Consequences of Disability Insurance Application Waiting Times on Benefit Receipt, Employment and Health Outcomes*

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Abstract

One major concern with application waiting times for disability insurance (DI) are decay effects: health conditions and employment prospects of applicants worsen over time. Using unique large-scale data of the Netherlands between 2014 and 2022, we study the importance of such effects on the likelihood of DI awards, employment, and health outcomes. For causal inference, we instrument waiting times with "leave-one-out-means" for offices by application months. We find positive effects on employment in the first months after application, reflecting a largely mechanical and transitory effect of permanent workers for whom the ending of formal contracts is delayed. Two years after application, however, there remain small but precise and significant negative effects on employment: one extra month of waiting results in a reduction in the employment probability of 0.20 percentage point. Concurrent with this, each additional month of waiting leads to a 0.44 percentage point increase in DI awards. These effects go together with a temporary increase in mental health care utilization of 0.4 percentage points after six months from application and an increase of prescriptions for rheumatological conditions, pain-related conditions and psychological diseases two years after application.

Keywords: application waiting times, disability insurance, employment, health
JEL codes : H53, I12, J22.

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1 Introduction

In modern welfare states, the screening of applications for disability insurance (DI) benefits is a complex process that can be time consuming. Applicants for Social Security Disability Insurance (SSDI) benefits in the US wait 4.3 months on average when awarded benefits in the first stage, and this accumulates to 57 months on average when they appeal all the way (Coe et al., 2014; Autor & Duggan, 2010). Autor et al. (2015) argue that long waiting times induce decay effects: in the absence of income from work, the health conditions and employment opportunities of applicants may further deteriorate (Prenovitz, 2021). Decay effects also change the interpretation of employment differentials between awarded and rejected applicants: since the counterfactual of rejected applicants has been prone to much longer waiting times leading to decay effects, one would underestimate the discouraging impact of SSDI benefits on awarded applicants (Autor et al., 2015). At the same time, differences in waiting times may have implications for the award decision itself: with prolonged application waiting times, the information and the decision context of assessors may have changed. This in turn raises questions on the targeting of DI benefits: does waiting longer lead to more accurate award decisions?

This paper studies the consequences of longer waiting times on employment, benefits, and health outcomes of DI applicants up to two years after benefit application. We use large-scale administrative application data for the Netherlands, where there were substantial increases in waiting times—mainly induced by examiner capacity constraints—since 2018. Similar to most disability schemes in OECD countries, but unlike SSDI benefits where most of the current literature focuses on, applicants received benefit prepayments while waiting. The income and consumption consequences of waiting were therefore limited. Alongside this, it is important to stress that permanent sick-listed workers were still formally employed at the time of the application. Although employment contracts could be dissolved by employers after two years of sick leave, longer waiting times had the potential to delay the decision to end contracts as well. This then would result in mechanical short-term effects that increase employment.

To obtain consistent estimates of the effect of application waiting times on employment, benefits outcomes, mental health treatments, and chronic conditions, we construct "leave-one-out means" of monthly office cohort wait times, using data from 27 offices over 108 months of applications. Following from the the institutional setup in the Netherlands, we find that longer waiting times increase the likelihood of continued employment in the first months after application; this reflects a largely mechanical

and transitory effect of the application delays for workers still formally employed at the time of application. Over a longer period of time, however, decay effects dominate. Specifically, we find that a one-month increase in the application waiting time results in a 0.20 percentage point lower probability of employment two years after application and a 0.42 increase in the likelihood of DI awards. The effect on employment is similar to Autor et al. (2015), who find that a one standard deviation (2.1 month) increase in processing time reduces long-run employment rates by 0.36 percentage points. Following from subgroup analyses we performed these decay effects are seemingly confined to workers who were unemployed at the time of application.

In terms of mental health care utilization, we find small but statistically significant effects in the first year after application only. Six months after application, a one-month increase in waiting time leads to a 0.4 percentage points (2.8%) increase in the likelihood of a mental health treatment. The effect appears to be mainly driven by individuals who were already using mental health care services in one of the 12 months before application, pointing at treatments that are prolonged or resumed. This finding is backed up by increased prescriptions for rheumatological conditions (2.2%), pain-related conditions (2.3%), and psychological conditions (1.3%) two years after application. As such, we add to a small literature on effects of DI application waiting times that extend beyond employment outcomes. In particular, Prenovitz (2021), who studies the health, healthcare access, and financial well-being effects of prolonged SSDI wait times, finds evidence only of increases in the number activity limitations. Since these findings are based on combined samples of the National Health Interview Survey (NHIS) and administrative data, however, the resulting limited sample sizes render it difficult to obtain precise estimates as in our study.

To delve deeper into the underlying mechanisms of our findings, we also conduct mediation analyses that acknowledge potential interrelations between employment, DI awards and (mental) health outcomes. We then find that the decreases in the employment probabilities due to longer waiting times represent genuine decay effects, and not any discouraging effects from the increased odds of being awarded DI benefits. Taking a reverse perspective, however, we do find that the increase in DI awards while waiting is explained by decreases in the baseline employment probability. That is, longer waiting times render it more likely that employment contracts are dissolved, which is perceived as a drop in the earnings capacity of applicants by medical examiners.

Finally, we study the consequences of longer waiting times on the targeting properties of DI decisions. The health and employment conditions of applicants may change over time, which then also changes the 'disability signal' at the time of the assessment.

If this signal is more predictive of long-term health and employment outcomes when more time has evolved, this potentially improves targeting. Following this line of thinking, and building on Godard et al. (2024), we construct targeting proxies that compare the long-term (un-)employment and mental health outcomes of awarded and rejected applicants per office and application cohort month. We then find no evidence pointing at improvements in targeting resulting from increased application waiting times.

With our findings on targeting effects, we add to a broader literature on non-take-up and the targeting of social insurance (Ko & Moffitt, 2024). While administrative barriers and costs, lack of information, and stigma all appear to be important drivers for benefit take-up of different programs, wait times and application costs can also be considered as screening devices that potentially improve the targeting of benefits to those who are most in need (Godard et al., 2024) or lead to perverse screening (Parsons, 1991; Deshpande & Li, 2019). An understudied issue in this literature is how waiting times might affect the disability decision itself.

In what follows, Section 2 explains the institutional settings of the sick leave and DI application process in the Netherlands and discusses the expected effects of prolonged waiting times on employment, health and DI awards. We next discuss the data at hand in Section 3, and the instrumental variable approach is explained in Section 4. The estimation results are presented in Section 5, mechanism and targeting in Section 6, and conclusions in Section 7.

2 Institutional setting

2.1 Sick leave and DI in the Netherlands

Figure 1 graphically displays the benefit conditions for the categorical DI transfer program in the Netherlands, as well as the two-year sick leave period that precedes DI application. The Employee Insurance Agency (UWV) is responsible for the implementation of the DI scheme, which provides public statutory insurance against loss of income due to work-related and non-work-related conditions—see e.g. Burkhauser et al. (2016) for an international comparison. DI benefits are determined by the assessed loss of earnings capacity as a fraction of the pre-application wage (i.e. the degree of disability), together with the assessed permanence of impairments. When the degree of disability is below 35%, the worker is rejected benefits. For degrees of disability between 35% and 80%, workers receive benefits that replace 70% of the loss of the earnings capacity (i.e. "partial WGA"). Losses in the earnings capacity equal to or exceeding 80%

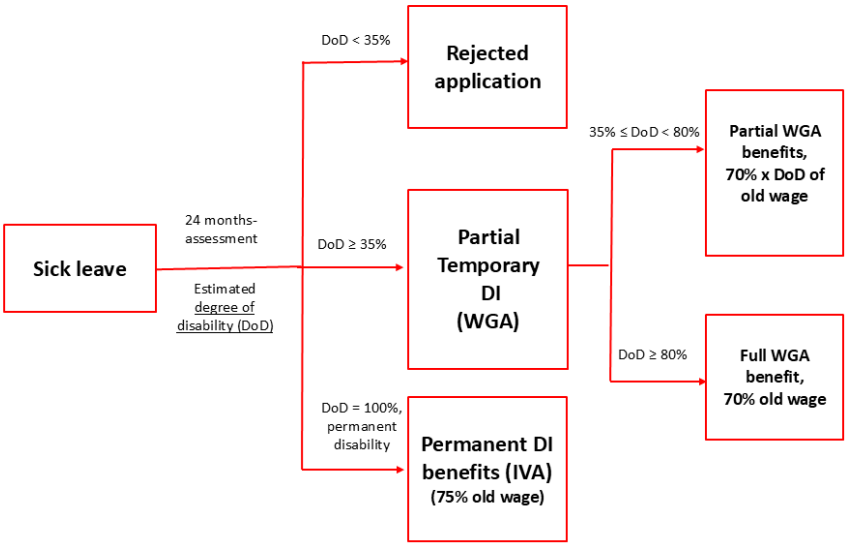


Figure 1: *Sick leave and disability insurance benefits in the Netherlands*

lead to entitlement to full benefits replacing 70% of the pre-DI-earnings in case of temporary impairments (i.e. "full WGA") and 75% of pre-DI-earnings in case of permanent impairments (i.e. "IVA" or "permanent DI").

During the two-year sick leave period before DI application, employers are financially responsible for the continued receipt of 100% of wages in the first year and 70% in the second year.[1] Ongoing employment contracts cannot be dissolved by employers during sickness, up to the end of the two-year sick leave period.[2] When workers report sick, employers and workers must meet reintegration obligations as defined by the 'Gatekeeper protocol' (Godard et al., 2024). The protocol requires that workers and their employers write a reintegration plan and implement suitable work accommodations. When the employer does not meet these conditions, DI applications are not ad-

[1]For temporary workers, continued payments end at the moment the contract dissolves during the waiting period. Since 2013, sickness benefits of (former) temporary workers of employers are experience rated. The degree of experience rating increases with respect to the size of the firm. See Koning et al. (2025) for details.

[2]This contrasts to the US, where mandatory sick leave programs—typically referred to as Temporary Disability Insurance (TDI) benefits or 'medical leave'—are limited in time, employers typically bear no responsibilities in the waiting period, and where workers need to initiate DI applications (Burkhauser et al., 2016; Pichler & Ziebarth, 2020). US workers who apply for public Social Security Disability Insurance (SSDI) benefits can therefore experience substantial income losses while waiting for the award decision.

missible after two years and the sick leave period is extended by one year.[3] Alongside the strong direct financial incentive there is to reduce costs during the waiting period, employers therefore also have an interest in meeting the specific reintegration obligations of the Gatekeeper protocol (Godard et al., 2024).

2.2 DI application waiting times

Workers receive a letter after about 90 weeks of sick leave informing them that the two-year sickness period is about to end and that they can schedule a DI assessment. As explained earlier, the outcome of the award decision critically depends on the assessed remaining earnings capacity of applicants relative to the old wage, i.e. the degree of disability. For this, a physician conducts a medical examination is and a subsequent interview is held with an occupational assessor—both employed by the Employee Insurance Agency.[4] The physician uses a standardized instrument to identify impairments arising from the nature and severity of the health conditions of the applicants. The occupational assessor then feeds this information, along with an applicant's education level and basic skills, into an algorithm that searches the agency's database to identify jobs the worker is deemed capable of performing. The standard wage of second-highest-paying job in this selection ultimately determines the earnings capacity, the degree of disability and the award decision (Figure 1).

As depicted in Figure 2, DI assessments should in principle be scheduled before the end of the two-year waiting period—so within a time frame of 13 weeks—to warrant a timely award decision. After the assessment and award decision, the start date for the awarded DI benefits can be set at the end of the two-year sickness period. Regardless of the award decision, employers can dissolve the employment contract with their worker at that time. Together with the award decision, these steps thus assume a timely start of the DI assessment without important delays in the application processing times.

However, in practice waiting time may exceed these 13 weeks.[5] In contrast to other schemes—like the SSDI in the US—waiting has no direct income consequences for applicants. Applicants then receive prepayments equal to full DI benefits (i.e. 70% of the old wage). When not awarded DI benefits ex-post, prepayments are settled with UI benefit entitlement rights or social assistance.[6] From the perspective of the employer,

[3] As Koning & Lindeboom (2015) argue, these 'wage sanctions' for employers rarely occur.

[4] Garcia-Gomez et al. (2025) describe the assessment system of the Netherlands in greater detail.

[5] In Section 3 we show this applies to many applications since 2018.

[6] Repayments were only relevant until 2021 for a small group of rejected DI applicants without eligibility to UI and with lower social assistance benefits than DI benefits. Since 2021, benefit prepayments of rejected applicants are fully remitted.

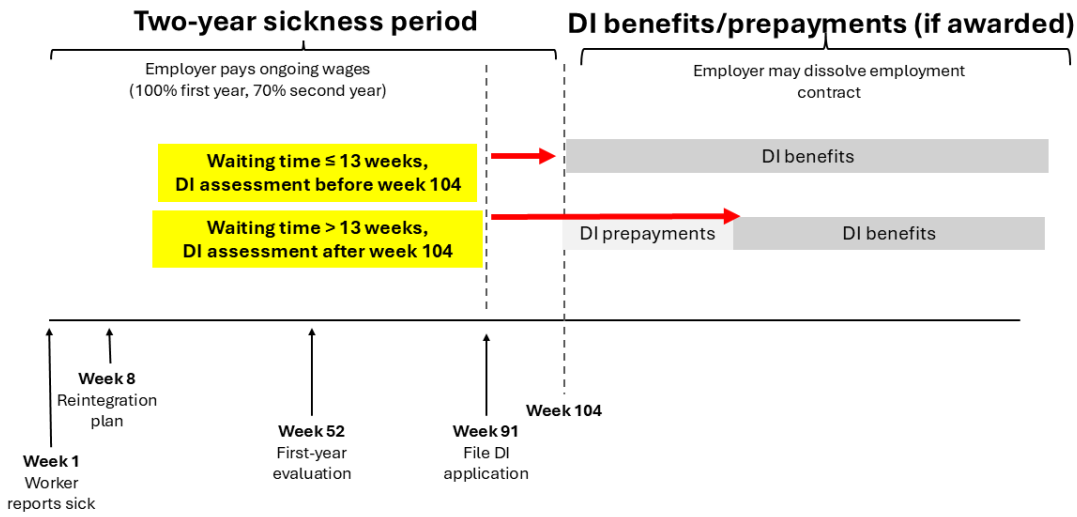


Figure 2: *Timeline of two-year sickness period, DI applications and DI benefit payments*

exceeding the two-year sickness period, however, changes the decision to continue or dissolve the employment contract: At the end of the two-year period, they could either instantly dissolve the employment contract of permanent workers who are employed until that moment, or delay this decision until the moment the assessment is completed. Since benefit prepayments are paid by the Employee Insurance Agency, delaying the employment decision does not give additional financial costs to the employer.

DI waiting times essentially come from two sources. First, delays in the DI application process result from capacity constraints that have the potential to increase waiting times of *all applicants*. This is essentially also the source of variation in our data we exploit for causal inference. Due to the constraints, medical evaluations usually begin later for *all applicants* within the relevant office at a certain point in time. Increased waiting times in UWV offices may originate from increases in the number of DI applications, increases in processing times, and worker turnover of physicians and occupational assessors. Since UWV offices are instructed to follow a "first come, first serve" policy, increases in waiting times due to capacity constraints should equally affect all workers applying at a specific office at a certain point in time.

Second, delays in the DI application process stem from a lack of information on the contextual or health conditions of *individual applicants*. To ensure that the award decision incorporates all the required specifics, physicians and occupational assessors may request additional information from applicants, which may be time consuming.

For instance, inferences on the ability to work of workers with mental conditions may be difficult and therefore require more background information on the types of tasks that are still deemed feasible. Still, medical examiners and occupational experts are not allowed to (deliberately) delay the award decision to improve their decision making.[7] Individual delays therefore should follow from a lack of information that is relevant at the time of the assessment.

2.3 Potential effects of DI application waiting times

Employment. Studies on causal effects of DI waiting times on employment are mostly centered on the concepts of deterrence and decay effects (Autor et al., 2015). Deterrence is not relevant in our context where all sick-listed workers apply for benefits, but decay effects are. Decay results from the loss of human capital or stigma that arises when DI applicants wait for the award decision, leading to lower employment. In the context of the Dutch DI system, this mechanism is most relevant for applicants who are not formally employed at the time of the DI assessment and stay out-of-the labor force for longer. This includes temporary workers and Unemployment Insurance (UI) recipients who have reported sick at the UWV offices.[8]

For workers with permanent contracts at the end of the two-year sickness period, the consequences of delayed employment decisions are theoretically ambiguous. Delay may cause contracts to be dissolved for workers who would have remained employed under the counterfactual without the delay. Again, this is due to the earlier-mentioned decay effects: additional losses of human capital of the worker due to waiting make the employer decide to dissolve the contract later on. Reversely, however, delayed employment decisions improve the situation for workers who stay employed while waiting but would have been fired instantly under the counterfactual without the delay. For them, prolonged waiting periods increase the time window for the employer to arrange suitable work accommodations or find alternative employment. Initially, this counteracting effect on employment is largely mechanical: as long as the delay continues, workers remain formally employed. However, over time, the extended time window can be used to resume work, leading to more persistent effects. Overall, the effect of longer waiting times on the employment of permanent workers is therefore ambiguous, with decay effects and the impact of increased employer commitment.

[7] Medical examiners cannot use ongoing medical treatments or expected recovery as an argument to delay the assessment.

[8] Note that these workers already have waited for a period of two years. Therefore, the (additional) loss of human capital is probably smaller than for SSDI applicants.

Health. In the literature, it is mostly argued that longer out-of-the-work time has detrimental effects on the health conditions of applicants (Prenovitz, 2021; Coe et al., 2014). Due to reduced income from earnings during the application, access to medical consumption and health care can be limited. These income effects are highlighted in studies on SSDI waiting times. This mechanism is however less relevant for the Netherlands, where benefit prepayments warrant sufficient income and access to care is not constrained and involves limited out-of-pocket spending. Prolonged waiting times can also provide workers with the opportunity to invest in their health and recover from their conditions (Prenovitz, 2021). Workers may need recovery time after a major medical surgery or they may face temporary disorders that would aggravate while working.

Extended waiting times may also directly affect the mental health and well-being of applicants without income loss (Prenovitz, 2021; Badji et al., 2023; Barr et al., 2016). Since the outcome award decision can have large future financial consequences for mostly vulnerable workers, waiting can be perceived as stressful. In the current policy debate on DI waiting times in the Netherlands, this mechanism is considered the main argument to combat DI waiting times.(Algemene Rekenkamer, 2023). However, empirical evidence on these effects is limited. Badji et al. (2023) finds that—also in cases without ex post income loss—medical re-assessments lead to more nervous system drug prescriptions. Using data on SSDI assessments, Prenovitz (2021) shows that longer waiting times lead to more health conditions, but not for mental health as a separate disorder. For the Netherlands, Keer et al. (2024) and Meurs et al. (2022) provide qualitative evidence on the direct health effects of prolonged DI waiting times. Keer et al. (2024) find that interviewed applicants experience long waiting times as "keeping their life on hold", "very stressful and aggravating their health problems", due to the continued uncertainty about the timing of the assessment.

Award decisions. Prolonged waiting times may not only affect the employment and health conditions of applicants, but also the screening process of assessors. Obviously, the most direct—and largely mechanical—effect of delays in the moment of the assessment could be that the employment and health conditions have changed and therefore change the award decision as well. When applications' employment contracts are dissolved in the extra waiting time, this may also change the context of the assessment: although physicians and occupational assessors from the Employee Insurance Agency are not allowed to incorporate the employment status in the estimation of the earnings capacity, they may deem the set of remaining feasible jobs to have become more limited. This then increases the likelihood of DI benefit awards. Such effects can be

aggravated by assessors who incorporate aspects in their decision that go beyond the objective information they have; they know that applicants have gone through a long and potentially stressful period, making them more hesitant to reject claims and risk Type 1 errors. When taking a broader perspective, one may argue that longer waiting times increase the information quality used for the assessment, and therefore the targeting of the award decision. The idea is that more information is gained on the types of disease and the impact of these diseases on the ability to work, making the assessment more accurate. However, at the same time, the stronger tendency to accept applications for more subjective or contextual reasons may worsen targeting efficiency.

3 Data

3.1 Data sources

We use unique data obtained from several administrative sources. Disability Insurance (DI) application data is provided by the Employee Insurance Agency (In Dutch: *Uitvoeringsinstituut Werknemersverzekeringen, UWV*). To assess the degree of disability and determine the types of jobs applicants can still perform, medical examiners and occupational experts use the Claims Assessment and Assurance System (In Dutch: *Claim Beoordelings- en Borgingssysteem, CBBS*). The original applications dataset spans the period from 2013 to 2022, including the dates of three critical steps in the application process: the application date, the date of the final decision, and the date on which, if awarded, the applicant should start receiving DI benefits—two years after the onset of sickness. We define waiting times as the time between application and the date of the final decision of the Employee Insurance Agency.[9] The CBBS dataset also includes information on the 27 offices responsible for processing DI applications, the final award decision (less than 35%, WGA between 35–80%, WGA between 80–100%, or IVA), and additional variables related to the applicant's health condition and employment status at the time of application.

Demographic characteristics such as date of birth, gender, and migration background are obtained from the Municipal Personal Records Database from Statistics Netherlands, which includes all individuals living in the Netherlands. Employment trajectories and wages of employees in Dutch companies are drawn from the earnings administration registers ("SPOLISBUS"), which provide extensive information starting

[9] As an alternative, waiting times can be defined as the time lag between the date that DI benefit receipt should have started (two years after the onset of sick leave) and the final decision date. This would then be misleading in cases where applications started after the two-year sickness period.

from 2009. These data also come from Statistics Netherlands. The employment trajectories are adjusted to allow tracking of each DI applicant from 12 months before to 24 months after the month of application.

The mental healthcare treatment dataset ("GGZDBCTRAJECTAB") from Statistics Netherlands collects all in-person and virtual interactions with mental health providers between 2011 and 2021 for all Dutch citizens. While treatments may involve both therapy and pharmaceuticals, the use of medication is not recorded in these data. For each treatment episode, we observe the start and end dates, the type of contact (e.g., initial consultation, intake, therapy session, administrative), the duration of the session in minutes, the mental health diagnosis, and the type of provider (a psychologist, psychiatrist, psychotherapist, or other mental health professional). Alongside this data source on treatments, we use data on medical prescriptions ("MEDICIJNTAB"), tracking yearly reimbursements covered by the statutory basic health insurance scheme between 2006 and 2022. Medications are classified using the World Health Organization's Anatomical Therapeutic Chemical (ATC) coding system. Following the methodology of Huber et al. (2013) and Danesh et al. (2024), we use this information to map prescriptions into 22 categories of chronic diseases. A detailed description of the mapping procedure and classification process is available in Campana et al. (2025).

Finally, we have obtained monthly information from the Employee Insurance Agency on the number of employed workers at offices, from January 2014 to December 2022. These records distinguish between medical examiners, occupational experts, social-medical nurses, and remaining supportive staff. Together with the application numbers, we use this information to calculate average caseloads per office worker.

3.2 Sample selection and statistics

Due to missings in 2013, we restrict the original sample of DI applicants to the years 2014–2022. We exclude applicants who are indicated as "special cases": foreign workers who are either lastly insured in the Netherlands, or insured Dutch workers living abroad. Since these cases are much more time demanding, waiting times for these are significantly higher than for regular ones.[10] When we observed multiple applications per person and the time distance between them is less than two years, we only keep the first observations. Finally, we exclude cases with waiting times above two years

[10]While foreign clients essentially follow the same WIA process as national cases, the intake and assessment of Dutch clients living abroad involves complex administrative assessments to calculate reimbursements from foreign organizations. This concerns a lower-priority process that is frequently delayed by slow responses from abroad.

and restrict the sample to individuals aged between 18 and 65 years at the time of application. The final sample comprises 441,047 DI applicants during the period under consideration.

Table 1: *Descriptive statistics of applicant cohorts (2014-2022); N = 441,047*

	Mean	Std.Dev.	Min	Max
Outcome variables				
Employment *at 6 months*	0.305	0.460	0	1
Employment *at 24 months*	0.265	0.442	0	1
Disability benefit receipt	0.691	0.462	0	1
Mental health care utilization *at 6 months*	0.165	0.372	0	1
Mental health care utilization *at 24 months*	0.110	0.313	0	1
Minutes of mental health care utilization *at 6 months*	23.46	103.74	0	7,010
Minutes of mental health care utilization *at 24 months*	13.87	78.51	0	4,778
Individual waiting times				
Elapsed waiting time *at 6 months* (*months*)	2.331	1.319	0	6
Elapsed waiting time *at 24 months* (*months*)	2.455	1.820	0	23.84
Individual characteristics and previous employment				
Age	48.28	11.57	18	65
Age groups				
18-34	0.165	0.371	0	1
35-44	0.191	0.393	0	1
45-55	0.302	0.459	0	1
56-65	0.343	0.475	0	1
Female	0.554	0.497	0	1
Migration background				
Native	0.738	0.440	0	1
First generation migrant	0.164	0.371	0	1
Second generation migrant	0.098	0.297	0	1
Contract type or UI				
Permanent worker	0.550	0.497	0	1
Temporary or flexible worker	0.213	0.409	0	1
Unemployment Insurance (UI)	0.229	0.420	0	1
Unknown	0.008	0.088	0	1
Months of employment (in previous 12 months)				
Zero	0.367	0.482	0	1
One to eleven	0.075	0.264	0	1
Twelve	0.557	0.497	0	1
Most prevalent chronic conditions in year before application				
Acid related diseases	0.289	0.453	0	1
Cardiovascular diseases	0.330	0.470	0	1
Rheumatological conditions	0.367	0.482	0	1
Pain	0.257	0.437	0	1
Psychological diseases	0.363	0.481	0	1
Number of chronic conditions/comorbidities in year before application				
Any	0.295	0.456	0	1
More than 2	0.225	0.418	0	1
More than 5	0.047	0.213	0	1

Table 1 shows the summary statistics of the resulting sample. Two years after application, the average waiting time elapsed is 2.45 months, while the average employment rate is 26.5% at the same time. 69% of the applicants are awarded DI benefits. The incidence of mental health care utilization is 16.5% at six months after application and decreases to 11% after 24 months. This trend is mirrored by a decrease in mental health care utilization minutes. The average age in the sample is 48 years, with 64% of people aged 45 years or older. Women represent 55% of the sample, and natives 73.8%. Finally, the most prevalent chronic conditions in the year before application are acid-related diseases (28.9%), cardiovascular diseases (33.0%), rheumatological conditions (36.7%), pain (25.7%) and psychological diseases (36.3%).

3.3 Application waiting times

Figure 3 displays the distribution of waiting times for application cohorts between 2014 and 2022, measured in days. For expositional reasons, we exclude cases longer than 365 days (about 2,700 observations). The average waiting time is around 75 days (red vertical line), well above the formal threshold of eight weeks (56 days), and half of the observations exceed 58 days. This highlights the fact that offices had difficulties in making timely award decisions.

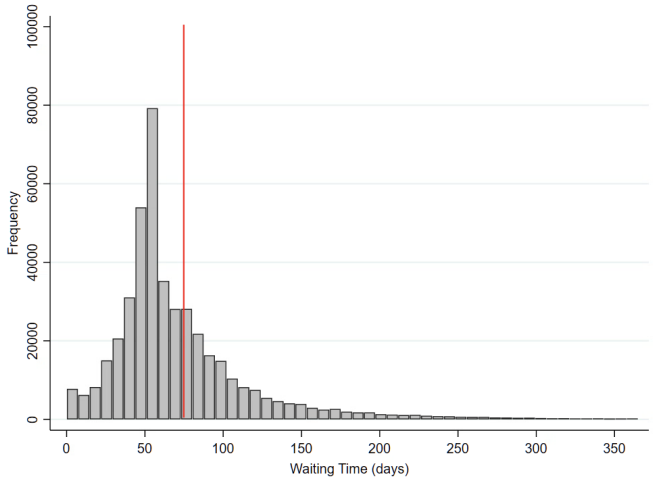


Figure 3: *Individual waiting time distribution in days (no obs > 365 days)*

Further insights on the evolution of waiting times are provided by Figure 4. The left panel shows that average waiting times among all offices remained relatively stable between 2014 and 2018, at around 55–60 days, before rising sharply from 2019 onwards,

and peaking at more than 110 days in 2021. The right panel depicts of quartiles across offices. While the upward trend after 2019 was general, the graph shows that the magnitude varied substantially across the offices.

Two main factors may explain the increase in waiting times. First, workloads per staff worker increased steadily since 2018, leading to longer delays until intake. Figure 5 illustrates this imbalance. The right-hand panel shows that the ratio of applicants to physicians rose markedly, from around 5 in January 2018 to about 7 in January 2022—an increase of roughly 40%. The left-hand panel adds further explanation: applications per office increased from fewer than 180 per month in January 2018 to more than 250 by January 2022—also an increase of about 40% as well. Over the same period, the share of physicians within total staff declined, with a particularly sharp drop after 2021. Together, these patterns point to a growing imbalance between demand and available medical staff.

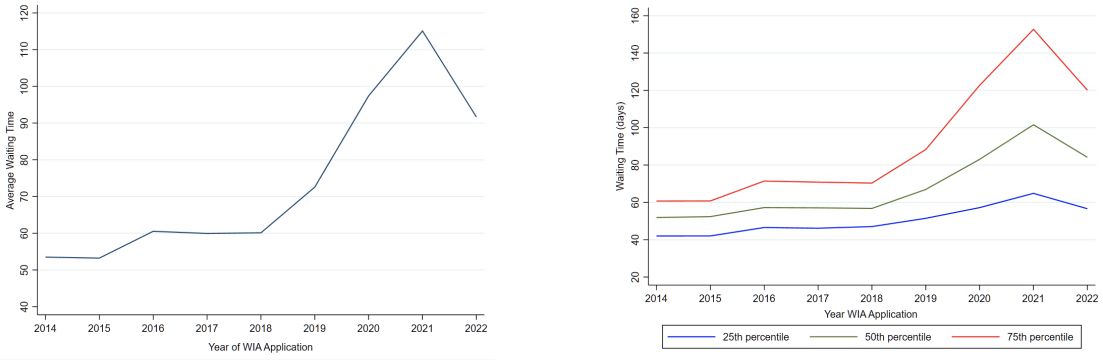


Figure 4: *Average waiting time over years among all offices (left hand side), and yearly office averages of the 25^{th}, 50^{th} and 75^{th} percentiles of waiting time (right hand side)*

Second, the pandemic and subsequent lockdowns increased the duration of individual assessments after intake. As was already visible in Figure 3, waiting times rose sharply after 2019, with some offices experiencing much larger increases than others. Figure A.1 in the Appendix further illustrates this shift: while in 2014–2019 the average waiting time was around 60 days, in 2020–2022 it exceeded 100 days. The entire distribution moved to the right, suggesting that beyond rising caseloads, the pandemic disrupted the efficiency of assessments—likely due to logistical constraints and difficulties in conducting in-person evaluations. In light of the substantial differences in waiting time increases, offices differed substantially in their ability and choices they made to adapt to the new situation.

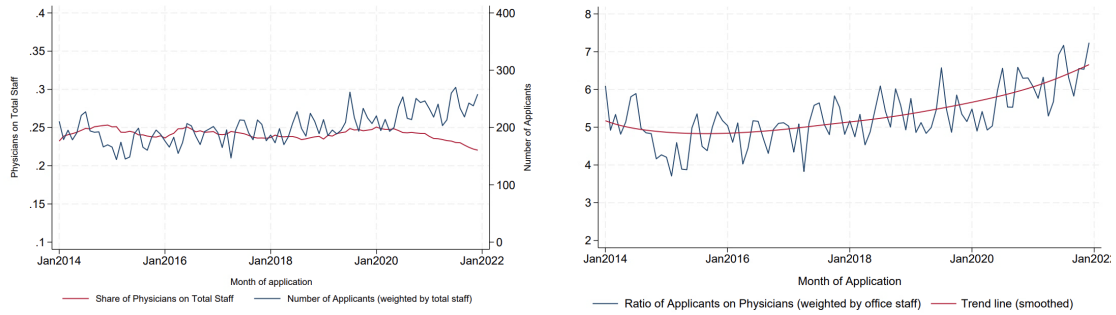


Figure 5: *Applicants relative to staff capacity. Left: number of applicants, weighted by office staff (blue, right axis) and physicians' share on total staff (red, left axis). Right: ratio of applicants to physicians, weighted by office staff*

3.4 Employment and health outcomes over time

To gauge the dynamics of employment and health of DI applicants, we center these outcome variables around the moment of WIA applications. Specifically, Figure 6 shows the employment rate trajectories for applicant cohorts with waiting times above and below the formal eight-weeks threshold, taking the application month as a reference point. Although this difference should not be interpreted as causal, employment rates are consistently higher for those with shorter waiting times. Employment rates start from about 60% in the year preceding DI application. This reflects the group of sick-listed workers with permanent contracts, who remain formally employed until the end of the statutory sickness period. After application, average employment declines rapidly, with rates falling to about 30–31% within six months and to around 25–26% after two years. This pattern shows that most job separations of (initially) permanent workers occur almost exactly at the time of (formal) WIA entitlement, i.e. two years after the start of sickness, when employers are allowed to terminate contracts.

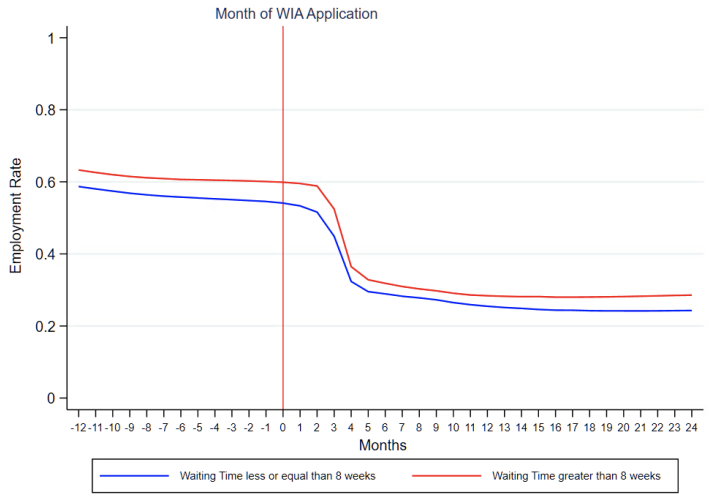


Figure 6: *Employment rate by waiting time (above/below 8 weeks), centered around the application month*

Similar to the employment rates, we examine the evolution of (monthly) mental health treatment rates from one year before and up to two years after DI benefits application. Figure 7 shows the treatment incidence trajectories for the applicant cohorts with waiting times above and below the 8-weeks threshold. Most notably, we see that the incidence of mental health treatments persists at a higher level for applicants with waiting times below 8 weeks. A possible explanation is that applicants expected to require longer or new mental health treatments are regarded by medical examiners as clearer cases for DI benefit receipt, requiring less decision time. This is more or less confirmed by Figure 8, which compares prevalence rates of the most chronic diseases for applicants with waiting times below and above 8 weeks.[11] Applicants with shorter waiting times generally show a lower prevalence of most chronic diseases, with the notable exception of psychological disorders. This pattern is consistent with the idea that medical examiners prioritize cases with acute or complex mental health problems, which are more likely to be processed quickly.

[11] Recall that chronic diseases are observed annually, which makes it difficult to construct trajectories.

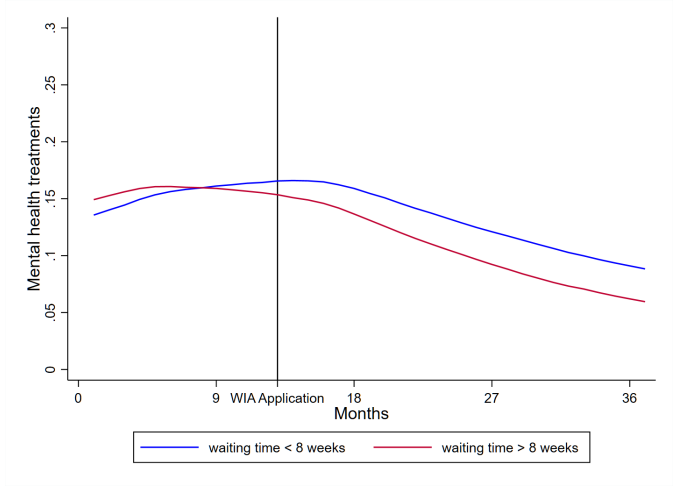


Figure 7: *Incidence of mental health treatments by waiting time period (below/above 8 weeks), centering around the month of application*

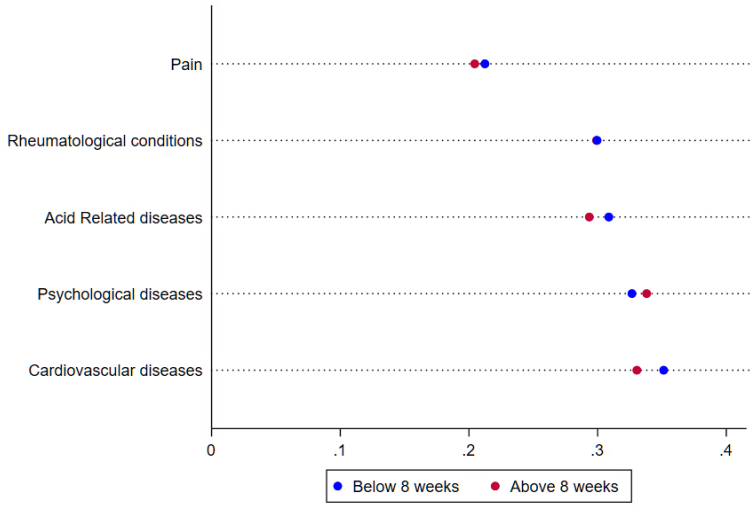


Figure 8: *Most prevalent chronic diseases by waiting time period*

4 Empirical Analysis

4.1 Methodology

Our descriptive analyses suggest that individual characteristics — such as the type and severity of impairments — are related to the length of application waiting times. Alongside this, we have argued that office-level conditions, such as examiner efficiency, staff

availability, and overall workload impact waiting times. Since individual characteristics are potentially correlated with our individual outcome variables of interest, waiting times are most likely endogenous. Not all relevant individual characteristics are observed in our data, leading to biased OLS estimates.

In light of these arguments, we employ instrumental variables (IV) estimation where we exploit variation in offices over time for causal inferences. This strategy assumes that changes in waiting times across offices are exogenous from the perspective of individual applicants. We instrument the individual elapsed waiting time with the *leave-one-out mean* as a propensity score. This propensity is defined as the average elapsed waiting time of all other applicants in the same office and same calendar month, while excluding the individual under consideration. This instrument-propensity design is used by Maestas et al. (2015) and Maestas et al. (2013) in the context of waiting times for SSDI applications, but then using variation between individual medical assessors.

We investigate the impact of waiting times on outcomes measured from one month up to 24 months after the application month t. Within this time frame, observed waiting times — defined as $WT_{i,t}$ for individual i with application month t — may still be ongoing. We therefore define the *elapsed waiting time*, $EWT_{it}(m)$, as the minimum between the relevant time window, m, and the individual's waiting time of the applicant cohort of month t, WT_{it} :

$$EWT_{it}(m) \;=\; min\{m\,, WT_{it}\}, \quad \text{with } \; m = 1, \ldots, 24 \tag{1}$$

Since most of our outcome variables are evaluated dynamically up to 24 months after the month of application, the leave-one-out-mean as an instrumental variable is constructed separately for all relevant values of m as well:

$$AEWT_{it}(m) = \frac{\sum_{j \in C(i,t),\, j \neq i} EWT_{j,t}(m)}{C(i,t) - 1}\,, \tag{2}$$

where $C(i,t)$ is the set of applicants in the same office and calendar month of individual i, and $EWT_{j,t}(m)$ is the elapsed waiting time m months after application of individual j with the same application calendar month t. Importantly, applicants cannot choose the office where their disability insurance application is processed; allocation is only determined by the place of residence. This ensures that variation in the instrument reflects office-level congestion, rather than individual-specific characteristics or choices.

We implement a two-stage least squares (2SLS) estimator to identify the causal effect of waiting time on applicant outcomes. For elapsed waiting times of m months

after application, the first-stage regression on the individuals' elapsed waiting time in months is:

$$EWT_{it}(m) = \alpha + \delta\, AEWT_{it}(m) + X_i'\boldsymbol{\beta} + \gamma_k + \gamma_t + \nu_i. \tag{3}$$

Here, $\mathbf{X}_i$ is the vector of time-constant individual covariates, including demographic characteristics such as age, gender, migration background, dummy indicators for chronic conditions measured at *t*-1 (i.e. the year before the application), and dummies for the number of employed months in the last year before application. γ_k and γ_t denote office-fixed effects and application-month time effects. As such, our baseline model controls for persistent cross-office differences and common time shocks. Finally, ν_{it} represents an error term that is assumed to be i.i.d.

In the second stage, we use the predicted values of elapsed waiting times to estimate Equation (4) on the outcome of interest, measured m months after application:

$$Y_{it}(m) = \alpha' + \theta\, \widehat{EWT}_{it}(m) + X_i'\boldsymbol{\beta}' + \gamma_k' + \gamma_t' + \varepsilon_i. \tag{4}$$

Similar to Equation (3), we assume the error term ε to be i.i.d. The relevant outcome variables Y in Equation (4) are: (i) employment status, a binary indicator observed monthly for one up to 24 months after the application; (ii) the final DI award decision, a binary and time-invariant outcome; (iii) an indicator for receiving any type of mental health treatment, observed monthly for one up to 24 months; (iv) the total number of minutes of mental health treatment, also measured monthly for one up to 24 months; and (v) binaries for the prevalence of chronic diseases in the first and second year after application. The parameter of interest, θ, captures the causal effect of waiting time on the relevant outcome. Given that time is measured in months, this parameter can be interpreted as the impact of one-month increase in waiting times.

4.2 Validity of the IV strategy

Individual waiting times vary substantially across offices and month of application. Table A1 in the Appendix shows that about one-fifth of this variation can be attributed to permanent office differences and common time shocks. Our empirical strategy, however, relies on the component arising by office-by-month interactions. This source of variation reflects congestion and fluctuations in staff capacity within offices at specific points in time. Although quantitatively smaller, it provides the key source of identifying information for our empirical design.

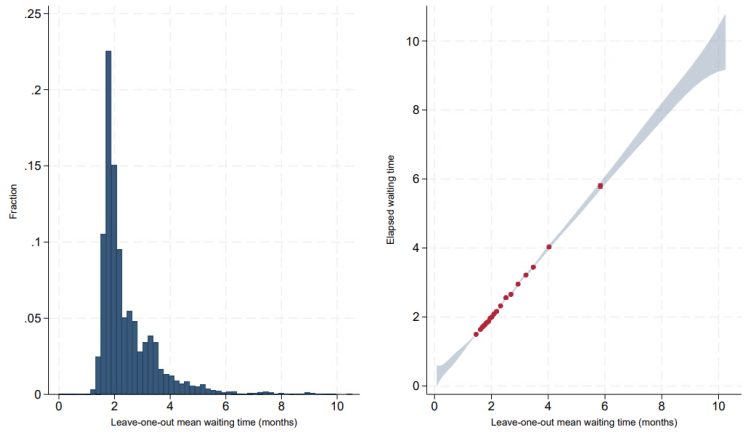


Figure 9: *Left panel: histogram of the leave-one-out mean waiting time. Right panel: binscatter of elapsed vs. leave-one-out mean waiting time with 95% confidence bands.*

For the IV design to be valid, the first requirement is that the wait time propensities are sufficiently strongly correlated with individual elapsed waiting times, i.e. *the relevance condition*. To shed light on this, Figure 9 shows the distribution of the propensities based on completed waiting times, together with average bins over the support of propensities. Over the relevant support of individual propensities, we see a tight relationship with individual elapsed waiting times. In line with this, the first-stage estimates reported in Table 2 confirm that the instrument is highly predictive, with coefficients close to one and F-statistics well above conventional thresholds, thus providing evidence of its strength and relevance.[12] Alongside these results, we find the first-stage estimates in the subgroup analyses we conduct in Section 5.3 to be close to one in all cases. This also lends credence to the *monotonicity condition* to hold for our IV strategy.

Next, the *exogeneity condition* for the validity of the IV design states that our instrument is not correlated with individual characteristics. In our context, this means that the variation in leave-one-out elapsed waiting times should reflect office-level shocks, rather than systematic differences between applicant types that are correlated with waiting times. If the instrument is correlated with applicant characteristics—such as health status or prior employment market attachment—it could directly predict outcomes such as employment, benefit receipt, or health, thus violating the exogeneity condition.

[12]With first-stage coefficients being close one, we also infer that there is only a limited effect of individuals with high or low expected waiting times sorting into specific offices or application months.

Table 2: *First-stage estimates of leave-one-out mean waiting time on indivdiual waiting time, 24 months after application*

	(1)	(2)	(3)
Leave-one-out mean application waiting time	0.987***	0.970***	0.972***
	(0.001)	(0.004)	(0.004)
Office FE	Yes	Yes	Yes
Month FE	No	Yes	Yes
Covariates [a]	No	No	Yes
Obs.	441,033	441,033	441,033
F-statistic	714,228	58,557	66,086

Notes: [a] Covariates include gender, age group indicators, migration background, dummies for the number of months worked in the 12 months prior to the DI application, dummies for the safety-net category at the time of application, and dummies for chronic conditions in the year preceding the application. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

To assess the plausibility of the exogeneity condition in a balance test, we regress the instrument on predetermined applicant covariates. Figure 10 presents the estimated coefficients while controlling for month-of-application fixed effects and excluding office fixed effects.[13] At both *t*+6 and *t*+24, nearly all coefficients are statistically insignificant, and the few significant ones—such as for unemployment benefit recipients or selected chronic conditions—are quantitatively negligible. Figure A2 in the Appendix reports the same specification including office-fixed effects. Alongside this. a complementary balance test based on the standardized coefficients ($|\hat{\beta}|/SD$) is reported in Table A2 in the Appendix. None of the ratios exceed the conventional threshold of 0.20, confirming that the instrument is not substantially related to observable applicant characteristics. Taken together, these results suggest that the instrument remains well balanced, lending credibility to the exclusion restriction.

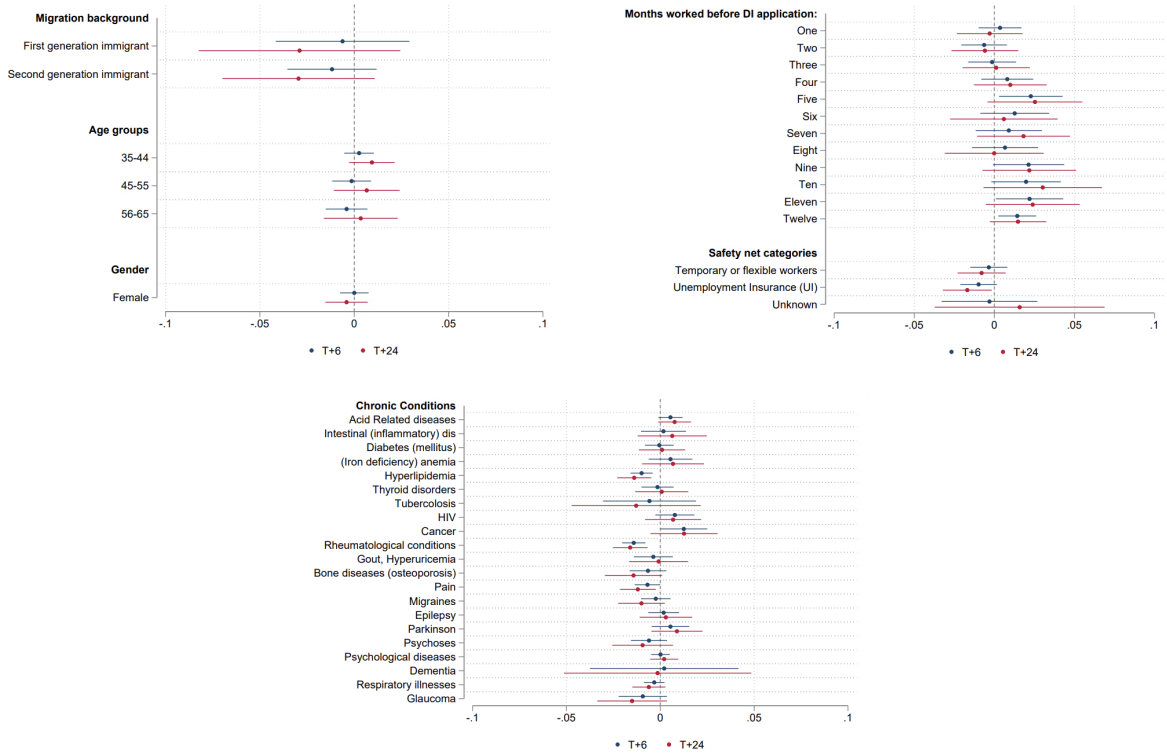
The final requirement that is needed for our IV strategy is the *exclusiveness condition* to hold: the effect of instrumental variable on our outcome measures should run exclusively through the elapsed application waiting times, and not be related to other office characteristics or policies driving the outcome variables. In Section 6.1, we will test for the exclusiveness condition by adding information on the staff composition at offices. Alongside this, we will also study the potentially mediating channel of (higher)

[13]Specifically, Figure 10 reports coefficients from the following regression model:

$$AEWT_{it}(m) = \beta X_i + \gamma_t + \nu_{it},$$

where $AEWT_{it}(m)$ denotes the leave-one-out mean elapsed waiting time for individual i in office and month t, X_i is the vector of applicants' covariates, and γ_t are month-of-application fixed effects.

Figure 10: *Balancing tests: regression coefficients of leave-one-out-mean elapsed waiting time on covariates, 6 and 12 months after application*



Notes: 95% confidence intervals; month-of-application fixed effects included but not displayed.

DI award rates of offices on changes in employment and health outcomes. For instance, additional benefit receipt may discourage the employment of individuals (Autor et al., 2015). Reversely, changes in employment and health outcomes while waiting can affect the DI award decision as well.

5 Results

5.1 Employment

We first focus on the relationship of application waiting times on employment outcomes. Table 3 shows estimates of the impact of an additional month of elapsed waiting time on employment six and twenty-four months after the DI application. Both OLS and IV specifications are presented, with the latter instrumenting individual waiting

times using leave-one-out office-by-month averages. Columns (b)–(d) progressively include office- and month fixed-effects as well as applicant covariates. Alongside this, the left panel of Figure 11 shows the impact of one extra month of waiting time following from the model specification of our preferred model in column (d) for all separate 24 months after application.

The OLS estimates show a small negative correlation between waiting time and employment at six months, and a positive but statistically insignificant effect after 24 months. As discussed in Section 4.1, these estimates are likely biased, as unobserved individual characteristics may jointly influence both the duration of the application process and subsequent employment outcomes. We therefore rely on the instrumental-variable approach, which exploits variation in office-by-application month congestion.

Among the alternative model specifications, we regard the model in column (d) as the most comprehensive and reliable, since it incorporates both office and month fixed effects together with detailed applicant-level controls. The corresponding results indicate that an additional month of waiting increases employment by about 0.8 percentage points six months after application, equivalent to roughly a 2.6 percent increase relative to the baseline employment rate. The short-term positive effect is largely mechanical, reflecting the fact that some employers delay the dismissal of permanent workers who are waiting. As shown by Figure 11, however, this mechanical effect disappears and decay effects start to dominate. Two years after application, a one-month increase in waiting time reduces employment by about 0.2 percentage points, corresponding to a relative decline of 0.75%. A six-month longer delay would therefore lower employment after two years by about 1.2 percentage points. This small but precisely estimated reduction is consistent with a decay effect: extended periods out of work weaken subsequent labor-market attachment through human-capital loss and stigma.

Table 3: *Estimation results: one-month effect of extra elapsed waiting time on employment, 6 and 24 months after application*

	6 months after application				***24 months after application***			
	OLS	**IV**^{a}			**OLS**	**IV**^{a}		
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Elapsed waiting time	-0.0040***	0.0195***	0.0095***	0.0078***	0.0007	0.0078***	-0.0018	-0.0020*
	(0.0012)	(0.0025)	(0.0031)	(0.0026)	(0.0008)	(0.0014)	(0.0012)	(0.0012)
	[-1.31%]	[6.39%]	[3.11%]	[2.56%]	[0.26%]	[2.94%]	[-0.68%]	[-0.75%]
Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Covariates^b	Yes	No	No	Yes	Yes	No	No	Yes
Observations	441,047	441,033	441,033	441,033	441,047	441,033	441,033	441,033
R-squared	0.196	0.004	0.009	0.195	0.089	0.004	0.006	0.089
F test (first-stage)	-	993,504	69,968	70,847	-	714,228	58,557	66,086
Endog.Test (*p-value*)	-	0.000	0.000	0.000	-	0.000	0.245	0.024

Notes: ^{a}: Elapsed waiting times are instrumented with the leave-one-out mean of elapsed waiting times per office and application month; ^{b}: Covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types; ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses; relative effect sizes in square brackets.

To examine whether these effects changed with the onset of the pandemic, Table 4 distinguishes between DI applicants before and after January 2020. This comparison is relevant because the COVID-19 crisis led to a marked increase in waiting times, with lockdowns and the suspension of in-person assessments making the evaluation process more complex. The IV estimates in Table 4 show that the relationship between waiting times and employment is different between these time periods, but also that estimates for the pre-2020 period are rather imprecise. While the effect of waiting one extra month was close to zero for the pre-2020 period, we find stronger and statistically significant negative long-run effects—equal to -0.44 percentage point—for the post-2020 period. One explanation for this is that the marginal effects of the much lengthier waiting times were larger and started to generate genuine decay effects. At the same time, the variation in waiting times was probably also too limited to obtain efficient estimates for this period. This also becomes apparent from the large confidence intervals in the right-hand panel of Figure 11.

Table 4: *Estimation results: one-month effect of extra elapsed waiting time on employment, pre- and post-January 2020, 6 and 24 months after application*

	6 months after application				***24 months after application***			
	OLS		**IV**[a]		**OLS**		**IV**[a]	
	Pre-2020	*Post-2020*	*Pre-2020*	*Post-2020*	*Pre-2020*	*Post-2020*	*Pre-2020*	*Post-2020*
Elapsed waiting time	0.0016	-0.0084***	0.0196**	0.0002	0.0085***	-0.0019**	0.0060	-0.0047***
	(0.0013)	(0.0017)	(0.0085)	(0.0027)	(0.0013)	(0.0007)	(0.0054)	(0.0014)
	[0.54%]	[-2.60%]	[6.64%]	[0.061%]	[3.28%]	[-0.68%]	[2.32%]	[-1.68%]
Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates[b]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	291,570	149,463	291,570	149,463	291,570	149,463	291,570	149,463
R-squared	0.201	0.186	0.200	0.186	0.091	0.087	0.091	0.087
F test	-	-	12,646	15,692	-	-	9,873	22,339
Endog.Test (*p-value*)	-	-	0.0498	0.0018	-	-	0.6433	0.0551

Notes: [a]: Elapsed waiting times are instrumented with the leave-one-out mean of elapsed waiting times per office and application month; [b]: Covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types; ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses; relative effect sizes in square brackets.

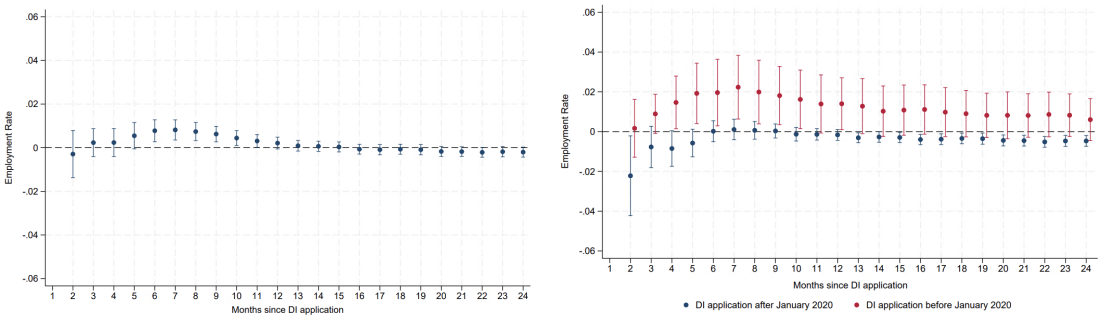


Figure 11: *IV estimates on effect of one month extra waiting times on employment (columns (d) of Table 3). Left panel: dynamic effects up to 24 months after application for full sample. Right panel: estimates by pre- and post-COVID-19 applicants. Coefficients are shown with 95% confidence intervals.*

5.2 DI awards

We next analyze how differences in waiting times affect the probability of a DI award of applicants. As argued earlier, longer waiting periods can coincide with a genuine deterioration in applicants' health and/or with the termination of their employment

contracts, both of which may increase the likelihood of being assessed as disabled. Examiners may become more lenient as evaluations take longer. These channels make it plausible that increases in waiting time are associated with higher award probabilities, a pattern confirmed by the estimates reported in Table 5. When moving from columns (b) to (d), the inclusion of month- and office-fixed effects together with individual-level covariates slightly reduces the magnitude of the coefficients but leaves the overall pattern unchanged. Column (d), our preferred specification, shows that a one-month-increase in elapsed waiting time raises the likelihood of receiving a DI benefit award by about 0.4 percentage points, corresponding to a 0.6% increase relative to the mean. As Table 5 shows, the point estimates pre- and post-January 20202 are very similar, but again much less precise in the first time period.

Table 5: *Estimation results: one-month effect of extra elapsed waiting time on disability award probability, overall and separately for pre- and post-COVID-19*

		Full period			**Pre-Post January 2020**			
	OLS	**IV**[a]			**OLS**		**IV**[a]	
	(a)	(b)	(c)	(d)	Pre-2020	Post-2020	Pre-2020	Post-2020
Elapsed waiting time	0.0090***	0.0126***	0.0040**	0.0042**	0.0109***	0.0088***	0.0041	0.0045**
	(0.0011)	(0.0024)	(0.0019)	(0.0019)	(0.0019)	(0.0013)	(0.0054)	(0.0021)
	[1.30%]	[1.82%]	[0.58%]	[0.61%]	[1.60%]	[1.24%]	[0.60%]	[0.64%]
Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Covariates[b]	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Observations	441,047	441,033	441,033	441,033	291,570	149,477	291,570	149,477
R-squared	0.074	0.012	0.018	0.074	0.071	0.083	0.071	0.083
F test	-	714,228	58,557	66,086	-	-	9,873	22,339
Endog.Test (*p-value*)	-	0.6339	0.0004	0.0027	-	-	0.2053	0.0185

Notes: [a]: Elapsed waiting times are instrumented with the leave-one-out mean of elapsed waiting times per office and application month; [b]: Covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types; ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses; relative effect sizes in square brackets.

5.3 Mental healthcare utilization and chronic conditions

We finally examine whether applicants' health outcomes are affected by longer application waiting times. We focus first on mental health care utilization and minutes of (mental health) treatment up to 24 months after the DI application, and then on the incidence of (most prevalent) chronic conditions measured one and two years after the

application year.

Table 6 presents the estimates for (monthly) mental health care utilization six and twenty-four months after application. Column (d) shows our preferred specification, including office- and month-of-application fixed effects and detailed applicant controls. The estimated coefficient of the six-month effect is positive and statistically significant: a one-month increase in waiting time raises the likelihood of receiving mental health treatment by 0.4 percentage points, corresponding to about 2.8% relative to the mean. Consistent with previous evidence, this short-term rise may reflect psychological distress caused by the uncertainty and stress of prolonged waiting, even in the Dutch setting (Badji et al., 2023; Keer et al., 2024). The effect, however, appears to be temporary, with estimates gradually turning negative and losing statistical significance after about eleven months, as shown in Figure 12a.

Table 6: *Estimation results: one-month effect of extra elapsed waiting time on mental health care utilization, 6 months and 24 months after application*

	6 months after application				***24 months after application***			
	OLS	IV[a]			OLS	IV[a]		
	(a)	(b)	(c)	(d)	(a)	(b)	(c)	(d)
Elapsed waiting time	0.0033***	-0.0303***	0.0044**	0.0047*	0.0013**	-0.0337***	-0.0032	-0.0031
	(0.0006)	(0.0016)	(0.0022)	(0.0021)	(0.0006)	(0.0024)	(0.0025)	(0.0025)
	[2.00%]	[-1.83%]	[2.66%]	[2.85%]	[1.18%]	[-30.63%]	[2.9%]	[-2.81%]
Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Covariates[b]	Yes	No	No	Yes	Yes	No	No	Yes
Observations[c]	378,027	378,027	378,027	378,027	291,570	291,570	291,570	291,570
R-squared	0.165	0.000	0.013	0.165	0.113	0.000	0.047	0.113
F test	-	2.7e+06	297,175	279,888	-	120,246	38,505	38,340
Endog.Test (p-value)	-	0.000	0.1083	0.000	-	0.000	0.001	0.064

Notes: [a]: Elapsed waiting times are instrumented with the leave-one-out mean of elapsed waiting times per office and application month; [b]: Covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types; [c]: The number of observations 24 months after application is smaller than in other analyses because mental health care utilization data are available only until the end of 2021. ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses; relative effect sizes in square brackets.

When splitting the sample into applicants who submitted their DI application before and after January 2020, we do not obtain statistically significant IV results for either period. This is shown in Table 7 and Figure 12b. At this point, it is worth noting that the sample size after January 2020 decreases substantially after the onset of COVID-19,

as data on health care utilization are right-censored at the end of 2021. This results in less precise estimates.

Table 7: *Estimation results: one-month effect of extra elapsed waiting time on mental health care utilization, pre- and post-January 2020, 6 and 24 months after application*

	6 months after application				***24 months after application***			
	OLS		**IV**[a]		**OLS**		**IV**[a]	
	Pre-2020	*Post-2020*	*Pre-2020*	*Post-2020*	*Pre-2020*	*Post-2020*	*Pre-2020*	*Post-2020*
Elapsed waiting time	0.0042***	-0-0018**	-0.0033	0.0028	0.0014***	-0.0004	-0.0029	-0.0003
	(0.0008)	(0.0007)	(0.0041)	(0.0031)	(0.0006)	(0.0018)	(0.0025)	(0.0054)
	[2.54%]	[-1.09%]	[-2.00%]	[1.69%]	[1.27%]	[-0.36%]	[-2.63%]	[-0.27%]
Office FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates[b]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations [c]	289,975	88,014	289,975	88,014	287,975	3,507	287,975	3,507
R-squared	0.172	0.134	0.171	0.1134	0.112	0.127	0.112	0.127
F test	-	-	47,695.1	25,725.3	-	-	36,359.5	230.7
Endog.Test (*p-value*)	-	-	0.050	0.7326	-	-	0.0764	0.9848

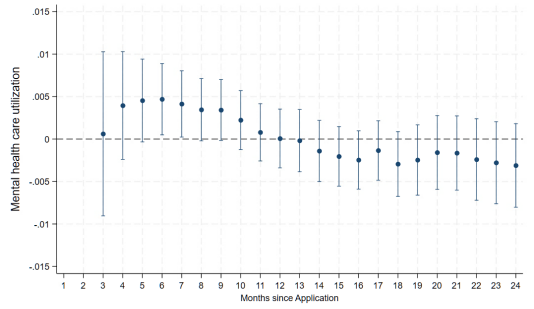
Notes: [a]: Elapsed waiting times are instrumented with the leave-one-out mean of elapsed waiting times per office and application month; [b]: Covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types; [c]: The number of observations 24 months after application is smaller than in other analyses because mental health care utilization data are available only until the end of 2021. ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses; relative effect sizes in square brackets.

Given that our estimates point at short-term increases in mental health treatments while waiting, a pertaining question is whether this mirrors a prolonging effect of (recent) treatments or the onset of new cases. To investigate this, Figure 12c stratifies our sample into applicants who had already received treatment in at least one of the twelve months prior to the application, and those who had not. We then infer that the increase is mainly driven by previously treated individuals, who may find it easier to resume or continue treatments than those entering for the first time.[14] Alongside this, another way to characterize extra treatments due to waiting is by switching from extensive margin (incidence) to the intensive margin effects in terms of the total minutes of mental health care utilization. Following from this, Figure 12d shows that a one-month increase in

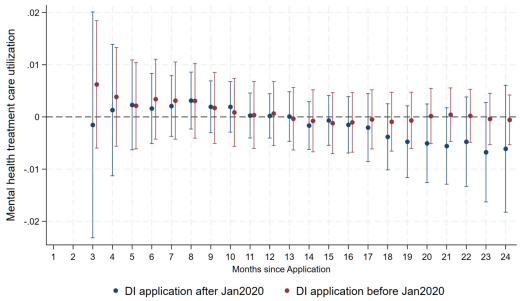
[14]In the Netherlands, individuals must first consult their general practitioner (GP), who acts as a gatekeeper by assessing the case and deciding whether to provide treatment within primary care or refer the patient to a specialized provider.

waiting time does not significantly affect the intensity of treatment. Although higher utilization is driven by previously treated individuals, this suggests that the intensity of their treatment does not increase or even decreases to some extent.

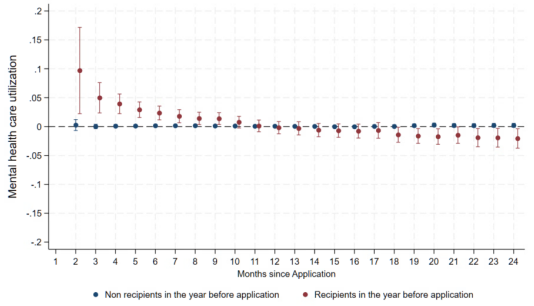
Figure 12: *IV results on the effect of one additional month of waiting time on mental health treatment outcomes up to 24 months after the application.*



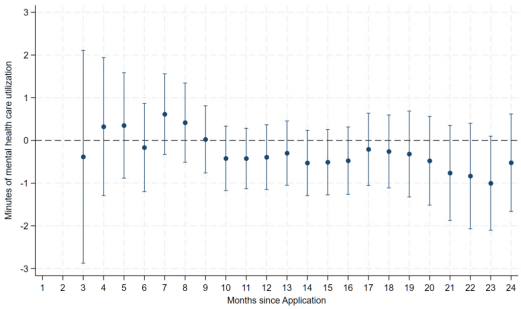
(a) *Mental health care utilization: Full sample*



(b) *Mental health care utilization: Pre- and post-January 2020*



(c) *Mental health care utilization: By prior treatment status*



(d) *Minutes of (mental health) treatment*

Notes: Panels (a)–(c) present results for mental health care utilization, considering the full sample, pre- and post-January 2020 samples, and applicants under mental health treatment before the DI application, respectively. Panel (d) presents the results for minutes of treatment. Coefficients are shown with 95% confidence intervals.

We complement these findings with analyses on the impact of wait times on chronic conditions one and two years after application. Accordingly, we broaden our perspective to physical conditions that can be inferred from the use of medical prescriptions. To ensure efficient and relevant results, Figure 13 focuses on the most prevalent chronic conditions observed during the year of application and on the total number of comorbidities. The effects for acid-related and cardiovascular diseases are small and not statistically significant, but we do find significant effects for rheumatological, pain-

related and psychological conditions. Specifically, after two years a one-month increase in waiting time increases the probability of receiving a prescription for rheumatological conditions by about 0.6 percentage points (2.2%), for pain-related conditions by 0.24 percentage points (2.3%), and for psychological diseases by 0.1 percentage points (1.3%). These small but precise and significant estimates suggest that prolonged application waiting times have the potential to increase the incidence of psychological and psychosomatic conditions. At the same time, one should bear in mind that the information on conditions follows from medical prescriptions. Rather than experiencing health deterioration that follow from the waiting, it may therefore be that applicants are more likely to consult their general practitioner and become diagnosed with already existing conditions. Finally, The effects on the occurrence of at least one, two or five comorbidities two years after application are significant in all cases. In particular, a one-month increase in waiting time increases the probability of having any chronic condition by 0.03 percentage points (0.38%), of having more than two by 0.045 (0.78%), and of having more than five by 0.023 (2.09%)). Again, these are all small but precise and statistically significant effects.

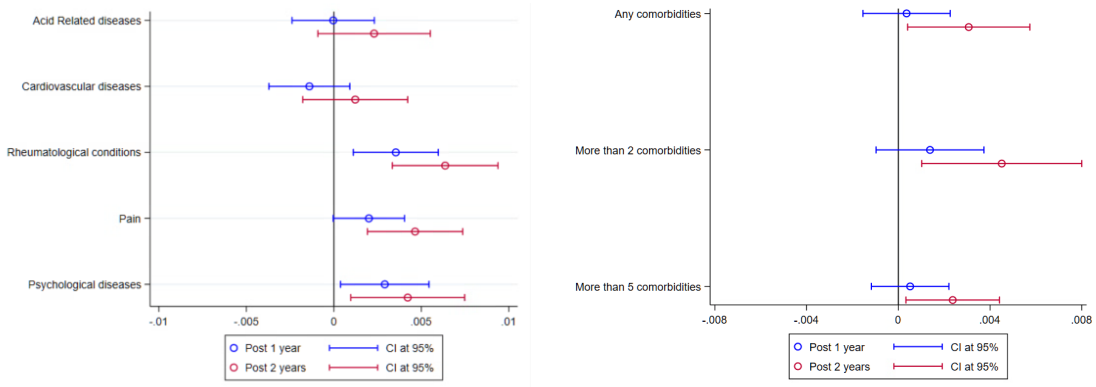


Figure 13: *IV estimates of the effect of one extra month of waiting time on the incidence of most prevalent chronic conditions (left panel) and on comorbidities (right panel) one and two years after application. Coefficients are shown with 95% confidence intervals.*

5.4 Heterogeneity analyses

To explore whether the effects of longer waiting times differ across applicant types, Table 5 and Appendix Figures A3 and A4 present estimates for our outcome variables by gender, age, primary diagnosis, and contract type at the time of application.

In terms of employment, there is limited heterogeneity in the effects of longer wait-

ing times, mainly across primary diagnosis and contract type dimensions. Among diagnostic categories, applicants with musculoskeletal disorders exhibit a relatively strong increase in employment, possibly because prolonged inactivity further limits their functional capacity.[15] In line with expectations, the detrimental impact of decay effects is also strong for temporary workers whose contracts have ended at application (see Appendix Figure A3 for a more detailed picture). We have argued earlier that there cannot be a prolonging (positive) employment effect while waiting for this group, explaining why (negative) decay effects are dominant.

For DI awards we find positive relationships between waiting times and the likelihood of benefit receipt across most groups. Statistically significant and larger effects are obtained only for older-aged and those with musculoskeletal diagnoses. For musculoskeletal disorders, a one-month increase in waiting time increases the probability of a DI award by about 1.2 percentage points. This may reflect that musculoskeletal conditions worsen or become more apparent over time, making them easier to assess. The effect is also strongest among older applicants (56–65), whose benefit probability increases by around 0.6 percentage points for each extra month of waiting.

Lastly, for all stratified samples we do not find any significant effects on mental health care utilization up to 24 months after DI application. As argued earlier, sample sizes may be too small to allow for more detailed analyses here—and particularly for stratified samples. Nevertheless, when focusing on the short-term effects that are shown in Appendix Figure A4, women appear to drive the positive impact on mental health care utilization. Specifically, a one-month increase in waiting time increases the probability of mental health care utilization by 0.05 percentage points up to six months after application. In addition, applicants with a mental health diagnosis from the medical assessor of UWV experience a positive and significant short-term effect of longer waiting times on mental health care utilization of 1.1 percentage point six months after application. Since the diagnosis is made when the waiting period has ended, this obviously mirrors a compositional effect of applicants with mental health treatments.

[15] As a cautionary note, the primary diagnosis of UWV is determined at the moment of the assessment (not application). We therefore cannot rule out that the diagnosis may be affected by the waiting time.

Table 8: *IV Estimation results: effect of one month extra elapsed waiting time on employment, DI awards and mental health treatment 24 months after application, by subgroups*

	Employment	**DI Award**	**Mental Health Treatment**
Gender:			
Male	-0.0018	0.0061***	-0.0046
	(0.0016)	(0.0021)	(0.0034)
Female	-0.0014	0.0020	-0.0018
	(0.0014)	(0.0021)	(0.0031)
Age groups:			
18 - 34	0.0004	-0.0001	-0.0048
	(0.0029)	(0.0037)	(0.0076)
35 - 44	-0.0032	0.0014	-0.0035
	(0.0029)	(0.0039)	(0.0071)
45 - 55	-0.0008	0.0047**	-0.00211
	(0.0020)	(0.0023)	(0.0040))
56 - 65	-0.0023	0.0061***	-0.0005
	(0.0018)	(0.0019)	(0.0029)
Primary diagnosis:			
Mental disorders	-0.0030	0.0015	-0.0093
	(0.0018)	(0.0022)	(0.0067)
Musculoskeletal disorders	-0.0053***	0.0119***	0.0012
	(0.0018)	(0.0024)	(0.0025)
Other disorders[a]	0.0007	0.0015	-0.0007
	(0.0017)	(0.0019)	(0.0029)
Contract type:			
Temporary worker	-0.0051***	0.0040	-0.0021
	(0.0019)	(0.0031)	(0.0054)
Unemployment Insurance (UI)	-0.0010	0.0043	-0.0005
	(0.0016)	(0.0031)	(0.0045)
Permanent workers	-0.0009	0.0036*	-0.0049
	(0.0015)	(0.0020)	(0.0030)
Office FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Covariates[b]	Yes	Yes	Yes

Notes: [a] The label "Other" includes the following primary diagnoses: (i) respiratory and infectious diseases, (ii) digestive and endocrine disorders, (iii) cardiovascular diseases, (iv) cancer, and (v) other residual conditions. [b]: Covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types (excluding the covariate which is stratified on); ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses.

6 Mechanisms and targeting

6.1 Mechanisms

Although waiting does not involve any direct contact between office workers and applicants, there can be differences across offices in the specific ways in which the DI assessment is subsequently conducted. In principle, this may violate the *exclusion condition* of the IV strategy. As an example, some offices may rely less on medical examiners and more on supportive staff, and these choices may interact with increased waiting times and DI award decisions. Given the office information we have on specific staff numbers, an obvious way to test for the exclusion restriction is therefore to expand our model with office-month staff fractions of medical examiners, occupational experts, process managers, social-medical nurses and other staff. The IV estimates following this sensitivity test are shown in Table 9. We then see that the effect estimates of waiting times remain more or less the same. This also holds for the DI award rate, which is probably most directly related to the composition of office staff. This confirms the assumption that waiting time effects are not reflecting office differences that also affect our outcome variables of interest, lending credence to the exclusiveness condition.

Table 9: *IV results: one-month effect of extra elapsed waiting time on outcomes, including office staff shares as controls*

	DI award		***Employment after 24 months***		***Mental health care after 24 months***	
Elapsed waiting time (months)	0.0042**	0.0040**	-0.0020*	-0.0025**	-0.0031	-0.0051**
	(0.0019)	0.0021)	(0.0012)	(0.0010)	(0.0025)	(0.0025)
Office FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates[a]	Yes	Yes	Yes	Yes	Yes	Yes
Staff shares[b] (log values)	No	Yes	No	Yes	No	Yes
Observations	441,033	441,033	441,033	441,033	291,570	291,570
R-squared	0.074	0.073	0.089	0.089	0.111	0.111

Notes: [a]: Other covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types; ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses. [b]: This includes medical examiners, occupational experts, process managers, social-medical nurses, and others.

Since health, employment and DI awards are most likely interrelated in our context, we can also examine the relevance of *mediation* effects to explain our findings. To start

with, one potential mechanisms behind the increase in DI awards due to extra waiting time are that applicants lose their employment and that their mental health worsens while waiting. Medical examiners and occupational experts can incorporate these decay effects in their DI decision. To shed light on this, we re-estimate the IV model for DI awards while including the employment and mental health treatment status measured one month before the actual assessment takes place. The results are shown in Table 10. Interestingly, the comparison of model variants suggests that the increase in DI awards is fully due to a lower probability of employment at the assessment. Each additional month of waiting implies that more employment contracts have ended, which in turn increases the likelihood of a DI benefit. We also see that mental health treatments increase the probability of DI awards, but the baseline does not increase while waiting. Therefore, there is no effect on DI awards running through this variable.

Table 10: *Estimation results: one-month effect of extra elapsed waiting time on DI award probability, including pre-decision information on employment and mental health treatment*

		DI awards		
	Baseline	(a)	(b)	(c)
Elapsed waiting time	0.0042**	-0.0001	0.0045**	0.0003
	(0.0019)	(0.0021)	(0.0020)	(0.0022)
Variables one month before the DI decision:				
– Employment		-0.1170***		-0.1160***
		(0.0055)		(0.0056)
– Mental health treatment			0.0909***	0.0902***
			(0.0027)	(0.0027)
Office FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Covariates[a]	Yes	Yes	Yes	Yes
Observations	441,033	441,033	441,033	441,033
R-squared	0.074	0.077	0.078	0.081

Notes: [a]: Covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types; ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses.

Following Maestas et al. (2015), we also consider the possibility of changes in DI award rates driving changes in employment (and health) outcomes. This then presupposes a reverse mediation channel: when longer application waiting times increase the likelihood of DI awards, the extra benefit receipt may in turn discourage applicants to continue working. Similarly, DI benefit receipt may reduce the mental stress of appli-

cants and thus decrease the use of mental health treatments. A natural way to isolate these mediating effects is to extend our framework with the "leave-out-mean" of DI offices in application months, i.e. the DI award propensity, as an additional control. This propensity should then control for effects channeled through increased DI receipt.

Table 11 shows both the estimates including the DI award probability for employment en mental health utilization, 6 and 24 months after application. In line with expectations, we then see that more DI awards decrease the employment probability (with 7.6 percentage point after two years) and decrease mental health care utilization (with 2.8 percentage points after two years. These effects are however too small too induce economically substantial changes in the (remaining) effect of elapsed waiting times on employment and mental health treatments. Stated differently, the bypassing effect of changes in DI receipt appear negligible.

6.2 Targeting effects

As application waiting times delay the DI award decision, employment and health conditions may have changed meanwhile. Accordingly, the 'disability signal' at the time of the assessment may change, raising the question whether later information is more predictive of long-term health and employment outcomes of applicants. This may then increase the targeting efficiency of the assessments: awardees are more likely to have long-lasting losses in work ability and more persistent health problems. In our context, we then can think of two outcomes that are indicative of targeting: the capability to work—which can be measured by the employment status—and the receipt of mental health treatments.

To investigate targeting effects of longer waiting times, we follow the approach as proposed by Godard et al. (2024). Using the long-term unemployment and mental health treatment outcomes—measured 24 months after application—we develop proxies for targeting efficiency. We define Y as a binary which is equal to one for applicants who are assumed to be more in need of benefits than those with value zero. In our context, Y is either unemployment or the incidence of mental health treatments. When DI decisions contribute to targeting, the average value of Y should be higher for the subpopulation of awarded applicants than for the full populations of applicants. Concurrently, it implies that the DI award probability for applicants with Y=1 should exceed that of applicants with Y=0.

To formalize this approach, Godard et al. (2024) derive the *relative DI award* of applicants with Y as a proxy for targeting. The relative award rate equals the ratio of the DI award rate for workers with Y=1, $A_{Y=1}$, and those with Y=0, $A_{Y=0}$. For each office

Table 11: *IV results: one-month effect of extra elapsed waiting time on employment (upper panel) and mental health care utilization (lower panel), including office DI award propensities*

	Employment			
	6 months after application		*24 months after application*	
Elapsed waiting time (months)	0.0078***	0.0081***	-0.0020*	-0.0017
	(0.0026)	(0.0025)	(0.0012)	(0.0011)
DI award propensity[a]		-0.0418***		-0.0757***
		(0.0156)		(0.0152)
Office FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Covariates[b]	Yes	Yes	Yes	Yes
Observations	441,033	441,033	441,033	441,033
R-squared	0.195	0.195	0.089	0.089

	Mental health care utilization			
	6 months after application		*24 months after application*	
Elapsed waiting time (months)	0.0047**	0.0052**	-0.0031	-0.0033
	(0.0021)	(0.0021)	(0.0025)	(0.0025)
DI award propensity[a]		-0.0669***		-0.0277***
		(0.0195)		(0.0164)
Office FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Covariates[b]	Yes	Yes	Yes	Yes
Observations	378,027	378,027	291,570	291,570
R-squared	0.165	0.165	0.110	0.089

Notes: [a]: The variable "DI award Propensity" measures the average DI rate among all other applicants within the same office and month, excluding the individual's own observation. [b]: Covariates include gender, age categories, migration background, work histories, chronic conditions, and pre-DI contract types; ***/**/* indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses.

and application month, the fraction of awarded applicants with Y=1 is defined as

$$\overline{Y}_{awarded} = \frac{A_{Y=1}\overline{Y}_{all}}{A_{Y=0}\,(1-\overline{Y}_{all}) + A_{Y=1}\,\overline{Y}_{all}}\,. \tag{5}$$

Rewriting Equation (5) in terms of the relative DI award rate of a given office and application month then gives:

$$\frac{A_{Y=1}}{A_{Y=0}} = \frac{\overline{Y}_{awarded}}{1-\overline{Y}_{awarded}} \times \frac{1-\overline{Y}_{all}}{\overline{Y}_{all}}\,. \tag{6}$$

Using the observed values of $\overline{Y}_{awarded}$ and $\overline{Y}_{all}$ per office and application cohort, we can calculate the relative DI award rate. This yields 2,832 observations of office application cohorts based on unemployment outcomes and 1,935 office application cohorts based on mental health treatment outcomes. In line with expectations, the averages of these proxies exceed one for both outcome variables. Specifically, the relative award rate of unemployed applicants equals 1.932, and 1.138 for applicants with mental health treatments. We next regress these proxies on the average elapsed application waiting times per office and application cohort. For this we use Weighed Least Squares (WLS) estimation, using the number of applications per office-month as analytic weights.

Table 12: *Weighed Least Squares (WLS) estimates of effect of extra waiting time on targeting based on unemployment and mental health care utilization—both 24 months after application*

Targeting proxy based on	***Unemployment***			***Mental healthcare utilization***		
	(a)	(b)	(c)	(a)	(b)	(c)
Average waiting time	0.0140*	0.0095	0.0022	-0.019*	-0.0370***	-0.0200
(months per office appl.cohort)	(0.0076)	(0.0080)	(0.0120)	(0.0116)	(0.0137)	(0.0188)
Office FE	No	Yes	Yes	No	Yes	Yes
Month FE	No	No	Yes	No	No	Yes
Mean	1.932	1.932	1.932	1.138	1.138	1.138
Observations	2,832	2,832	2,832	1,935	1,935	1,935
R-squared	0.001	0.096	0.141	0.002	0.033	0.081

Notes: Estimates are obtained by Weighted Least Squares, using the number of applications per office–month as analytic weights. This accounts for differences in observation size across office–months. $^{***}/^{**}/^{*}$ indicate significance at 1%/5%/10%. Standard errors clustered at the office–application month level are shown in parentheses.

Table 12 reports the estimation results that follow from this approach. For the tar-

geting proxy that is based on unemployment outcomes 24 months after application, we find positive effects of longer waiting times. This then points at improvements in targeting. When controlling for office and application-month fixed effects, however, the coefficient becomes statistically insignificant and small (0.22% of the mean value). In terms of mental health treatments, we also find no robust evidence of any changes in targeting efficiency. This also leads us to conclude that longer application waiting times do not lead to improvements in targeting of the DI decision.

7 Conclusion and discussion

In this paper we have studied the consequences of prolonged application waiting times on the employment, (mental) health and award outcomes of DI applicants. Given that we use the universe of DI applications for the Netherlands between 2014 and 2022, we generally find small but precise effects on our outcomes measures between one to 24 months after application. To delve deeper into the mechanisms underlying our results, we also have analyzed the potentially mediating effects between employment, DI receipt and health outcomes. On the one hand, changes in employment and mental health induced by longer waiting times may affect the DI award probability of applicants. On the other hand, there may be a discouraging effect of increased DI awards on employment.

Inherent with the institutional setting where employment contracts are often dissolved at the moment of the DI decision, we show short-term positive effects of longer waiting times. When these largely mechanical effects have ended, we find decay effects on employment that are similar in size as obtained by Autor et al. (2015): two years after application, one month of extra waiting time leads to a 0.20 percentage point reduction in the probability of employment. Our mediation analyses indicate that this decrease cannot be explained by a bypassing effect of increased benefit receipt. Rather, it suggests that workers experience losses in human capital or increased stigma from (new) employers. These decay effects appear strongest for the group of applicants without formal employment at the start of application.

In terms of health outcomes, we find mixed results on short- and long-term effects of prolonged waiting times. Our results show that longer application waiting time increase the use of mental health treatments of applicants, up to 2.8% per additional months when measured six months after application. This sizable short-term effect comes primarily from prolonged treatments or the resumption of treatments that ended in the year prior to application. Together with this, we also find evidence of small

but significant increases in the long-term prevalence of rheumatological, psychological, and pain-related conditions. Although we cannot rule out the possibility that these effects mirror increases in prescription behaviors rather than a worsening of health, we still consider it likely that a small group of applicants experiences increased stress that potentially affects health outcomes.

Finally, our findings point to higher DI award rates for applicants who wait longer. Each additional month of waiting increases the probability of DI awards by 0.44 percentage points. Interestingly, this increase can be fully explained by decreases in the baseline employment probability: longer waiting times render it more likely that employment contracts have been dissolved meanwhile, which medical examiners and occupational experts perceive as a drop in the earnings capacity of applicants. Still, comparisons of long-term employment and (mental) health outcomes of awarded and rejected applicants do not suggest that these DI decisions lead to a better targeting of DI benefits.

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A Online Appendix : Figures

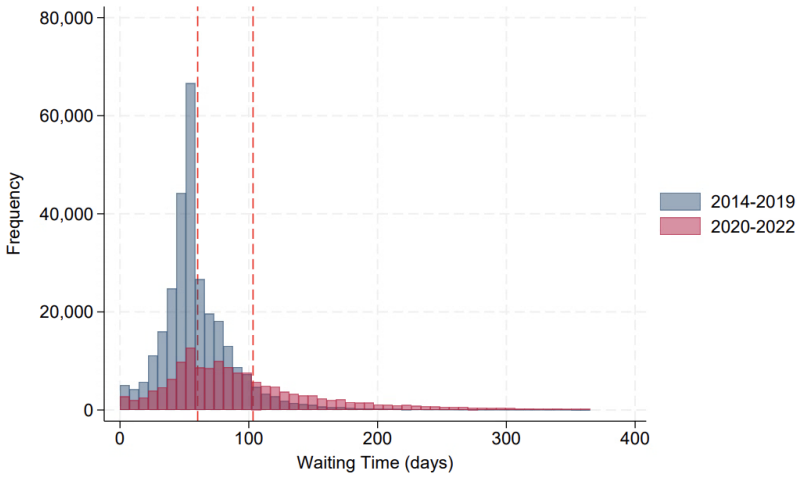


Figure A1: *Distribution of individual waiting times, shown separately for 2014–2019 and 2020–2022 (no obs > 365 days)*

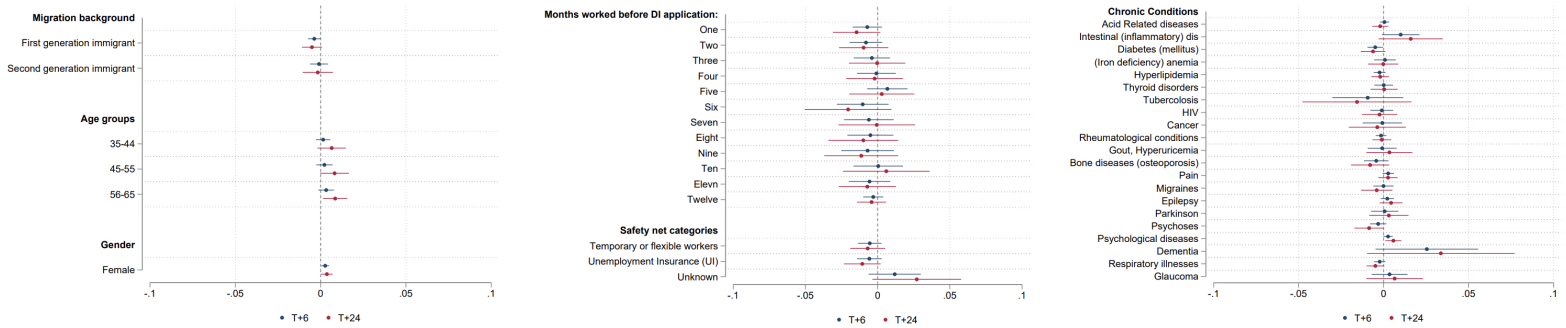


Figure A2: *Regression coefficients of the leave-out-mean waiting time on covariates. Office and month-of-application fixed effects are included in the model but not displayed.*

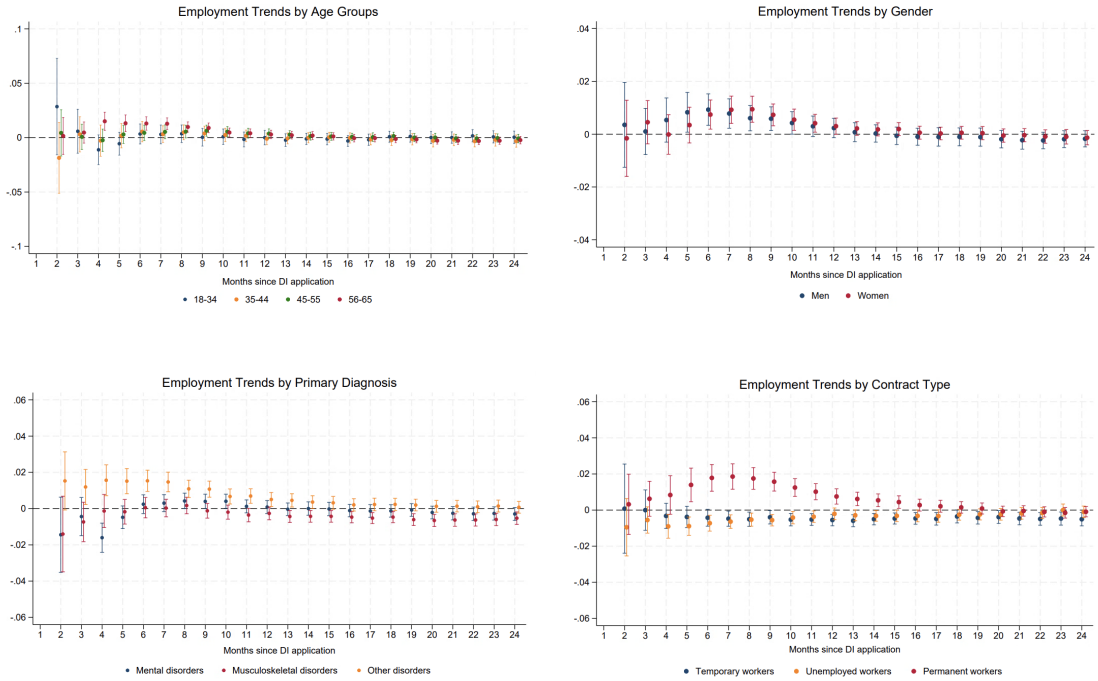


Figure A3: *Estimated employment effects, up to 24 months, of one month extra waiting times on employment by sub-samples: (a) by age groups (top-left); (b) by gender (top-right); (c) by primary diagnosis group (bottom-left); and (d) by type of contract at the time of application (bottom-right))*

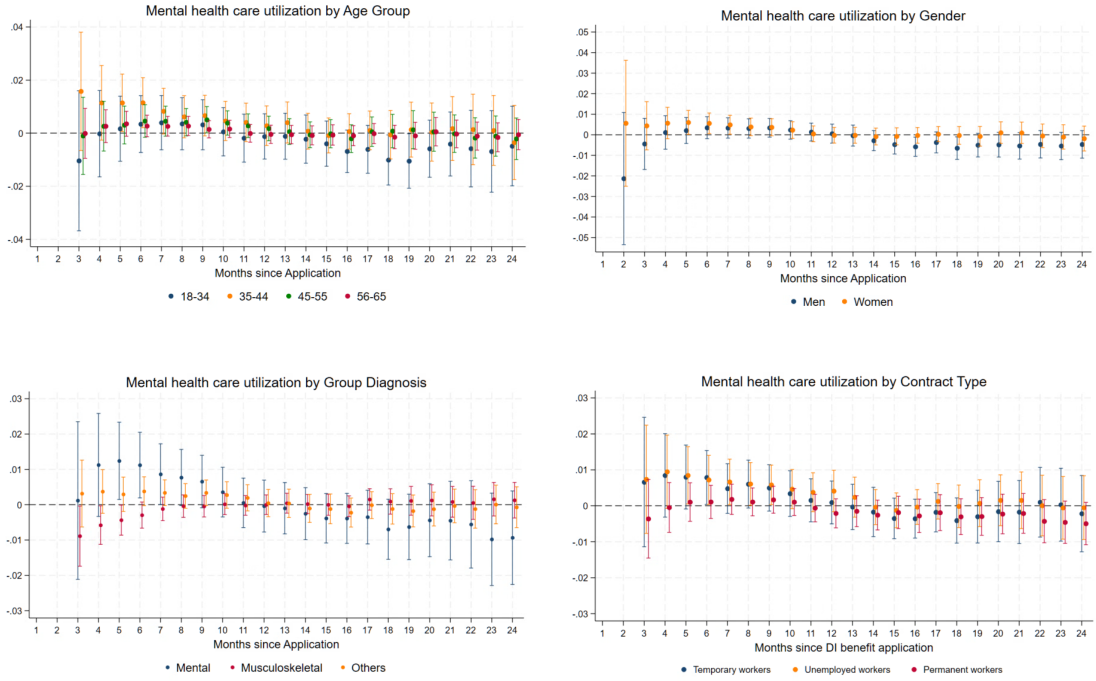


Figure A4: *Estimated effects, up to 24 months, of one month extra waiting times on mental health care utilization by sub-samples: (a) by age groups (top-left); (b) by gender (top-right); (c) by primary diagnosis group (bottom-left); and (d) by type of contract at the time of application (bottom-right))*

B Variance Decomposition

To investigate the drivers of waiting times in more detail, Table A1 reports the explained variance from a sequence of OLS regressions with different sets of controls. The results highlight that most of the variation in individual waiting times is accounted for by office and month-of-application effects. For instance, column (c) shows that including both office and month fixed effects raises the R^2 to about 0.21, while the inclusion of additional individual-level covariates such as demographics, work history and chronic conditions only marginally increases the explanatory power (from 0.209 to 0.219).

Table A1: *R-squared of regressions on individual waiting times*

Dependent variable: *Individual Waiting Time*						
	(a)	(b)	(c)	(d)	(e)	(f)
R-squared	0.040	0.169	0.209	0.211	0.211	0.219
Explanatory variables:						
Office Fixed Effects	Yes	No	Yes	Yes	Yes	Yes
Month-of-application Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Demographic characteristics	No	No	No	Yes	Yes	Yes
Chronic conditions (dummies) (year *t-1*)	No	No	No	No	Yes	Yes
Work history (dummies)	No	No	No	No	No	Yes
Observations	441,047	441,047	441,047	441,047	441,047	441,047

[a] Elapsed waiting times are instrumented with the leave-out mean of elapsed waiting times per office and month. [b] Covariates include gender, age categories, etc. ***, **, * indicate significance at 1%, 5%, and 10%.

Table A2: *Balance test of covariates on the leave-one-out mean 24 months after application*

Variable	$\hat{\beta}$	SE		$\lvert\hat{\beta}\rvert$/SD
Female	-0.0041	0.0057		0.0039
Migration background:				
1st generation	-0.0290	0.0271		0.0272
2nd generation	-0.0295	0.0205		0.0277
Age groups:				
35–44	0.0094	0.0061		0.0088
45–55	0.0066	0.0089		0.0062
56–65	0.0035	0.0099		0.0032
Months of (previous) employment:				
One	-0.0029	0.0104		0.0027
Two	-0.0059	0.0106		0.0055
Three	0.0012	0.0107		0.0011
Four	0.0100	0.0116		0.0094
Five	0.0254	0.0150	*	0.0238
Six	0.0060	0.0171		0.0056
Seven	0.0183	0.0147		0.0171
Eight	-0.00005	0.0157		0.00004
Nine	0.0219	0.0148		0.0205
Ten	0.0303	0.0188		0.0284
Eleven	0.0240	0.0149		0.0225
Twelve	0.0148	0.0090		0.0139
Safety net categories:				
Temporary workers	-0.0079	0.0076		0.0074
Unemployed	-0.0169	0.0078	**	0.0158
Unknown	0.0159	0.0269		0.0149
Chronic conditions (in *t-1*):				
Acid related diseases	0.0076	0.0044		0.0071
Intestinal disorders	0.0064	0.0093		0.0060
Diabetes	0.0010	0.0063		0.0009
Anemia (iron deficiency)	0.0068	0.0084		0.0063
Hyperlipidemia	-0.0139	0.0046		0.0130
Thyroid disorders	0.0008	0.0072		0.0007
Tuberculosis	-0.0128	0.0175		0.0120
HIV	0.0068	0.0076		0.0064
Cancer	0.0127	0.0091		0.0119
Rheumatological conditions	-0.0161	0.0047	***	0.0150
Gout, Hyperuricemia	-0.0009	0.0080		0.0008
Bone disorders (osteoporosis)	-0.0143	0.0077	*	0.0134
Pain	0.0120	0.0049	**	0.0112
Migraines	-0.0100	0.0063		0.0094
Epilepsy	0.0030	0.0071		0.0028
Parkinson	0.0089	0.0070		0.0083
Psychoses	-0.0094	0.0082		0.0088
Psychological diseases	0.0020	0.0038		0.0019
Dementia	-0.0014	0.0253		0.0014
Respiratory illnesses	-0.0061	0.0045		0.0057
Glaucoma	-0.0150	0.0094		0.0141