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# Night Shift Work and Mental Health*

Søren Skotte Bjerregaard† Astrid Sophie Fugleholm‡

*Night shift work leads to inadequate sleep, which has been linked to impaired mental health. This raises a natural question: Do night shift workers suffer from poorer mental health? In this paper, we examine the mental health effects of cumulative exposure to night shift work. We show that each additional year of night shift work increases the likelihood of redeeming prescriptions for mental health medication by 24%. While cumulative exposure to adverse working conditions can have more severe health consequences than temporary exposure, prior studies often underestimate these effects due to selection bias, commonly referred to as the "healthy worker effect"; healthier workers are better equipped to remain in physically and mentally demanding jobs. We address this bias by applying a sequentially weighted matching (SWM) procedure to detailed time-stamp data from approximately 3,500 graduate nurses in Denmark, tracking their shift work schedules over six years and linking this to administrative records on their prescription medication use. Our results underscore the importance of accounting for the healthy worker effect when analyzing the health consequences of adverse working conditions and suggest that the mental health costs of night shift work may be substantially larger than previously estimated.*

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## 1. Introduction

Inadequate sleep can lead to cognitive and social challenges that negatively affect a person's daily performance and interactions. Research in sleep finds that sleep-deprived individuals more often exhibit behaviors indicative of social distancing and experience symptoms of mental health conditions such as depression, anxiety, and stress (Walker and van der Helm, 2009, Giuntella et al., 2017, Ben Simon and Walker, 2018, D'Oliveira and Anagnostopoulos, 2021, Scott et al., 2021). Night shift work has consistently been linked to sleep deprivation; it disrupts the body's circadian rhythms, which can cause disturbances in sleep, chronic fatigue, and elevated stress levels (Kecklund and Axelsson, 2016, James et al., 2017, Boivin et al., 2022).

The well-documented effects of night shift work on sleep and the established link between sleep and mental health raise an important question: Do night shift workers suffer from poorer mental health? Although there is substantial research on this topic, a paradox emerges. Albeit night workers report mild mental health symptoms (Torquati et al., 2019, D'Oliveira and Anagnostopoulos, 2021, Zhao et al., 2019), existing studies find little or no impact of night shift work on the use of mental health-related medication (Albertsen et al., 2022, 2020, Hall et al., 2019).

In this paper, we investigate the mental health effects of cumulative exposure to night shift work. This relates to research in health and labor economics concerned with the health effects of adverse working conditions (e.g., Fletcher et al., 2011, Nicholas et al., 2020, Belloni et al., 2022). A significant theme in this body of research is the recognition that cumulative exposure to poor working conditions can have more serious health consequences than temporary exposure. However, estimating these cumulative effects presents challenges in adjusting for the dynamic interaction between exposure and health (Currie and Madrian, 1999, Jolivet and Postel-Vinay, 2025). Studies such as Fletcher et al. (2011) and Nicholas et al. (2020) address this using a conventional regression framework under the assumption that, conditional on observables, exposure is as good as random (the conditional independence assumption, CIA). Nevertheless, they acknowledge that this assumption limits the causal interpretation of their findings. A key threat to the CIA is the healthy worker effect (HWE), wherein healthier individuals are more likely to remain in more demanding jobs, while those in poorer health are more likely to switch to less demanding roles. We suspect that the HWE may explain the weak link between night shift work on mental health-related medication found in previous studies.

We build on the methodological foundations of Fletcher et al. (2011) and Nicholas et al. (2020) and implement a sequential weighted matching (SWM) approach (Hernán et al., 2002, Robins et al., 2000). In the context of health consequences of cumulative exposure to adverse working conditions, this approach offers one key advantage over standard regression techniques, such as probit, by explicitly addressing the dynamic relationship between night work and mental health. The central issue is that individuals' current health affects both their future health and their continued exposure to adverse working conditions. As a result, simply controlling for health as a time-varying confounder in a standard regression model can bias estimates because it blocks part of the effect we aim to capture, specifically the pathway through which health determines future exposure (Rosenbaum, 1984, Angrist and Pischke, 2008, Daniel et al., 2013). In contrast, by continuously reweighting and matching groups of treated (night workers) and controls (non-night workers), SWM ensures alignment on both fixed and time-varying covariates, including health. This dynamic adjustment improves comparability between the treatment and control groups and allows for more credible causal inference.

Our approach relates to several studies in labor economics that apply variations of sequential (weighted) matching to investigate the impact of dynamically assigned job training programs on labor market outcomes (Lechner, 2009, Lechner and Miquel, 2010, Lechner and Wiehler, 2013, van den Berg and Vikström, 2022). The identification strategy in SWM relies on the dynamic conditional independence assumption (DCIA), as opposed to the stronger conditional independence assumption (CIA) used in Fletcher et al. (2011) and Nicholas et al. (2020). The CIA assumes there are no time-varying confounders affecting cumulative exposure, whereas the DCIA relaxes this by allowing for time-varying confounders. Although neither assumption can be empirically tested, SWM is better equipped to accommodate time-varying covariates and thus is more likely to satisfy the DCIA. We elaborate on these assumptions and the SWM methodology in more detail in section 2.

Implementing the SWM approach requires high-quality data with objective measures of both night shift exposure and mental health outcomes. We use the Danish Work Hour Database (DWHD) with minute-level timestamps of all publicly employed nurses' paid activities from 2008 to 2020. We link this to annual administrative records on their healthcare utilization, as well as demographic and socioeconomic characteristics. Following previous studies using the DWHD (Garde et al., 2016, 2018, Larsen et al., 2023), we define night shifts as at least three hours of work between 11 pm and 6 am, and we classify nurses as night workers if they have $> 6.7\%$ night shifts in one year and non-night workers otherwise. We focus on a sample of approximately 3,500 graduate nurses, whom we follow for six years to evaluate whether cumulative exposure to night work is associated with increased use of mental health medication. To better isolate the effects of night work on mental health, we restrict the sample to graduate nurses with no history of night work or mental health issues at baseline. Although nurses may differ from the general population, we expect our results to generalize across occupations if sleep deprivation is the primary mechanism underlying the mental health effects. Thus, we consider the external validity of our study to be significant.

We find that night shift work has sizable, adverse mental health effects. For each additional year of night shift work, nurses' odds of redeeming prescriptions for psychotropic medication increase by 24%. This response seems to be primarily driven by an increased uptake of antidepressants (psychoanaleptics) rather than medication for anxiety or sleep disorders (psycholeptics). We hypothesize that reversing the typical pattern of daytime work and nighttime sleep to accommodate night shifts creates challenges in creating and maintaining a family life. To test this, we examine whether night work affects nurses' probability of having a partner or a child. Our results show that an additional year of night shift work decreases nurses' odds of having a child by 20%, but it does not change their probability of having a partner. In line with the theory of compensating wage differentials, nurses are compensated for the inconvenience of night shifts along three dimensions: wages, working hours, and off-duty time, that is, the length of the interval between consecutive shifts. In particular, we find that night workers earn around 18,000 DKK (5%) more, work 23 (2%) fewer hours, and have 4 (2%) fewer shifts per year. As a result, they benefit from longer intervals between shifts and fewer returns to work within 24 and 48 hours of their last shift.

With our study, we make three contributions to the existing literature on shift work and mental health. First, we use objective measures of both exposure and outcomes. Relying on administrative data to capture night shift work reduces mis-classification and, thereby, measurement bias, causing attenuation. Similarly, using prescription medication data as a measure of mental health avoids self-reporting bias common in survey-based studies. Second, we follow nurses over several years, allowing us to evaluate cumulative effects, which can lead to more serious health conditions. However, these cumulative effects are likely confounded by the healthy worker effect. Our third and central contribution is therefore to address this selection bias using the SWM approach. We show that adjusting for the HWE is important since it substantially changes the estimated effect of night shift work on mental health, with important implications for both interpretation and policy. Previous work in health and labor economics has addressed the endogenous selection problem by controlling for past health and exposure in linear regression (Fletcher et al., 2011), fixed or random correlated effects models (Lakdawalla and Philipson, 2007, Schmitz, 2016, Ravesteijn et al., 2018, Nicholas et al., 2020), or by instrumenting for occupation (Fletcher and Sindelar, 2009, Kelly et al., 2014). These studies often rely on self-reported measures of health as well as occupation-level exposure to working conditions, which does not capture within-occupation differences in exposure (Peters, 2020). The epidemiological literature on the relation between night shift work and mental health has primarily focused on survey-based mild mental health symptoms, such as scores above 4 on the 12-item General Health Questionnaire, with scores ranging from 0 to 12 (Bara and Arber, 2009, Driesen et al., 2011, Zhao et al., 2019). Only three studies have analyzed the impact of self-reported night shift work on prescriptions for psychotropic medication, but they do not account for endogenous selection and may thus underestimate the true effect (Hall et al., 2019, Albertsen et al., 2020, 2022).

The remainder of the paper is organized as follows. In section 2, we describe our identification and estimation strategies. In section 3, we present our data and provide descriptive statistics on our sample of graduate nurses. In section 4, we show and discuss our results. Finally, we summarize our findings and identify areas for future research in section 5.

## 2. Empirical Framework

### 2.1 Identification Strategy

In an ideal experiment examining the cumulative effects of night work on mental health, the study subjects are randomized into either night or non-night work each year without the possibility of dropping out of the experiment during the study period. After the study period, the effect of cumulative exposure on mental health can be assessed using the following regression model:

$$MH_{it+1} = \alpha + \beta^{RCT} \sum_{k=1}^{t} E_{ik} + \epsilon_{it}, \tag{1}$$

where $MH_{it}$ indicates whether nurse $i$ experiences mental health issues in period $t$; $E_{it}$ is an indicator for being a nigher worker; $\sum_{k=1}^{t} E_{ik}$ denotes cumulative exposure to night work; and $\epsilon_{it}$ represents an idiosyncratic error term.

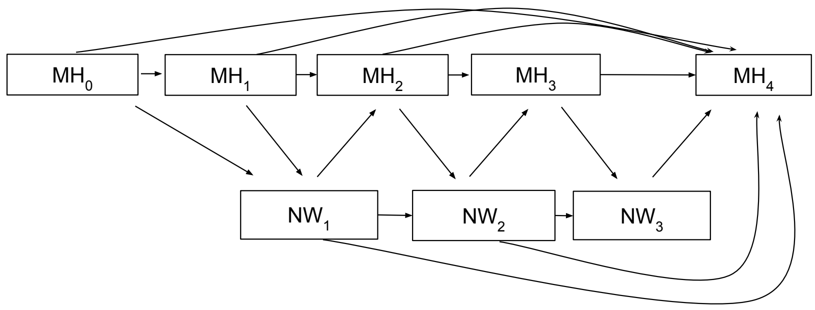
In practice, this type of randomized control trial (RCT) is not feasible for ethical and practical reasons. It is only possible to examine the effect of years of night work on mental health with observational data. With some assumptions, however, it is possible to approximate RCTs with observational data. For cumulative effects, this becomes more complicated because dynamic selection processes are at play, such as the healthy worker effect (HWE).

In the presence of the HWE, the sequential weighted matching (SWM) approach may prove to be more suitable than standard regression methods (Robins et al., 2000, Hernán et al., 2002).[1] To clarify the issue and illustrate the appropriateness of SWM, consider the directed acyclic graph (DAG) in Figure 1a. DAGs consist of nodes linked by directed edges, with edges indicating the influence of one node on another (Cunningham, 2021). Here, $MH_t$ denotes mental health in period $t$, and $NW_t$ denotes whether the nurse worked night shifts in period $t$. For simplicity, we omit other covariates that may affect night work participation. In Figure 1a, the edge from $MH_0$ to $NW_1$ illustrates that mental health status in period 0 can influence whether a nurse takes on night work the following year; particularly, it is perceivable that individuals experiencing a decline

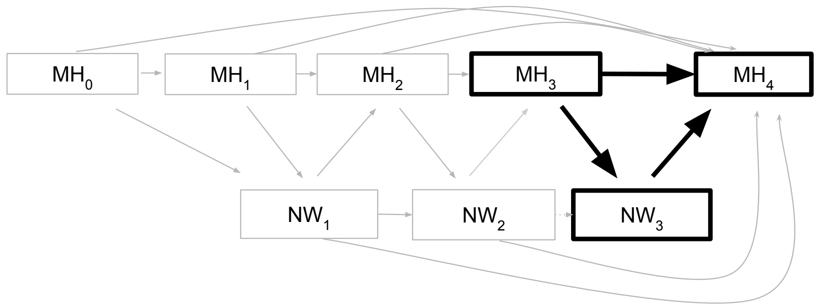
[1]This methodology originates from epidemiology and is known as Marginal Structural Models. Lechner and Miquel (2010) and van den Berg and Vikström (2022) have suggested variations of these techniques but without using a consistent terminology, leading us to adopt the term sequential weighted matching (SWM) as it aptly describes the methodology.

Figure 1: Directed Acyclic Graph: Night Work Exposure and Mental Health

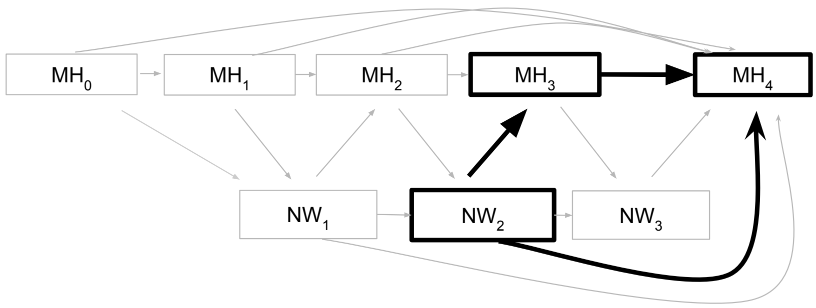
(a) Dynamics Between Night Work and Mental Health




(b) Mental Health as a Confounder




(c) Mental Health as a Mediator




*Note:* The figures show the dynamic relationship between night work exposure and mental health in Directed Acyclic Graphs (DAGs), where arrows represent potentially causal effects. Panel (a) shows the baseline DAG, and panels (b) and (c) illustrate the roles of mental health as a confounder and mediator, respectively. In Figure 1b, mental health in period 3 ($MH_3$) confounds the effect of night work in period 4 ($NW_4$) on mental health in period 4 ($MH_4$), because $MH_3$ affects both $NW_4$ and $MH_4$. In Figure 1c, $NW_3$ affects $MH_4$ directly and through $MH_3$, and $MH_3$ is therefore considered a mediator.

in mental health are less inclined to work night shifts the following year. Furthermore, the existing literature (e.g., Torquati et al., 2019, D'Oliveira and Anagnostopoulos, 2021, Zhao et al., 2019) suggests a reciprocal influence, where $NW_1$ can affect $MH_2$. This interactive dynamic persists throughout the periods depicted in the DAG.

The first issue to address is the confounding role of health history. This is highlighted in Figure 1b, where the effect of interest is $NW_3$ on $MH_4$. In this example, the DAG indicates that $MH_3$ influences both $NW_3$ and $MH_4$, potentially resulting in a spurious correlation between these variables. Thus, $MH_3$ acts as a confounder. Adjusting for $MH_3$ would eliminate the directed edges from $MH_3$ to both $NW_3$ and $MH_4$, such that the relationship between $NW_3$ and $MH_4$ is no longer confounded by $MH_3$.

The second problem to consider is that health history also acts as a mediator.[2] In examining the cumulative effect of night work on mental health, the influence of $NW_2$ on $MH_4$ is also of interest. The DAG in Figure 1c indicates that $NW_2$ affects $MH_4$ both directly but also indirectly through $MH_3$. Here, $MH_3$ functions as a mediator. Conditioning on $MH_3$ amounts to adjusting for a post-treatment variable, a practice generally associated with bias (Rosenbaum, 1984, Wooldridge, 2005, Angrist and Pischke, 2008).[3] This adjustment effectively blocks the influence of $NW_2$ on $MH_4$ via $MH_3$, which in turn underestimates the total effect of $NW_2$ (Daniel et al., 2013). Therefore, conditioning on $MH_3$ in a standard regression model would be inappropriate.

In standard regression analysis, where the focus is on the cumulative effect of exposure $E$ on outcome $Y$, it is inadvisable to adjust for intermediate outcomes during the exposure measurement period. Rather, the advised approach is to fix control variables before treatment (Angrist and Pischke, 2008), as suggested in the following equation:

$$MH_{it+1} = \alpha + \beta^{Con} \sum_{k=1}^{t} E_{ik} + \delta MH_{i1} + \theta X_{i1} + \epsilon_i, \tag{2}$$

where the notation follows (1) and $X_{i1}$ is a vector of control variables measured at baseline; and $MH_{i1}$ is an indicator for baseline mental health.

This aligns with the approach taken by Fletcher et al. (2011) and Nicholas et al. (2020), who examine the cumulative effects of demanding working conditions on health-related outcomes. Fletcher et al. (2011) avoids conditioning on post-treatment variables by controlling for health metrics prior to the cumulative exposure measurement period, and Nicholas et al. (2020) does so as part of a robustness check. We refer to the state-

[2] An illustrative example of mediation is the relationship between educational attainment and wages, where occupation mediates the impact of a college degree on earnings by providing access to higher-paying jobs. For instance, controlling for occupation blocks the effect of education on wages that operates through occupation, since much of the effect of education on wages is channeled through better occupational prospects (Angrist and Pischke, 2008, Cunningham, 2021). Refer to Cunningham (2021) for further examples. For a more comprehensive discussion of mediators, see Imbens (2020).

[3] This phenomenon is what Angrist and Pischke (2008) terms a "bad control".

of-the-art methodologies used by Fletcher et al. (2011) and Nicholas et al. (2020) as the conventional approach. Our study builds on the conventional approach, addressing the healthy worker effect by incorporating the dynamic interplay between working conditions and mental health. Thus, our approach should address the notion that mental health history simultaneously acts as both a confounder and a mediator.

To achieve this, we employ sequential weighted matching, which removes directed edges influencing $NW_t$ while maintaining those extending from $NW_t$ to $MH_{t+1}$ (Daniel et al., 2013, Robins et al., 2000) in Figure 1a. This method allows us to mitigate the confounding effects of mental health while avoiding the bias typically associated with conditioning on post-treatment variables within standard regression analyses. The empirical strategy underlying SWM has also been pursued previously in the economics literature in various formats, primarily in relation to evaluating labor market programs.[4]

SWM models rely on three key assumptions. (1) Dynamic Conditional Independence (DCIA), which ensures that, once adjusted for confounders, the treatment (night work) is independent of past time-varying confounders and other background characteristics. (2) Overlap, which means that for each period, there should be some non-zero probability of receiving both treatments (night and non-night shifts) across all observed values of confounders. (3) Correct model specification, which requires precise modelling of inverse probability weights to ensure proper covariate balance. We discuss each of these assumptions in turn and, where possible, how they are empirically assessed.

*Dynamic Conditional Independence (DCIA).* To understand the intuition behind SWM methods and their assumptions, it is useful to consider the more familiar static framework, where weighted matching is achieved with inverse probability weighting. In the static weighted matching framework, the goal is to balance covariates between night and non-night workers by assigning weights to observations such that treatment becomes statistically independent of health history and background characteristics (e.g., balancing mean age across treatment and control groups). Thus, it is necessary to adjust for all variables that jointly determine exposure and outcome, which is the conditional independence assumption (CIA). This assumption is often disputed in economics because it is impossible to test empirically, and omitted variable bias will always be a concern. Still, having more informative data makes the CIA more tractable (Lechner and Wunsch,

[4] See, e.g., Lechner (2009), Lechner and Miquel (2010), Lechner and Wiehler (2013), van den Berg and Vikström (2022).

2013, Heckman et al., 2016). In the absence of instrumental variables, the CIA is the underlying assumption when Fletcher et al. (2011) and Nicholas et al. (2020) examine the cumulative effects of demanding working conditions on health using the conventional approach. SWM, on the other hand, rests on the DCIA. Although applying the DCIA in each time period may appear more restrictive, this sequential approach is, in fact, less restrictive. It enables us to address the time-varying confounders that the treatment itself can influence. In contrast, standard regression methods typically assume that these confounders remain constant over time, exposing them to issues such as the HWE. Even though SWM requires weaker assumptions, we still cannot control for unobservable factors and therefore exercise caution when interpreting estimates as causal effects.

*Overlap.* The overlap assumption implies that for all non-night workers, there is a night worker with a similar estimated propensity to be a night worker, and vice versa. In practice, overlapping propensity scores depict the regions where the two groups share comparable characteristics. In section 4.1, we test the overlap assumption by visualizing the distribution of propensity scores across treatment groups.

*Correct model specification for inverse propensity scores.* This assumption, which requires a substantial sample size, is necessary to achieve stochastic balance across covariates. Nonetheless, challenges regarding balance levels may persist. The use of propensity scores can inadvertently hinder bias reduction in subsequent analyses, as optimizing balance for some covariates might adversely affect the balance for others (Iacus et al., 2012, Hainmueller, 2012). Thus, we also explore weights generated through entropy balancing, a method devised by Hainmueller (2012). This technique produces weights that enforce equality for the mean and possibly higher moments of covariates across treatment and control groups. Simultaneously, entropy balancing seeks to minimize weight variability, thereby reducing complications associated with extreme weights. There are a few limitations to entropy balancing; it is computationally intensive, and the resulting weights do not have an intuitive interpretation, unlike the propensity scores used for inverse probability weighting. To ensure that treatment assignment is independent of confounders, we conduct balance checks on the covariates in section 4.1 after applying SWM for weights generated from both propensity scores and entropy balancing.

## 2.2 Estimation Strategy

We estimate the effect of cumulative night work on mental health by applying SWM with repeated measurements in the following equation:

$$MH_{it+1} = \alpha + \beta^{SWM} \sum_{k=1}^{t} E_{ik} + \epsilon_{it}, \tag{3}$$

where $MH_{it}$ indicates whether nurse $i$ experiences mental health issues in period $t$; $\sum_{k=1}^{t} E_{ik}$ denotes cumulative exposure to night work; and $\epsilon_{it}$ represents an idiosyncratic error term. Equation (3) accounts for confounders, including potentially time-varying confounders, by applying balancing weights. In addition to the weights aimed at balancing across treatment groups, the regression is weighted with censoring weights to adjust for systematic differences between censored and uncensored groups of night and non-night workers. The censoring weights account for workers who are lost to follow-up—because they become part-time workers, emigrate, die, or leave public hospital employment—ensuring that their absence does not create bias in the results. The weights applied to the estimation are thus the product of the individual-time-specific cumulative products of the exposure and censoring weights. This approach, summarized in Algorithm 1 ensures that the estimation model adjusts for both the exposure (night work) and the censoring process in each period. We estimate the model employing the Generalized Estimating Equations (GEE) estimator, with the assumption that the working covariance matrix exhibits an exchangeable correlation structure—meaning all mental health responses from a nurse are equally correlated across time (Wooldridge, 2010). We model equation (3) using logistic and linear regressions for binary and continuous outcomes, respectively, employing a sandwich estimator to obtain panel-robust variance estimates that are robust to potential misspecifications of the working covariance matrix (Cameron and Trivedi, 2006).

## 2.3 Weights and confounders

We apply two methods for generating individual-specific time weights: inverse probability weights (IPW) using propensity scores derived from a logistic regression (e.g., Robins et al., 2000) and weights generated via entropy balancing (Hainmueller, 2012). To maximize the balance between exposed and unexposed groups, we base the weights on all

**Algorithm 1** SWM Estimation

1. For each period:

 1.1 Estimate balancing weights: $\hat{w}_{it}$

 1.2 Estimate censoring weights: $\hat{w}_{it}^{c}$

 1.3 Calculate final weights as: $\hat{w}_{it}^{final} = \prod_{k=1}^{t} \hat{w}_{ik} \times \prod_{k=1}^{t} \hat{w}_{ik}^{c}$

2. Estimate equation 3 weighted by $\hat{w}_{it}^{final}$

observable factors that may influence nurses' night worker status.[5]

To generate IPW with logistic regression, we estimate both an extensive and a parsimonious model to determine the propensity scores. The extensive model is pooled across follow-up years 2-6 to derive a predictive equation for the propensity to be a night worker, and it serves to generate weights throughout follow-up years 2-6. The parsimonious model considers the likelihood of nurses undertaking night work during their first year of employment in the regions and only takes into account information available prior to their hospital hire. This model generates weights used for balancing night and non-night workers prior to their hiring. To address extreme weights, we apply stabilized weights as detailed in Robins et al. (2000) and winzorize weights at the 1st and 99th percentiles.

In the extensive specification, night worker status is regressed on time-fixed characteristics (such as gender, age, and origin) and time-varying characteristics, including mental health (current and lagged one to three periods), the age of the youngest child, contacts with psychiatric hospitals, psychologists, and psychiatrists, and a one period lag for employment region, partnership status, working hours, wage income, and sick days.[6] The parsimonious model considers all variables as time-fixed characteristics and excludes mental health history, as we only consider nurses with no prior history of mental health issues in the past 5 years, and work-related variables like lagged night worker status, annual income, working hours, and sickness absence since this information is irrelevant or unavailable before nurses are hired in the regions. For entropy balancing, the same set of covariates is applied to each period (i.e., the balancing model is not pooled over several periods). The same methodology is applied to generate censoring weights via both

[5] See Table B.1 for a description of these covariates.
[6] Refer to Table B.1 for a detailed overview of the covariates employed.

IPW and entropy balancing, substituting the night worker indicator with an indicator for being censored and mental health history, contacts with psychiatric hospitals, therapists, and psychiatrists with lagged versions.

A strength of using objective measures concerning both the outcome and exposure variable is their ability to reduce bias. Objective measures from administrative data help maximize the sample size, reduce measurement error from self-reporting, and eliminate sampling bias due to non-response. The registry data on working hours also allows us to assess the robustness of different definitions of night work. Objective measurement of mental health with prescription medication usage reduces self-reporting biases in mental health. However, a key strength of self-reported mental health is that it is often more granular, which can increase statistical power and also capture mild to moderate cases of mental health issues. In contrast, prescription medication usage only captures the most severe cases, and only those seeking help will have access to medication, which excludes individuals who do not recognize their mental health problems or are otherwise resistant to seeking help. If mild to moderate mental health symptoms influence whether a nurse continues working night shifts or decides to leave their job, then our results could be affected by omitted variable bias. Nevertheless, since our models account for sick days and visits to specialized mental healthcare—variables that presumably correlate with mild to moderate mental health symptoms—we argue that this bias is likely minimized.

## 3. Data and Descriptives

### 3.1 Data Sources and Sample

We acquire information on working hours from the Danish Work Hours Database (DWHD), a unique database containing rich, high-frequency employment-related data on all nurses employed in the Danish Regions (primarily public hospitals). The DWHD contains payroll records detailing the exact start and end times of each shift for public hospital employees in Denmark from 2008 to 2020, alongside their hiring dates. This data enables us to create variables that identify whether a shift is classified as a night shift or a non-night shift, in addition to other relevant metrics such as sickness absence days, annual working hours, region of employment, and the intervals between shifts. Following the definitions established by Garde et al. (2018), we designate a night shift as any work period exceeding three hours between 23:00 and 06:00, and shifts falling outside this timeframe are categorized as non-night shifts.

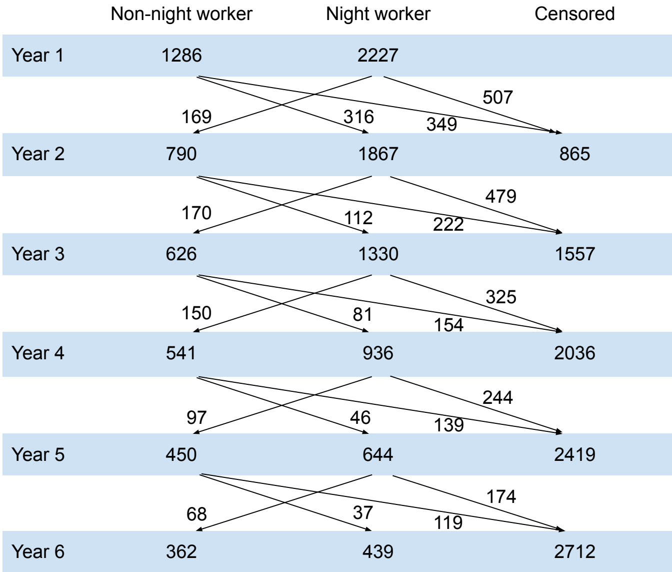
We standardize the timing of follow-up years to the date of each nurse's hiring, evaluating their exposure and outcomes in relation to this date. For each year following their hire, we evaluate the number of night and non-night shifts worked by the nurses. Nurses are identified as night or non-night workers based on the percentage of night shifts they have completed in a given year. Specifically, nurses are classified as night workers if they have more than 6.7% of their shifts during one year designated as night shifts, as per the criteria outlined by Garde et al. (2018).

We link DWHD with various demographic, socioeconomic, and health-related characteristics from Danish administrative data provided by Statistics Denmark and the Danish Health Agency.[7] This data includes information on redeemed prescriptions for medication, age, gender, country of origin, regional residency, partnership status, parental status, the age of the youngest child, and visits to mental healthcare professionals. The medication data is sourced from the National Patient Pharmaceutical Database, which holds detailed records of all prescriptions filled in Denmark. We specifically utilize data on redeemed prescriptions for psychotropic drugs, which are categorized as psycholeptics (N05, including antipsychotics and anxiolytics) and psychoanaleptics (N06, including antidepressants and psychostimulants) according to the Anatomical Therapeutic Chemical (ATC) Classification system (WHO, 2022). We examine extensive margin responses using an indicator for redeeming prescriptions for psychotropic drugs.

From these data, we create a sample of all individuals who completed their bachelor's degree in nursing from 2009 to 2015 and were hired at a public hospital within one year of graduation. By focusing on this inception cohort of graduate nurses, we minimize the effects of prior exposure to night work. We impose two key restrictions on our sample. First, we focus exclusively on nurses employed full-time (defined as at least 900 hours, or approximately 120 shifts) in their first year to ensure a more uniform experience with respect to work intensity. Second, we exclude nurses who redeemed prescriptions for mental health medications (psycholeptics or psychoanaleptics) within five years before their hospital hire to limit the influence of any early life health disparities, which can be important according to Fletcher et al. (2011). Ultimately, our final sample comprises

[7]See Table B.2 for a description of all variables used in the analysis.

Figure 2: Work Arrangement Dynamics, Follow-Up Year 1-6




*Note*: The figure shows the number of non-night, night, and censored workers in our sample, by follow-up year. Follow-up year 1 begins when individuals are hired at a hospital in the regions. Individuals are censored if they die, emigrate, or work part-time or outside the region. Arrows indicate transitions from one group to the other, from one year to the next.

3,513 nurses, followed for a period of up to six years of employment or until they are censored. Figure 2 illustrates how work arrangements and sample censoring evolve over this period of time. The number of nurses classified as night and non-night workers declines gradually, and the two groups become similar in size. Meanwhile, the number of censured nurses increases, with night and non-night workers contributing in similar proportions.

Table 1 displays descriptive statistics for our sample of nurses in their first full year of employment in a public hospital.[8] The majority are young women in their mid-20s, most of whom are in relationships but do not have children. They work 18% of their shifts at night and 64% are classified as night workers. Of approximately 1,500 annual working hours, roughly 200 hours are spent on night shifts, averaging about two per month. The EU Working Time Directive (The European Parliament and the Council, 2003) stipulates that the average number of night work hours within a 24-hour period for four consecutive months cannot exceed eight. Although we do not analyze this in detail, it is unlikely that our cohort would violate this regulation. As shown in Figure 3, around 10% of shifts start between 23:00 and midnight and last for eight hours, and only 1% of shifts begin between 19:00 and 20:00, lasting 12 hours.

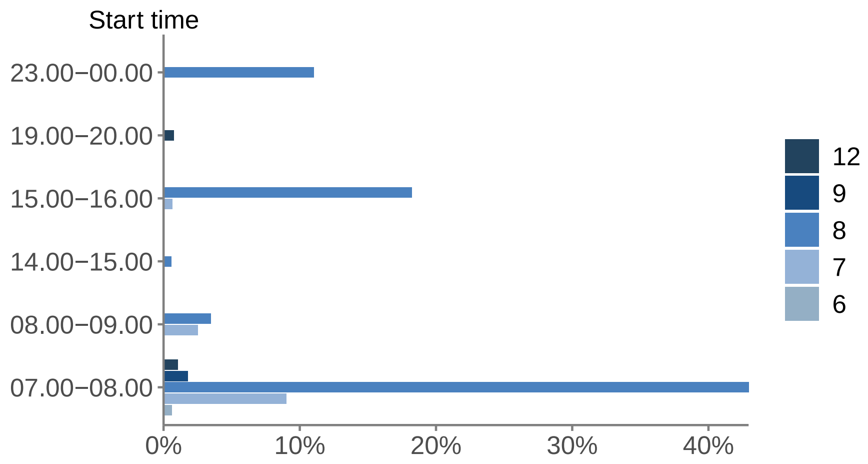
[8] Table B.3 presents descriptive statistics on the estimation sample, including nurses who are censored or have prior use of mental health medication.

Table 1: Summary Statistics on Estimation Sample

| Variable | Mean | SD |
|---|---|---|
| *Demographic characteristics* | | |
| Age | 27.7 | 5.5 |
| Female | 0.950 | 0.217 |
| Is Danish | 0.890 | 0.313 |
| Single | 0.338 | 0.473 |
| Has partner (not empl. in regions) | 0.653 | 0.476 |
| Has partner (empl. in regions) | 0.009 | 0.092 |
| Has children | 0.300 | 0.458 |
| Number of children | 0.502 | 0.857 |
| Youngest child aged 0-2 | 0.147 | 0.354 |
| Youngest child aged 3-6 | 0.083 | 0.276 |
| Youngest child aged 7-12 | 0.051 | 0.220 |
| Youngest child aged 13-18 | 0.019 | 0.137 |
| Lives in the Northern region | 0.073 | 0.260 |
| Lives in the Central region | 0.253 | 0.435 |
| Lives in the Southern region | 0.178 | 0.383 |
| Lives in the Capital region | 0.373 | 0.484 |
| Lives in the Zealand region | 0.123 | 0.328 |
| *Health characteristics* | | |
| Any use of mental health medication | 0.025 | 0.155 |
| Any use of psycholeptic medication | 0.011 | 0.103 |
| Any use of psychoanaleptic medication | 0.015 | 0.122 |
| Any hosp. visit related to mood, anxiety, or stress-disorder | 0.002 | 0.048 |
| Any mental health related visit to hospital | 0.005 | 0.069 |
| Any psychiatrist or psychologist visit | 0.029 | 0.168 |
| *Socioeconomic characteristics* | | |
| Wage income (in 2015 prices, in DKK) | 316,817 | 52,255 |
| Night worker | 0.634 | 0.482 |
| Working hours | 1500.0 | 200.9 |
| Working hours, night shifts | 199.3 | 177.9 |
| No. shifts | 187.8 | 24.6 |
| No. night shifts | 23.5 | 20.9 |
| Share of night shifts | 0.126 | 0.114 |
| No. quick returns | 9.55 | 7.87 |
| No. early starts | 0.11 | 0.97 |
| Sick | 0.92 | 0.28 |
| Sick days | 12.0 | 16.1 |
| Sick periods | 1.47 | 1.25 |
| On maternity leave or pregnant | 0.082 | 0.274 |
| Individuals | 3,515 | |

*Note*: The table presents summary statistics on our sample of nurses graduating in 2009-2015, who are hired at a public hospital within a year of graduation, work full-time in their first year of employment, and have not redeemed prescriptions for mental health medication in the five years before employment. Follow-up year refers to years since hire at the public hospital. Variables are measured in follow-up year 1 (nurses' first full year of employment) and reflect yearly averages.
A night shift is defined as $\geq$ 3 hours of work between 23:00 and 06:00. A quick return is defined as a shift starting less than 11 hours after the end of the prior shift. An early start is defined as a shift starting between 3:00 and 6:00.

Figure 3: Share of Shifts by Starting Time and Hourly Length of Shift, Follow-Up Year 1



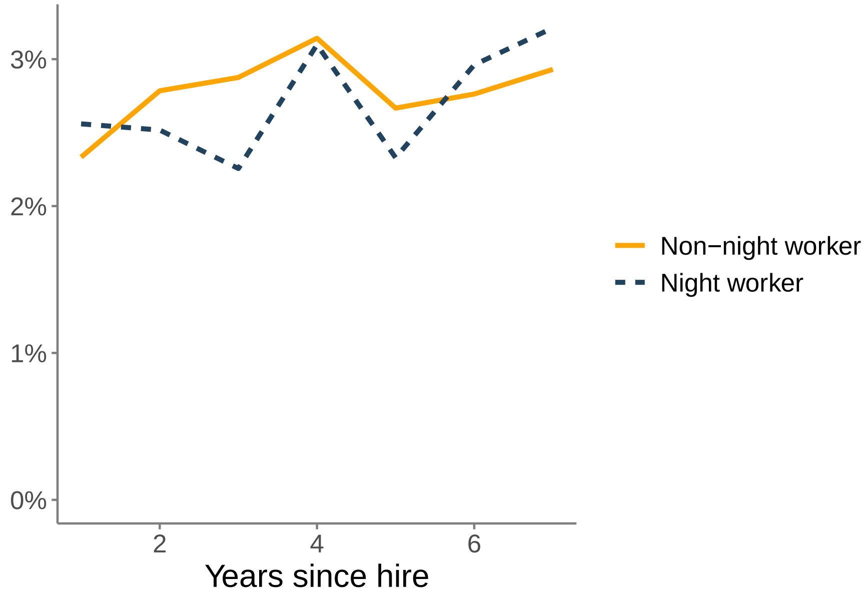

*Note*: The figure illustrates the distribution of shifts within our sample during their first year of employment, categorized by the starting time and duration of the shifts in hours. Darker blue bars correspond to longer shifts, and the length of the bars indicates the proportion of shifts at each time point.

Workers are entitled to at least 11 hours of rest between shifts, although this can be reduced to 8 hours twice a week, provided these shifts are not consecutive (The European Parliament and the Council, 2003). Our cohort averages 10 instances of rest periods shorter than 11 hours (termed 'quick returns'). Hospitals may issue local recommendations for the composition of shift schedules, such as minimizing night shifts or limiting consecutive night work to a maximum of 2-4 shifts (e.g., Regionernes Lønnings- og Takstnævn et al., 2018). Apart from the EU regulations, no official guidelines exist during our study period.

Nurses are sick around 12 days per year on average (median: 7 days), with a right-skewed distribution that includes instances of prolonged sick leave. Interestingly, in their first year of employment, about 2.5% of nurses redeem prescriptions for psychotropic medication, with a larger share taking up psychoanaleptics compared to psycholeptics medication (note that we exclude nurses with use prior to their employment). Figure 4 illustrates that the proportion of nurses redeeming prescriptions for psychotropic medication remains consistent among both night and non-night shift workers over time. One year after their hire at a public hospital, approximately 2.5% of each group is taking up medication, with this share gradually rising to just over 3% after seven years.[9]

[9]Table B.4 shows that the take-up rate of psychotropic medication among all nurses hired at public hospitals is 9-10%, and that take-up of psychoanaleptics is higher than that of psycholeptics. Table B.5 shows that the general take-up rate among Danish 25-44 year-olds is higher (12.5%-15%), with take-up of psychoanaleptics being higher than that of psycholeptics.

Figure 4: Take-Up of Mental Health Medication by Night Worker Status, Follow-Up Year 1-7




*Note*: The figure shows the share of nurses in our sample redeeming prescriptions for psychotropic (psycholeptics or psychoanaleptics) medication by follow-up year. Nurses are classified as night and non-night workers each year. Censored person-years are not included.

Mental health-related hospital visits among nurses are infrequent; however, consultations with psychiatrists or psychologists are more prevalent, with 3% of nurses reporting at least one visit per year. When examining the broader population of nurses employed in public hospitals (see Table B.4), our sample appears to be younger, less likely to have families, generally in better mental health, and work more hours, including night shifts. Nurses are compensated for the inconvenience of night shifts along three dimensions: wages, working hours, and off-duty time, that is, time between consecutive shifts. Given that nurses receive a 27%-50% wage compensation for working non-standard hours (refer to Table B.6 for compensation rates), it is reasonable that our younger cohort earns higher wages compared to more tenured nurses who typically work fewer hours and fewer night shifts. Nevertheless, the rates of sickness and pregnancy-related absences within our cohort are comparable to those of the broader nursing population.

## 4. Results and Discussion

In this section, we first assess violations of the overlap assumption and the ability of our matching procedures to generate a counterfactual group of non-night workers. Next, we present the results from our empirical analysis of the effects of night shift work, including their robustness. Our main results focus on the impact on mental health, and our additional results investigate responses along compensatory and social dimensions.

### 4.1 Assessing the Matching Procedures

The first step in our matching procedures is to estimate the propensity for being a night worker in a given year. Table 2 presents the results from a pooled logistic regression with an indicator for being a night worker in year $t$ as the outcome in panel A and an indicator for being censored in year $t+1$ in column B. The control variables are the characteristics we use to match night and non-night workers.

Sick days are the primary health-related predictor, which reduces the propensity for being a night worker, while increasing the propensity to be censored in the following year. A Wald test shows *Sick days* and *(Sick days)*$^2$ are jointly significant in predicting the propensity of nurses to be night workers ($p = 0.02$) and censored ($p < 0.001$). The estimates are also practically relevant; 10 sick days reduce the odds of being a night worker by 8% and increase the odds of being censored by 16% (see Figure A.1 and Figure A.2 for a more detailed presentation of the odds ratio related to sick days). Mental health-related variables such as medicine usage history, psychiatric hospitalization and visits to a psychiatrist or psychologist are imprecise and not jointly significant predictors. For instance, the indicators for medicine usage in the model for being a night worker are not jointly significant in a Wald test ($p = 0.63$). The same applies when we include any psychiatric hospitalization and visits to a psychiatrist or psychologist in the Wald test ($p = 0.44$). We get similar results in the censoring model when we test the joint significance for the medicine usage dummies (Wald test: $p = 0.17$) and if we further include any psychiatric hospitalization and visits to a psychiatrist or psychologist in the Wald test ($p = 0.25$). Although the variables directly related to mental health are noisy, the joint significance of the sick day variables suggests that deteriorating health influences nurses' propensity to become night workers and their likelihood of remaining nurses on a full-time basis. While sick days are not a direct indicator of mental health-related problems, it is likely correlated with subclinical symptoms because some nurses will have sick leave due to mental health problems even if they do not receive any treatment. This underscores the importance of accounting for the influence of health on exposure and censoring over time, supporting the use case for SWM, which addresses this dynamic.

Table 2: Estimated Propensity for Being a Night Worker and Being Censored

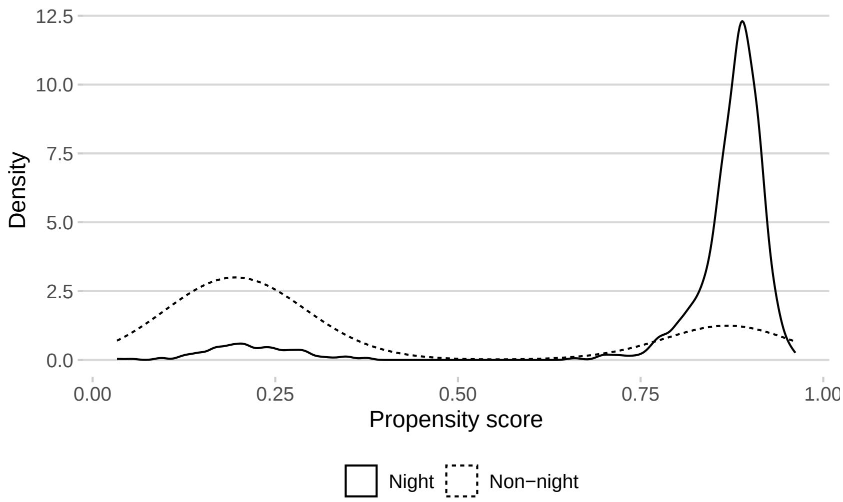
| Outcome | A. Night Worker in Year $t$ | | | B. Censored in Year $t+1$ | | |
|---|---|---|---|---|---|---|
| | | 95% CI | | | 95% CI | |
| Variable | $e^{\beta}$ | Lower | Upper | $e^{\beta}$ | Lower | Upper |
| Night worker* | 23.771 | 20.890 | 27.100 | 1.003 | 0.880 | 1.140 |
| log(Annual wage income)* | 7.460 | 4.450 | 12.560 | 0.780 | 0.540 | 1.100 |
| Any medicine (t) | 1.166 | 0.760 | 1.810 | 0.987 | 0.660 | 1.450 |
| Any medicine (t-1) | 0.766 | 0.490 | 1.220 | 1.543 | 1.020 | 2.300 |
| Any medicine (t-2) | 1.313 | 0.750 | 2.300 | 0.716 | 0.410 | 1.220 |
| Any medicine (t-3) | 0.720 | 0.380 | 1.400 | 1.405 | 0.750 | 2.600 |
| Age | 0.986 | 0.970 | 1.000 | 0.968 | 0.950 | 0.980 |
| Female | 0.772 | 0.590 | 1.000 | 4.082 | 3.000 | 5.620 |
| No children (t) | 1.195 | 0.990 | 1.440 | 0.050 | 0.040 | 0.060 |
| Youngest child aged: 3-6 (t) | 0.926 | 0.680 | 1.270 | 0.062 | 0.050 | 0.080 |
| Youngest child aged: 7-12 (t) | 0.923 | 0.700 | 1.220 | 0.033 | 0.020 | 0.040 |
| Youngest child aged: 13-18 (t) | 0.810 | 0.540 | 1.210 | 0.076 | 0.050 | 0.110 |
| Partner not employed in regions* | 0.925 | 0.800 | 1.070 | 1.309 | 1.140 | 1.510 |
| Partner employed in regions* | 0.756 | 0.450 | 1.290 | 0.203 | 0.100 | 0.380 |
| Non-Danish origin | 0.830 | 0.680 | 1.020 | 1.041 | 0.850 | 1.270 |
| log(Annual work hours)* | 0.462 | 0.260 | 0.820 | 0.023 | 0.010 | 0.040 |
| Psychiatric hospitalization (t) | 0.371 | 0.120 | 1.230 | 0.520 | 0.120 | 1.690 |
| Psychiatrist/psychologist visit (t) | 0.917 | 0.650 | 1.310 | 0.847 | 0.600 | 1.180 |
| Sick days* | 0.991 | 0.980 | 1.000 | 1.016 | 1.010 | 1.020 |
| (Sick days)$^2$ * | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| Person-years | | 7,985 | | | 7,985 | |
| Persons | | 2,657 | | | 2,657 | |
| Year fixed effects | | X | | | X | |
| Dummies for regional workplace | | X | | | X | |

*Note*: The table presents results from a pooled logistic regression with an indicator for being a night worker or censored as the outcome. The reference category for the age of youngest child is 0-2.
*The variable is measured in year $t-1$ when the outcome is an indicator for being a night worker in year $t$, and the variable is measured in year $t$ when the outcome is an indicator for being censored in year $t+1$. This follows Hernán et al. (2002). See note in Table 3 for further details.

### 4.1.1 Overlapping Propensity Scores

We assess the validity of the overlap assumption by plotting the distributions of propensity scores for night and non-night workers in Figure 5. The propensity score distributions are bimodal for both groups because last year's work arrangement is highly predictive of this year's. For nurses who were night or non-night workers last year, scores are distributed around the right and left peaks, respectively. Importantly, there is an overlap in propensity scores around each peak, which shows that we have individuals with comparable characteristics in each group. Although the distributions differ in density across

Figure 5: Distribution of Propensity Scores among Night and Non-Night Workers




*Note*: The figure shows the distribution of propensity scores among night and non-night workers based on the results reported in column A of Table 2.

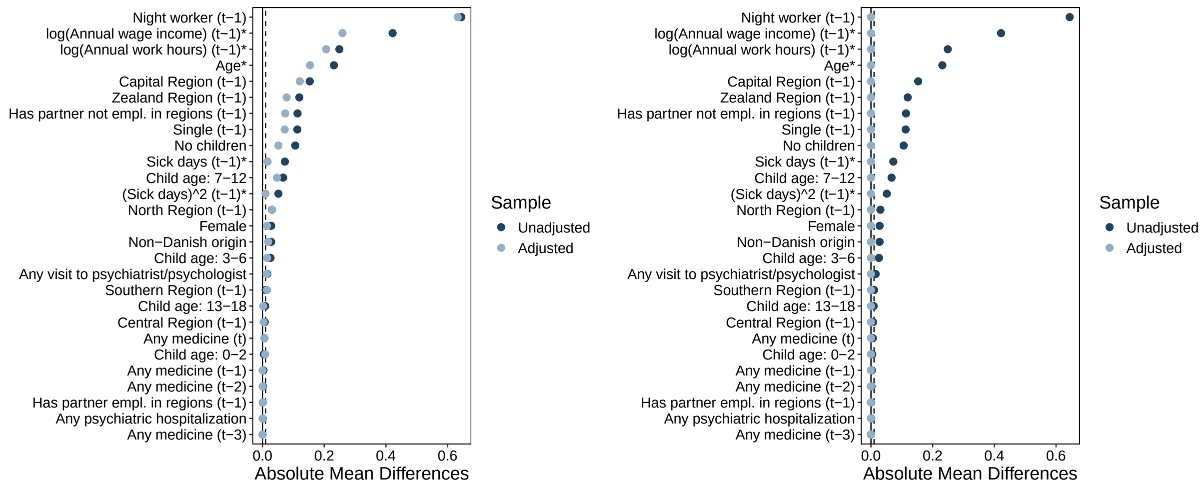
the propensity score, we exploit the overlap to improve the similarity of the two groups by scaling them with inverse probability weights.

### 4.1.2 Covariate Balance

Our empirical strategy aims to construct two groups of nurses who are identical in all aspects except that one group is exposed to an additional year of night shift work, while the other is not. To achieve this, we adjust for differences in observable characteristics by applying weights to both groups of exposed and unexposed nurses. Specifically, we weigh individuals according to their characteristics so that those who are underrepresented in the opposite group are given more weight. For example, unexposed nurses who are less similar to exposed nurses are given a higher weight. This weighting approach enables us to balance the characteristics of nurses within each group to the extent permitted by our data. We examine the balancing of each characteristic across the groups in Figure 6. Darker blue dots represent differences in average characteristics before weighting, and lighter blue dots show differences after weighting. Figure 6a shows that the two groups become more similar when we apply IPW weights. However, they are still significantly different on various dimensions, including their previous night work experience, wage income, and age. The larger the discrepancies in characteristics of the two groups, the more likely it is that our estimates will be biased due to endogeneity concerns raised in section

Figure 6: Differences in Covariate Averages across Night and Non-Night Workers

(a) Inverse Probability Weighting (b) Entropy Balancing




*Note:* The figures show the difference in average characteristics between the two groups of nurses, who are exposed or unexposed to night shift work, exemplified by follow-up year 3. The patterns and conclusions are similar for other follow-up years. Figure 6a (Figure 6b) shows the results of using the inverse probability weighting (entropy balancing) method to weight the sample. The dark blue dots reflect differences before weighting the sample, and the light blue dots illustrate differences after weighting the sample.
*Indicate continuous variables where we show the standardized mean difference.

2.1. Therefore, we turn to entropy balancing to improve the balancing of characteristics across the groups. Figure 6b shows that the two groups' average characteristics are identical when we apply entropy balancing weights. This is because the entropy balancing procedure mechanically ensures that the average of characteristics is exactly identical across the two groups. The high degree of similarity between the groups increases the validity of our identification strategy and thus minimizes bias in our estimation results. We therefore continue our analysis, using sequential weighted matching with entropy balancing as our preferred specification.

## 4.2 The Mental Health Effects of Night Shift Work

### 4.2.1 Main Results

The main outcome in our analysis is mental health measured as an indicator of whether a nurse redeems prescriptions for psychotropic medication. To investigate drivers of the change in medication use, we also split by its two subgroups, psycholeptics and psychoanaleptics. Psycholeptics have a calming effect and are prescribed for conditions such as anxiety and sleep disorders. In contrast, psychoanaleptics have a mood-enhancing

Table 3: Mental Health Effects of Cumulative Exposure to Night Shift Work

| Model | $e^{\beta}$ | t-statistic | 95% CI Lower | 95% CI Upper | Persons | Person-Years |
|---|---|---|---|---|---|---|
| A. Any Use of Psychotropic Medication (N05 & N06) | | | | | | |
| Conventional | 1.04 | 0.71 | 0.95 | 1.15 | 3,513 | 11,498 |
| SWM-IPW | 1.12 | 3.62 | 1.00 | 1.25 | 3,513 | 11,498 |
| SWM-Ebal | 1.24 | 4.38 | 1.01 | 1.52 | 3,513 | 11,498 |
| B. Any Use of Psycholeptic Medication (N05) | | | | | | |
| Conventional | 1.05 | 0.39 | 0.90 | 1.22 | 3,513 | 11,498 |
| MSM-IPW | 1.06 | 0.72 | 0.93 | 1.22 | 3,513 | 11,498 |
| MSM-Ebal | 1.10 | 0.57 | 0.85 | 1.43 | 3,513 | 11,498 |
| C. Any Use of Psychoanaleptic Medication (N06) | | | | | | |
| Conventional | 1.05 | 0.51 | 0.91 | 1.22 | 3,513 | 11,498 |
| MSM-IPW | 1.11 | 2.20 | 0.97 | 1.29 | 3,513 | 11,498 |
| MSM-Ebal | 1.26 | 3.36 | 0.98 | 1.61 | 3,513 | 11,498 |

*Note*: The table presents mental health effects of cumulative exposure to night shift work, estimated using the conventional and the SWM approaches. Conventional: Follows the conventional approach with outcome on the LHS and cumulative exposure and all covariates on the RHS as specified in equation (2). SWM-IPW: Sequential weighted matching using inverse probability weighting, where propensity scores are based on logistic regression. SWM-Ebal: Sequential weighted matching using balancing weights generated from entropy balancing. The SWM approach is specified in equation (3). Weights are winzorised at the 1st and 99th percentiles. Any use of medication: The outcome variable is an indicator for redeeming prescriptions for psychotropic (psycholeptic or psychoanaleptic) medication. The estimating equation is modeled using logistic regression, and the parameter estimates are measured as odds ratios, i.e., the relative risk for night workers compared to non-night workers, with $OR > 1$ indicating a higher risk for night compared to non-night workers. We control for mental health history, age, gender, age of youngest kids, origin, visits to psychologist or psychiatrist, mental-health related hospitalization, and lagged work characteristics (work arrangement, log(annual work hours), log(wage income), sick days, sick days$^2$, and region of employment). See Table 2 and Figure 6 for more details on control variables.

effect by stimulating brain activity and are used to treat conditions such as depression and ADHD (Christman et al., 2022). Table 3 shows the mental health effects of night shift work, estimated following the conventional or the SWM approach specified in equations (2) and (3), respectively. The results demonstrate the importance of accounting for the healthy worker effect, as estimates otherwise attenuate, indicating that night shift work has no or limited impact on mental health.

The results from the conventional model show little to no mental health effect of night shift work. The odds ratio of taking up psychotropic medication is 1.04, implying that an additional year of night shift work increases the odds of take-up by 4%. There is no difference in the odds ratio of taking up psycholeptics or psychoanaleptics when considered separately. None of the estimates are statistically significant, implying that there are no mental health effects of night work.

In contrast, the results from the SWM models show that the odds ratio of taking up psychotropic medication ranges from 1.12 to 1.24, which implies that night shift work increases the odds by 12-24% with each additional year of night shift work. Given a

Table 4: Mental Health Effects of Cumulative Exposure to Night Shift Work with Categorical Instead of Continuous Exposure Assessment

| | $e^{\beta}$ | t-statistic | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|
| A. Any Use of Psychotropic Medication (N05 & N06) | | | | |
| 1 Year | 0.84 | 0.56 | 0.53 | 1.33 |
| 2 Years | 1.55 | 1.65 | 0.79 | 3.03 |
| 3 Years | 1.04 | 0.01 | 0.45 | 2.43 |
| 4 Years | 2.46 | 3.00 | 0.89 | 6.81 |
| 5 Years | 2.57 | 3.28 | 0.92 | 7.16 |
| 6 Years | 1.04 | 0.00 | 0.31 | 3.44 |
| B. Any Use of Psycholeptic Medication (N05) | | | | |
| 1 Year | 0.93 | 0.06 | 0.53 | 1.64 |
| 2 Years | 1.06 | 0.01 | 0.41 | 2.71 |
| 3 Years | 0.65 | 1.27 | 0.31 | 1.38 |
| 4 Years | 1.16 | 0.06 | 0.35 | 3.82 |
| 5 Years | 3.23 | 2.48 | 0.75 | 13.85 |
| 6 Years | 1.16 | 0.04 | 0.27 | 5.01 |
| C. Any Use of Psychoanaleptic Medication (N06) | | | | |
| 1 Year | 0.72 | 1.47 | 0.42 | 1.23 |
| 2 Years | 1.28 | 0.32 | 0.55 | 2.99 |
| 3 Years | 1.08 | 0.02 | 0.40 | 2.89 |
| 4 Years | 2.65 | 2.77 | 0.84 | 8.35 |
| 5 Years | 1.29 | 0.24 | 0.47 | 3.58 |
| 6 Years | 0.87 | 0.06 | 0.28 | 2.75 |
| Person-years | 11,498 | | | |
| Persons | 3,513 | | | |

*Note*: The table presents results from sequential weighted matching employing balancing weights generated with entropy balancing, estimated with GEE and modeled using logistic regression. Rather than utilizing a continuous measure of cumulative exposure to night work as in Table 3, we modify equation (3) and use indicator variables for cumulative years of exposure ranging from 1 to 6 years. The parameter estimates are measured as odds ratios. See note in Table 3 for further details.

baseline take-up rate of around 30 per 1,000 nurses, this corresponds to an increase of approximately 4-7 nurses initiating medication. These results indicate that a nurse with 5 years of night shift work has $1.24^5 \approx 3$ times higher odds of taking up psychotropic medication compared to a nurse with 5 years of non-night shift work. Importantly, the effects are driven by psychoanaleptics rather than psycholeptics, suggesting that the worsening of mental health comes mainly from depressive conditions and not anxiety or sleep disorders.

A useful way of illustrating how we can interpret our results from Table 3 is to estimate the effects of cumulative exposure to night shift work with exposure modelled not continuously but as categorical variables. Table 4 shows the results from this estimation.

We note that the estimates are noisier than those from the parsimonious specification, because we lose power when we split exposure into seven categories. For the parameters with a stronger signal-to-noise ratio (larger t-statistic), e.g., 4 or 5 years of cumulative exposure, results suggest that an additional year of night shift work increases the odds of having any mental health issues by a factor of 1.21-1.25 ($2.57^{(1/5)} \approx 1.21$, $2.45^{(1/4)} \approx 1.25$), which is similar to the estimated odds ratio of 1.24 from the specification with cumulative exposure modeled linearly. Interestingly, the results in panels B and C point to differential time patterns in the take-up of psycholeptics and psychoanaleptics. Individuals who have been night workers for four years are more likely to take up psychoanaleptics, whereas those who have been night workers for five years are more likely to take up psycholeptics. However, as the results carry a degree of uncertainty illustrated by the wide confidence intervals, we are cautious about making strong inferences based on this pattern.

#### 4.2.2 Sequential Results

The underlying assumption in our main model specification is that the effect of an additional year of night shift work is the same; going from 0 to 1 year of night shift work and from 4 to 5 years of night shift work has the same effect on mental health. However, the estimated mental health effects gradually increase when we consecutively add more follow-up years to the estimation sample. This is the pattern we see in table Table 5. When evaluating effects after 5 compared to 4 years, the odds ratio of taking up psychotropic medication increases from 1.10 to 1.26.[10] The results therefore suggest that the cumulative effects of an additional year of night shift work also depend on how many years a person has previously been exposed to night or non-night shift work. Hence, our main results in Table 3 may overestimate the impact of going from 0 to 1 year of night shift work and underestimate the effect of going from 4 to 5 years. Moreover, by consecutively adding more follow-up years to the estimation sample, we also show that our results are sensitive to too short periods of follow-up.

Further, the results in panels B and C illustrate that the increase in take-up of psychotropic medication is attributable to psycholeptics when evaluating a shorter period of 1-5 years, whereas the increase is attributable to psychoanaleptics when evaluating a

[10] At follow-up year 1, the estimate is only based on 1 vs. 0 years of night shift work. At follow-up year 5, the estimate is based on several combinations of increases in night shift work (e.g., 2 to 3 years or 4 to 5 years).

Table 5: Mental Health Effects of Cumulative Exposure to Night Shift Work Evaluated at Varying Follow Up Years

| | $e^{\beta}$ | t-statistic | 95% CI Lower | 95% CI Upper | Persons | Person-Years |
|---|---|---|---|---|---|---|
| A. Any Use of Psychotropic Medication (N05 & N06) | | | | | | |
| Year 1 | 0.92 | 0.14 | 0.59 | 1.43 | 3,513 | 3,513 |
| Year 1-2 | 0.98 | 0.03 | 0.76 | 1.25 | 3,513 | 6,170 |
| Year 1-3 | 1.02 | 0.03 | 0.83 | 1.24 | 3,513 | 8,126 |
| Year 1-4 | 1.10 | 0.75 | 0.88 | 1.37 | 3,513 | 9,603 |
| Year 1-5 | 1.26 | 4.02 | 1.01 | 1.58 | 3,513 | 10,697 |
| Year 1-6 | 1.24 | 4.38 | 1.01 | 1.52 | 3,513 | 11,498 |
| B. Any Use of Psycholeptic Medication (N05) | | | | | | |
| Year 1 | 0.96 | 0.01 | 0.50 | 1.83 | 3,513 | 3,513 |
| Year 1-2 | 1.01 | 0.01 | 0.73 | 1.40 | 3,513 | 6,170 |
| Year 1-3 | 1.11 | 0.58 | 0.85 | 1.43 | 3,513 | 8,126 |
| Year 1-4 | 1.17 | 0.96 | 0.86 | 1.59 | 3,513 | 9,603 |
| Year 1-5 | 1.20 | 1.18 | 0.86 | 1.66 | 3,513 | 10,697 |
| Year 1-6 | 1.11 | 0.57 | 0.85 | 1.43 | 3,513 | 11,498 |
| C. Any Use of Psychoanaleptic Medication (N06) | | | | | | |
| Year 1 | 0.74 | 1.31 | 0.45 | 1.24 | 3,513 | 3,513 |
| Year 1-2 | 0.86 | 0.99 | 0.64 | 1.16 | 3,513 | 6,170 |
| Year 1-3 | 0.82 | 2.86 | 0.66 | 1.03 | 3,513 | 8,126 |
| Year 1-4 | 1.01 | 0.00 | 0.75 | 1.36 | 3,513 | 9,603 |
| Year 1-5 | 1.21 | 1.94 | 0.92 | 1.60 | 3,513 | 10,697 |
| Year 1-6 | 1.26 | 3.36 | 0.98 | 1.61 | 3,513 | 11,498 |

*Note*: The table presents results from SWM using balancing weights estimated with entropy balancing, estimated using GEE and modeled using logistic regression. Equation (3) is estimated with a gradually increasing sample of follow-up years. At follow-up year 1, the estimate is based on nurses observed in one year, and at follow-up year 1-6, the estimate is based on nurses observed over six years. See note in Table 3 for further details.

longer period of 5-6 years. This may seem contradictory to the pattern reported in Table 4. The divergence arises because the categorical results in Table 4 are estimated for individuals with a specific number of years of night work, whereas the dynamic results in Table 5 are estimated for individuals with the same duration in the sample but varying combinations of night and non-night work exposure.

### 4.3 Robustness Checks

We begin by testing the sensitivity of our results to the threshold for being a night worker. In the epidemiological literature on the health effects of various work arrangements, a standard threshold of 6.7% night shifts per year classifies a subject as a night worker (Garde et al., 2016). In contrast to classifying all workers with some night shifts as night shift workers, this threshold allows for flexibility since nurses with only a few night shifts a year do not necessarily consider themselves night workers. The results reported in Table 6 show that the odds ratio of having any mental health issue increases from 1.24 to 1.3 and remains significant when the threshold is lowered by a factor of 0.5. Increasing the threshold by a factor of 1.5 and 2 lowers the odds ratio to 1.18 and 1.17, respectively. These estimates are only significant at a 10% level. However, it is important to note that while increasing the threshold increases the average number of night shifts in the exposed group, it also increases the average number of night shifts in the control group. This adjustment can increase the risk of misclassifying night workers; specifically, an increased threshold may result in too many night shift workers being incorrectly categorized as non-night shift workers, and vice versa when the threshold is lowered. An alternative approach would be to fix the threshold at 6.7% for the control group and remove observations that fall between this and a new, higher threshold. We can then compare the original control group to night shift workers with a higher intensity of night shift work. Though feasible in a static framework where exposures are measured once, the approach results in too many observations dropping out of the sample in the dynamic setup. Another approach is to model night work continuously using the share of night shifts as our measure of exposure. This can be implemented in the conventional approach, but we must employ a threshold to divide nurses into two groups in the SWM approach to balance weights.

Our main sample excludes individuals with prior mental health issues, and we proceed by examining how our results change when we include these individuals. As shown in Panel B of Table 6, the odds ratio drops from 1.24 in our main specification to 1.10 when individuals with prior mental health issues are included.[11] This substantial reduction suggests that their inclusion introduces a downward bias in the estimated mental health effects of night shift work. Nurses with a history of mental health issues are more likely to work non-night shifts, which may lead to the mistaken impression that non-night work is associated with worse mental health. Since their mental health issues predate their hospital hire and are thus unrelated to night work, their inclusion distorts the estimated relationship.

Compensating wage differentials theory predicts that jobs with worse working conditions are compensated with higher wages. But if working conditions are a normal good, the demand for better conditions should rise with income, which can explain why better

[11]See Table B.9 for results on the extended sample in the dynamic and categorical versions of our model.

Table 6: Mental Health Effects of Cumulative Exposure to Night Shift Work, with Varying Night Worker Thresholds and Weight Adjustments

| Any Use of Psychotropic Medication (N05 & N06) | | | 95% CI | | | |
|---|---|---|---|---|---|---|
| Model | $e^{\beta}$ | t-statistic | Lower | Upper | Persons | Person-Yearrs |
| A. Night worker threshold | | | | | | |
| 6.7 pct. $\times$ 0.5 | 1.30 | 7.30 | 1.07 | 1.57 | 3,513 | 11,498 |
| 6.7 pct. | 1.24 | 4.38 | 1.01 | 1.52 | 3,513 | 11,498 |
| 6.7 pct. $\times$ 1.5 | 1.18 | 3.56 | 0.99 | 1.40 | 3,513 | 11,498 |
| 6.7 pct. $\times$ 2 | 1.17 | 1.77 | 0.93 | 1.48 | 3,513 | 11,498 |
| B. Sample including individuals | | | | | | |
| With prior mental health issues | 1.10 | 2.06 | 0.96 | 1.26 | 4,106 | 13,340 |
| C. Weights adjusted for | | | | | | |
| Equivalized disposable income† | 1.28 | 5.78 | 1.05 | 1.56 | 3,513 | 11,498 |
| D. Weights not adjusted for | | | | | | |
| Lagged night worker status | 1.21 | 6.27 | 1.04 | 1.41 | 3,513 | 11,498 |
| Working hours and wage income | 1.22 | 3.89 | 1.00 | 1.48 | 3,513 | 11,498 |
| Current mental health | 1.27 | 5.09 | 1.03 | 1.56 | 3,513 | 11,498 |
| E. Excluding the Year 2020 | | | | | | |
| MSM-Ebal | 1.19 | 4.14 | 1.01 | 1.41 | 3,513 | 11,149 |

*Note*: The table presents results from sequential weighted matching using balancing weights estimated with entropy balancing, estimated using GEE and modeled using logistic regression.
†Equivalized disposable income (actual) replaces log(annual income). See note in Table 3 for further details.

working conditions and better wages can bundle together (Lavetti, 2023). Because wage income mechanically increases when nurses work more night shifts, it fails to capture the nuanced effects of income. Equivalized disposable income provides a more accurate measure by accounting for economies of scale within households; two adults living together require less than double the resources of a single adult. Two nurses earning similar salaries have different economic incentives, because one is single and the other is in a couple. From a theoretical perspective, the single nurse is more inclined to work night shifts because the financial gains outweigh the costs. The nurse in a couple is less inclined to work night shifts because the added income provides less marginal utility, so it does not outweigh the benefits of avoiding those hours. Yet, when we adjust the weights based on equivalized disposable income rather than wage income, the odds ratio rises only slightly to 1.28, indicating that income effects have a limited influence on the decision to work night shifts.

A concern in the conventional approach is whether to include working hours and wage income as time-varying covariates, as they can act as mediators. This is not a concern in the SWM approach when we include variables in the sequential balancing. Excluding these variables can, on the contrary, bias results if they jointly serve to predict mental health outcomes and night worker status. Yet, the results in Table 6 show that excluding these variables only results in a slightly lower odds ratio of 1.22.

It might initially seem counterintuitive to incorporate the history of night work (modeled as a single lag representing prior exposure) in our calculation of balancing weights, especially since our primary interest is to estimate the effect of night work on mental health. However, by conditioning on $Night\ work_{t-1}$ in generating these weights, we ensure that the future mental health outcome, $Mental\ health_{t+1}$, is statistically independent of $Night\ work_t$, conditional on prior exposure. This helps mitigate confounding and improves the comparability between current night and non-night workers by balancing their prior experiences with night shift work before period $t$. Nonetheless, Table 6 shows that not adjusting for $Night\ work_t$ produces a modestly lower odds ratio of 1.21.

Finally, we analyze the impact of our choice to account for current mental health when evaluating the propensity to be a night worker. The findings presented in Table 6 indicate that excluding current mental health and only considering lags (as in the main specification) yields an odds ratio of 1.27 for the use of psychotropic medication, closely resembling our primary result of 1.24 found in Table 3. Furthermore, as demonstrated in Table B.7, not adjusting for current mental health also leads to similar results in both the dynamic and categorical versions of our model.

### 4.4 Mechanisms

The proposed mechanisms behind the mental health effects of night shift work can be categorized into two primary strands: a biological and a social perspective. The biological perspective emphasizes the critical role of sleep in cognitive functioning (Walker and van der Helm, 2009) and the disruption of circadian rhythms (Kecklund and Axelsson, 2016, James et al., 2017, Boivin et al., 2022). The social perspective highlights how atypical work hours often lead to irregular leisure times, complicating the maintenance of social relationships and family engagements, including child care (Akerstedt and Torsvall, 1978, Bambra et al., 2008, Vitale et al., 2015, Jensen et al., 2017, Begum et al., 2024). On the other hand, night workers are compensated with more off-duty hours, which frees up time for social relations and improves work-life balance. Although we lack direct data on sleep patterns, we examine outcomes that may indicate whether the effects of night shift work are operating through the social channel. Specifically, we consider how night shift work influences nurses' partnership status and fertility. If night shift work impairs fertility

Table 7: Compensatory and Social Effects of Cumulative Exposure to Night Shift Work

| Model | Intercept | Estimate | t-statistic ($\beta$) | 95% CI ($\beta$) Lower | Upper |
|---|---|---|---|---|---|
| Social Outcomes | | | | | |
| Gets child(ren) | 0.16 | 0.80 | 4.61 | 0.65 | 0.98 |
| Has partner | 2.35 | 1.05 | 1.20 | 0.97 | 1.13 |
| Compensatory Outcomes | | | | | |
| Working hours | 1470.22 | -23.42 | 46.02 | -30.19 | -16.66 |
| Off-duty hours | 16.48 | 0.10 | 9.89 | 0.04 | 0.17 |
| Quick returns | 9.04 | -0.23 | 2.44 | -0.51 | 0.06 |
| Returns within 24h | 115.34 | -2.67 | 34.16 | -3.57 | -1.78 |
| Returns within 48h | 118.56 | -2.36 | 25.79 | -3.27 | -1.45 |
| Shifts | 185.06 | -3.74 | 69.41 | -4.62 | -2.86 |
| Annual wage income (DKK) | 304,890.1 | 18,326.5 | 226.1 | 15,937.6 | 20,715.3 |
| log(annual wage income) | 12.62 | 0.05 | 189.88 | 0.04 | 0.06 |
| Works part-time | 0.06 | 1.05 | 0.45 | 0.90 | 1.23 |
| Leaves region | 0.00 | 0.90 | 1.12 | 0.74 | 1.10 |
| Persons | | | 3,513 | | |
| Person-years | | | 11,498 | | |

*Note*: The table presents results from sequential weighted matching using balancing weights estimated with entropy balancing, estimated using GEE. Social outcomes are evaluated at $t+1$, while compensatory outcomes are evaluated at $t$. Social outcomes are modeled using logistic regression, and the parameter estimates are measured as odds ratios. Compensatory outcomes are modeled using linear regression, and the parameter estimates are measured as absolute changes in outcomes (e.g., *working hours per year*, *number of returns within 24 hours per year*) or percentage changes for outcomes in logarithms. Additionally, the variables *Works part-time* and *Leave region* are presented as odds ratios. See note in Table 3 for further details.

and the ability to find a partner, it may worsen mental health. Results in Table 7 show that an additional year of night shift work does not change the probability of having a partner in the next year. In spite of that, it significantly reduces the odds of having a child in the following year by 20%. This result may indicate a negative impact of night shift work that could extend to mental health, but we urge caution in our interpretation, as our control variables may not fully account for individual preferences regarding parenthood. Based on this analysis, it is challenging to draw strong conclusions about the primary channel through which night shift work impacts mental health.

### 4.5 The Compensatory Effects of Night Shift Work

Wage compensations can be necessary for workers to accept jobs with undesirable characteristics (Lavetti, 2023). Here, we explore how nurses are compensated for night shift work with respect to wage income, working hours, and off-duty time. The results reported in table Table 7 show that nurses are compensated for working night shifts along the expected dimensions: wage income, working hours, and off-duty time. An additional year of night shift work reduces annual working hours by around 23, corresponding to a yearly reduction of about 2%, which is also reflected in approximately 4 fewer shifts per year. Also, night workers have around 3 fewer returns to work within 24 hours of their prior shift and around 2 fewer returns within 48 hours, reflecting longer rest periods. We find no evidence to suggest that night workers have fewer quick returns (within 11 hours of the prior shift), which is also considered to have adverse health effects because of the shorter rest period (Härmä et al., 2015). Finally, an additional year of night shift work increases nurses' wage income by around DKK 18,326 (EUR 2,457), corresponding to a 5% wage premium relative to nurses with an additional year of regular (non-night) shift work.[12] We can compare this income benefit of night work to the estimated mental health costs. Based on the results in Table 3, we compute the average partial effect of night work on mental health (see Appendix A for details). This tells us that the probability of taking up psychotropic medication increases by 0.85 percentage points when nurses switch from being non-night workers to night workers, holding all other covariates constant. We calculate an implied semi-elasticity of income with respect to mental health of 5.9 ($0.05/0.0085 = 0.59$). This suggests that a 1 percentage point increase in the risk of experiencing poor mental health is associated with a 5.9% increase in income. Of course, if night workers are more likely to work part-time or leave the regions, it could reflect a sense of under-compensation among night workers. However, our analysis does not reveal significant evidence that night shift work drives individuals to transition to part-time roles or to leave public hospital employment. Prior research shows that mental illness leads to long-lasting earnings reductions of 10-20% (Benham and Benham, 1982, Bartel and Taubman, 1986, Ettner et al., 1997), and that adverse physical health shocks result in a long-term decline in income of about 5-20% (García-Gómez et al., 2013, Dobkin et al., 2018, Meyer and Mok, 2019, Fadlon and Nielsen, 2021). Based on this literature, a conservative estimate of the expected income gain from night work is 5.6% ($-0.2 \times 0.01 + 0.059 \times 0.99 = 0.056$). In this context, foregoing 5% of earnings to avoid a certain severe mental health shock with certainty would appear too costly to rationalize for nurses in our sample. Albeit the implied semi-elasticity and expected income gain may seem high, it is important to note that the wage premium compensates for all costs associated with night shift work, including physical health and the general inconvenience

[12] Table B.8 shows that the effect on absolute income is increasing in the threshold value for being a night worker, but the effect on the percentage change in income is relatively stable across thresholds.

of night work.

## 4.6 Discussion

Our analysis assumes that workers with greater health capital are more likely to remain in jobs with higher exposure to night work. Nevertheless, it is possible that healthier workers prefer less health-demanding, non-night work schedules. For instance, some nurses may be healthier because they generally engage in beneficial health behaviors, such as exercising regularly, maintaining a balanced diet, and practicing good sleep hygiene. These workers may also tend to sort themselves more strongly into non-night work in an effort to safeguard their health. Despite this possibility, we believe that such selection does not substantially bias our results, for several reasons. First, one motivation for engaging in healthier behaviors may be a lower discount rate, that is, a stronger preference for future benefits over short-term outcomes. However, since all nurses complete the same length of education, which can serve as a proxy for time preferences, variation in discount rates within our sample is likely minimal. Second, our weighting procedure accounts for selection into night work based on observable health characteristics. Although this adjustment cannot account for unobserved traits, our results reveal that healthier workers are, in fact, more likely to remain in night shift work. This is evident from the relatively large change in magnitude and significance of our main estimates in Table 3 after adjusting for endogenous selection. Finally, though we cannot observe all aspects of health capital, it is unlikely that unobserved health conditions systematically drive sorting into non-night work arrangements. These characteristics would also be unobservable to employers and are therefore unlikely to influence job assignment. In summary, it seems unreasonable that our findings are significantly biased by healthier nurses leveraging their health capital to avoid night shift work.

The legitimacy of our SWM approach relies on the notion that matches on observable characteristics also achieve balance on unobserved factors that correlate with those observables. This assumption may not hold if some unobserved variables are correlated with both the treatment and the outcome but not with other observables (Stuart, 2010). In particular, if we fail to observe health conditions that are crucial to the joint determination of night work and future mental health, we cannot fully account for endogenous selection driven by the healthy worker effect. For instance, while sick days may correlate with mild symptoms of anxiety or depression, they do not encompass all situations in which nurses experience these symptoms and switch to non-night work as a coping strategy instead of pursuing psychotropic treatment. While this limitation implies that our results may represent a lower bound of the true effect, the extensive set of control variables included in our analysis likely mitigates this bias (Lechner and Wunsch, 2013).

Our research design also rests on the stable unit treatment value assumption (SUTVA), which states that one individual's treatment status should not affect another individual's outcome. In our framework, assigning night shifts to one nurse could, in principle, affect the mental health of other nurses. For instance, if night workers are more likely to call in sick, their absence could increase the workload and stress levels of colleagues in the same department. Moreover, untreated mental health issues may indirectly affect coworkers. But such spill-overs would require that the nurses in our sample work closely together, in the same, relatively small department, so that any absence must be covered by a limited number of staff. Although we find that night work increases the risk of mental health issues, the proportion of nurses with mental health issues in our sample remains relatively small. If properly treated, the likelihood that these mental health issues spill over to other nurses in our sample is low. As a result, any potential violation of the SUTVA is unlikely to meaningfully bias our estimates.

Focusing on graduate nurses as a sample offers both strengths and limitations. Their relatively homogeneous demographic characteristics, institutional settings, and education reduce variability stemming from differences in work arrangements and stressors across occupations. Also, they have not been exposed to night shift work before, so our estimates are more likely to capture the effect of the exposure we can measure rather than the influence of past exposure. However, they may differ systematically from the general population in ways that affect the external validity of our findings. Firstly, their lack of night work experience means they are relatively young, and night shift work may impact nurses differently across the age distribution. Secondly, nurses' health education likely enhances their awareness of the potential well-being effects of night shift work, making them more proactive in addressing early symptoms before they develop into more serious conditions. In that case, our results reflect a lower bound on the mental health effects. Thirdly, nursing may disproportionately attract individuals with evening-oriented preferences, while those with morning-oriented preferences may be deterred by the profession's irregular hours. If this is the case, night shift work might have a less pronounced impact on nurses compared to other groups. Nevertheless, similar patterns in diurnal preferences might exist in other night shift-intensive occupations, such as those in the industrial, transportation, or hospitality sectors, suggesting that our findings are informative beyond the nursing context. Moreover, if sleep deprivation is the primary mechanism underlying the observed mental health effects, our results are more likely to generalize across occupations. Sleep disruption is a potential consequence of night shift work, regardless of the specific job or sector.

While our analysis focuses on the effects of night shift work, another relevant perspective is to examine the impact of evening shifts. We argue that working night shifts may disrupt nurses' family life due to misaligned leisure hours, which can make it difficult for them to maintain social relationships and participate in family activities, such as childcare. Yet, one could argue that evening shifts are even more detrimental to social life. Working in the evening often means missing out on social events and activities that typically occur during that time. In contrast, individuals with standard daytime schedules are usually asleep at night, so night workers are less likely to miss social interactions. This implies that evening shifts may inflict greater social costs than night shifts. Hence, it would be relevant to examine the effects of evening shifts, particularly on social outcomes. However, as discussed in section 3.1 and illustrated in Figure 3, relatively few nurses work evening shifts. Therefore, we have not been able to conduct a proper analysis of the effects of evening work. This may be feasible in a different setting with a larger study population.

## 5. Summary and Concluding Remarks

This paper explores the mental health impacts of night shift work. Estimating these effects is especially challenging due to the healthy worker effect; healthier workers are better equipped to handle physically and mentally demanding jobs. We address this endogenous selection issue by applying sequential weighted matching with inverse probability weights and entropy balancing to timestamped data from approximately 3,500 graduate nurses' shifts over seven years, combined with administrative data on prescriptions for psychotropic medication in Denmark.

We find that night shift work has sizable adverse mental health effects. Specifically, nurses' risk of redeeming prescriptions for psychotropic medication increases by 12-24% with each additional year of night work. This response seems to be primarily driven by an increased uptake of psychoanaleptics, rather than psycholeptics, although the timing of uptake may differ between these two types of medication. Although we cannot pinpoint the underlying mechanisms, we explore the potential role of social factors. Night shift work does not significantly change the probability that nurses have a partner, but reduces the odds of having a child by 20%. Hence, we cannot rule out that the adverse mental health effects of night work (partly) runs through disruptions to nurses' social life. At the same time, this leaves open a potentially important role for biological factors in driving the mental health effects of night shift work.

Given the documented costs of night work, it is important to consider the extent to which night workers are compensated. Nurses receive various forms of compensation for the disadvantages associated with night shifts, including the inconvenience of working irregular hours, disruptions to sleep and circadian rhythms, as well as adverse health effects. We document nurses' compensation along several dimensions: increased earnings and off-duty time between shifts, as well as reduced working hours, shifts, and returns within 24 or 48 hours. In sum, while night work imposes substantial mental health costs, it also offers compensatory benefits in terms of earnings and work intensity. Whether these benefits outweigh the cost is an important question, but one that is beyond the scope of our paper.

We show that the conventional approach to estimating health impacts of working conditions is susceptible to bias from the healthy worker effect. Simply controlling for past health and exposure in a regression model produces estimates suggesting that night shift work does not affect mental health. Hence, using the conventional and the SWM approach generates diverging results. This demonstrates the importance of accounting for the healthy worker effect when considering policy implications and that SWM can more effectively address this bias.

Our study makes three contributions to the literature on shift work and mental health. First, we use objective measures of exposure and outcomes to minimize measurement and self-reporting bias. Second, we follow nurses for several years, allowing us to evaluate the effects of cumulative exposure, which can lead to more serious health conditions. Finally, we employ methods that adjust for the healthy worker effect, which we show is important because it alters the policy implications of our analysis.

Despite its contributions, our study has some noteworthy limitations. First of all, night workers with mild symptoms of mental illness who switch to non-night work are not captured as ill in our analysis. Although we partly capture this by controlling for sick days, our results represent a lower bound of the true mental health effect of night shift work. Second, our sample of graduate nurses may reduce the external validity of our results because nurses differ in their characteristics from other populations of shift workers, e.g., those employed in construction or manufacturing. However, if sleep deprivation is the primary mechanism underlying the mental health effects, we consider the external validity of our study to be significant.

With its limitations in mind, our analysis provides evidence that underscores the significance of considering the mental health impact of night shift work when organizing shift work. There are several ways of doing so. One is to increase compensation for night shift work. Higher earnings combined with fewer working hours gives night workers more time to rest, thereby reducing sleep deprivation and its associated mental health risks. Another approach is to include explicit recommendations regarding shift schedule compositions in nurses' collective agreements that recognize the mental health risks of night shift. Finally, more systematic monitoring of night workers' mental health can help identify early signs of adverse mental health and ensure that nurses who are unfit for night work are not assigned to it. Nonetheless, it is important to keep in mind that our findings and evidence for effects for such interventions should substantiated by further studies before they are implemented on a broad scale.

We recognize several directions for future research. First, even though our approach adjusts for the healthy worker effect more effectively than in previous studies, future research should improve the causal identification using better econometric methods or exogenous variation in long-term exposure to night shift work. Second, our analysis examines the impact of being exposed to night work versus not being exposed, and future research should investigate how the intensity of exposure affects mental health. Third, we analyze the effects of night shift work, but another relevant perspective is the effects of evening shift work, especially in relation to social outcomes. Finally, the mental health effects of night shift work among other shift workers should be investigated to establish better external validity of the findings.

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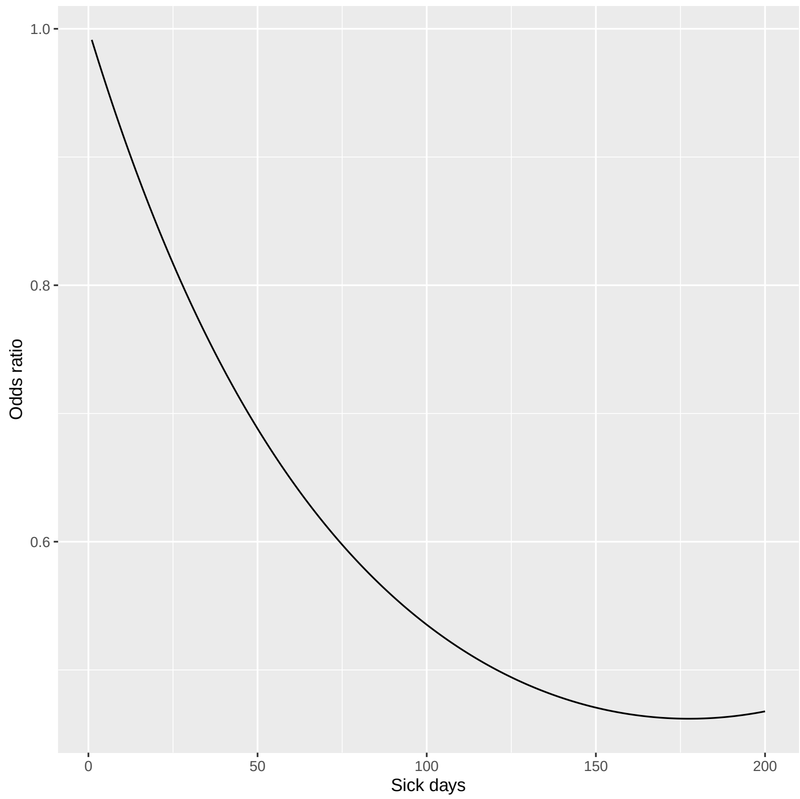
# A. Average partial effects

Based on estimates from equation (3), we estimate the average partial effect (APE) of an additional year of night work as:

$$APE = \frac{1}{N}\sum_{i=1}^{N}(G(\hat{\alpha} + \hat{\beta}(E_i + 1) - G(\hat{\alpha} + \hat{\beta}E_i)),$$

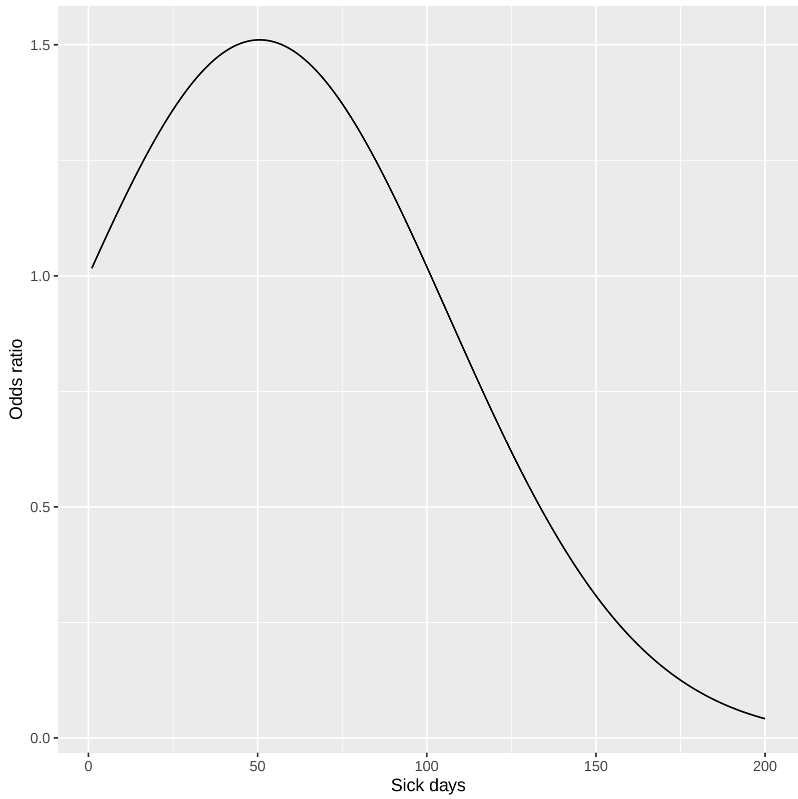
where $E_i$ denotes cumulative exposure to night work; $G(E) = \frac{e^{\alpha+\beta E}}{1+e^{\alpha+\beta E}}$; and $\hat{\alpha}$ and $\hat{\beta}$ are estimates from equation (3). See, for example, Wooldridge (2010) for more details on estimating average partial effects.

Figure A.1: Odds Ratio for Being a Night Worker as a Function of Number of Sick Days




*Note*: The figure shows the estimated odds ratio of being a night worker in year $t$ as a function of the squared number of sick days in year $t-1$. Odds ratio $= e^{-0.00871 \times \text{Sick days}_{t-1} + 0.0000254 \times \text{Sick days}^2_{t-1}}$. 99% of the sample has less than 86 sick days. The maximum must be censored, but all observations have fewer than 200 sick days.

Figure A.2: Odds Ratio for Being Censored $(t+1)$ as a Function of Number of Sick Days




*Note*: The figure shows the estimated odds ratio of being censored in year $t+1$ as a function of the squared number of sick days in year $t$. Odds ratio $= e^{0.016298 \times \text{Sick days}_t - 0.000161 \times \text{Sick days}_t^2}$. 99% of the sample has less than 86 sick days. The maximum must be censored, but all observations have fewer than 200 sick days.

# B. Figures and Tables

Table B.1: Data Description for Selected Variables

| **Variable** | **Description** |
|---|---|
| Age | Age in years |
| Female | Indicator for being female (based on social security number) |
| Single | Indicator for being single (i.e., not cohabiting or married) |
| Has partner (not empl. in regions) | Indicator for having a partner (i.e., cohabiting or married) employed not in the regions |
| Has partner (empl. in regions) | Indicator for having a partner (i.e., cohabiting or married) employed in the regions |
| Non-Danish origin | Indicator for being of non-Danish origin (i.e., immigrant or descendant) |
| No children | Has no children |
| Number of children | Number of children, conditional on having any children |
| Child age 0-2 | Indicator for youngest child being 0-2 years old |
| Child age 3-6 | Indicator for youngest child being 3-6 years old |
| Child age 7-12 | Indicator for youngest child being 7-12 years old |
| Child age 13-18 | Indicator for youngest child being 13-18 years old |
| Capital Region | Indicator for living in the Capital Region |
| Zealand Region | Indicator for living in the Zealand Region |
| Northern Region | Indicator for living in the Northern Region |
| Central Region | Indicator for living in the Central Region |
| Southern Region | Indicator for living in the Southern Region |
| Annual wage income | Taxable income including fringe benefits, tax-exempted income, anniversary and severance payments, share options, and fees for board member work. Includes income received during sickness absence and parental leave. Adjusted to 2015-prices. |
| log(Annual wage income) | Logarithm of annual wage income |
| Annual working hours | Annual working hours at the public hospital |
| log(Annual working hours) | Logarithm of annual working hours |
| Night worker | Indicator for being a night worker |
| Sick days | Number of sick days |
| (Sick days)$^2$ | Number of sick days, squared |
| Any medicine | Indicator for redeeming a prescription for psychotropic medication: psycholeptics (ATC N05) or psychoanaleptics (ATC N06) in t |
| Any medicine | Indicator for redeeming a prescription for psychotropic medication: psycholeptics (ATC N05) or psychoanaleptics (ATC N06) in t-1 |
| Any medicine | Indicator for redeeming a prescription for psychotropic medication: psycholeptics (ATC N05) or psychoanaleptics (ATC N06) in t-2 |
| Any medicine | Indicator for redeeming a prescription for psychotropic medication: psycholeptics (ATC N05) or psychoanaleptics (ATC N06) in t-3 |
| Any visit to psychiatrist / psychologist | Indicator for visiting a psychiatrist or psychologist |
| Any mental health related hospital visit | Indicator for having a mental health related hospital visit |

*Note*: The table describes covariates used for estimating weights employing the inverse probability weighting and entropy balancing methods. For the inverse probability weighting method, the covariates enter the estimating equation determining the propensity to be a night worker in period $t$. For the entropy balancing method, the covariates enter as the list of mean characteristics that should be equalized.

Table B.2: Description of Variables Used in Analysis

| Variable | Description |
|---|---|
| | *From the Population Registry* |
| Age | Age in years |
| Female | Indicator for being a female (based on social security number) |
| Age of youngest child | Categorical: 0-2, 3-6, 7-12, 13-18 years |
| Civil Status | Categorical: Unmarried, married, divorced, widow/widower |
| Region of Residence | Categorical: Capital, Zealand, Southern, Central, or Northern Region |
| Origin | Danish, Non-Danish |
| | *From the Education Registry* |
| Degree | Highest obtained degree of education |
| Starting date | Date starting highest level of education |
| Ending date | Date reaching highest level of education |
| | *From the Registry of Historical Migration* |
| Date | Date of migration or emigration |
| Code | Migration or emigration code |
| Country | Country migrated from or emigrated to |
| | *From the Registry of Death Causes* |
| Death date | Date of death (registered at the hospital) |
| | *From the Pharmaceutical Database* |
| Date | Date redeeming prescription medicine |
| ATC | The Anatomical Therapeutic Chemical code, N06 and N05 |
| | *From the Danish Work Hour Database* |
| Start date | Date person starts working in department |
| Activity code | Categorical: Shift, vacation, occupational injury, maternity/paternity leave, Sick, Pregnant, Sick child, (Very) sick child, Child hospitalized, Take care of next of kin, On-call shift, Non-work, No registration |
| DICSO code | DISCO code for present job at public hospital |
| Start date-time | Starting date and time (hours and minutes) for activity |
| End date-time | Ending date and time (hours and minutes) for activity |
| | *From the Health Insurance Registry* |
| Fee period | Week receiving fee for service, used to identify date of contact |
| Specialty | Specialty of physician visited with first two digits identifying overall category (24, 26, 35, 63) |
| Service type | Type of service provided by the physician (24, 25, 30, 35, 92, 93) |
| | *From the National Patient Registry* |
| Admission date | Date of admission to the hospital |
| Diagnosis | Diagnosis related to hospital visit (coded following ICD-10) |
| | *From the Income Registry* |
| Annual wage income | Taxable income including fringe benefits, tax-exempted income, anniversary and severance payments, share options, and fees for board member work. Includes income received during sickness absence and parental leave. All amounts are adjusted to 2015 prices and expressed in DKK. |
| Equivalized disposable income | Total income of all household members divided by a weighted average of the number of individuals in the household. All amounts are adjusted to 2015 prices and expressed in DKK. |

*Note*: The table presents the variables used in our analysis, including the registries from which they are obtained.
*Sources*: Statistics Denmark (2024a), Statistics Denmark (2024d), Statistics Denmark (2024c), Statistics Denmark (2024b), Statistics Denmark (2024h), DAD Steering Committee (2024), Statistics Denmark (2024i), Statistics Denmark (2024f), Statistics Denmark (2024g), Statistics Denmark (2024e).

Table B.3: Summary Statistics on Variations of Estimation Samples

| Variable | A. Censored Mean | A. Censored SD | B. Medication Mean | B. Medication SD |
|---|---|---|---|---|
| *Demographic characteristics* | | | | |
| Age | 27.7 | 5.5 | 28.0 | 5.8 |
| Female | 0.951 | 0.217 | 0.953 | 0.211 |
| Is Danish | 0.889 | 0.314 | 0.893 | 0.309 |
| Single | 0.335 | 0.472 | 0.336 | 0.472 |
| Has partner (not empl. in regions) | 0.656 | 0.475 | 0.656 | 0.475 |
| Has partner (empl. in regions) | 0.008 | 0.090 | 0.009 | 0.093 |
| Has children | 0.308 | 0.462 | 0.312 | 0.464 |
| No children | 0.516 | 0.867 | 0.521 | 0.865 |
| Youngest child aged 0-2 | 0.155 | 0.362 | 0.143 | 0.351 |
| Youngest child aged 3-6 | 0.083 | 0.277 | 0.089 | 0.285 |
| Youngest child aged 7-12 | 0.051 | 0.220 | 0.058 | 0.233 |
| Youngest child aged 13-18 | 0.019 | 0.137 | 0.022 | 0.146 |
| Lives in the Northern region | 0.076 | 0.264 | 0.072 | 0.258 |
| Lives in the Central region | 0.252 | 0.434 | 0.251 | 0.434 |
| Lives in the Southern region | 0.179 | 0.384 | 0.18 | 0.384 |
| Lives in the Capital region | 0.370 | 0.483 | 0.369 | 0.483 |
| Lives in the Zealand region | 0.124 | 0.329 | 0.128 | 0.335 |
| *Health characteristics* | | | | |
| Any use of mental health medication | 0.026 | 0.159 | 0.073 | 0.261 |
| Any use of psycholeptic medication | 0.012 | 0.107 | 0.023 | 0.15 |
| Any use of psychoanaleptic medication | 0.016 | 0.124 | 0.059 | 0.235 |
| Any hospital visit for mood, anxiety, or stress-disorder | 0.002 | 0.050 | 0.006 | 0.078 |
| Any mental health related visit to hospital | 0.005 | 0.074 | 0.009 | 0.095 |
| Any psychiatrist or psychologist visit | 0.030 | 0.171 | 0.048 | 0.213 |
| *Socioeconomic characteristics* | | | | |
| Wage income (in 2015 prices, in DKK) | 314,358 | 55,013 | 316,794 | 51,653 |
| Night worker | 0.612 | 0.487 | 0.629 | 0.483 |
| Working hours | 1466.1 | 271.7 | 1493.0 | 202.4 |
| Working hours, night shifts | 193.7 | 177.6 | 198.4 | 180.9 |
| No. shifts | 183.6 | 33.5 | 186.8 | 24.6 |
| No. night shifts | 22.9 | 20.9 | 23.4 | 21.3 |
| Share of night shifts | 0.124 | 0.114 | 0.126 | 0.117 |
| No. quick returns | 9.31 | 7.86 | 9.40 | 7.82 |
| No. early starts | 0.11 | 0.95 | 0.11 | 0.93 |
| Sick | 0.906 | 0.292 | 0.923 | 0.267 |
| Sick days | 12.1 | 17.1 | 13.0 | 17.2 |
| Sick periods | 1.46 | 1.26 | 1.53 | 1.32 |
| On maternity leave or pregnant | 0.088 | 0.283 | 0.08 | 0.272 |
| Individuals | 3641 | | 4106 | |

*Note*: The table shows summary statistics on a sample of nurses graduating in 2009-2015, who are hired at a public hospital within a year of graduation, and work full time during their first year of employment. In the estimation sample, we exclude individuals who have redeemed prescriptions for mental health medication during the five years before employment. Moreover, individuals are censored if they die, emigrate, or work part time or outside the region. The table shows statistics for the estimation sample, including censored in panel A and individuals with prior mental health medication use in panel B. Follow-up year refers to years since hire at the public hospital. Variables are measured in follow-up year 1 (nurses' first full year of employment) and reflect yearly averages. A night shift is defined as $\geq 3$ hours of work between 23:00 and 06:00. A quick return is defined as a shift starting less than 11 hours after the end of the prior shift. An early start is defined as a shift starting between 3:00 and 6:00.

Table B.4: Summary Statistics on Nurses Hired at a Public Hospital, 2008-2018

| Variable | 2008 | 2013 | 2018 |
|---|---|---|---|
| *Demographic characteristics* | | | |
| Female | 0.958 | 0.958 | 0.952 |
| Age | 42.401 | 43.024 | 43.532 |
| Is Danish | 0.942 | 0.939 | 0.931 |
| Single | 0.141 | 0.15 | 0.155 |
| Has partner (not empl. in regions) | 0.843 | 0.835 | 0.828 |
| Has partner (empl. in regions) | 0.017 | 0.015 | 0.017 |
| Has children | 0.562 | 0.524 | 0.487 |
| No children | 1.146 | 1.084 | 0.988 |
| Youngest child aged 0-2 | 0.154 | 0.132 | 0.141 |
| Youngest child aged 3-6 | 0.125 | 0.127 | 0.098 |
| Youngest child aged 7-12 | 0.148 | 0.138 | 0.131 |
| Youngest child aged 13-18 | 0.136 | 0.126 | 0.116 |
| Lives in the Northern region | 0.109 | 0.112 | 0.105 |
| Lives in the Central region | 0.241 | 0.237 | 0.235 |
| Lives in the Southern region | 0.209 | 0.21 | 0.213 |
| Lives in the Capital region | 0.3 | 0.31 | 0.311 |
| Lives in the Zealand region | 0.13 | 0.126 | 0.132 |
| *Health characteristics* | | | |
| Any mental health medication | 0.099 | 0.097 | 0.09 |
| Any psycholeptic medication | 0.051 | 0.045 | 0.043 |
| Any psychoanaleptic medication | 0.067 | 0.068 | 0.061 |
| Any hospital visit related to mood, anxiety, or stress-disorder | 0.002 | 0.003 | 0.004 |
| Any mental health related visit to hospital | 0.004 | 0.005 | 0.005 |
| Any visit to psychiatric hospital | 0.034 | 0.045 | 0.04 |
| *Socioeconomic characteristics* | | | |
| Wage income (in 2015 prices, in DKK) | 305,217 | 342,842 | 369,949 |
| Night worker | 0.25 | 0.26 | 0.27 |
| Working hours | 1044.2 | 1104.0 | 1159.6 |
| Working hours, night shifts | 112.3 | 116.4 | 130.5 |
| No. shifts | 133.0 | 140.4 | 146.8 |
| No. night shifts | 25.1 | 24.7 | 26.7 |
| Share of night shifts | 0.107 | 0.111 | 0.111 |
| No. quick returns | 4.82 | 4.52 | 4.31 |
| No. early starts | 0.339 | 0.350 | 0.396 |
| Sick | 0.781 | 0.769 | 0.734 |
| Sick days | 11.7 | 11.6 | 10.5 |
| Sick periods | 3.53 | 3.55 | 3.46 |
| Individuals | 41,795 | 42,919 | 46,974 |

*Note*: The table shows summary statistics on nurses hired at a public hospital during the period from 2008 to 2018. A night shift is defined as $\geq 3$ hours of work between 23:00 and 06:00. A quick return is defined as a shift starting less than 11 hours after the end of the prior shift. An early start is defined as a shift starting between 3:00 and 6:00.

Table B.5: Share of Danish Population Aged 25-44 With Take-Up of Psychotropic Medication, 2005-2021

| | 2005 | 2007 | 2009 | 2011 | 2013 | 2015 | 2017 | 2019 | 2021 |
|---|---|---|---|---|---|---|---|---|---|
| Psychotropic medication (N05 & N06) | 12,6 | 13,5 | 14,0 | 14,8 | 13,8 | 12,9 | 12,5 | 12,5 | 13,7 |
| Psycholeptics (N05) | 6,1 | 6,0 | 5,6 | 5,5 | 5,3 | 5,1 | 5,0 | 4,8 | 5,3 |
| Psychoanaleptics (N06) | 6,5 | 7,5 | 8,4 | 9,2 | 8,5 | 7,8 | 7,5 | 7,7 | 8,4 |

*Note*: The table shows the share of the Danish population aged 25-44 taking up psychotropic medication (N05 & N06), overall and split by psycholeptics (N05) and psychoanaleptics (N06), by calendar year.
*Source*: Sundhedsdatastyrelsen (2025), Statistics Denmark (2025).

Table B.6: Work-Time Agreements for Nurses, Danish Regions

| Period | Type | Compensation* |
|---|---|---|
| 1/4/2005-31/4-2008 | 18.00-23.00 | 27% |
| | 23.00-06.00 | 30.5% |
| | Saturday 8.00 - Sunday 24.00 | 40% |
| | Other public holidays | 50% |
| 1/4/2008-31/4-2011 | 18.00-23.00 | 27% |
| | 23.00-06.00 | 32.5%† |
| | Saturday 8.00 - Sunday 24.00 | 42%† |
| | Other public holidays | 50% |
| 1/4/2011-31/4-2013 | 18.00-23.00 | 27% |
| | 23.00-06.00 | 32.5% |
| | Saturday 8.00 - Sunday 24.00 | 42% |
| | Other public holidays | 50% |
| 1/4/2013-31/4-2015 | 18.00-23.00 | 27% |
| | 23.00-06.00 | 32.5% |
| | Saturday 8.00 - Sunday 24.00 | 42% |
| | Other public holidays | 50% |
| 1/4/2015-31/4-2018 | 18.00-23.00 | 27% |
| | 23.00-06.00 | 32.5% |
| | Saturday 8.00 - Sunday 24.00 | 42% |
| | Other public holidays | 50% |
| 1/4/2018-31/4-2021 | 18.00-23.00 | 27% |
| | 23.00-06.00 | 32.5% |
| | Saturday 8.00 - Sunday 24.00 | 42% |
| | Other public holidays | 50% |

*Note*: The table presents the wage compensation rates for non-standard working hours as specified in collective agreements. *Additional hourly wage or time off in lieu pr. hour worked in time-period. †Change from previous level implemented 1/4-2010.
*Source*: Collective agreements - Amtrådsforeningen et al. (2005), Regionernes Lønnings- og Takstnævn et al. (2008, 2011, 2013, 2018, 2021).

Table B.7: Mental Health Effects of Cumulative Exposure to Night Shift Work, Not Controlling for Current Mental Health

| Any Use of Psychotropic Medication (N05 & N06) | | | 95% CI | | | |
|---|---|---|---|---|---|---|
| Model | $e^{\beta}$ | t-statistic | Lower | Upper | Persons | Person-Years |
| Static | | | | | | |
| Conventional | 1.04 | 0.71 | 0.95 | 1.15 | 3,513 | 11,498 |
| MSM-IPW | 1.12 | 3.75 | 1.00 | 1.25 | 3,513 | 11,498 |
| MSM-Ebal | 1.24 | 4.23 | 1.01 | 1.52 | 3,513 | 11,498 |
| Dynamic | | | | | | |
| Year 1 | 0.92 | 0.14 | 0.59 | 1.43 | 3,513 | 3,513 |
| Years 1-2 | 0.98 | 0.02 | 0.77 | 1.26 | 3,513 | 6,170 |
| Years 1-3 | 1.00 | 0.00 | 0.82 | 1.22 | 3,513 | 8,126 |
| Years 1-4 | 1.09 | 0.60 | 0.87 | 1.36 | 3,513 | 9,603 |
| Years 1-5 | 1.26 | 3.83 | 1.00 | 1.58 | 3,513 | 10,697 |
| Years 1-6 | 1.24 | 4.23 | 1.01 | 1.52 | 3,513 | 11,498 |
| Categorical | | | | | | |
| 1 Year | 0.83 | 0.66 | 0.53 | 1.30 | 3,513 | 11,498 |
| 2 Years | 1.50 | 1.45 | 0.78 | 2.88 | 3,513 | 11,498 |
| 3 Years | 1.01 | 0.00 | 0.44 | 2.35 | 3,513 | 11,498 |
| 4 Years | 2.44 | 2.93 | 0.88 | 6.75 | 3,513 | 11,498 |
| 5 Years | 2.55 | 3.21 | 0.92 | 7.10 | 3,513 | 11,498 |
| 6 Years | 1.06 | 0.01 | 0.32 | 3.51 | 3,513 | 11,498 |

*Note*: The table presents mental health effects of cumulative exposure to night shift work, estimated using the conventional and the SWM approaches. Weights are not adjusted for current mental health. Conventional: Follows the conventional approach with outcome on the LHS and cumulative exposure and all covariates on the RHS as specified in equation (2). SWM-IPW: Sequential weighted matching using inverse probability weighting where propensity scores are based on logistic regression. SWM-Ebal: Sequential weighted matching using balancing weights generated from entropy balancing. The SWM approach is specified in equation (3). Static: Evaluating mental health effects for the full period from year 1 to 6. Dynamic: Evaluating mental health effects with varying follow-up years, where the number of years corresponds to the number of years hired as a night or non-night worker. Categorical: Evaluating mental health effects with categorical instead of continuous exposure assessment, where the number of years corresponds to the number of years as a night worker. See note in Table 3 for further details.

Table B.8: Income Effects of Cumulative Exposure to Night Shift Work, with Varying Night Worker Thresholds

| | | | 95% CI | | | |
|---|---|---|---|---|---|---|
| Model | $e^{\beta}$ | t-statistic | Lower | Upper | Persons | Person-Years |
| Night Worker Threshold, Annual Wage Income | | | | | | |
| 6.7 pct. × 0.5 | 17,004.42 | 245.07 | 14,875.49 | 19,133.35 | 3,513 | 11,498 |
| 6.7 pct. | 18,326.48 | 226.09 | 15,937.62 | 20,715.33 | 3,513 | 11,498 |
| 6.7 pct. × 1.5 | 19,079.77 | 245.64 | 16,693.74 | 21,465.81 | 3,513 | 11,498 |
| 6.7 pct. × 2 | 20,820.37 | 201.66 | 17,946.79 | 23,693.94 | 3,513 | 11,498 |
| Night Worker Threshold, log(Annual Wage Income) | | | | | | |
| 6.7 pct. × 0.5 | 0.05 | 201.88 | 0.04 | 0.05 | 3,513 | 11,498 |
| 6.7 pct. | 0.05 | 189.88 | 0.04 | 0.06 | 3,513 | 11,498 |
| 6.7 pct. × 1.5 | 0.05 | 240.30 | 0.05 | 0.06 | 3,513 | 11,498 |
| 6.7 pct. × 2 | 0.06 | 249.14 | 0.05 | 0.07 | 3,513 | 11,498 |

*Note*: The table presents results from sequential weighted matching using balancing weights estimated with entropy balancing, estimated using GEE and modelled using logistic regression. The parameter estimates are measured as absolute changes when the outcome is annual wage income (DKK per year) and percentage changes when the outcome is log(annual wage income). See note in Table 3 for further details.

Table B.9: Mental Health Effects of Cumulative Exposure to Night Shift Work, No Restrictions on Prior Mental Health

| Any Use of Psychotropic Medication (N05 & N06) | | | 95% CI | | | |
|---|---|---|---|---|---|---|
| Model | $e^{\beta}$ | t-statistic | Lower | Upper | Persons | Person-Years |
| Static | | | | | | |
| Conventional | 1.00 | 0.01 | 0.93 | 1.08 | 4,106 | 13,340 |
| MSM-IPW | 1.07 | 4.23 | 1.00 | 1.15 | 4,106 | 13,340 |
| MSM-Ebal | 1.10 | 1.81 | 0.96 | 1.25 | 4,106 | 13,340 |
| Dynamic | | | | | | |
| Year 1 | 0.95 | 0.12 | 0.72 | 1.26 | 4,106 | 4,106 |
| Years 1-2 | 0.98 | 0.09 | 0.84 | 1.13 | 4,106 | 7,184 |
| Years 1-3 | 1.03 | 0.21 | 0.91 | 1.17 | 4,106 | 9,455 |
| Years 1-4 | 1.08 | 1.37 | 0.95 | 1.24 | 4,106 | 11,155 |
| Years 1-5 | 1.12 | 2.70 | 0.98 | 1.29 | 4,106 | 12,419 |
| Years 1-6 | 1.10 | 1.81 | 0.96 | 1.25 | 4,106 | 13,340 |
| Categorical | | | | | | |
| 1 year | 0.96 | 0.09 | 0.75 | 1.24 | 4,106 | 13,340 |
| 2 years | 1.13 | 0.43 | 0.79 | 1.62 | 4,106 | 13,340 |
| 3 years | 0.73 | 1.42 | 0.43 | 1.23 | 4,106 | 13,340 |
| 4 years | 1.87 | 3.70 | 0.99 | 3.53 | 4,106 | 13,340 |
| 5 years | 1.47 | 1.15 | 0.73 | 2.98 | 4,106 | 13,340 |
| 6 years | 0.99 | 0.00 | 0.44 | 2.22 | 4,106 | 13,340 |

*Note*: The table presents mental health effects of cumulative exposure to night shift work, estimated using the conventional and the SWM approaches. Individuals redeeming prescriptions for psychotropic medication within five years prior to their hospital hire are not excluded from the sample. Conventional: Follows the conventional approach with outcome on the LHS and cumulative exposure and all covariates on the RHS as specified in equation (2). SWM-IPW: Sequential weighted matching using inverse probability weighting where propensity scores are based on logistic regression. SWM-Ebal: Sequential weighted matching using balancing weights generated from entropy balancing. The SWM approach is specified in equation (3). Static: Evaluating mental health effects for the full period from year 1 to 6. Dynamic: Evaluating mental health effects with varying follow-up years, where the number of years corresponds to the number of years hired as a night or non-night worker. Categorical: Evaluating mental health effects with categorical instead of continuous exposure assessment, where the number of years corresponds to the number of years as a night worker. See note in Table 3 for further details.

Table B.10: Mental Health Effects of Cumulative Exposure to Night Shift Work, Excluding the Year 2020

| Model | $e^{\beta}$ | t-statistic | 95% CI Lower | 95% CI Upper | Persons | Person-Years |
|---|---|---|---|---|---|---|
| Any Use of Psychotropic Medication (N05 & N06) | | | | | | |
| Traditional | 1.05 | 1.05 | 0.95 | 1.16 | 3,513 | 11,149 |
| MSM-IPW | 1.09 | 2.40 | 0.98 | 1.21 | 3,513 | 11,149 |
| MSM-Ebal | 1.19 | 4.14 | 1.01 | 1.41 | 3,513 | 11,149 |

*Note*: The table presents mental health effects of cumulative exposure to night shift work, estimated using the conventional and the SWM approaches. We exclude 2020 from the estimation sample to test the sensitivity of the results to the COVID-19 pandemic. Conventional: Follows the conventional approach with outcome on the LHS and cumulative exposure and all covariates on the RHS as specified in equation (2). SWM-IPW: Sequential weighted matching using inverse probability weighting, where propensity scores are based on logistic regression. SWM-Ebal: Sequential weighted matching using balancing weights generated from entropy balancing. The SWM approach is specified in equation (3). Weights are winzorised at the 1 and 99 percentile. See note in Table 3 for further details.