = £2,550 per patient over a three-year period. This yields net benefits of £2,550 - £680 = £1,870 per patient three years after the end of treatment, or a benefit-cost ratio of 3.8.

[56] Serena (2022), however, finds no long-term labour market effects of extending health insurance coverage of psychotherapy in Denmark up to seven years after treatment. The author looks at prime-working-age patients between 18 and 37 years with mild-to-moderate symptoms.

6 Discussion and Conclusion

Mental ill health deeply affects individuals, their families, and society, while also posing a substantial economic challenge. Yet, it is often relegated to the sidelines of healthcare priorities, overshadowed by physical health issues. This does not have to be the case, as there are now successful examples of evidence-based programmes that address mental health needs.

This paper is the first to estimate the casual effects of a nationwide mental health service at a scale that well represents the English patient population. We use data on all patients who started treatment in the IAPT programme between April 2016 and December 2018 and exploit oversubscription and resulting exogenous variations in waiting times across services and over time for identification. Our empirical strategy can be used to evaluate the effectiveness of other public services too, in contexts where demand for services exceeds supply, leading to variations in waiting times.

Our findings show that a nationwide mental health service "works" in providing evidence-based psychological therapies to the general public in a cost-effective manner. We found that the programme provides significant mental health benefits. In particular, the mental health of treated patients' is more likely to have *reliably improved*, relative to a quasi-experimental waitlist control group, with a *reliable recovery* rate from mental ill health of about 43%. When exploring treatment heterogeneities, we found that, although the programme benefits all categories of patients we looked at, some groups benefit less than others, e.g. those living with a disability or those residing in deprived areas.

We also found evidence of positive short-term effects of treatment beyond mental health outcomes. In particular, treated patients report less impairment in their work and social life due to mental ill health. Amongst those who were initially unemployed or on long-term sick leave, treated patients are more likely to report being employed and less likely to receive statutory sick pay at the end of treatment. Although these impacts are small, it should be noted that more sizeable labour market effects of psychological therapy have been found to materialise only two to three years after the end of treatment (cf. Smith et al., 2024). Taken together, being treated within the IAPT programme significantly and strongly improves patients' lives.

Our causal estimates of the IAPT treatment's effectiveness generally align qualitatively with previous findings from non-causal studies, which also observed im-

provements in patients after receiving treatment. However, the magnitudes of our estimates are smaller. The reason for this difference is that our quasi-experimental approach is able to isolate the treatment effect from natural recovery that happens over time.

Our cost-benefit calculation shows that for every pound spent, the programme generates a benefit worth £5.50. This is likely to be a conservative estimate, as it does not account for ripple effects on physical health, employment and productivity, as well as spillovers on family members or the wider community. This estimate also overlooks potential future public savings in the form of additional tax income, reduced disability benefits, or savings to the healthcare system.

Our work has limitations, some of which offer promising opportunities for future research. A notable extension of our analysis would involve evaluating the long-term impacts of the programme by collecting data that extend beyond the end of therapy, when systematic patient-level outcome monitoring stops. This prospective analysis would align closely with the ethos of the IAPT programme, which, from its start, has adopted a scientific evaluation mindset.

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Appendix

A Summary Statistics

Table A.I: Summary Statistics – Outcomes at Initial Assessment

	Average		Treatment Group		Control Group	
	Mean	SD	Mean	SD	Mean	SD
PHQ-9	15.765	5.497	15.688	5.504	15.841	5.490
GAD-7	14.389	4.338	14.310	4.350	14.468	4.324
Mental Health Index	0.434	0.685	0.421	0.686	0.446	0.683
Work and Social Adjustment Scale - Overall	20.044	9.229	19.849	9.153	20.236	9.298
Work and Social Adjustment Scale - Work	4.372	2.596	4.380	2.587	4.365	2.604
Work and Social Adjustment Scale - Home Management	3.620	2.393	3.584	2.369	3.656	2.416
Work and Social Adjustment Scale - Social Leisure	4.492	2.447	4.438	2.431	4.545	2.461
Work and Social Adjustment Scale - Private Leisure	3.687	2.541	3.634	2.515	3.739	2.564
Work and Social Adjustment Scale - Close Relationships	3.957	2.468	3.916	2.451	3.996	2.483
Employed (As Opposed To Unemployed)	0.857	0.350	0.858	0.349	0.856	0.351
Employed (As Opposed To Long-Term Sick)	0.880	0.324	0.894	0.308	0.867	0.339
Receiving Statutory Sick Pay	0.077	0.267	0.084	0.278	0.071	0.257

Table A.II: Summary Statistics – Covariates at Initial Assessment

Covariate	Mean	SD
Therapy Controls		
Mental Health Index (Pre-Treatment)	0.434	0.685
Referral: Acute Secondary Care	0.007	0.081
Child Health	0.000	0.016
Employer	0.000	0.022
IAPT Stepped Care	0.004	0.064
Independent/Voluntary Sector	0.004	0.062
Internal Referral	0.000	0.010
Internal Referral From Inpatient Service (Within Own NHS Trust)	0.000	0.009
Internal Referral from Community Mental Health Team	0.018	0.134
Justice System	0.001	0.031
Local Authority Services	0.001	0.033
Other	0.029	0.168
Other Mental Health NHS Trust	0.000	0.018
Primary Health Care	0.217	0.412
Self-Referral	0.715	0.451
Transfer by Graduation (Within Own NHS Trust)	0.000	0.009
Unknown	0.000	0.001
Referral Time Lapsed	3.029	3.713
Treatment Mode: Face-to-Face Communication	0.279	0.449
Telephone	0.684	0.465
Telemedicine	0.009	0.096
Talk Type for Person Unable to Speak	0.000	0.009
E-Mail	0.017	0.128
Text Messaging	0.002	0.040
Online Triage	0.000	0.004
No Response	0.008	0.092
Medication: Prescribed But Not Taking	0.045	0.208
Prescribed and Taking	0.477	0.499
Not Prescribed	0.415	0.493
No Response	0.063	0.243
Initial Diagnosis: Agoraphobia	0.007	0.083
Generalised Anxiety Disorder	0.221	0.415
Mixed Anxiety and Depressive Disorder	0.111	0.314
Obsessive-Compulsive Disorder	0.023	0.149
Other Anxiety or Stress-Related Disorder	0.039	0.193
Panic Disorder (Episodic Paroxysmal Anxiety)	0.028	0.166
Post-Traumatic Stress Disorder	0.041	0.198
Social Phobias	0.028	0.165
Specific (Isolated) Phobias	0.008	0.087
Depression	0.373	0.484
Invalid Data Supplied	0.001	0.031
Other Mental Health Problem	0.043	0.204
Other Recorded Problem	0.012	0.109
No Response	0.065	0.247

Treatment Intensity: Low Intensity	0.395	0.489
High Intensity	0.221	0.415
Step Up: Low to High Intensity	0.036	0.185
Step Down: High to Low Intensity	0.311	0.463
Multiple Changes in Intensity	0.037	0.189
Individual Controls		
Age	40.200	14.907
Gender: Male	0.247	0.432
Female	0.496	0.500
Non-Binary	0.000	0.022
No Response	0.256	0.436
Ethnicity: British	0.595	0.491
Irish	0.006	0.075
Any Other White Background	0.032	0.175
White and Black Caribbean	0.006	0.076
White and Black African	0.002	0.039
White and Asian	0.003	0.054
Any Other Mixed Background	0.006	0.077
Indian	0.014	0.116
Pakistani	0.010	0.099
Bangladeshi	0.003	0.056
Any Other Asian Background	0.007	0.086
Caribbean	0.010	0.098
African	0.007	0.085
Any Other Black Background	0.003	0.055
Chinese	0.002	0.041
Any Other Ethnic Group	0.009	0.094
No Response	0.287	0.452
Religion: Baha'i	0.000	0.010
Buddhist	0.002	0.050
Christian	0.190	0.393
Hindu	0.004	0.067
Jew	0.002	0.047
Muslim	0.020	0.139
Pagan	0.001	0.035
Sikh	0.004	0.060
Zoroastrian	0.000	0.008
Other	0.020	0.141
Not Religious	0.328	0.470
No Response	0.427	0.495
Sexual Orientation: Heterosexual or Straight	0.564	0.496
Gay or Lesbian	0.017	0.128
Bisexual	0.014	0.117
Other	0.009	0.094
No Response	0.397	0.489
Long-Term Health Condition: Yes	0.202	0.402
No	0.452	0.498
No Response	0.345	0.476
Employment Status: Employed	0.569	0.495

Unemployed and Seeking Work	0.095	0.293
Student	0.054	0.226
Long-Term Sick or Disabled	0.077	0.267
Homemaker Looking After a Family or Home	0.049	0.215
Not Receiving Benefits and Not Working	0.023	0.151
Unpaid Voluntary Work and Not Working or Actively Seeking	0.004	0.060
Retired	0.070	0.256
Refused	0.000	0.001
No Response	0.058	0.235
Services Member: Yes	0.000	0.015
Former	0.013	0.114
Not Former or Their Dependent	0.566	0.496
Dependent of Services Member	0.000	0.009
Dependent of Former Services Member	0.003	0.050
No Response	0.418	0.493
Service Controls		
CCG Number of Staff	116.387	90.115
CCG Number of Registered Patients	31,231.043	18,634.715
CCG Allocations Per Registered Patient	1,272.071	205.494
CCG Unemployment Rate	4.367	1.302
CCG Median Wage	457.250	69.245
Local-Area Controls		
Index of Multiple Deprivation: Average Rank	97.626	56.962
Income: Average Rank	16,810.156	4,453.149
Employment: Average Rank	16,724.635	4,657.311
Education, Skills, and Training: Average Rank	16,585.929	4,236.536
Health Deprivation and Disability: Average Rank	16,819.675	6,320.952
Crime: Average Rank	16,882.870	5,232.891
Barriers to Housing and Services: Average Rank	16,596.357	5,466.127
Living Environment: Average Rank	16,756.243	6,099.622

B Identification and Estimation Proofs

Proposition 1 proves that Assumptions 1 and 2 enable us to identify ATT and CATT.

Proposition 1. Under Assumptions 1 and 2, ATT and CATT are identified from the joint distribution of $(\Delta Y_i, D_i, X_i)$.

Proof. Under Assumption 1, expanding out $\Delta Y_i(0)$ and re-arranging gives:

$$E[Y_{it_2}(0)|D_i = 1, X_i] = E[Y_{it_1}(0)|D_i = 1, X_i] + E[\Delta Y_i(0)|D_i = 0, X_i].$$

By Assumption 2, the first term on the right-hand-side of the equation above becomes $E[Y_{it_1}(1)|D_i = 1, X_i]$, so that $E[Y_{it_2}(0)|D_i = 1, X_i]$ is equal to $E[Y_{it_1}|D_i = 1, X_i] + E[Y_{it_2} - Y_{it_1}|D_i = 0, X_i]$. Subsequently, CATT is identified from the joint distribution of $(\Delta Y_i, D_i, X_i)$ since,

$$\theta(X_i) = E[\Delta Y_i|D_i = 1, X_i] - E[\Delta Y_i|D_i = 0, X_i].$$

Hence, ATT is also identified because, by the law of iterated expectation, $\theta = E[\theta(X_i)|D_i = 1]$.■

The proof strategy used in Proposition 1 is the conditional version of the was used in Section 2 of J. Roth et al., 2023. J. Roth et al., 2023 also discussed the importance of another condition for nonparametric inference known as *Strong Overlap* (see their Assumption 7), which requires $P(D_i|X_i)$ to be uniformly bounded away from 1 almost surely and $E[D_i] > 0$. The Strong Overlap condition is clearly supported empirically by our estimating sample as we have numerous untreated patients for every combination of covariates observed and we have a large shares of treated and untreated patients unconditionally.

Proposition 2 proves our nonparametric estimator for $\{\theta(w, q)\}$ can be obtained from OLS estimation.

Proposition 2. OLS estimator of $\theta(w, q)$ in equation (6) is the same as the nonparametric matching estimator in Section 4.2.2.

Proof. We start by re-writing equation (6) as,

$$\Delta Y_i = \sum_{w,q} [\beta(w, q) + \theta(w, q) \times D_i] \times \mathbf{1}\{Q_i = q, W_i = w\} + u_i,$$

which has the following matrix representation,

$$\mathbf{\Delta Y} = \sum_{w,q} [\iota(w, q) : \mathbf{D}(w, q)] \begin{bmatrix} \beta(w, q) \\ \theta(w, q) \end{bmatrix} + \mathbf{u},$$

where $\mathbf{\Delta Y}$ is an $n \times 1$ vector of $\{\Delta Y_i\}_{i=1}^n$, $\iota(w, q)$ and $\mathbf{D}(w, q)$ are vectors of $1'$s and $0'$s such that elements in $\iota(w, q)$ and $\mathbf{D}(w, q)$ respectively take value 1 if and only if i corresponds to $(W_i = w, Q_i = q)$ and $(D_i = 1, W_i = w, Q_i = q,)$, and $\mathbf{u}$ is a vector of $\{u_i\}_{i=1}^n$. By construction, $[\iota(w, q) : \mathbf{D}(w, q)]$ is orthogonal

to $[\iota(w', q') : \mathbf{D}(w', q')]$ for all $(w, q) \neq (w', q')$, so that an orthogonal projection of $[\iota(w', q') : \mathbf{D}(w', q')]$ onto the space spanned by the columns of $[\iota(w, q) : \mathbf{D}(w, q)]$ is an $n \times 2$ matrix of $0'$s. Thus, applying the partition regression result (Frisch & Waugh, 1933), the OLS estimator from estimating (6) is the same as the OLS estimator obtained from estimating,

$$\Delta Y_i = \beta(w, q) + \theta(w, q) \times D_i + u_i,$$

when only observations of i's that correspond to $(W_i = w, Q_i = q)$ are used. In this case, the OLS estimator for $\theta(w, q)$ is the difference between the averages of the treatment and control values of the dependent variable (e.g., see Imbens and Rubin, 2015). This proves our claim. ■

C Summary Statistics on Waiting Times

Figure C.I: Histograms for Waiting Times in Weeks, All Treatments Intensities, All Years and by Year.

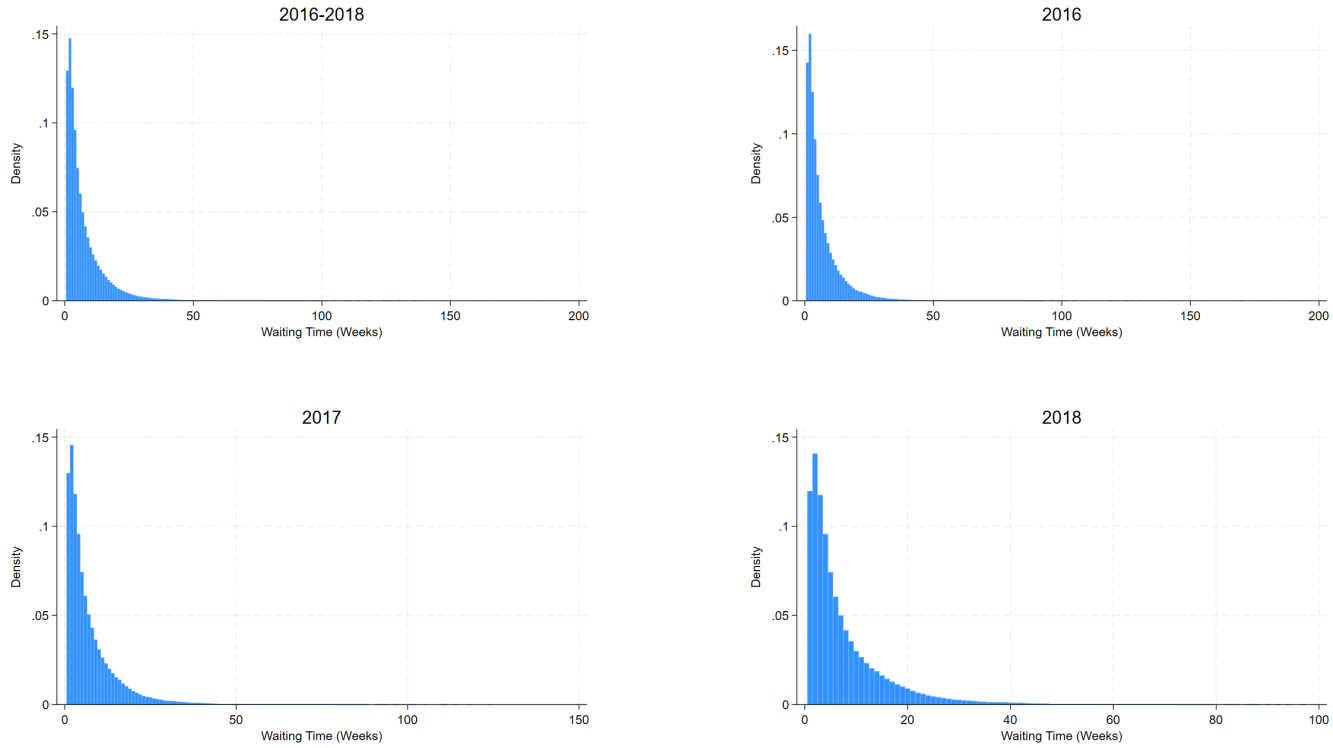
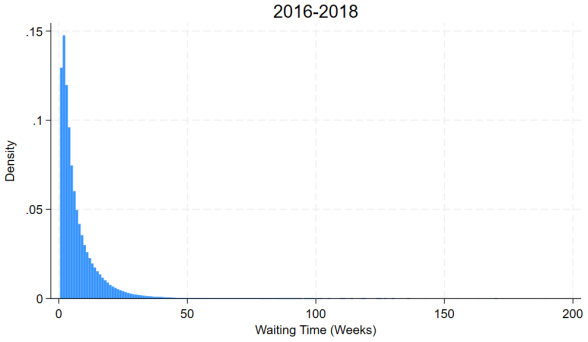
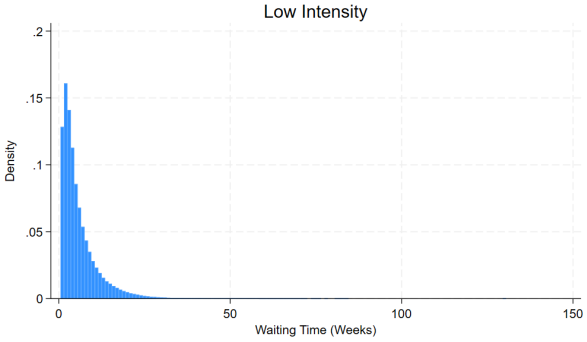


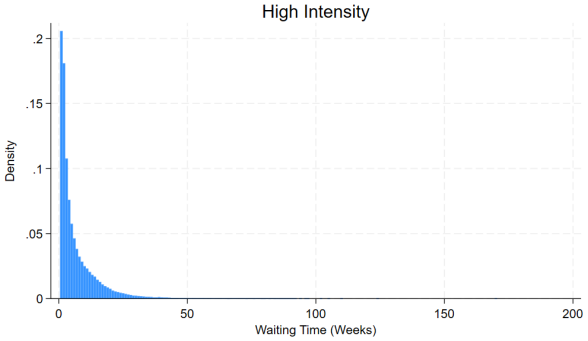
Figure C.II: Histograms for Waiting Times, by Treatments Intensities, All Years.



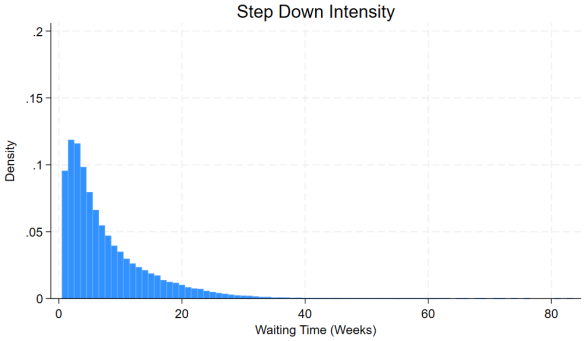
(a) All Intensities



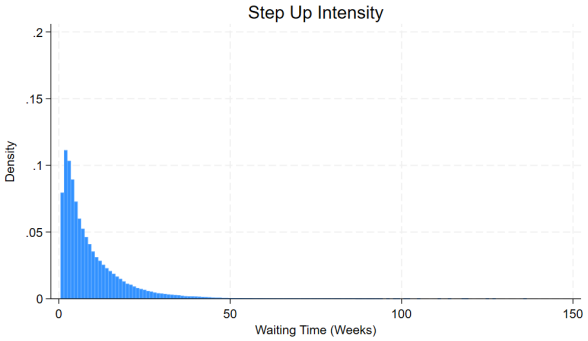
(b) Low Intensity



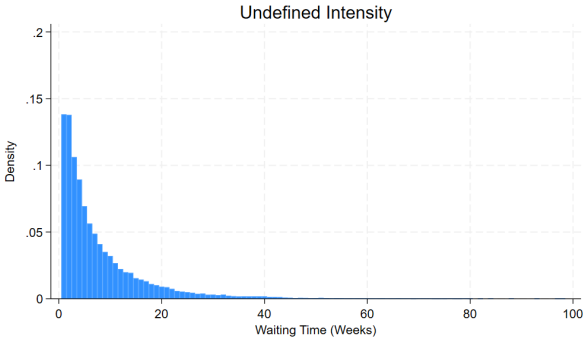
(c) High Intensity



(d) Step Down



(e) Step Up

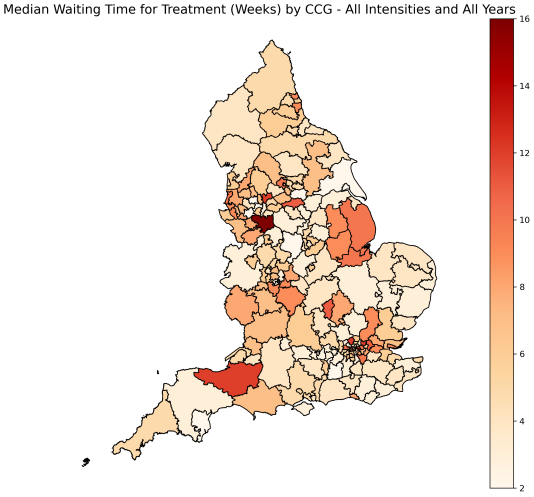


(f) Undefined

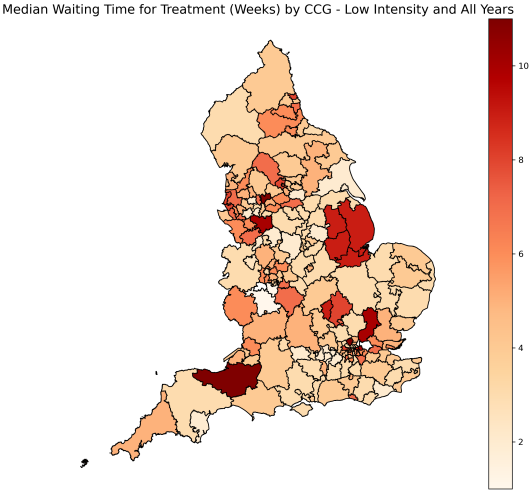
Table C.I: Summary Statistics for Waiting Time in Weeks, by Treatment Intensity

Variable	Mean	SD
Low Intensity	5.857	5.553
High Intensity	6.669	7.910
Step Down	7.780	7.195
Step Up	9.349	9.324
Undefined	8.057	8.898

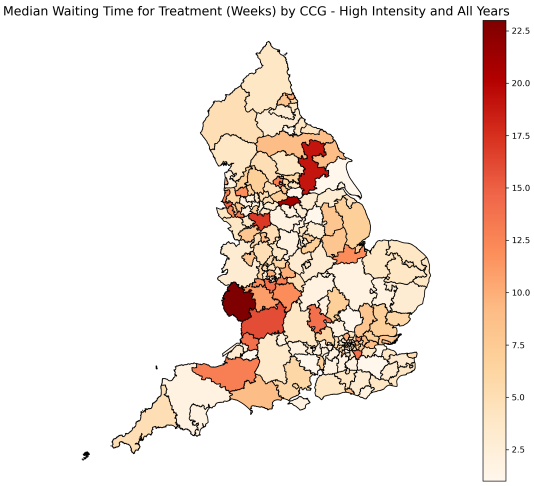
Figure C.III: Median Waiting Times in Weeks for Treatment by Clinical Commissioning Groups (CCGs) and Treatment Intensity, All Years



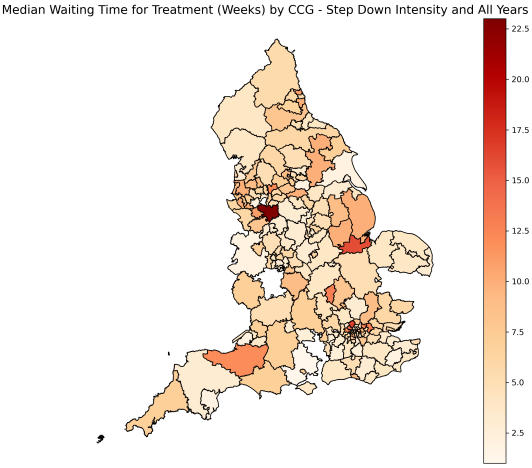
(a) All Intensities



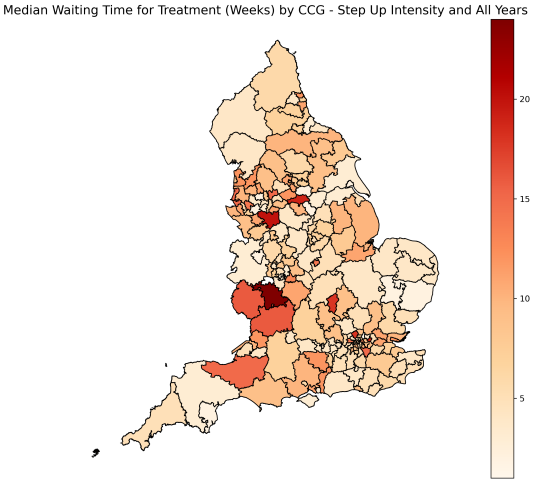
(b) Low Intensity



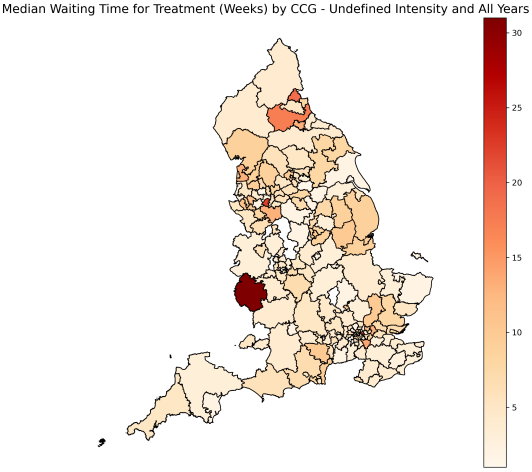
(c) High Intensity



(d) Step Down

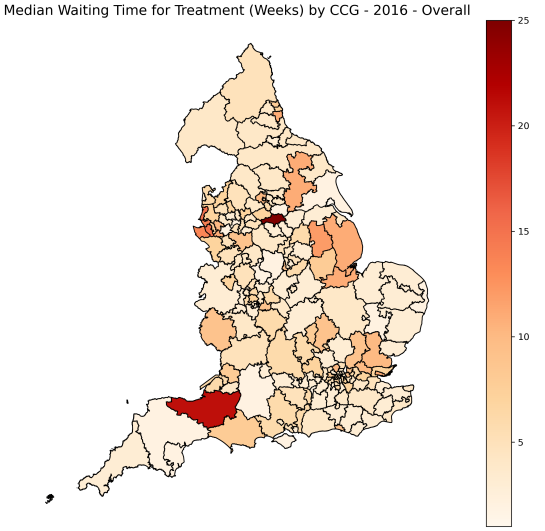


(e) Step Up

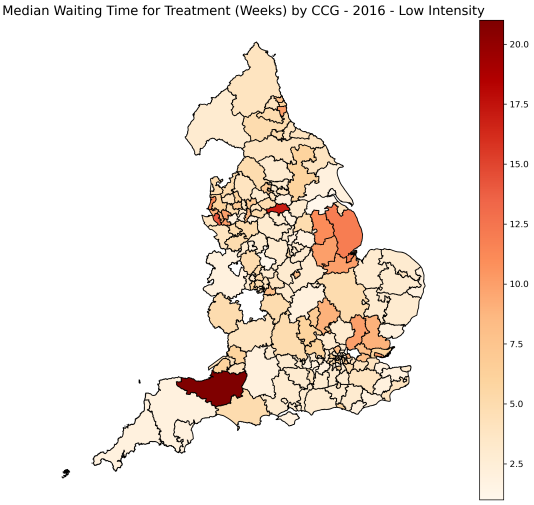


(f) Undefined

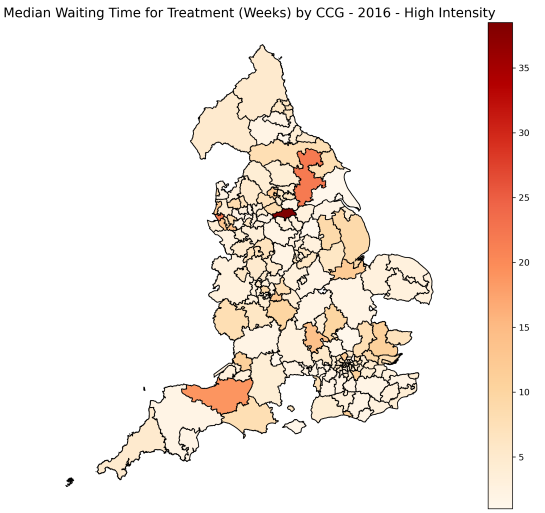
Figure C.IV: Median Waiting Times in Weeks for Treatment by Clinical Commissioning Groups (CCGs) and Treatment Intensity, 2016



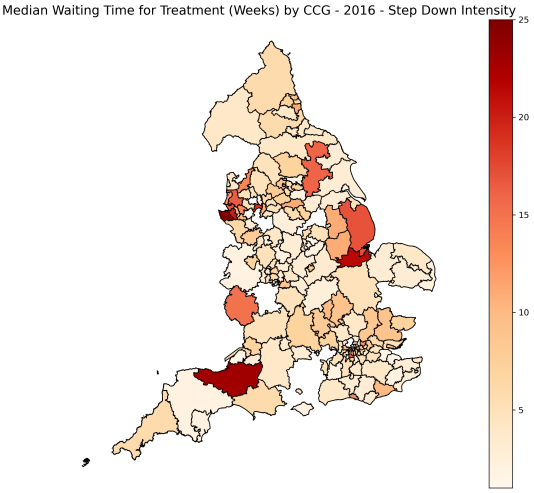
(a) All Intensities



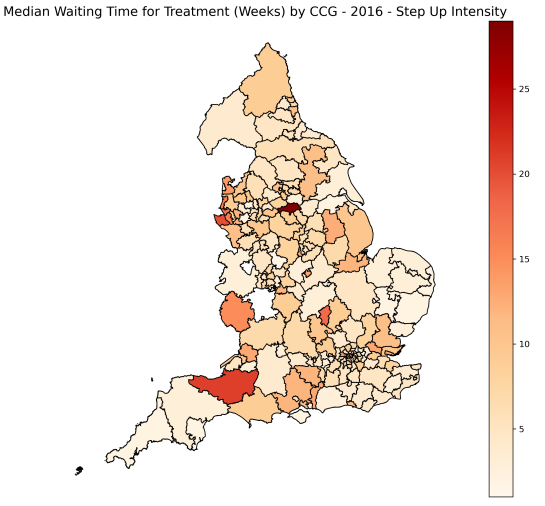
(b) Low Intensity



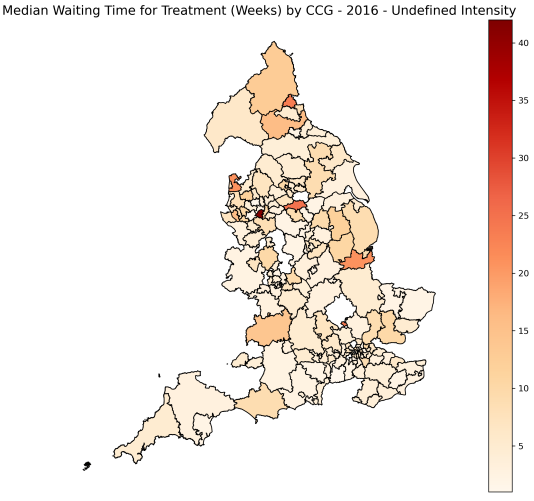
(c) High Intensity



(d) Step Down

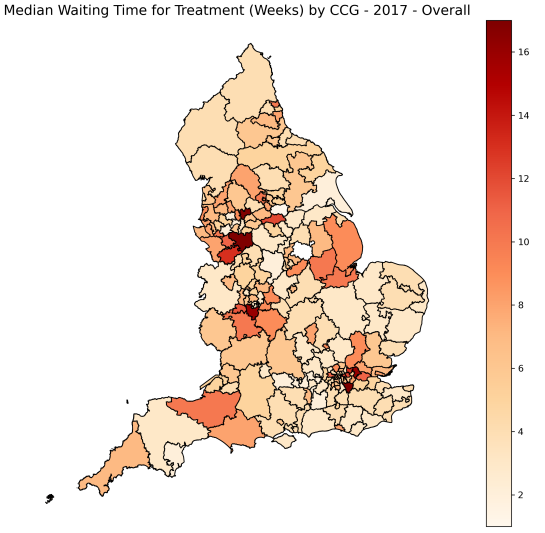


(e) Step Up

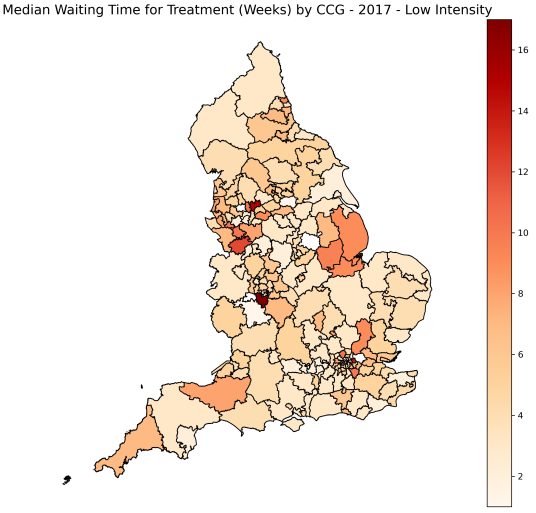


(f) Undefined

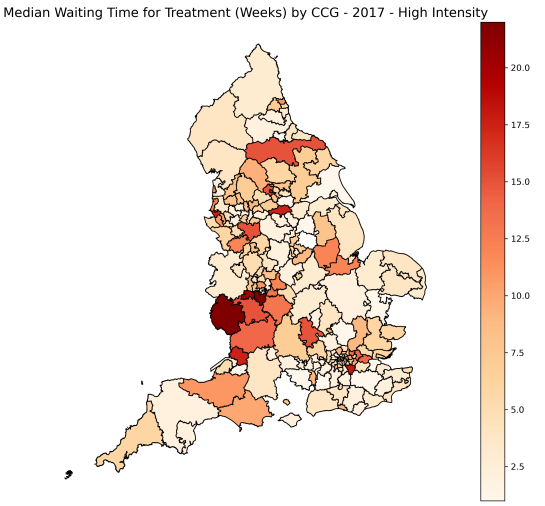
Figure C.V: Median Waiting Times in Weeks for Treatment by Clinical Commissioning Groups (CCGs) and Treatment Intensity, 2017



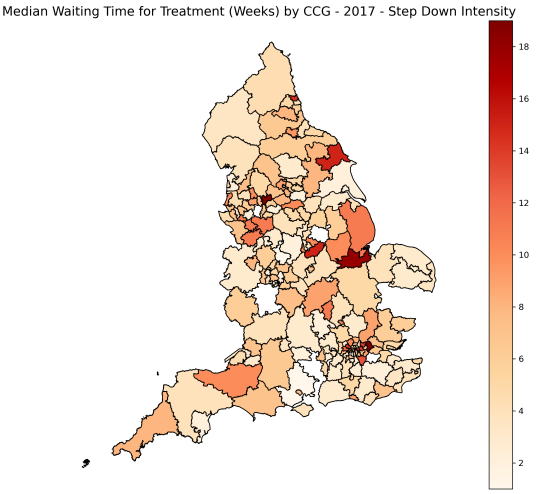
(a) All Intensities



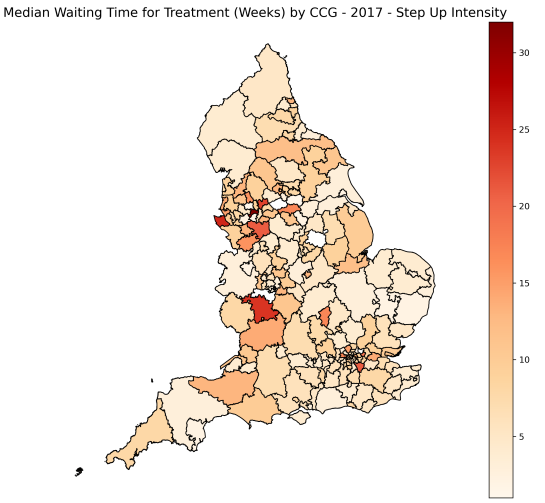
(b) Low Intensity



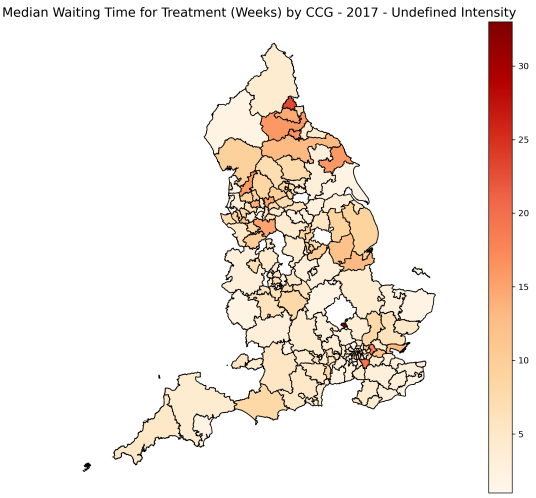
(c) High Intensity



(d) Step Down

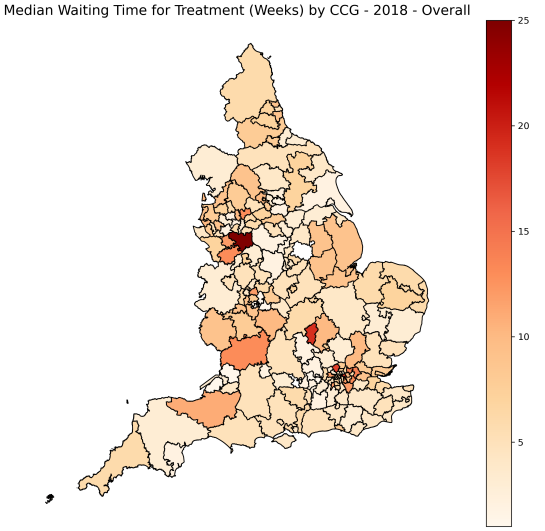


(e) Step Up

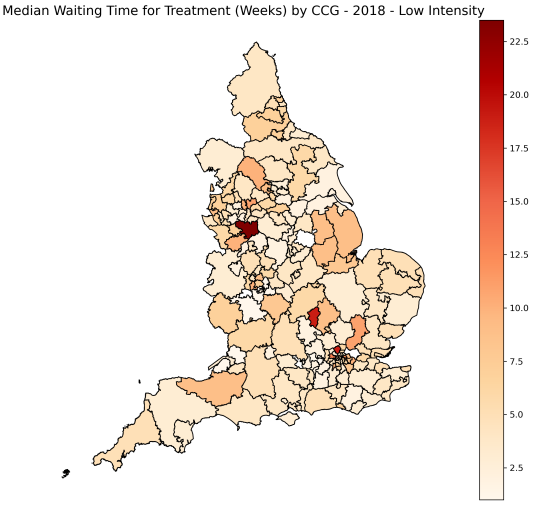


(f) Undefined

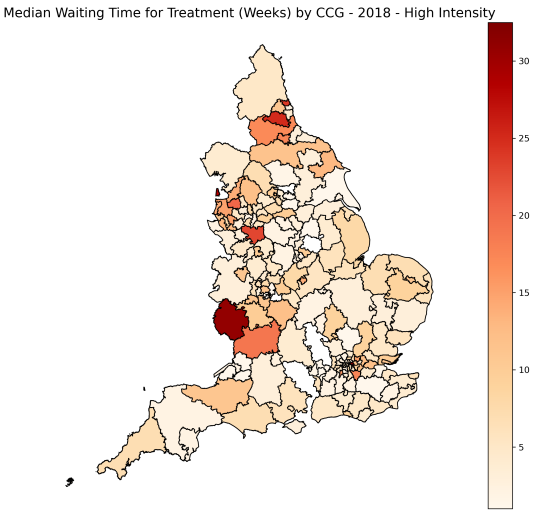
Figure C.VI: Median Waiting Times in Weeks for Treatment by Clinical Commissioning Groups (CCGs) and Treatment Intensity, 2018



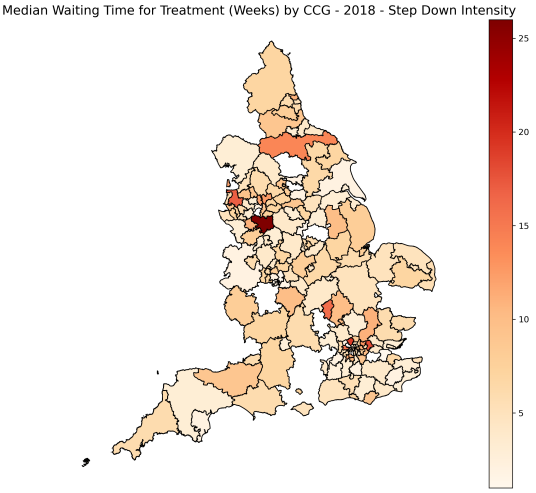
(a) All Intensities



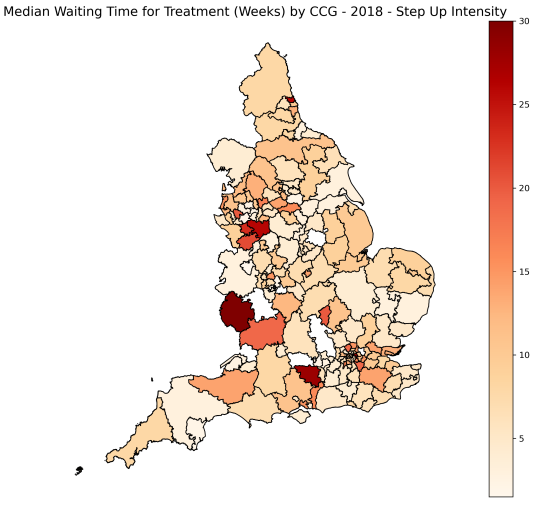
(b) Low Intensity



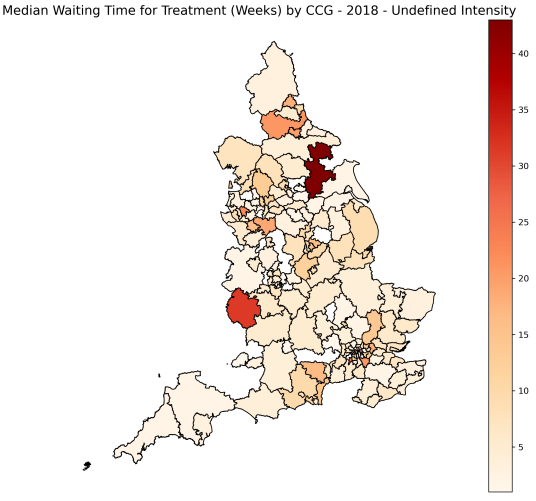
(c) High Intensity



(d) Step Down

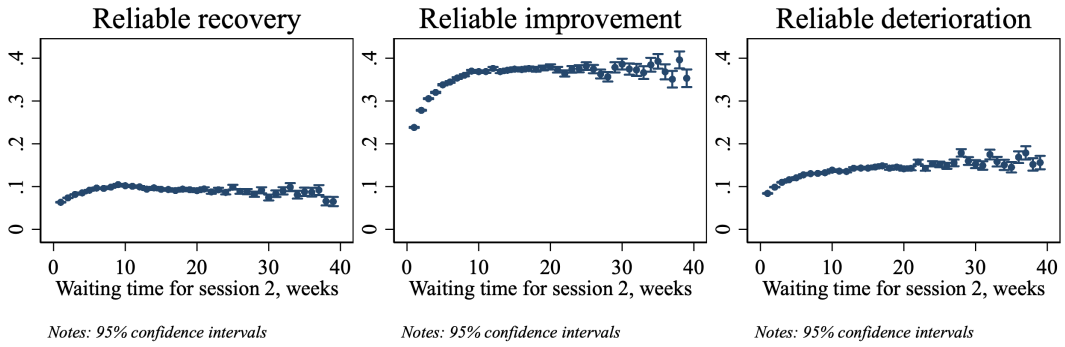


(e) Step Up



(f) Undefined

Figure C.VII: Main Outcomes for Different Waiting Times



Note: Own calculations.

D Balancing Properties

Table D.I: Balancing Properties of Covariates Between Default Treatment and Control Group (50th Percentile of Waiting Time)

	Treatment $N_T = 618,574$		Control $N_c = 628,218$		Overlap Measures			
	Mean	SD	Mean	SD	Norm. Diff.	Log Ratio of STD	$\pi^{0.05}$ Treatment	Control
Therapy Controls								
Mental Health Index (Pre-Treatment)	0.421	0.686	0.446	0.683	-0.037	0.005	0.050	0.047
Referral: Acute Secondary Care	0.007	0.083	0.006	0.079	0.008	0.048	0.000	0.000
Child Health	0.000	0.016	0.000	0.016	-0.001	-0.037	0.000	0.000
Employer	0.001	0.025	0.000	0.018	0.013	0.301	0.000	0.000
IAPT Stepped Care	0.005	0.074	0.003	0.053	0.042	0.337	0.000	0.000
Independent/Voluntary Sector	0.004	0.066	0.003	0.057	0.020	0.161	0.000	0.000
Internal Referral	0.000	0.011	0.000	0.010	0.002	0.114	0.000	0.000
Internal Referral From Inpatient Service (Within Own NHS Trust)	0.000	0.009	0.000	0.009	0.000	0.027	0.000	0.000
Internal Referral from Community Mental Health Team	0.016	0.125	0.020	0.142	-0.034	-0.123	0.000	0.000
Justice System	0.001	0.037	0.001	0.025	0.023	0.377	0.000	0.000
Local Authority Services	0.001	0.035	0.001	0.030	0.009	0.133	0.000	0.000
Other	0.032	0.175	0.027	0.161	0.029	0.081	0.000	0.000
Other Mental Health NHS Trust	0.000	0.017	0.000	0.019	-0.003	-0.086	0.000	0.000
Primary Health Care	0.206	0.405	0.227	0.419	-0.050	-0.035	0.000	0.000
Self-Referral	0.721	0.448	0.709	0.454	0.028	-0.013	0.000	0.000
Transfer by Graduation (Within Own NHS Trust)	0.000	0.007	0.000	0.010	-0.005	-0.307	0.000	0.000
Unknown	0.000	0.000	0.000	0.001	-0.002	-	0.000	0.000
Referral Time Lapsed	3.227	4.370	2.833	2.912	0.106	0.406	0.049	0.009
Treatment Mode: Face-to-Face Communication	0.345	0.475	0.214	0.410	0.295	0.147	0.000	0.000
Telephone	0.606	0.489	0.761	0.426	-0.337	0.136	0.000	0.000
Telemedicine	0.018	0.133	0.001	0.028	0.179	1.552	0.000	0.000
Talk Type for Person Unable to Speak	0.000	0.011	0.000	0.007	0.008	0.434	0.000	0.000
E-Mail	0.020	0.140	0.013	0.115	0.053	0.202	0.000	0.000
Text Messaging	0.001	0.035	0.002	0.045	-0.018	-0.232	0.000	0.000
Online Triage	0.000	0.005	0.000	0.003	0.005	0.760	0.000	0.000
No Response	0.009	0.093	0.008	0.090	0.007	0.037	0.000	0.000
Medication: Prescribed But Not Taking	0.043	0.204	0.047	0.213	-0.019	-0.042	0.000	0.000
Prescribed and Taking	0.464	0.499	0.489	0.500	-0.051	-0.002	0.000	0.000
Not Prescribed	0.416	0.493	0.414	0.492	0.005	0.001	0.000	0.000
No Response	0.076	0.266	0.049	0.217	0.111	0.203	0.000	0.000
Initial Diagnosis: Agoraphobia	0.006	0.079	0.007	0.086	-0.014	-0.085	0.000	0.000
Generalised Anxiety Disorder	0.222	0.415	0.219	0.414	0.006	0.004	0.000	0.000
Mixed Anxiety and Depressive Disorder	0.119	0.324	0.103	0.304	0.051	0.064	0.000	0.000
Obsessive-Compulsive Disorder	0.021	0.143	0.025	0.155	-0.027	-0.085	0.000	0.000
Other Anxiety or Stress-Related Disorder	0.037	0.189	0.040	0.197	-0.017	-0.040	0.000	0.000

Panic Disorder (Episodic Paroxysmal Anxiety)	0.029	0.167	0.028	0.166	0.001	0.004	0.000	0.000
Post-Traumatic Stress Disorder	0.036	0.187	0.046	0.209	-0.048	-0.112	0.000	0.000
Social Phobias	0.026	0.158	0.030	0.171	-0.028	-0.080	0.000	0.000
Specific (Isolated) Phobias	0.007	0.084	0.008	0.090	-0.012	-0.071	0.000	0.000
Depression	0.362	0.481	0.384	0.486	-0.046	-0.012	0.000	0.000
Invalid Data Supplied	0.001	0.033	0.001	0.029	0.008	0.123	0.000	0.000
Other Mental Health Problem	0.047	0.212	0.040	0.195	0.036	0.080	0.000	0.000
Other Recorded Problem	0.011	0.107	0.013	0.112	-0.011	-0.051	0.000	0.000
No Response	0.076	0.265	0.055	0.228	0.084	0.149	0.000	0.000
Treatment Intensity: Low Intensity	0.397	0.489	0.392	0.488	0.009	0.002	0.000	0.000
High Intensity	0.220	0.415	0.222	0.416	-0.004	-0.003	0.000	0.000
Step Up: Low to High Intensity	0.035	0.184	0.036	0.186	-0.005	-0.012	0.000	0.000
Step Down: High to Low Intensity	0.310	0.463	0.312	0.463	-0.005	-0.002	0.000	0.000
Multiple Changes in Intensity	0.037	0.190	0.037	0.189	0.003	0.007	0.000	0.000
Individual Controls								
Age	39.975	14.924	40.420	14.887	-0.030	0.002	0.042	0.041
Gender: Male	0.247	0.431	0.248	0.432	-0.003	-0.002	0.000	0.000
Female	0.489	0.500	0.504	0.500	-0.031	0.000	0.000	0.000
Non-Binary	0.000	0.022	0.000	0.022	-0.001	-0.022	0.000	0.000
No Response	0.264	0.441	0.247	0.432	0.038	0.021	0.000	0.000
Ethnicity: British	0.594	0.491	0.596	0.491	-0.005	0.001	0.000	0.000
Irish	0.005	0.073	0.006	0.077	-0.007	-0.045	0.000	0.000
Any Other White Background	0.030	0.171	0.033	0.179	-0.017	-0.045	0.000	0.000
White and Black Caribbean	0.005	0.074	0.006	0.078	-0.008	-0.053	0.000	0.000
White and Black African	0.001	0.038	0.002	0.040	-0.005	-0.063	0.000	0.000
White and Asian	0.003	0.055	0.003	0.054	0.001	0.011	0.000	0.000
Any Other Mixed Background	0.005	0.074	0.006	0.080	-0.012	-0.079	0.000	0.000
Indian	0.013	0.112	0.014	0.119	-0.015	-0.063	0.000	0.000
Pakistani	0.009	0.094	0.011	0.104	-0.021	-0.103	0.000	0.000
Bangladeshi	0.002	0.048	0.004	0.062	-0.029	-0.262	0.000	0.000
Any Other Asian Background	0.007	0.083	0.008	0.089	-0.013	-0.073	0.000	0.000
Caribbean	0.009	0.096	0.010	0.100	-0.008	-0.039	0.000	0.000
African	0.007	0.081	0.008	0.088	-0.014	-0.084	0.000	0.000
Any Other Black Background	0.003	0.052	0.003	0.057	-0.009	-0.086	0.000	0.000
Chinese	0.002	0.040	0.002	0.042	-0.004	-0.043	0.000	0.000
Any Other Ethnic Group	0.008	0.090	0.010	0.099	-0.019	-0.098	0.000	0.000
No Response	0.296	0.457	0.278	0.448	0.041	0.019	0.000	0.000
Religion: Baha'i	0.000	0.010	0.000	0.009	0.001	0.034	0.000	0.000
Buddhist	0.003	0.051	0.002	0.048	0.005	0.051	0.000	0.000
Christian	0.184	0.388	0.197	0.398	-0.033	-0.026	0.000	0.000
Hindu	0.004	0.064	0.005	0.070	-0.012	-0.091	0.000	0.000
Jew	0.002	0.044	0.003	0.050	-0.012	-0.131	0.000	0.000
Muslim	0.017	0.128	0.023	0.150	-0.045	-0.156	0.000	0.000
Pagan	0.001	0.034	0.001	0.036	-0.003	-0.043	0.000	0.000
Sikh	0.003	0.056	0.004	0.064	-0.015	-0.124	0.000	0.000
Zoroastrian	0.000	0.008	0.000	0.007	0.003	0.222	0.000	0.000
Other	0.019	0.137	0.021	0.144	-0.015	-0.050	0.000	0.000
Not Religious	0.324	0.468	0.333	0.471	-0.019	-0.007	0.000	0.000
No Response	0.443	0.497	0.411	0.492	0.065	0.010	0.000	0.000
Sexual Orientation: Heterosexual or Straight	0.552	0.497	0.576	0.494	-0.049	0.006	0.000	0.000
Gay or Lesbian	0.016	0.126	0.017	0.130	-0.009	-0.033	0.000	0.000
Bisexual	0.014	0.116	0.014	0.118	-0.004	-0.017	0.000	0.000
Other	0.008	0.088	0.010	0.100	-0.023	-0.118	0.000	0.000

No Response	0.411	0.492	0.383	0.486	0.057	0.012	0.000	0.000
Long-Term Health Condition: Yes	0.196	0.397	0.208	0.406	-0.031	-0.023	0.000	0.000
No	0.452	0.498	0.453	0.498	-0.003	0.000	0.000	0.000
No Response	0.352	0.478	0.339	0.473	0.029	0.009	0.000	0.000
Employment Status: Employed	0.572	0.495	0.566	0.496	0.012	-0.002	0.000	0.000
Unemployed and Seeking Work	0.095	0.293	0.096	0.294	-0.003	-0.004	0.000	0.000
Student	0.055	0.228	0.053	0.224	0.009	0.017	0.000	0.000
Long-Term Sick or Disabled	0.068	0.252	0.087	0.281	-0.069	-0.111	0.000	0.000
Homemaker Looking After a Family or Home	0.049	0.215	0.048	0.215	0.002	0.003	0.000	0.000
Not Receiving Benefits and Not Working	0.021	0.145	0.025	0.157	-0.026	-0.082	0.000	0.000
Unpaid Voluntary Work and Not Working or Actively Seeking	0.003	0.059	0.004	0.060	-0.003	-0.023	0.000	0.000
Retired	0.069	0.254	0.071	0.257	-0.007	-0.012	0.000	0.000
Refused	0.000	0.000	0.000	0.001	-0.002	-	0.000	0.000
No Response	0.067	0.250	0.050	0.218	0.072	0.136	0.000	0.000
Services Member: Yes	0.000	0.020	0.000	0.007	0.024	1.091	0.000	0.000
Former	0.014	0.119	0.012	0.109	0.019	0.082	0.000	0.000
Not Former or Their Dependent	0.548	0.498	0.583	0.493	-0.072	0.009	0.000	0.000
Dependent of Services Member	0.000	0.008	0.000	0.010	-0.004	-0.222	0.000	0.000
Dependent of Former Services Member	0.002	0.050	0.003	0.050	-0.001	-0.009	0.000	0.000
No Response	0.435	0.496	0.402	0.490	0.067	0.011	0.000	0.000
Service Controls								
CCG Number of Staff	119.737	93.331	113.089	86.706	0.074	0.074	0.072	0.038
CCG Number of Registered Patients	31,551.943	18,936.964	30,915.069	18,326.762	0.034	0.033	0.054	0.041
CCG Allocations Per Registered Patient	1,259.523	225.230	1,284.427	183.167	-0.121	0.207	0.056	0.061
CCG Unemployment Rate	4.360	1.335	4.373	1.269	-0.010	0.051	0.058	0.043
CCG Median Wage	454.474	67.593	459.984	70.727	-0.080	-0.045	0.052	0.053
Local-Area Controls								
Index of Multiple Deprivation: Average Rank	99.195	57.403	96.083	56.482	0.055	0.016	0.054	0.044
Income: Average Rank	16,648.934	4,489.914	16,968.902	4,410.900	-0.072	0.018	0.050	0.051
Employment: Average Rank	16,616.696	4,701.454	16,830.916	4,610.969	-0.046	0.019	0.053	0.051
Education, Skills, and Training: Average Rank	16,650.542	4,187.294	16,522.309	4,283.521	0.030	-0.023	0.051	0.043
Health Deprivation and Disability: Average Rank	16,721.574	6,333.467	16,916.271	6,307.118	-0.031	0.004	0.051	0.053
Crime: Average Rank	16,739.634	5,245.765	17,023.908	5,216.346	-0.054	0.006	0.047	0.050
Barriers to Housing and Services: Average Rank	16,584.651	5,248.194	16,607.885	5,672.520	-0.004	-0.078	0.042	0.060
Living Environment: Average Rank	16,635.006	5,985.810	16,875.619	6,207.341	-0.039	-0.036	0.046	0.055

Note: The normalised difference is calculated as $\Delta x = (\bar{x}_t - \bar{x}_c)/\sqrt{(\sigma_t^2 + \sigma_c^2)}$, where $\bar{x}_t$ and $\bar{x}_c$ is the sample mean of variable x in the treatment and control group, respectively. σ^2 denotes the respective variance. A normalised difference greater than 0.25 indicates unbalancedness. The log of the ratio of standard deviations is calculated as $LR = ln(\frac{\sigma_t}{\sigma_c})$. The share of the control (treated) units outside the 0.025 and 0.975 quantiles of the covariate distribution of the treated (control) units is calculate as $(1 - F_t(F_c^{-1}(1-\alpha/2))) + F_t(F_c^{-1}(\alpha/2))$ for treatment and $(1 - F_c(F_t^{-1}(1-\alpha/2))) + F_c(F_t^{-1}(\alpha/2))$ (Imbens & Rubin, 2015; Imbens & Wooldridge, 2009).

Table D.II: Balancing Properties of Outcomes Between Default Treatment and Control Group (50th Percentile of Waiting Time)

	Treatment		Control			Overlap Measures		
	$N_T = 618,574$		$N_c = 628,218$		Norm.	Log Ratio	$\pi^{0.05}$	
	Mean	SD	Mean	SD	Diff.	of STD	Treatment	Control
Initial Assessment								
Reliable Recovery	0.000	0.000	0.000	0.000	0.000	-	0.000	0.000
Reliable Improvement	0.000	0.000	0.000	0.000	0.000	-	0.000	0.000
Reliable Deterioration	0.000	0.000	0.000	0.000	0.000	-	0.000	0.000
PHQ-9	15.688	5.504	15.841	5.490	-0.028	0.002	0.048	0.048
GAD-7	14.310	4.350	14.468	4.324	-0.037	0.006	0.017	0.016
Mental Health Index	0.421	0.686	0.446	0.683	-0.037	0.005	0.050	0.047
WSAS - Overall	19.849	9.153	20.236	9.298	-0.042	-0.016	0.115	0.116
WSAS - Work	4.380	2.587	4.365	2.604	0.006	-0.006	0.416	0.408
WSAS - Home Management	3.584	2.369	3.656	2.416	-0.030	-0.020	0.075	0.066
WSAS - Social Leisure	4.438	2.431	4.545	2.461	-0.044	-0.012	0.075	0.067
WSAS - Private Leisure	3.634	2.515	3.739	2.564	-0.041	-0.019	0.075	0.066
WSAS - Close Relationships	3.916	2.451	3.996	2.483	-0.032	-0.013	0.075	0.066
Employed (Not Unemployed)	0.858	0.349	0.856	0.351	0.007	-0.007	0.499	0.511
Employed (Not Long-Term Sick)	0.894	0.308	0.867	0.339	0.081	-0.096	0.562	0.532
Receiving Statutory Sick Pay	0.084	0.278	0.071	0.257	0.050	0.080	0.093	0.069
First Clinical Session								
Reliable Recovery	0.068	0.252	0.092	0.289	-0.088	-0.137	0.000	0.000
Reliable Improvement	0.273	0.445	0.356	0.479	-0.180	-0.072	0.000	0.000
Reliable Deterioration	0.105	0.306	0.136	0.342	-0.096	-0.113	0.000	0.000
PHQ-9	14.380	5.943	14.115	6.066	0.044	-0.020	0.038	0.043
GAD-7	13.180	4.942	12.972	5.111	0.041	-0.034	0.015	0.021
Mental Health Index	0.225	0.793	0.187	0.820	0.047	-0.033	0.037	0.056
WSAS - Overall	18.872	9.269	18.488	9.434	0.041	-0.018	0.116	0.126
WSAS - Work	4.065	2.590	3.796	2.572	0.104	0.007	0.435	0.405
WSAS - Home Management	3.476	2.298	3.442	2.342	0.015	-0.019	0.092	0.070
WSAS - Social Leisure	4.228	2.399	4.205	2.451	0.009	-0.022	0.092	0.070
WSAS - Private Leisure	3.489	2.419	3.401	2.461	0.036	-0.017	0.092	0.070
WSAS - Close Relationships	3.686	2.380	3.647	2.404	0.016	-0.010	0.092	0.070
Employed (Not Unemployed)	0.860	0.347	0.860	0.347	-0.001	0.001	0.554	0.561
Employed (Not Long-Term Sick)	0.893	0.309	0.863	0.344	0.093	-0.108	0.614	0.566
Receiving Statutory Sick Pay	0.074	0.261	0.048	0.214	0.107	0.199	0.136	0.103
Last Clinical Session								
Reliable Recovery	0.536	0.499	0.525	0.499	0.022	-0.001	0.000	0.000
Reliable Improvement	0.745	0.436	0.742	0.438	0.007	-0.004	0.000	0.000
Reliable Deterioration	0.050	0.219	0.057	0.231	-0.028	-0.056	0.000	0.000
PHQ-9	8.737	6.454	8.957	6.552	-0.034	-0.015	0.018	0.020
GAD-7	7.879	5.616	8.072	5.704	-0.034	-0.016	0.000	0.000
Mental Health Index	-0.657	0.935	-0.623	0.950	-0.035	-0.016	0.049	0.053
WSAS - Overall	12.622	9.815	12.883	9.986	-0.026	-0.017	0.105	0.094
WSAS - Work	2.742	2.472	2.702	2.471	0.016	0.001	0.443	0.432
WSAS - Home Management	2.405	2.163	2.474	2.206	-0.032	-0.020	0.085	0.096
WSAS - Social Leisure	2.757	2.352	2.829	2.394	-0.031	-0.018	0.085	0.070
WSAS - Private Leisure	2.260	2.220	2.331	2.265	-0.032	-0.020	0.085	0.070
WSAS - Close Relationships	2.477	2.249	2.521	2.270	-0.019	-0.010	0.085	0.070
Employed (Not Unemployed)	0.866	0.341	0.864	0.342	0.003	-0.004	0.547	0.560

Employed (Not Long-Term Sick)	0.888	0.315	0.860	0.347	0.084	-0.095	0.587	0.553
Receiving Statutory Sick Pay	0.040	0.197	0.030	0.172	0.054	0.138	0.118	0.097

Note: WSAS: Working and Social Adjustment Scale (Mundt et al., 2002). The normalised difference is calculated as $\Delta x = (\bar{x}_t - \bar{x}_c)/\sqrt{(\sigma_t^2 + \sigma_c^2)}$, where $\bar{x}_t$ and $\bar{x}_c$ is the sample mean of variable x in the treatment and control group, respectively. σ^2 denotes the respective variance. A normalised difference greater than 0.25 indicates unbalancedness. The log of the ratio of standard deviations is calculated as $LR = ln(\frac{\sigma_t}{\sigma_c})$. The share of the control (treated) units outside the 0.025 and 0.975 quantiles of the covariate distribution of the treated (control) units is calculate as $(1 - F_t(F_c^{-1}(1-\alpha/2))) + F_t(F_c^{-1}(\alpha/2))$ for treatment and $(1 - F_c(F_t^{-1}(1-\alpha/2))) + F_c(F_t^{-1}(\alpha/2))$ (Imbens & Rubin, 2015; Imbens & Wooldridge, 2009).

E Summary Statistics for Treatment Durations and Outcomes by Waiting Times

Figure E.I: Histograms for Total Number of Sessions by Quartile of Waiting Time, All Treatments Intensities

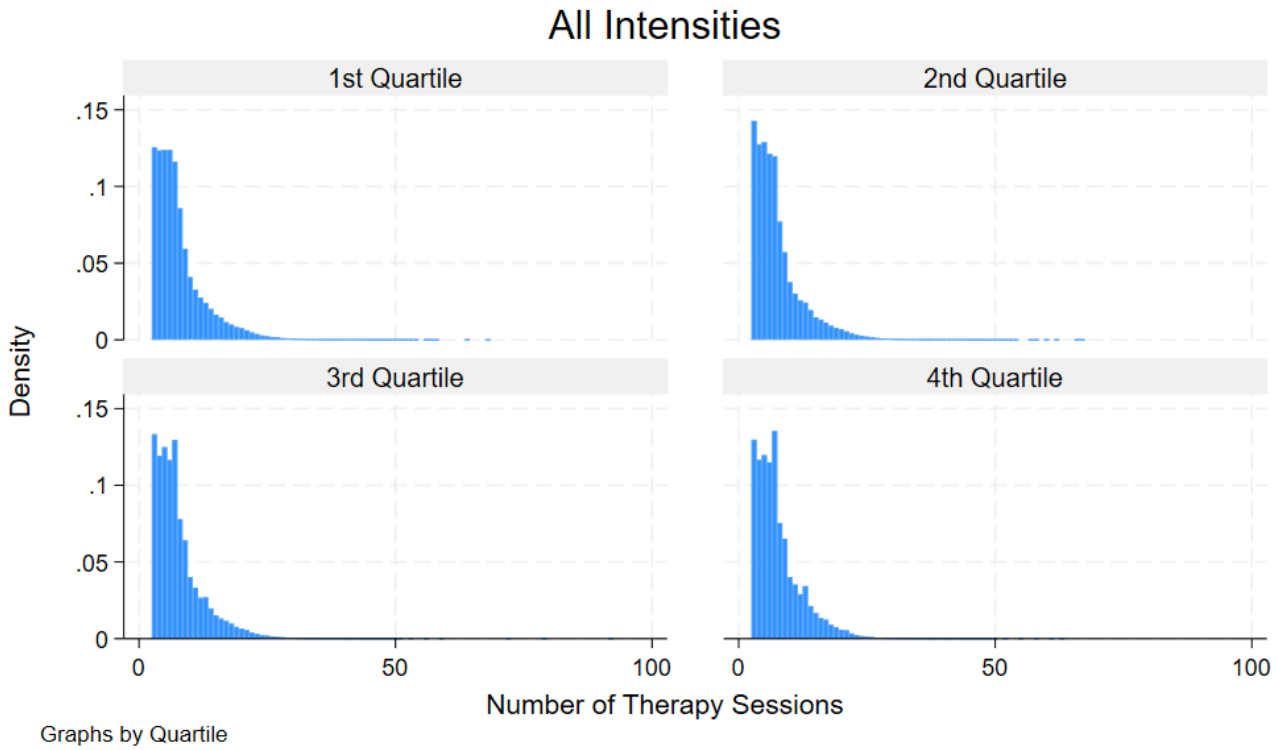


Table E.I: Summary Statistics for Total Number of Sessions by Quartile of Waiting Time, All Treatment Intensities

Quartile	Mean	SD
1	7.826	4.821
2	7.583	4.715
3	7.690	4.623
4	7.695	4.417

Note: The table shows the means and standard deviations of Total Number of Sessions by quartile of waiting time for all intensities combined. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.II: Histograms for Treatment Duration in Weeks by Quartile of Waiting Time, by Treatments Intensities

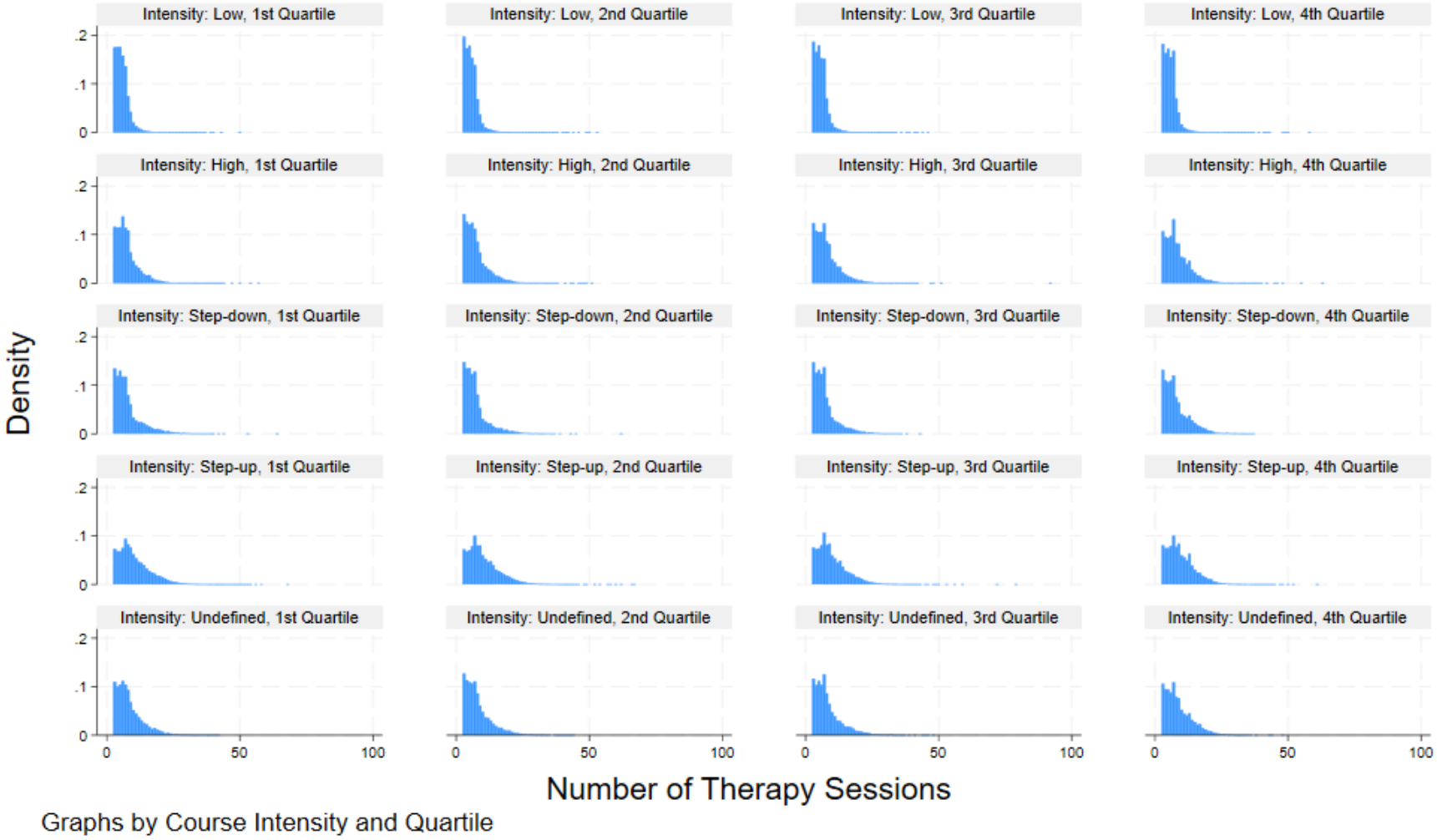


Table E.II: Summary Statistics for Total Number of Sessions by Quartile of Waiting Time and Treatment Intensity

Intensity	**Quartile 1**	**Quartile 2**	**Quartile 3**	**Quartile 4**
Low Intensity	5.751 (2.518)	5.627 (2.508)	5.698 (2.479)	5.716 (2.471)
High Intensity	7.616 (4.172)	7.468 (4.323)	7.967 (4.503)	8.351 (4.465)
Step Down	7.971 (5.240)	7.382 (4.706)	7.414 (4.570)	8.099 (4.744)
Step Up	10.405 (5.928)	10.229 (5.794)	9.854 (5.520)	9.622 (5.125)
Undefined	8.463 (5.002)	8.217 (5.078)	8.372 (5.134)	8.888 (5.083)

Note: The table shows the mean number of sessions (with standard deviations in parentheses) for each quartile of waiting time by treatment intensity. Quartiles represent waiting time distributions, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.III: Histograms for Treatment Duration in Weeks by Quartile of Waiting Time, All Treatments Intensities

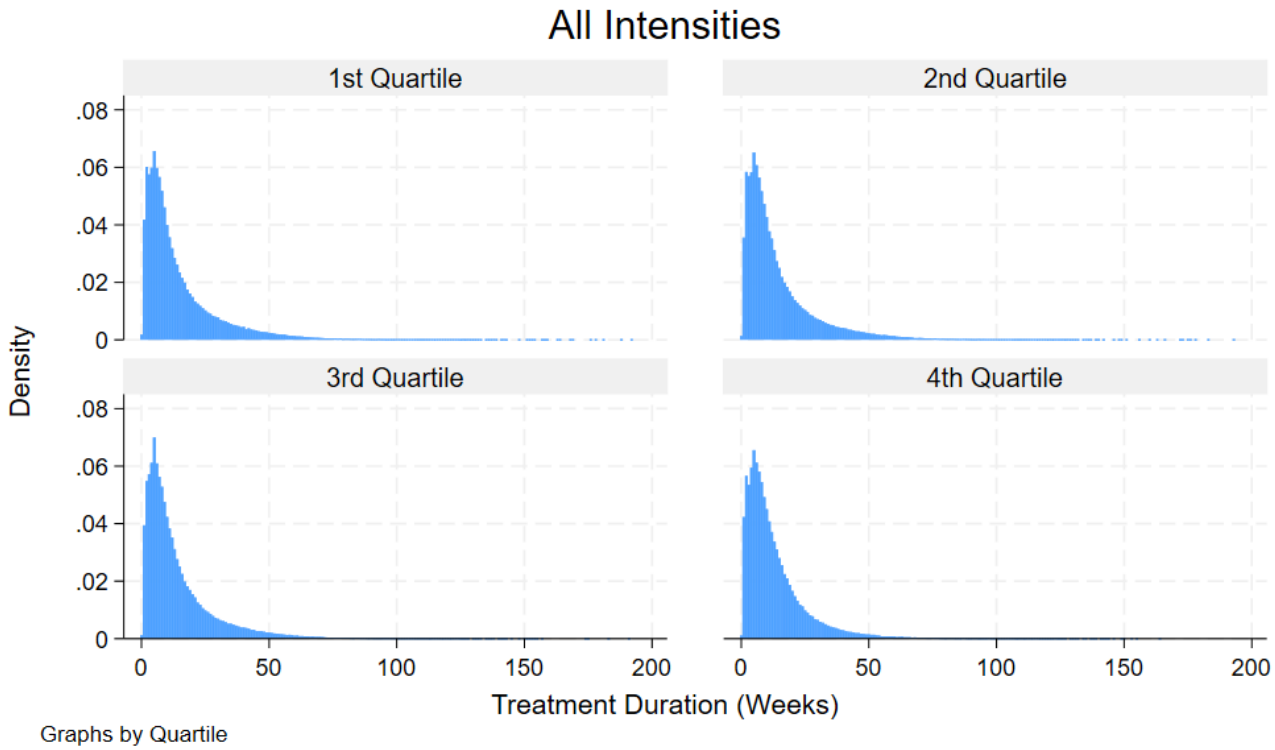


Table E.III: Summary Statistics for Treatment Duration in Weeks by Quartile of Waiting Time, All Treatment Intensities

Quartile	Mean	SD
1	14.520	14.563
2	14.415	14.257
3	13.986	13.777
4	12.986	12.016

Note: The table shows the means and standard deviations of Treatment Duration in Weeks by quartile of waiting time for all intensities combined. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.IV: Histograms for Treatment Duration in Weeks by Quartile of Waiting Time, by Treatments Intensities

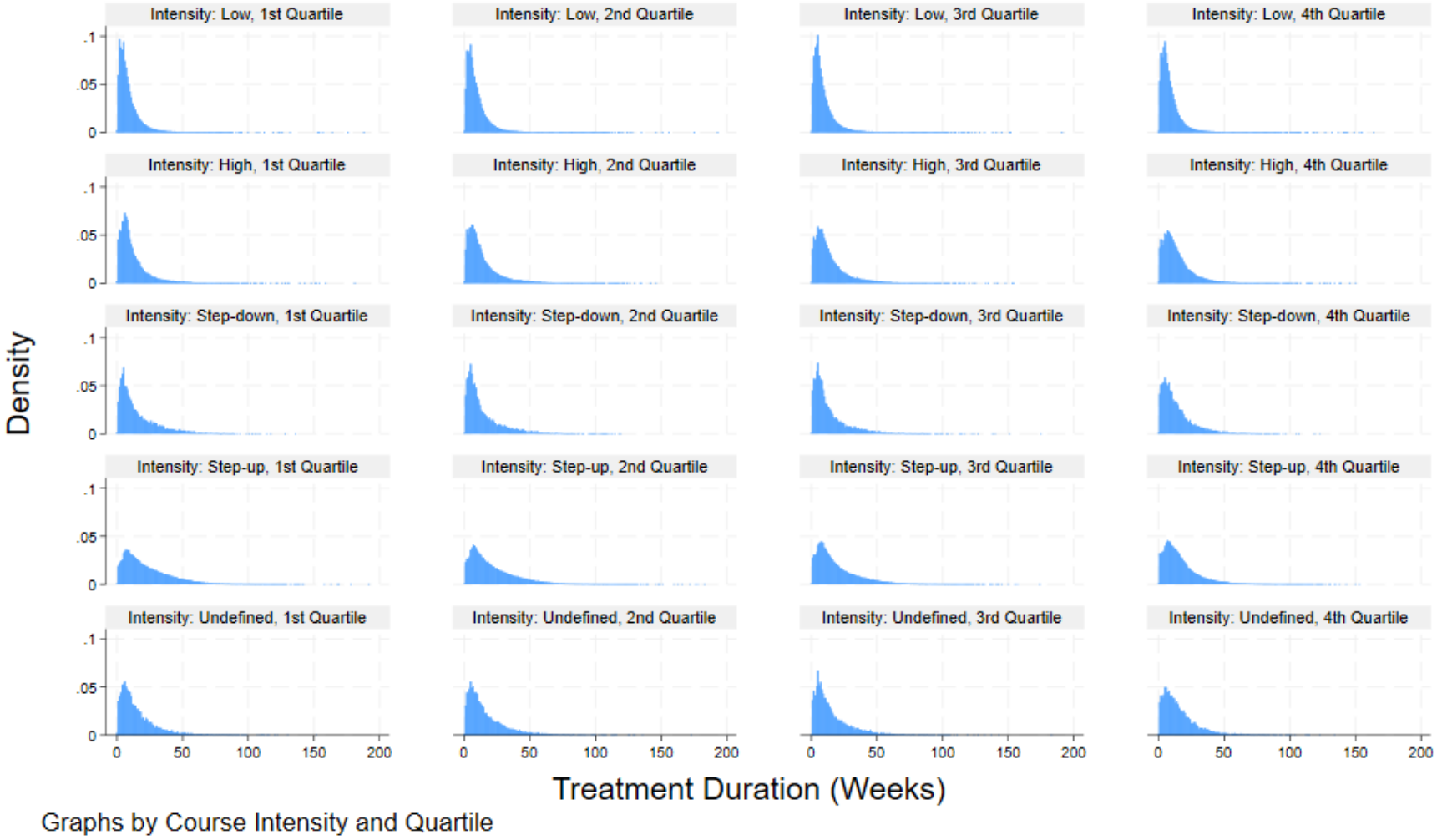


Table E.IV: Summary Statistics for Treatment Duration in Weeks by Quartile of Waiting Time and Treatment Intensity

Intensity	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Low Intensity	8.890 (8.416)	9.465 (8.951)	9.267 (9.024)	8.954 (8.217)
High Intensity	12.084 (11.411)	13.743 (13.007)	14.292 (13.085)	13.998 (11.747)
Step Down	16.357 (15.889)	14.815 (14.970)	14.258 (14.687)	14.444 (13.283)
Step Up	22.684 (18.028)	21.219 (17.512)	19.218 (16.495)	16.997 (14.153)
Undefined	15.701 (14.614)	16.572 (15.376)	15.912 (15.105)	16.003 (13.837)

Note: The table shows the means (with standard deviations in parentheses) of treatment duration in weeks by quartile of waiting time and treatment intensity. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.V: Histograms for PHQ-9 Measured at the First Session by Quartile of Waiting Time, All Treatments Intensities.

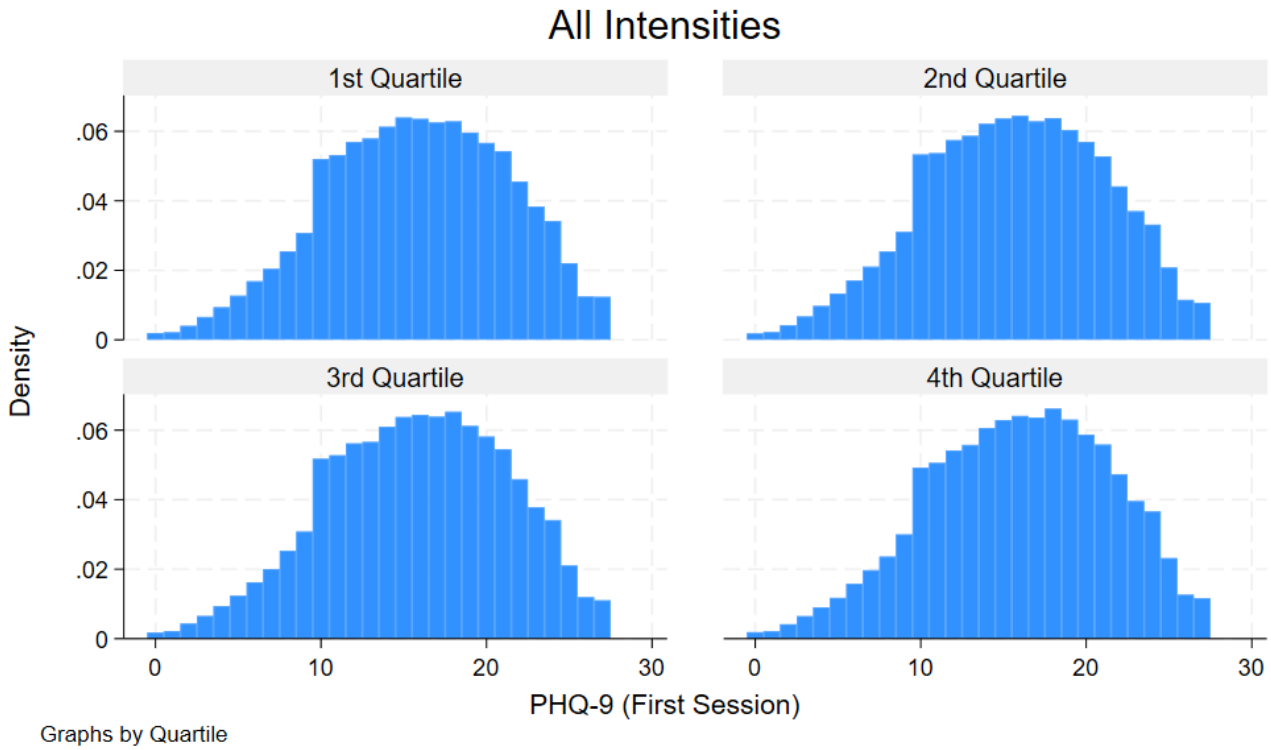


Table E.V: Summary Statistics for PHQ-9 Scores at First Session by Quartile of Waiting Time, All Intensities

Quartile	Mean	SD
1	15.744	5.520
2	15.636	5.488
3	15.755	5.482
4	15.923	5.497

Note: The table shows the means and standard deviations of PHQ-9 scores at the first session by quartile of waiting time for all intensities combined. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.VI: Histograms for PHQ-9 Measured at the First Session by Quartile of Waiting Time, by Treatments Intensities

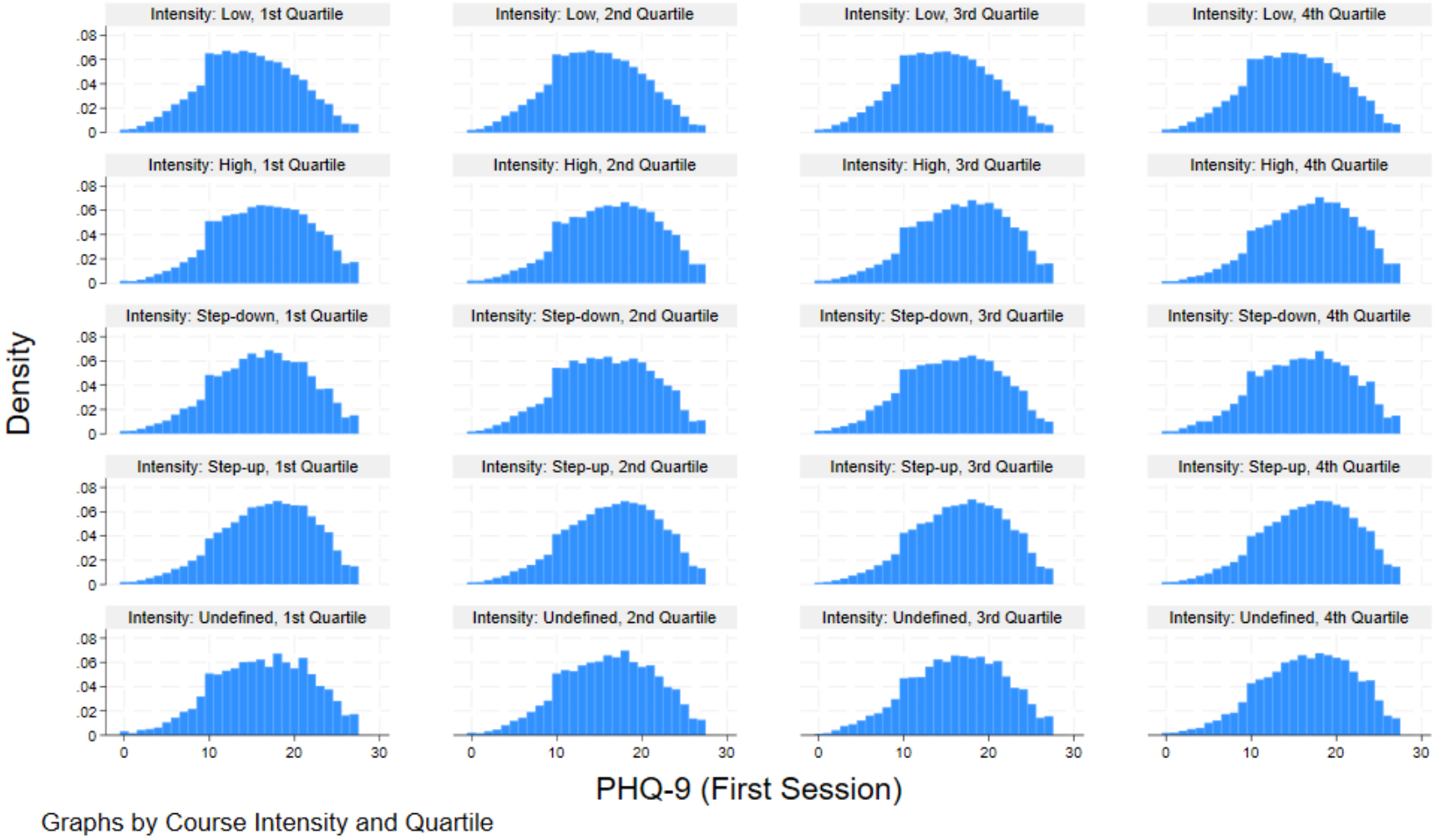


Table E.VI: Summary Statistics for PHQ-9 Scores at First Session by Quartile of Waiting Time and Treatment Intensity

Intensity	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Low Intensity	14.596 (5.422)	14.585 (5.385)	14.628 (5.381)	14.882 (5.450)
High Intensity	16.275 (5.479)	16.334 (5.451)	16.544 (5.445)	16.659 (5.392)
Step Down	16.051 (5.518)	15.618 (5.538)	15.667 (5.547)	16.042 (5.581)
Step Up	16.692 (5.414)	16.478 (5.419)	16.515 (5.379)	16.677 (5.410)
Undefined	16.201 (5.568)	16.050 (5.442)	16.119 (5.529)	16.537 (5.435)

Note: The table shows the means (with standard deviations in parentheses) of PHQ-9 scores at the first session by quartile of waiting time and treatment intensity. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.VII: Histograms for PHQ-9 Measured at the Last Session by Quartile of Waiting Time, All Treatments Intensities

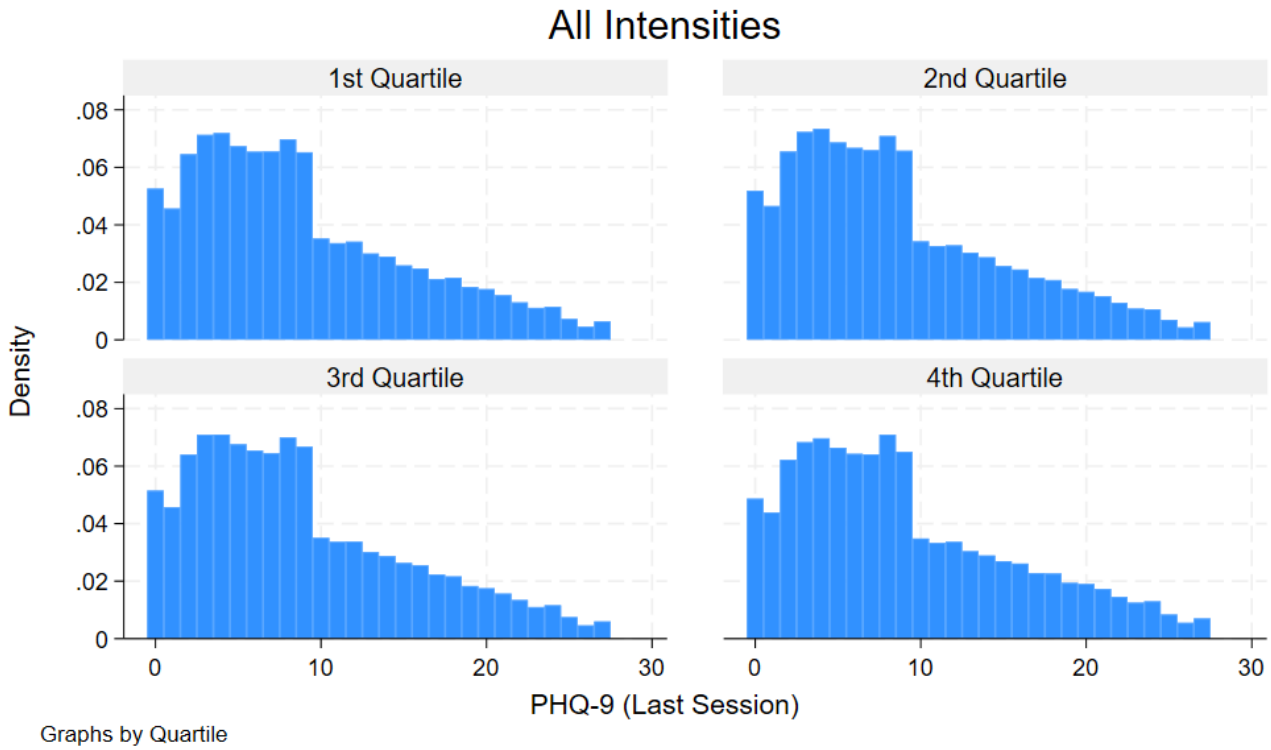


Table E.VII: Summary Statistics for PHQ-9 Scores at Last Session by Quartile of Waiting Time, All Intensities

Quartile	Mean	SD
1	8.788	6.482
2	8.690	6.428
3	8.826	6.481
4	9.083	6.617

Note: The table shows the means and standard deviations of PHQ-9 scores at the last session by quartile of waiting time for all intensities combined. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.VIII: Histograms for PHQ-9 Measured at the Last Session by Quartile of Waiting Time, by Treatments Intensities

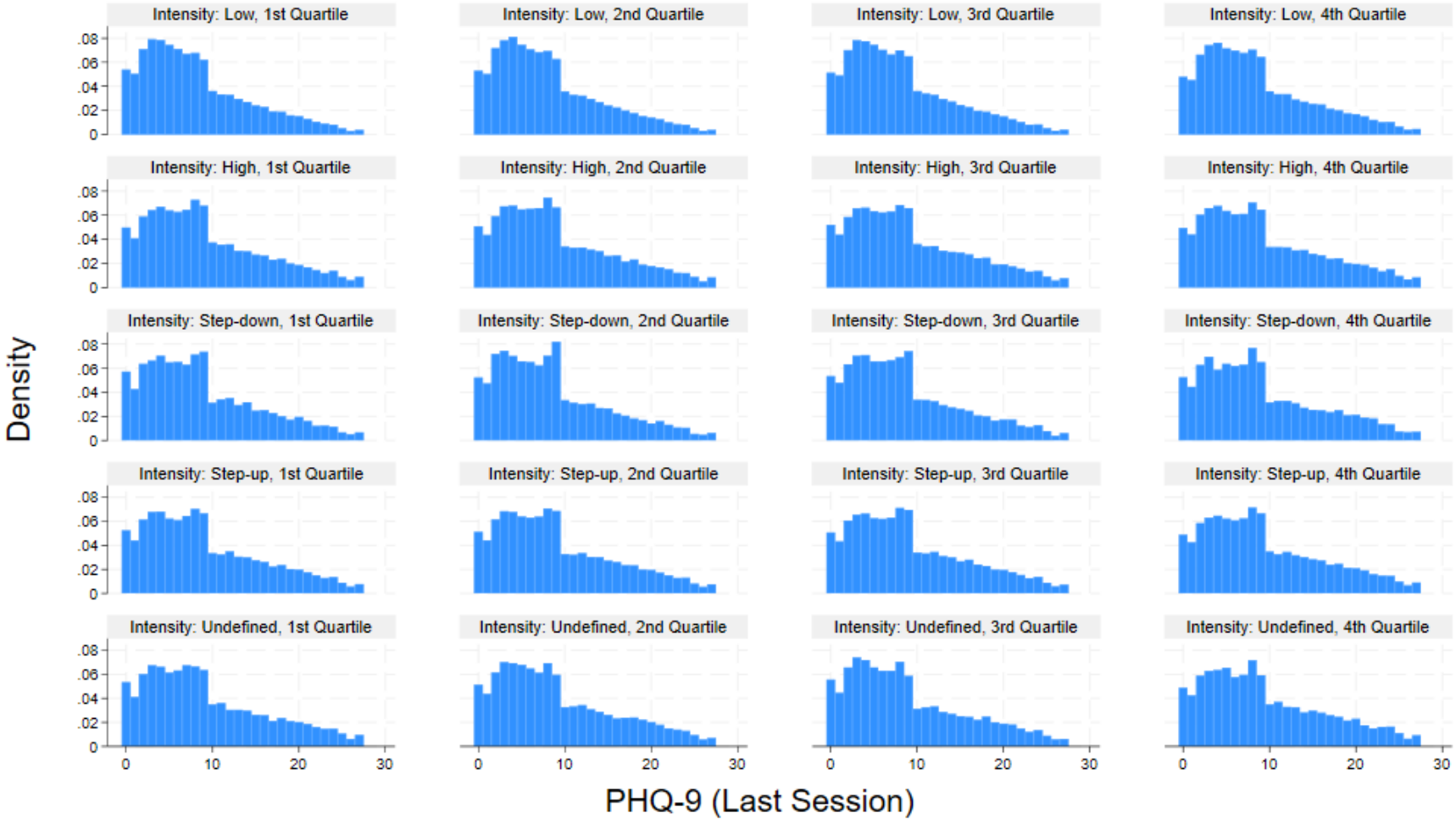


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Table E.VIII: Summary Statistics for PHQ-9 Scores at Last Session by Quartile of Waiting Time and Treatment Intensity

Intensity	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Low Intensity	8.168 (6.122)	8.121 (6.082)	8.234 (6.112)	8.590 (6.307)
High Intensity	9.236 (6.632)	9.073 (6.598)	9.252 (6.697)	9.331 (6.778)
Step Down	8.861 (6.505)	8.555 (6.369)	8.742 (6.463)	9.230 (6.751)
Step Up	9.171 (6.698)	9.125 (6.656)	9.231 (6.676)	9.476 (6.805)
Undefined	9.326 (6.831)	9.145 (6.721)	8.947 (6.700)	9.572 (6.878)

Note: The table shows the means (with standard deviations in parentheses) of PHQ-9 scores at the last session by quartile of waiting time and treatment intensity. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.IX: Histograms for GAD-7 Measured at the First Session by Quartile of Waiting Time, All Treatments Intensities.

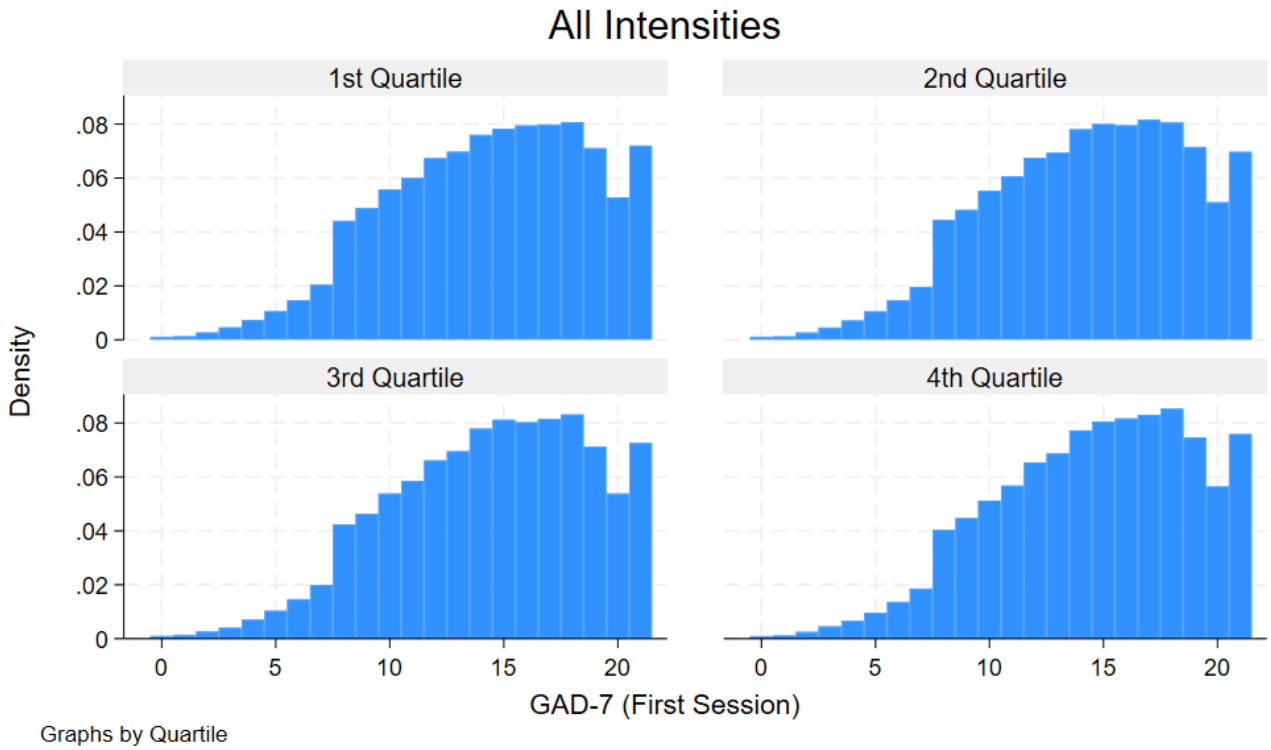

Table E.IX: Summary Statistics for GAD-7 Scores at First Session by Quartile of Waiting Time, All Intensities

Quartile	Mean	SD
1	14.312	4.366
2	14.307	4.336
3	14.397	4.332
4	14.536	4.315

Note: The table shows the means and standard deviations of GAD-7 scores at the first session by quartile of waiting time for all intensities combined. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.X: Histograms for GAD-7 Measured at the First Session by Quartile of Waiting Time, by Treatments Intensities

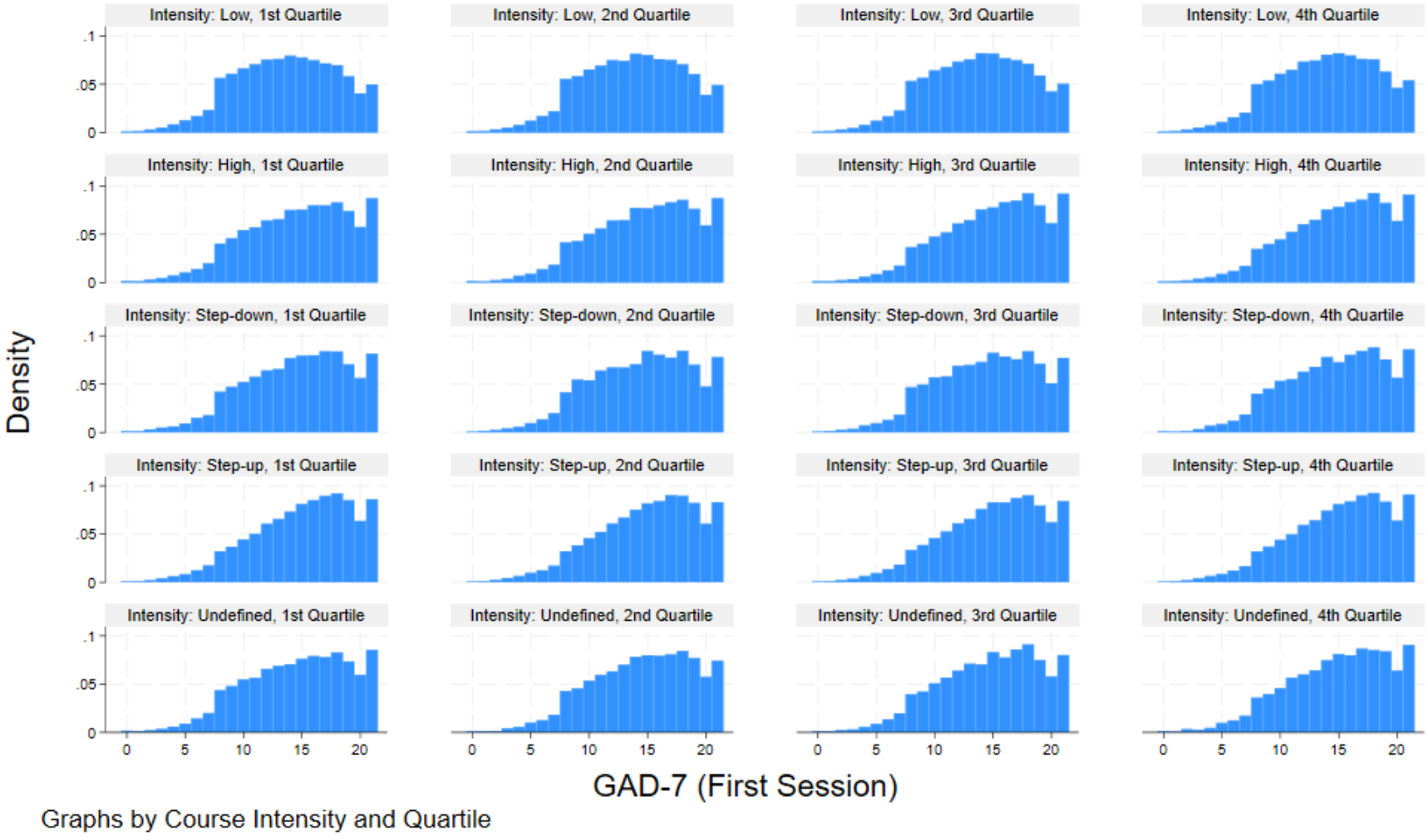

Table E.X: Summary Statistics for GAD-7 Scores at First Session by Quartile of Waiting Time and Treatment Intensity

Intensity	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Low Intensity	13.634 (4.313)	13.698 (4.290)	13.754 (4.293)	13.948 (4.286)
High Intensity	14.539 (4.418)	14.660 (4.357)	14.868 (4.309)	14.926 (4.289)
Step Down	14.503 (4.375)	14.356 (4.340)	14.372 (4.341)	14.658 (4.316)
Step Up	14.936 (4.274)	14.830 (4.289)	14.808 (4.303)	14.975 (4.284)
Undefined	14.525 (4.394)	14.525 (4.289)	14.644 (4.293)	14.878 (4.300)

Note: The table shows the means (with standard deviations in parentheses) of GAD-7 scores at the first session by quartile of waiting time and treatment intensity. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.XI: Histograms for GAD-7 Measured at the Last Session by Quartile of Waiting Time, All Treatments Intensities.

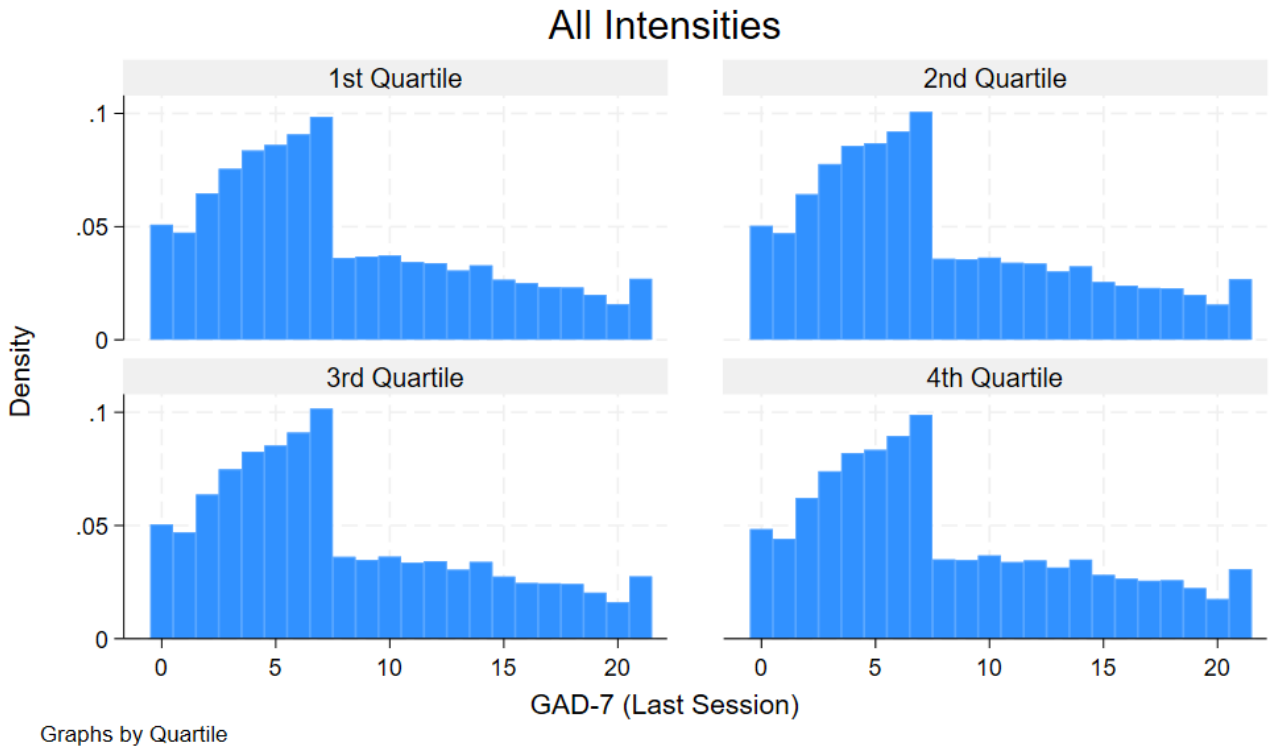

Table E.XI: Summary Statistics for GAD-7 Scores at Last Session by Quartile of Waiting Time, All Intensities

Quartile	Mean	SD
1	7.908	5.628
2	7.852	5.604
3	7.967	5.655
4	8.172	5.749

Note: The table shows the means and standard deviations of GAD-7 scores at the last session by quartile of waiting time for all intensities combined. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Figure E.XII: Histograms for GAD-7 Measured at the Last Session by Quartile of Waiting Time, by Treatments Intensities

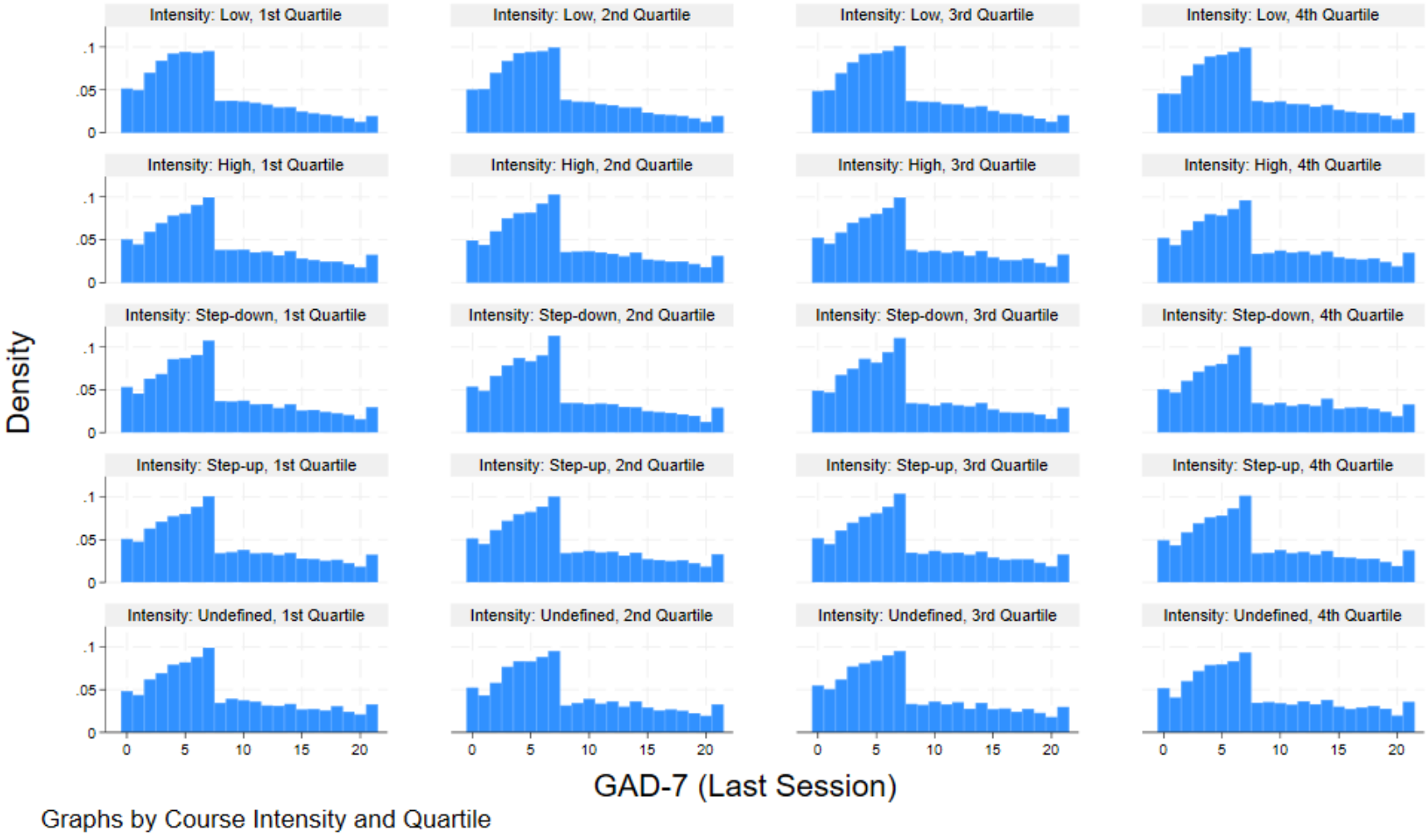

Table E.XII: Summary Statistics for GAD-7 Scores at Last Session by Quartile of Waiting Time and Treatment Intensity

Intensity	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Low Intensity	7.440 (5.367)	7.407 (5.346)	7.508 (5.379)	7.801 (5.522)
High Intensity	8.222 (5.730)	8.134 (5.718)	8.303 (5.810)	8.352 (5.869)
Step Down	7.941 (5.639)	7.730 (5.581)	7.917 (5.652)	8.318 (5.864)
Step Up	8.211 (5.801)	8.206 (5.787)	8.276 (5.809)	8.473 (5.888)
Undefined	8.335 (5.839)	8.225 (5.815)	8.046 (5.803)	8.508 (5.946)

Note: The table shows the means (with standard deviations in parentheses) of GAD-7 scores at the last session by quartile of waiting time and treatment intensity. Quartiles represent the distribution of waiting times, with Quartile 1 being the shortest waiting times and Quartile 4 the longest.

Table E.XIII: A Model for Waiting Time Between Initial Assessment and First Clinical Session in Weeks

	All Intensities	Low Int.	High Int.	Step Up	Step Down	Not Recorded
	(1)	(2)	(3)	(4)	(5)	(6)
Mental Health Index,	0.118***	0.130***	0.123***	0.035	-0.031	0.275***
Pre-Treatment (Z-Score)	(0.029)	(0.032)	(0.033)	(0.046)	(0.071)	(0.076)
Number of Individuals	1,246,792	491,942	275,990	388,136	44,396	46,328
R Squared	0.219	0.197	0.285	0.231	0.201	0.239
Therapy Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Controls	Yes	Yes	Yes	Yes	Yes	Yes
Local-Area Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at the clinical-commissioning-group level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

F Additional Results

Table F.I: Average Treatment Effects on Mental Health by Treatment Intensity (Full Table 2)

	Reliable Recovery (0-1)		Reliable Improvement (0-1)		Reliable Deterioration (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low Intensity						
Treatment	0.440***	0.430***	0.368***	0.360***	-0.078***	-0.078***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Number of Individuals	491,942	491,942	491,942	491,942	491,942	491,942
Treatment Group	245,433	245,433	245,433	245,433	245,433	245,433
Control Group	246,509	246,509	246,509	246,509	246,509	246,509
R Squared	0.216	0.284	0.138	0.179	0.020	0.053
Panel B: High Intensity						
Treatment	0.439***	0.429***	0.404***	0.393***	-0.084***	-0.084***
	(0.008)	(0.008)	(0.007)	(0.006)	(0.003)	(0.002)
Number of Individuals	275,990	275,990	275,990	275,990	275990	275990
Treatment Group	136,379	136,379	136,379	136,379	136379	136379
Control Group	139,611	139,611	139,611	139,611	139611	139611
R Squared	0.234	0.298	0.164	0.198	0.021	0.069
Panel C: Step Up (Low to High Intensity)						
Treatment	0.449***	0.435***	0.404***	0.385***	-0.095***	-0.090***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Number of Individuals	388,136	388,136	388,136	388,136	388136	388136
Treatment Group	191,868	191,868	191,868	191,868	191868	191868
Control Group	196,268	196,268	196,268	196,268	196268	196268
R Squared	0.244	0.296	0.164	0.200	0.024	0.078
Panel D: Step Down (High to Low Intensity)						
Treatment	0.452***	0.443***	0.395***	0.379***	-0.087***	-0.084***
	(0.009)	(0.008)	(0.010)	(0.007)	(0.004)	(0.004)
Number of Individuals	44,396	44,396	44,396	44,396	44396	44396
Treatment Group	21,752	21,752	21,752	21,752	21752	21752
Control Group	22,644	22,644	22,644	22,644	22644	22644
R Squared	0.235	0.307	0.158	0.208	0.022	0.077
Panel E: Intensity Not Recorded						
Treatment	0.427***	0.426***	0.367***	0.371***	-0.088***	-0.095***
	(0.012)	(0.013)	(0.009)	(0.008)	(0.004)	(0.004)

Number of Individuals	46,328	46,328	46,328	46,328	46328	46328
Treatment Group	23,142	23,142	23,142	23,142	23142	23142
Control Group	23,186	23,186	23,186	23,186	23186	23186
R Squared	0.217	0.292	0.135	0.184	0.021	0.079
Therapy Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Service Controls	No	Yes	No	Yes	No	Yes
Local-Area Controls	No	Yes	No	Yes	No	Yes
Service Fixed Effects	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table F.II: Average Treatment Effects on Mental Health by Treatment Intensity

	Δ PHQ-9 (0-27)		Δ GAD-7 (0-21)		Δ Mental Health Index (Z-Score)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low Intensity						
Treatment	-4.579***	-4.514***	-4.488***	-4.409***	-0.732***	-0.720***
	(0.059)	(0.054)	(0.054)	(0.050)	(0.009)	(0.008)
Number of Individuals	491,942	491,942	491,942	491,942	491,942	491,942
Treatment Group	245,433	245,433	245,433	245,433	245,433	245,433
Control Group	246,509	246,509	246,509	246,509	246,509	
R Squared	0.147	0.274	0.166	0.271	0.187	0.313
Panel B: High Intensity						
Treatment	-5.458***	-5.486***	-5.047***	-5.035***	-0.846***	-0.847***
	(0.110)	(0.084)	(0.084)	(0.077)	(0.015)	(0.013)
Number of Individuals	275,990	275,990	275,990	275,990	275,990	275,990
Treatment Group	136,379	136,379	136,379	136,379	136,379	136,379
Control Group	139,611	139,611	139,611	139,611	139,611	139,611
R Squared	0.186	0.291	0.196	0.283	0.223	0.329
Panel C: Step Up (Low to High Intensity)						
Treatment	-5.879***	-5.662***	-5.422***	-5.161***	-0.910***	-0.090***
	(0.063)	(0.060)	(0.051)	(0.049)	(0.009)	(0.002)
Number of Individuals	388,136	388,136	388,136	388,136	388,136	388,136
Treatment Group	191,868	191,868	191,868	191,868	191,868	191,868
Control Group	196,268	196,268	196,268	196,268	196,268	196,268
R Squared	0.199	0.309	0.210	0.304	0.237	0.078
Panel D: Step Down (High to Low Intensity)						
Treatment	-5.359***	-5.235***	-5.105***	-4.937***	-0.844***	-0.820***
	(0.180)	(0.147)	(0.150)	(0.120)	(0.026)	(0.021)
Number of Individuals	44,396	44,396	44,396	44,396	44,396	44,396
Treatment Group	21,752	21,752	21,752	21,752	21,752	21,752
Control Group	22,644	22,644	22,644	22,644	22,644	22,644
R Squared	0.175	0.311	0.193	0.305	0.215	0.351
Panel E: Intensity Not Recorded						
Treatment	-5.147***	-5.338***	-4.752***	-4.893***	-0.797***	-0.823***
	(0.114)	(0.128)	(0.108)	(0.123)	(0.017)	(0.020)
Number of Individuals	46,328	46,328	46,328	46,328	46,328	46,328
Treatment Group	23,142	23,142	23,142	23,142	23,142	23,142
Control Group	23,186	23,186	23,186	23,186	23,186	23,186

R Squared	0.160	0.282	0.168	0.274	0.191	0.317
Therapy Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Service Controls	No	Yes	No	Yes	No	Yes
Local-Area Controls	No	Yes	No	Yes	No	Yes
Service Fixed Effects	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes

Note: Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table F.III: Average Treatment Effects on Work and Social Functioning

	Work and Social Adjustment Scale					
	Δ Overall (0-40)	Δ Work (0-8)	Δ Home Management (0-8)	Δ Social Leisure (0-8)	Δ Private Leisure (0-8)	Δ Close Relationships (0-8)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-5.709***	-1.091***	-0.998***	-1.390***	-1.084***	-1.145***
	(0.079)	(0.019)	(0.016)	(0.017)	(0.017)	(0.017)
Therapy Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Controls	Yes	Yes	Yes	Yes	Yes	Yes
Local-Area Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Individuals	750,351	750,351	750,351	750,351	750,351	750,351
Treatment Group	369,506	369,506	369,506	369,506	369,506	369,506
Control Group	380,845	380,845	380,845	380,845	380,845	380,845
R Squared	0.138	0.069	0.068	0.104	0.072	0.074

Note: Robust standard errors clustered at service level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table F.IV: Average Treatment Effects on Employment and Benefits

	Employed (*vs.* Unemployed)		Employed (*vs.* Long-Term Sick)		Receiving Statutory Sick Pay	
	Average	If Unemployed At Baseline	Average	If LT Sick At Baseline	Average	If St. Sick Pay at Baseline
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.001	0.029***	0.004***	0.023***	-0.005***	-0.032***
	(0.001)	(0.004)	(0.001)	(0.006)	(0.001)	(0.004)
Pre-Treatment Outcome	Yes	No	Yes	No	Yes	No
Therapy Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Controls	Yes	Yes	Yes	Yes	Yes	Yes
Local-Area Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Individuals	721,523	80,137	694,187	63,546	1,081,196	83,000
Treatment Group	359,089	39,993	340,429	27,872	531,560	44,331
Control Group	362,434	40,144	353,758	35,674	549,636	38,669
R Squared	0.549	0.106	0.767	0.079	0.106	0.101

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

G Robustness Checks

Table G.I: Robustness Check: Selection on Outcome – Redefining Treatment Completion

	Reliable Recovery (0-1)		Reliable Improvement (0-1)		Reliable Deterioration (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: End of Treatment = Last Clinical Session - 1						
Treatment	0.267***	0.269***	0.325***	0.324***	-0.076***	-0.075***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)
Number of Individuals	1,163,182	1,163,182	1,163,182	1,163,182	1,163,182	1,163,182
Treatment Group	535,881	535,881	535,881	535,881	535,881	535,881
Control Group	627,301	627,301	627,301	627,301	627,301	627,301
R Squared	0.105	0.170	0.105	0.145	0.016	0.065
Panel B: End of Treatment = Last Clinical Session - 2						
Treatment	0.196***	0.199***	0.281***	0.283***	-0.068***	-0.067***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Number of Individuals	1,085,231	1,085,231	1,085,231	1,085,231	1,085,231	1,085,231
Treatment Group	457,930	457,930	457,930	457,930	457,930	457,930
Control Group	627,301	627,301	627,301	627,301	627,301	627,301
R Squared	0.065	0.129	0.077	0.118	0.012	0.065
Individual Controls	No	Yes	No	Yes	No	Yes
Therapy Controls	No	Yes	No	Yes	No	Yes
Local-Area Controls	No	Yes	No	Yes	No	Yes
Local-Area Fixed Effects	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table G.II: Robustness Check: Selection on Outcome – Grouping Treatment Intensities

	Reliable Recovery (0-1)		Reliable Improvement (0-1)		Reliable Deterioration (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low Intensity + Step Up						
Treatment	0.445***	0.431***	0.385***	0.370***	-0.086***	-0.083***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)
Number of Individuals	880,078	880,078	880,078	880,078	880,078	880,078
Treatment Group	432,092	432,092	432,092	432,092	432,092	432,092
Control Group	447,986	447,986	447,986	447,986	447,986	447,986
R Squared	0.229	0.290	0.149	0.186	0.022	0.064
Panel B: High Intensity + Step Down						
Treatment	0.440***	0.432***	0.400***	0.394***	-0.085***	-0.085***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.003)	(0.002)
Number of Individuals	320,386	320,386	320,386	320,386	320,386	320,386
Treatment Group	163,955	163,955	163,955	163,955	163,955	163,955
Control Group	156,431	156,431	156,431	156,431	156,431	156,431
R Squared	0.228	0.292	0.162	0.196	0.022	0.068
Therapy Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Service Controls	No	Yes	No	Yes	No	Yes
Local-Area Controls	No	Yes	No	Yes	No	Yes
Service Fixed Effects	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table G.III: Average Treatment Effects on Mental Health - Additionally Controlling for Total Number of Sessions and Total Treatment Duration

	Reliable Recovery (0-1)	Reliable Improvement (0-1)	Reliable Deterioration (0-1)
	(1)	(2)	(3)
Treatment	0.430***	0.372***	-0.083***
	(0.004)	(0.003)	(0.001)
Number of Individuals	1,246,792	1,246,792	1,246,792
Treatment Group	618,574	618,574	618,574
Control Group	628,218	628,218	628,218
R Squared	0.292	0.191	0.065
Individual Controls	Yes	Yes	Yes
Therapy Controls	Yes	Yes	Yes
Local-Area Controls	Yes	Yes	Yes
Local-Area Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

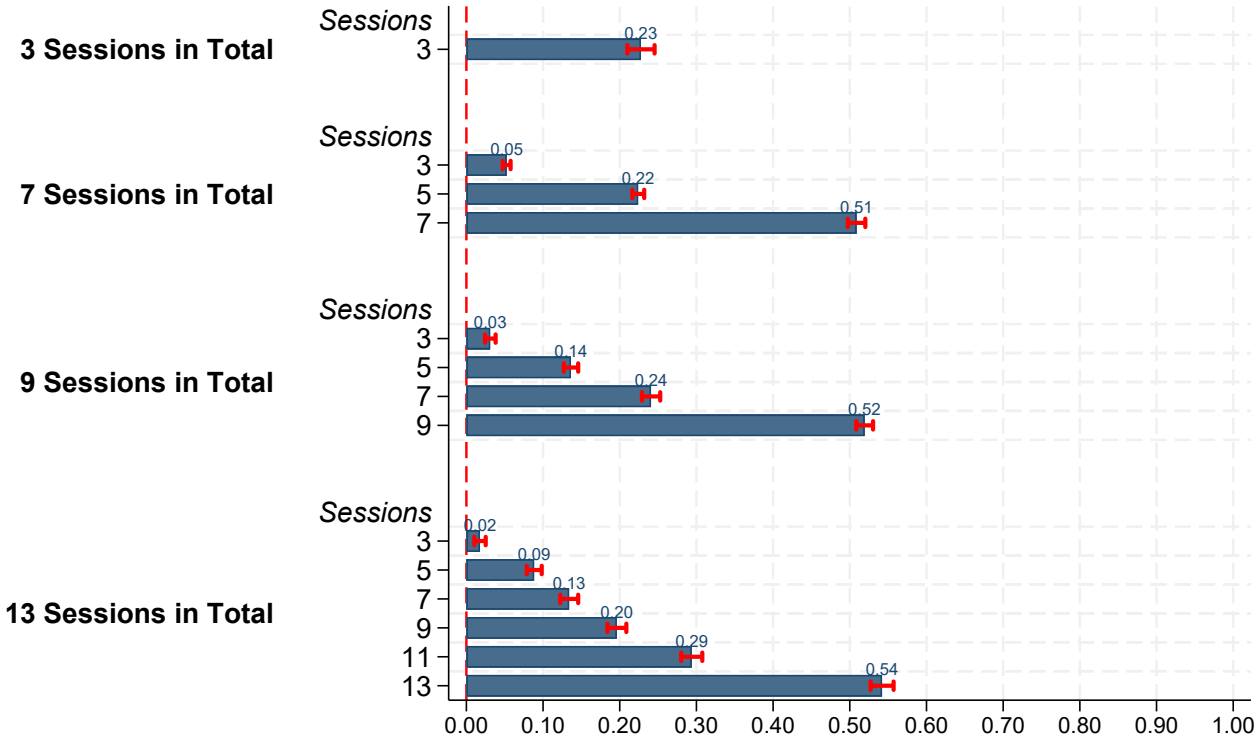

Figure G.I: Reliable Recovery – Session Value Added

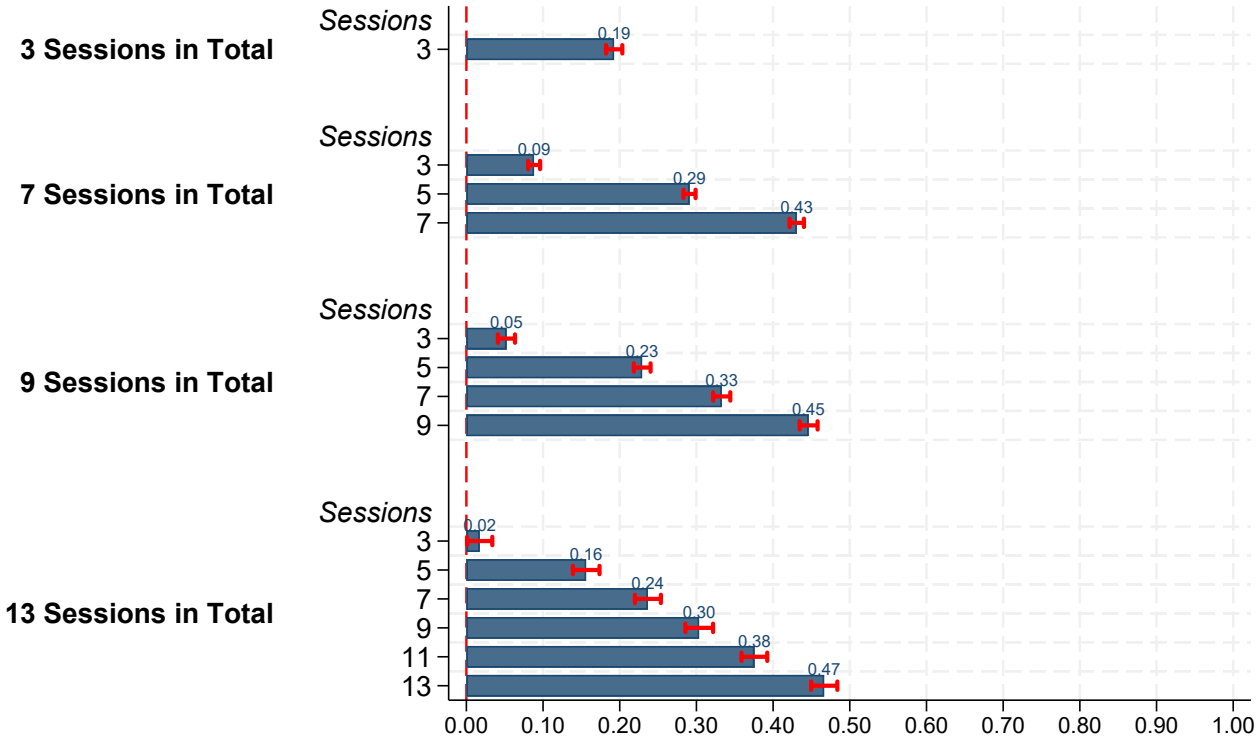

Figure G.II: Reliable Improvement – Session Value Added

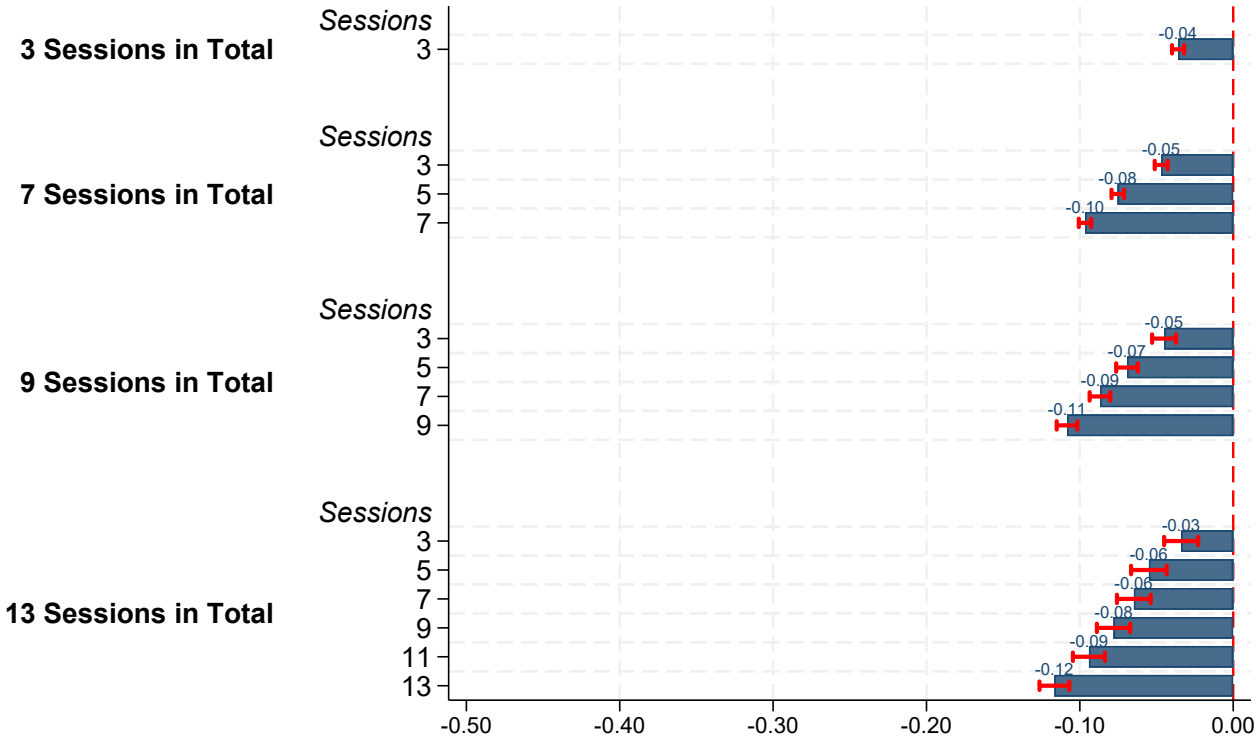

Figure G.III: Reliable Deterioration – Session Value Added

Table G.IV: Average Treatment Effects on Mental Health - Additionally Controlling for Session Spacing

	Reliable Recovery (0-1)		Reliable Improvement (0-1)		Reliable Deterioration (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.431***	0.430***	0.377***	0.376***	-0.084***	-0.084***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.001)	(0.001)
Weeks Per Session	No	Yes	No	Yes	No	Yes
Therapy Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Controls	Yes	Yes	Yes	Yes	Yes	Yes
Local-Area Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Individuals	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792
Treatment Group	619,491	619,491	619,491	619,491	619,491	619,491
Control Group	627,301	627,301	627,301	627,301	627,301	627,301
R Squared	0.289	0.290	0.187	0.189	0.064	0.064

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table G.V: Average Treatment Effects: Number of Weeks Between Sessions (Session Spacing)

	Reliable Recovery (1)	Reliable Improvement (2)	Reliable Deterioration (3)
≤25th Percentile (1.1 Weeks)			
Treatment	0.402***	0.356***	-0.077***
	(0.005)	(0.004)	(0.001)
Number of Individuals	311,675	311,675	311,675
Treatment Group	153,032	153,032	153,032
Control Group	158,643	158,643	158,643
R Squared	0.249	0.140	0.056
≥75th Percentile (2.4 Weeks)			
Treatment	0.391***	0.343***	-0.082***
	(0.006)	(0.005)	(0.002)
Number of Individuals	311,884	311,884	311,884
Treatment Group	166,638	166,638	166,638
Control Group	145,246	145,246	145,246
R Squared	0.284	0.200	0.071
≥90th Percentile (3.5 Weeks)			
Treatment	0.330***	0.291***	-0.070***
	(0.009)	(0.008)	(0.003)
Number of Individuals	128,479	128,479	128,479
Treatment Group	70,949	70,949	70,949
Control Group	57,530	57,530	57,530
R Squared	0.260	0.178	0.075
Individual Controls	Yes	Yes	Yes
Therapy Controls	Yes	Yes	Yes
Local-Area Controls	Yes	Yes	Yes
Local-Area Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes

Note: Robust standard errors clustered at service level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table G.VI: Predicting Repeat Enrolment From Weeks on Waitlist Amongst Control-Group Patients

	Repeat Enrolment (0-1)	
	(1)	(2)
Weeks on Waitlist	-0.001***	-0.001***
	(0.000)	(0.000)
Individual Controls	No	Yes
Therapy Controls	No	Yes
Local-Area Controls	No	Yes
Local-Area Fixed Effects	No	Yes
Time Fixed Effects	No	Yes
Number of Individuals	627,301	627,301
Treatment Group	0	0
Control Group	627,301	627,301
R Squared	0.000	0.069

Note: Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table G.VII: Average Treatment Effects: Robustness – Excluding Repeat Enrolments

	Reliable Recovery (0-1)		Reliable Improvement (0-1)		Reliable Deterioration (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.454***	0.441***	0.391***	0.380***	-0.087***	-0.085***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.001)
Individual Controls	No	Yes	No	Yes	No	Yes
Therapy Controls	No	Yes	No	Yes	No	Yes
Local-Area Controls	No	Yes	No	Yes	No	Yes
Local-Area Fixed Effects	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes
Number of Individuals	1,059,644	1,059,644	1,059,644	1,059,644	1,059,644	1,059,644
Treatment Group	518,366	518,366	518,366	518,366	518,366	518,366
Control Group	541,278	541,278	541,278	541,278	541,278	541,278
R Squared	0.237	0.299	0.155	0.19	0.022	0.064

Note: Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table G.VIII: Average Treatment Effects: Robustness – Other Percentiles of Waiting Time

	Reliable Recovery (0-1)		Reliable Improvement (0-1)		Reliable Deterioration (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)
25th Percentile of Waiting Time						
Treatment	0.443***	0.458***	0.402***	0.419***	-0.079***	-0.076***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	(0.001)
Number of Individuals	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792
Treatment Group	294,571	294,571	294,571	294,571	294,571	294,571
Control Group	952,221	952,221	952,221	952,221	952,221	952,221
R Squared	0.228	0.280	0.119	0.148	0.011	0.062
75th Percentile of Waiting Time						
Treatment	0.438***	0.464***	0.373***	0.396***	-0.092***	-0.093***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)
Number of Individuals	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792
Treatment Group	926,894	926,894	926,894	926,894	926,894	926,894
Control Group	319,898	319,898	319,898	319,898	319,898	319,898
R Squared	0.145	0.222	0.116	0.155	0.023	0.058
90th Percentile of Waiting Time						
Treatment	0.437***	0.456***	0.365***	0.385***	-0.097***	-0.095***
	(0.004)	(0.005)	(0.003)	(0.004)	(0.002)	(0.002)
Number of Individuals	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792	1,246,792
Treatment Group	1,121,181	1,121,181	1,121,181	1,121,181	1,121,181	1,121,181
Control Group	125,611	125,611	125,611	125,611	125,611	125,611
R Squared	0.069	0.153	0.058	0.101	0.015	0.044
Therapy Controls	No	Yes	No	Yes	No	Yes
Individual Controls	No	Yes	No	Yes	No	Yes
Service Controls	No	Yes	No	Yes	No	Yes
Local-Area Controls	No	Yes	No	Yes	No	Yes
Service Fixed Effects	No	Yes	No	Yes	No	Yes
Time Fixed Effects	No	Yes	No	Yes	No	Yes

Note: Linear probability models. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table G.IX: Average Treatment Effects: Robustness – Other Models and Outcomes

	Reliable Recovery (0-1)			Other Outcomes		
	Logit Marginal Effect	Without Substance Abuse	Only Depression, Anxiety	Δ PHQ-9 (0-27)	Δ GAD-7 (0-21)	Δ Mental Health Index (Z-Score)
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.381***	0.431***	0.431***	-5.126***	-4.808***	-0.800***
	(0.003)	(0.004)	(0.004)	(0.052)	(0.044)	(0.008)
Therapy Controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Controls	Yes	Yes	Yes	Yes	Yes	Yes
Local-Area Controls	Yes	Yes	Yes	Yes	Yes	Yes
Service Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Individuals	1,246,729	1,246,155	996,358	1,246,792	1,246,792	1,246,792
Treatment Group	618,521	618,239	491,358	618,574	618,574	618,574
Control Group	628,208	627,916	504,761	628,218	628,218	628,218
(Pseudo) R Squared	0.263	0.289	0.290	0.286	0.281	0.324

Note: Robust standard errors clustered at service level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

H Robustness Checks: Attrition

Our primary analysis includes patients who attended at least three sessions, including an initial assessment session. During the initial assessment, the therapist and the patient decide whether the patient should continue with treatment in the programme. Patients unsuitable for IAPT treatment are referred to other services. Those within the program's scope can choose not to participate. In this section, our focus is on patients who were accepted into the program, agreed to participate, but subsequently dropped out before the second session, totaling 260,200 patients.

If attrition is selective, i.e. the probability of dropping out is correlated with the probability of recovery, it can bias our treatment effect estimates. Since we do not observe these patients after the first session, we lack information on whether their condition improved or deteriorated. We investigate potential impact of attrition on our programme effectiveness estimates by assuming various recovery rates for this group.

We impute the waiting time for patients who dropped out based on the average waiting time for the treatment intensity they were assigned to at the service they attended in the month of assessment. Subsequently, based on their waiting time, we allocate them to the treatment or control group using the same thresholds as in our main results.[57]

To bounds the estimates for three main outcomes (reliable recovery, reliable improvement, and reliable deterioration), we consider four scenarios:

- *Scenario 1:* All patients who dropped out of the treatment group deteriorated; hence, none recovered. All patients who dropped out of the control group improved and recovered, none deteriorated. This scenario provides an extreme lower bound for the treatment effect estimate because it elevates natural recovery rates estimated on the control group and suppresses recovery rates at the end of the program, estimated on the treatment group.

- *Scenario 2:* All patients who dropped out of the treatment and the control group improved and recovered, none deteriorated.

- *Scenario 3:* All patients who dropped out of the treatment and the control group deteriorated, and none improved or recovered.

- *Scenario 4:* All patients who dropped out of the treatment group improved and recovered, and none deteriorated. All patients who dropped out of the control group deteriorated; hence, none recovered. This scenario is the opposite of the first option and provides an extreme upper bound.

Table H.I reports the outcomes of models that include all controls for the four specified scenarios. Column 1 presents the main results for the reference. Across all scenarios, the programme significantly increases the

[57] Patients who drop out are typically located in services with longer waiting times; 74.56% of them were assigned to the control group. They are more likely to receive low-intensity treatment, 67.07% compared to 39.46% in the main sample. The symptoms of low-intensity patients who dropped out are slightly more severe than in the main sample, whereas symptoms are slightly less severe for other treatment intensities.

probability of recovery and improvement. Additionally, in all scenarios except the most extreme Scenario 1, the programme significantly reduces the probability of deterioration.

Table H.I: Average Treatment Effects on Mental Health for Different Recovery Scenarios of Drop-Out Patients

	Main result Table 1	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	(1)	(2)	(3)	(4)	(5)
Reliable Recovery					
Treatment	0.431***	0.218***	0.296***	0.404***	0.483***
	(0.004)	(0.009)	(0.007)	(0.004)	(0.004)
R Squared	0.29	0.10	0.16	0.27	0.36
Reliable Improvement					
Treatment	0.377***	0.195***	0.273***	0.381***	0.460***
	(0.003)	(0.008)	(0.005)	(0.005)	(0.004)
R Squared	0.19	0.07	0.12	0.21	0.28
Reliable Deterioration					
Treatment	-0.084***	0.016***	-0.063***	-0.171***	-0.249***
	(0.001)	(0.005)	(0.001)	(0.007)	(0.007)
R Squared	0.06	0.06	0.05	0.16	0.21
Number of Individuals	1,246,792	1,507,012	1,507,012	1,507,012	1,507,012
Treatment Group	628,218	684,786	684,786	684,786	684,786
Control Group	618,574	822,226	822,226	822,226	822,226

Note: Linear probability model with all controls. Binary dependent variables. Robust standard errors clustered at service level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

I Heterogeneous Treatment Effects

Table I.I: Summary statistics of for the full sample and the nonparametric estimation sample

	Full sample		Nonparametric sample	
	Mean	Standard Deviation	Mean	Standard Deviation
Outcomes				
Reliable recovery	0.312	0.463	0.309	0.462
Reliable improvement	0.549	0.498	0.546	0.498
Reliable deterioration	0.093	0.291	0.091	0.287
Covariates				
Course intensity: Low intensity	0.395	0.489	0.445	0.497
High intensity	0.221	0.415	0.215	0.411
Step down	0.036	0.185	0.007	0.083
Step up	0.311	0.463	0.328	0.469
Undefined	0.037	0.189	0.005	0.073
Severity above median	0.497	0.500	0.490	0.500
Long-term health condition	0.202	0.402	0.131	0.337
Religion: Christian	0.191	0.393	0.163	0.369
Not religious	0.328	0.470	0.347	0.476
Other religion and missing	0.481	0.500	0.490	0.500
Ethnicity: White British	0.632	0.482	0.637	0.481
Other	0.081	0.273	0.017	0.128
Missing	0.287	0.452	0.347	0.476
Deprivation above median	0.551	0.497	0.551	0.497
Service size above median (number of staff)	0.500	0.500	0.506	0.500
Service funding per patient above median	0.499	0.500	0.514	0.500
Months: 2 or less	0.380	0.485	0.441	0.496
3	0.213	0.409	0.229	0.420
4	0.132	0.339	0.125	0.330
5	0.082	0.275	0.065	0.246
6	0.053	0.223	0.026	0.160
7 or above	0.140	0.347	0.115	0.319
Observations	1,246,792		947,547	

Table I.II: Heterogeneous treatment effect estimates. Full result for Table 5.3.

	Reliable recovery	Reliable improvement	Reliable deterioration
Treated	0.461***	0.371***	-0.099***
	(0.003)	(0.003)	(0.002)
Course intensity: Low intensity	0	0	0
	(.)	(.)	(.)
High intensity	-0.030***	-0.054***	0.021***
	(0.002)	(0.002)	(0.001)
Step down	-0.001	-0.014*	0.006
	(0.007)	(0.008)	(0.005)
Step up	-0.040***	-0.063***	0.036***
	(0.002)	(0.002)	(0.001)
Undefined	-0.002	0.023**	0.024***
	(0.008)	(0.009)	(0.006)
Severity above median	-0.105***	0.103***	-0.131***
	(0.001)	(0.001)	(0.001)
Deprivation above median, 1 if true	-0.023***	-0.044***	0.026***
	(0.001)	(0.001)	(0.001)
Long-term health condition	-0.013***	-0.039***	0.016***
	(0.002)	(0.002)	(0.001)
Service size above median (number of staff)	-0.001	0.003**	-0.002***
	(0.001)	(0.001)	(0.001)
Service funding per patient above median	-0.006***	-0.022***	0.010***
	(0.001)	(0.001)	(0.001)
Christian	0	0	0
	(.)	(.)	(.)
Not religious	-0.014***	-0.006***	-0.002*
	(0.002)	(0.002)	(0.001)
Other religion and missing	-0.012***	-0.009***	0.001
	(0.002)	(0.003)	(0.002)
White	0	0	0
	(.)	(.)	(.)
Other	-0.006	-0.026***	0.031***
	(0.005)	(0.006)	(0.004)
Missing	0.006***	0.007***	0.002*
	(0.002)	(0.002)	(0.001)
Months: 2 or less	0	0	0
	(.)	(.)	(.)
3	0.011***	0.025***	0.013***
	(0.002)	(0.002)	(0.001)
4	0.013***	0.032***	0.019***
	(0.002)	(0.002)	(0.001)
5	0.012***	0.037***	0.021***
	(0.002)	(0.003)	(0.002)
6	0.017***	0.043***	0.020***
	(0.004)	(0.004)	(0.003)
7 or above	0.013***	0.047***	0.028***
	(0.002)	(0.002)	(0.001)

Low intensity * Treated	0	0	0
	(.)	(.)	(.)
High intensity * Treated	0.002	0.039***	-0.016***
	(0.002)	(0.003)	(0.002)
Step down * Treated	0.003	0.017	0.001
	(0.010)	(0.012)	(0.007)
Step up * Treated	-0.018***	0.021***	-0.019***
	(0.002)	(0.003)	(0.002)
Undefined * Treated	-0.036***	-0.066***	-0.011
	(0.012)	(0.013)	(0.008)
Severity above median * Treated	-0.088***	-0.071***	0.096***
	(0.002)	(0.002)	(0.001)
Deprivation above median, 1 if true * Treated	-0.027***	0.004**	-0.014***
	(0.002)	(0.002)	(0.001)
Long-term health condition * Treated	-0.026***	0.003	-0.008***
	(0.003)	(0.003)	(0.002)
Service size above median (number of staff) * Treated	-0.004**	-0.006***	0.003**
	(0.002)	(0.002)	(0.001)
Service funding per patient above median * Treated	0.021***	0.026***	-0.010***
	(0.002)	(0.002)	(0.001)
Christian * Treated	0	0	0
	(.)	(.)	(.)
Not religious * Treated	-0.025***	-0.013***	0.007***
	(0.003)	(0.003)	(0.002)
Other religion and missing * Treated	-0.030***	-0.021***	0.006***
	(0.003)	(0.004)	(0.002)
White * Treated	0	0	0
	(.)	(.)	(.)
Other * Treated	-0.018**	0	-0.016***
	(0.007)	(0.008)	(0.005)
Missing * Treated	-0.055***	-0.030***	0.002
	(0.003)	(0.003)	(0.002)
2 or less * Treated	0	0	0
	(.)	(.)	(.)
3 * Treated	0.111***	0.069***	-0.025***
	(0.002)	(0.003)	(0.002)
4 * Treated	0.129***	0.076***	-0.033***
	(0.003)	(0.003)	(0.002)
5 * Treated	0.125***	0.065***	-0.030***
	(0.003)	(0.004)	(0.002)
6 * Treated	0.132***	0.064***	-0.033***
	(0.005)	(0.006)	(0.004)
7 or above * Treated	0.115***	0.050***	-0.032***
	(0.003)	(0.003)	(0.002)
Constant	0.188***	0.368***	0.149***
	(0.002)	(0.002)	(0.001)
R2	0.26	0.16	0.05
Observations	947,547	947,547	947,547

Table I.III: Average values of covariates by quartiles of estimated treatment effects. Reliable recovery.

	1 quartile	2 quartile	3 quartile	4 quartile
Individual characteristics				
Age, standardised	-0.141	0.037	0.063	0.041
Ex-services member of armed forces	0.012	0.012	0.012	0.018
Not an ex-services member or their dependant	0.484	0.520	0.482	0.778
Dependant of an ex-services member	0.002	0.002	0.002	0.003
No Response (armed forces)	0.502	0.466	0.504	0.201
Employed	0.338	0.536	0.588	0.815
Unemployed and Seeking Work	0.186	0.093	0.100	0.002
Students FT	0.072	0.051	0.064	0.028
Long-term sick or disabled	0.193	0.107	0.010	0.000
Homemaker	0.065	0.051	0.053	0.025
Not receiving benefits and not working or searching	0.037	0.022	0.024	0.011
Unpaid voluntary work	0.004	0.004	0.004	0.002
Retired	0.028	0.073	0.093	0.087
No Response (employment)	0.078	0.062	0.064	0.029
White background	0.527	0.579	0.530	0.893
Mixed background	0.017	0.015	0.018	0.015
Asian background	0.041	0.030	0.037	0.028
Black background	0.023	0.018	0.021	0.016
Other background (ethnicity)	0.013	0.010	0.012	0.008
No Response (ethnicity)	0.378	0.348	0.381	0.040
Male	0.222	0.237	0.218	0.313
Female	0.435	0.450	0.438	0.663
Indeterminate gender	0.000	0.000	0.001	0.000
No Response (gender)	0.343	0.313	0.344	0.024
Long term health condition	0.214	0.185	0.178	0.231
No long term health condition	0.354	0.413	0.389	0.653
No Response (health condition)	0.432	0.401	0.433	0.116
Religion: Christian	0.155	0.168	0.169	0.269
Not religious	0.286	0.306	0.268	0.454
Other religion	0.060	0.047	0.054	0.055
No Response (religion)	0.498	0.479	0.509	0.222
Heterosexual or Straight	0.481	0.517	0.481	0.776
Gay or Lesbian	0.016	0.015	0.015	0.021
Bisexual	0.014	0.013	0.013	0.016
Other sexual orientation or not listed	0.010	0.009	0.009	0.008
No Response (sexual orientation)	0.480	0.447	0.482	0.178
Relative deprivation of patient postcode (by LSOA), std.	-0.203	0.026	0.067	0.111
Treatment characteristics				
Course intensity: Low intensity	0.400	0.489	0.362	0.327
Course intensity: High intensity	0.274	0.219	0.202	0.190
Course intensity: Step down	0.034	0.033	0.038	0.038

Course intensity: Step up	0.253	0.226	0.359	0.407
Course intensity: Undefined	0.038	0.033	0.039	0.038
Initial diagnosis: Anxiety and stress related disorders	0.010	0.007	0.006	0.004
Initial diagnosis: Depression	0.163	0.232	0.229	0.258
Initial diagnosis: Other problems	0.049	0.059	0.067	0.071
Initial diagnosis: Unspecified or Invalid Data	0.778	0.702	0.697	0.667
Medication usage: Prescribed but not taking	0.048	0.043	0.046	0.045
Medication usage: Prescribed and taking	0.557	0.454	0.446	0.449
Medication usage: Not Prescribed	0.322	0.432	0.446	0.460
No Response (medication usage)	0.073	0.071	0.062	0.045
Symptoms severity at start	0.998	0.209	0.265	0.263
Appointment month	-0.010	-0.014	-0.001	0.024
Referral type: Primary Health Care	0.240	0.219	0.223	0.185
Referral type: Self Referral	0.675	0.712	0.714	0.759
Referral type: Other	0.086	0.068	0.063	0.056
Treatment mode: Face to face communication	0.316	0.294	0.264	0.243
Treatment mode: Telephone	0.646	0.667	0.699	0.726
Treatment mode: Other	0.038	0.039	0.037	0.030
Appointment weekday	2.914	2.921	2.914	2.921
Service characteristics				
CCG Allocations per registered patient, standardised	0.026	-0.024	-0.037	0.035
CCG Estimated registered patients, standardised	-0.003	0.010	0.051	-0.058
CCG Number of Staff, standardised	0.007	0.002	0.021	-0.030
CCG Number of Staff, missing	0.055	0.049	0.048	0.061
Local area characteristics				
IMD: Crime - Average rank, standardised	0.052	-0.021	-0.008	-0.022
IMD: Education, Skills and Training - Average rank, std.	0.037	-0.041	-0.085	0.089
IMD: Employment - Average rank, standardised	0.046	-0.051	-0.075	0.080
IMD: Living Environment - Average rank, standardised	0.006	-0.002	0.039	-0.044
IMD: Health Deprivation and Disability - Average rank, std.	0.039	-0.042	-0.082	0.086
IMD: Barriers to Housing and Services - Average rank, std.	0.015	0.015	0.097	-0.128
IMD: Income - Average rank, standardised	0.053	-0.044	-0.039	0.031
IMD - Average rank, standardised	-0.049	0.042	0.043	-0.036
CCG Median Wage, standardised	-0.012	0.025	0.090	-0.103
CCG Unemployment Rate	4.429	4.321	4.325	4.392
Waiting times				
Months wait: 2 or less	0.736	0.673	0.112	0.000
Months wait: 3	0.080	0.110	0.316	0.345
Months wait: 4	0.053	0.066	0.190	0.219
Months wait: 5	0.036	0.044	0.117	0.132
Months wait: 6	0.024	0.029	0.074	0.083
Months wait: 7	0.017	0.020	0.049	0.057
Months wait: 8 or above	0.054	0.057	0.141	0.164

Table I.IV: Average values of covariates by quartiles of estimated treatment effects. Reliable improvement.

	1 quartile	2 quartile	3 quartile	4 quartile
Individual characteristics				
Age, standardised	-0.053	0.010	0.050	-0.007
Ex-services member of armed forces	0.011	0.012	0.014	0.016
Not an ex-services member or their dependant	0.437	0.522	0.555	0.749
Dependant of an ex-services member	0.002	0.002	0.003	0.003
No Response (armed forces)	0.550	0.464	0.428	0.232
Employed	0.547	0.554	0.576	0.600
Unemployed and Seeking Work	0.116	0.106	0.085	0.072
Students FT	0.054	0.053	0.051	0.058
Long-term sick or disabled	0.091	0.084	0.076	0.059
Homemaker	0.051	0.049	0.046	0.047
Not receiving benefits and not working or searching	0.026	0.024	0.023	0.020
Unpaid voluntary work	0.003	0.004	0.004	0.004
Retired	0.054	0.067	0.080	0.080
No Response (employment)	0.058	0.058	0.059	0.058
White background	0.484	0.566	0.623	0.856
Mixed background	0.014	0.019	0.015	0.017
Asian background	0.030	0.043	0.030	0.033
Black background	0.018	0.026	0.016	0.019
Other background (ethnicity)	0.009	0.014	0.009	0.010
No Response (ethnicity)	0.445	0.332	0.306	0.064
Male	0.197	0.237	0.242	0.313
Female	0.391	0.468	0.485	0.641
Indeterminate gender	0.000	0.000	0.001	0.001
No Response (gender)	0.412	0.294	0.272	0.045
Long term health condition	0.166	0.201	0.198	0.243
No long term health condition	0.346	0.417	0.438	0.609
No Response (health condition)	0.488	0.382	0.364	0.148
Religion: Christian	0.142	0.171	0.193	0.256
Not religious	0.260	0.299	0.319	0.436
Other religion	0.045	0.059	0.051	0.062
No Response (religion)	0.553	0.471	0.437	0.247
Heterosexual or Straight	0.436	0.524	0.550	0.744
Gay or Lesbian	0.014	0.017	0.015	0.020
Bisexual	0.012	0.014	0.013	0.017
Other sexual orientation or not listed	0.007	0.010	0.009	0.010
No Response (sexual orientation)	0.531	0.434	0.413	0.208
Relative deprivation of patient postcode (by LSOA), std.	-0.015	0.019	-0.022	0.018
Treatment characteristics				
Course intensity: Low intensity	0.491	0.416	0.350	0.321
Course intensity: High intensity	0.248	0.213	0.220	0.204
Course intensity: Step down	0.030	0.033	0.038	0.042
Course intensity: Step up	0.198	0.302	0.353	0.393
Course intensity: Undefined	0.033	0.036	0.039	0.041
Initial diagnosis: Anxiety and stress related disorders	0.008	0.008	0.006	0.006
Initial diagnosis: Depression	0.203	0.213	0.228	0.237

Initial diagnosis: Other problems	0.049	0.059	0.064	0.074
Initial diagnosis: Unspecified or Invalid Data	0.740	0.720	0.701	0.683
Medication usage: Prescribed but not taking	0.048	0.048	0.045	0.042
Medication usage: Prescribed and taking	0.523	0.487	0.465	0.432
Medication usage: Not Prescribed	0.364	0.399	0.429	0.467
No Response (medication usage)	0.065	0.066	0.062	0.058
Symptoms severity at start	0.887	0.566	0.328	-0.046
Appointment month	-0.002	-0.007	-0.003	0.012
Referral type: Primary Health Care	0.226	0.229	0.214	0.198
Referral type: Self Referral	0.707	0.704	0.716	0.734
Referral type: Other	0.067	0.067	0.070	0.068
Treatment mode: Face to face communication	0.291	0.276	0.281	0.269
Treatment mode: Telephone	0.668	0.685	0.687	0.698
Treatment mode: Other	0.041	0.039	0.032	0.033
Appointment weekday	2.922	2.913	2.919	2.915
Service characteristics				
CCG Allocations per registered patient, standardised	-0.062	-0.090	0.066	0.085
CCG Estimated registered patients, standardised	0.069	0.116	-0.105	-0.080
CCG Number of Staff, standardised	0.036	0.042	-0.055	-0.024
CCG Number of Staff, missing	0.047	0.038	0.063	0.066
Local area characteristics				
IMD: Crime - Average rank, standardised	-0.073	-0.045	0.057	0.061
IMD: Education, Skills and Training - Average rank, std.	-0.117	-0.154	0.119	0.153
IMD: Employment - Average rank, standardised	-0.153	-0.173	0.142	0.183
IMD: Living Environment - Average rank, standardised	-0.042	0.082	-0.024	-0.016
IMD: Health Deprivation and Disability - Average rank, std.	-0.153	-0.173	0.141	0.185
IMD: Barriers to Housing and Services - Average rank, std.	0.086	0.188	-0.126	-0.148
IMD: Income - Average rank, standardised	-0.128	-0.109	0.104	0.134
IMD - Average rank, standardised	0.127	0.108	-0.101	-0.134
CCG Median Wage, standardised	0.095	0.139	-0.090	-0.144
CCG Unemployment Rate	4.234	4.229	4.491	4.513
Waiting times				
Months wait: 2 or less	0.873	0.434	0.215	0.000
Months wait: 3	0.046	0.183	0.270	0.353
Months wait: 4	0.022	0.112	0.170	0.223
Months wait: 5	0.018	0.077	0.104	0.130
Months wait: 6	0.012	0.051	0.066	0.082
Months wait: 7	0.008	0.034	0.044	0.056
Months wait: 8 or above	0.021	0.109	0.130	0.157

Table I.V: Average values of covariates by quartiles of estimated treatment effects. Reliable deterioration.

	1 quartile	2 quartile	3 quartile	4 quartile
Individual characteristics				
Age, standardised	0.029	-0.005	-0.043	0.019
Ex-services member of armed forces	0.013	0.012	0.013	0.015
Not an ex-services member or their dependant	0.592	0.540	0.569	0.562
Dependant of an ex-services member	0.002	0.002	0.003	0.003
No Response (armed forces)	0.393	0.445	0.415	0.421
Employed	0.600	0.613	0.571	0.493
Unemployed and Seeking Work	0.073	0.075	0.098	0.134
Students FT	0.058	0.059	0.057	0.042
Long-term sick or disabled	0.049	0.047	0.079	0.134
Homemaker	0.048	0.045	0.049	0.052
Not receiving benefits and not working or searching	0.019	0.018	0.024	0.033
Unpaid voluntary work	0.004	0.004	0.003	0.003
Retired	0.088	0.083	0.062	0.049
No Response (employment)	0.061	0.056	0.056	0.060
White background	0.666	0.608	0.632	0.624
Mixed background	0.017	0.015	0.016	0.017
Asian background	0.033	0.027	0.034	0.042
Black background	0.020	0.017	0.020	0.022
Other background (ethnicity)	0.010	0.009	0.011	0.013
No Response (ethnicity)	0.255	0.323	0.286	0.283
Male	0.264	0.242	0.240	0.244
Female	0.512	0.466	0.503	0.504
Indeterminate gender	0.001	0.000	0.001	0.000
No Response (gender)	0.224	0.291	0.256	0.252
Long term health condition	0.195	0.174	0.202	0.238
No long term health condition	0.484	0.450	0.455	0.421
No Response (health condition)	0.321	0.376	0.343	0.341
Religion: Christian	0.204	0.181	0.187	0.189
Not religious	0.335	0.316	0.335	0.328
Other religion	0.053	0.045	0.054	0.064
No Response (religion)	0.408	0.457	0.424	0.418
Heterosexual or Straight	0.589	0.540	0.562	0.564
Gay or Lesbian	0.016	0.015	0.017	0.018
Bisexual	0.013	0.013	0.015	0.014
Other sexual orientation or not listed	0.009	0.008	0.009	0.010
No Response (sexual orientation)	0.372	0.424	0.397	0.395
Relative deprivation of patient postcode (by LSOA), std.	0.021	0.142	-0.012	-0.151
Treatment characteristics				
Course intensity: Low intensity	0.340	0.522	0.389	0.328
Course intensity: High intensity	0.208	0.198	0.219	0.260
Course intensity: Step down	0.042	0.031	0.034	0.036
Course intensity: Step up	0.368	0.219	0.322	0.337
Course intensity: Undefined	0.042	0.031	0.036	0.040
Initial diagnosis: Anxiety and stress related disorders	0.006	0.006	0.007	0.009
Initial diagnosis: Depression	0.226	0.259	0.224	0.174

Initial diagnosis: Other problems	0.077	0.059	0.057	0.053
Initial diagnosis: Unspecified or Invalid Data	0.691	0.676	0.712	0.764
Medication usage: Prescribed but not taking	0.042	0.043	0.048	0.050
Medication usage: Prescribed and taking	0.403	0.415	0.498	0.590
Medication usage: Not Prescribed	0.492	0.474	0.394	0.299
No Response (medication usage)	0.063	0.068	0.060	0.061
Symptoms severity at start	-0.278	0.023	0.698	1.292
Appointment month	0.004	-0.002	0.001	-0.003
Referral type: Primary Health Care	0.214	0.208	0.213	0.233
Referral type: Self Referral	0.718	0.733	0.720	0.690
Referral type: Other	0.068	0.060	0.067	0.078
Treatment mode: Face to face communication	0.277	0.273	0.269	0.299
Treatment mode: Telephone	0.688	0.685	0.697	0.668
Treatment mode: Other	0.035	0.042	0.035	0.033
Appointment weekday	2.919	2.922	2.914	2.915
Service characteristics				
CCG Allocations per registered patient, standardised	0.023	-0.062	0.007	0.032
CCG Estimated registered patients, standardised	-0.002	0.006	-0.005	0.001
CCG Number of Staff, standardised	0.001	-0.009	-0.003	0.010
CCG Number of Staff, missing	0.050	0.049	0.054	0.061
Local area characteristics				
IMD: Crime - Average rank, standardised	0.089	-0.075	-0.011	-0.002
IMD: Education, Skills and Training - Average rank, std.	0.049	-0.118	0.007	0.063
IMD: Employment - Average rank, standardised	0.086	-0.134	0.000	0.048
IMD: Living Environment - Average rank, standardised	0.084	-0.027	-0.017	-0.040
IMD: Health Deprivation and Disability - Average rank, std.	0.080	-0.116	0.002	0.034
IMD: Barriers to Housing and Services - Average rank, std.	0.023	0.020	-0.024	-0.018
IMD: Income - Average rank, standardised	0.102	-0.124	-0.008	0.030
IMD - Average rank, standardised	-0.102	0.121	0.007	-0.026
CCG Median Wage, standardised	-0.011	0.080	-0.012	-0.057
CCG Unemployment Rate	4.481	4.239	4.354	4.394
Waiting times				
Months wait: 2 or less	0.073	0.613	0.396	0.439
Months wait: 3	0.336	0.138	0.199	0.178
Months wait: 4	0.204	0.083	0.129	0.112
Months wait: 5	0.122	0.051	0.080	0.075
Months wait: 6	0.076	0.032	0.052	0.050
Months wait: 7	0.051	0.021	0.035	0.035
Months wait: 8 or above	0.138	0.060	0.108	0.110

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