Shift Work and Mental Health*

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This paper explores the link between cumulative night shift work and mental health. The existing literature suggests that night shift work is associated with mild self-reported mental health symptoms and a small or no change in long-term use of prescription medicine. However, these studies are likely biased due to the "healthy worker effect"; healthier workers are better equipped to remain in physically and mentally demanding jobs. We address this selection issue by applying a sequentially weighted matching procedure to time-stamp data from approximately 3.500 graduate nurses' shifts across six years and administrative data on prescription medicine in Denmark. We show that night shift work increases the odds of redeeming prescription medicine for mental health conditions by 12-24 pct. and consumption at the intensive margin but no evidence for increased sickness absence. These findings suggest that employers should be attentive to mental health concerns when organizing night shift work. Further research should examine the heterogeneity of night shift intensity to suggest how different organizations of night work can reduce health impacts.

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1 Introduction

Night shift work reduces sleep duration, and sleep deficiency adversely affects mental health, so it appears reasonable to hypothesize that shift work impairs mental health. Working at night disrupts the circadian rhythms of the body, which can cause disturbances in sleep, chronic fatigue, and elevated stress levels. As sleep is important for emotional processing, sleep deprivation increases the risk of experiencing mental health challenges such as depression, anxiety, stress, phobias, and burnout. Given the established influences of night shift work on sleep and of sleep on mental health, it is puzzling that the existing literature finds little or no impact of night shift work on mental health-related medication consumption. A plausible explanation is that these studies are biased due to the "healthy worker effect"; healthier workers are better equipped to remain in physically and mentally demanding jobs. We attempt to solve this puzzle by estimating the mental health effects of night shift work while adjusting for the healthy worker bias using a unique combination of rich and high-frequency data sources.

This paper investigates the mental health effects of night shift work. We focus on nurses because night shift work is a considerable and imperative part of a nurse's job. After all, patients need care around the clock. By following a cohort of nurses from graduation through their first six years of employment at a public hospital, we analyze how one additional year of night shift work affects their use of prescription medication for mental health issues, both on the extensive and intensive margins, as well as their sickness absence. We find that night shift work has sizable, adverse mental health effects. For each additional year of night shift work, nurses' risk of redeeming prescriptions for psychotropic medication increases by 24 pct., and their medication dose increases by around 110 pct. relative to the first year employed at the public hospitals. There is no change in nurses' sickness absence, likely because it is directly related to nurses' number of planned shifts.

Since working odd hours creates challenges in creating and maintaining a family life, we also explore the effects of night shift work on nurses' partnership status and fertility. We show that night shift work does not affect nurses' likelihood of having a partner or a child, working part-time, or leaving public hospital employment. We interpret this as nurses being able to uphold a family life despite working night shifts. Finally, nurses are compensated for working night shifts through work time and income, and we study their degree of realized compensation and its main source. We document that night workers are compensated along three dimensions: wages, working hours, and off-duty time. During a year with night work, they earn around 18,000 DKK or 6% more, work 26 or 2% fewer hours, and have 4 or 2% fewer shifts. As a corollary, they have more vacation days, more time between shifts, and fewer returns to work within 24 and 48 hours since their last shift.

With our study, we make three contributions to the existing literature. First, we use objective measures of night shift work and mental health, which reduces misclassification and self-reporting bias. Second, we follow workers over several years, allowing us to evaluate cumulative effects, which can lead to more serious health conditions. But cumulative effects are likely tainted by the healthy worker bias. Therefore, an important third contribution is adjusting for this bias, which we show is important since it changes the policy implications of our analysis.

The ideal experiment for estimating the mental health effects of night shift work is to randomly assign night shifts among workers and compute differences in mental health depending on the amount of night shift work. As this is not feasible in our setting, we instead turn to high-quality data and an econometric method, which helps us mimic the ideal experiment. We rely on data from the Danish Work Hour Database (DWHD), which contains daily timestamps for all nurses employed at public hospitals in Denmark from 2008 to 2020. This data allows us to track nurses' paid activities at the minute level,

including working times, sickness, leave, and vacation. We combine the DWHD with yearly information on demographic, health, and socioeconomic characteristics from registry data. With these data in hand, we estimate the mental health effects of night shift work by comparing a group of night workers with an otherwise similar group of non-night workers. For each year working at the public hospital, we first estimate each nurse's propensity to be a night worker based on a wide range of characteristics, including age, partnership status, children, region of employment, income, working hours, hospital visits, and redeemed prescriptions for psychotropic medication.[1] We then divide the graduate cohorts into night and non-night workers and re-weight the groups using the estimated propensities. Then, we end up with two groups of nurses each year that are similar in all dimensions except their night worker status. We can then identify the mental health effects of cumulative exposure to night shift work by comparing the next year's mental health between the night and non-night workers under the assumption that the characteristics in our weights capture all non-random differences in years of night shift work. We label this approach Sequential Weighted Matching (SWM) (Vikström, 2017; van den Berg and Vikström, 2022a).[2]

We benchmark results from SWM against the traditional approach to estimating effects of cumulative exposure to unfavourable working conditions. We anchor our evaluation in Fletcher et al. (2011) and estimate the effects of cumulative exposure to night shift work by simply controlling for past mental health and other characteristics in a logistic regression. This approach does not handle the endogenous selection problem; it does not properly account for the interplay between mental health and night shift work. Hence, if the healthy worker bias is present, we expect that the estimates are downward biased. Indeed, our results imply that night shift work has a protective effect on mental health. We estimate that an additional year of exposure reduces the risk of developing mental health issues by 9%. Consistent with this, medication doses and sick days also decline with additional years of night shift work. However, none of these three estimates are statistically significant. These findings and their divergence from our main results demonstrate that our SWM approach more effectively addresses the healthy worker bias than the method typically applied in these types of studies. This highlights the importance of accounting for selection bias when considering policy implications.

We contribute to three strands of literature. First, the health economics literature on the health effects of cumulative exposure to occupational demands. Earlier studies attend to 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; Belloni et al., 2022; Cottini and Lucifora, 2013). In addition, these analyses are based on self-reported measures of health and occupation, with exposure to working conditions evaluated at the occupation level. We address the selection issue more effectively and use objective measures of health and exposure. Second, we contribute to the labor economics literature on the effects of dynamic treatment assignment by applying the SWM approach to a health economics setting. Finally, we contribute to the epidemiological literature on the relation between night shift work and mental health by providing estimates, which are adjusted for the healthy worker bias and based on observational data. The literature has primarily focused on mild mental health symptoms reported in surveys (Bara and Arber, 2009; Driesen et al., 2011; Zhao et al., 2019). Two studies analyze the impact of self-reported night shift work on prescriptions for psychotropic medication, but they do not adjust for endogenous selection and thus potentially underestimate the true mental health effect (Hall et al., 2019; Albertsen et al., 2022).

[1] See Figure 7.2 for a full list of control variables.

[2] The approach is traditionally referred to as Dynamic Inverse Probability Weighting (DIPW), but as we use both Inverse Probability Weighting and Entropy Balancing to create weights, we refer to it as Sequential Weighted Matching.

The rest of the paper is organized as follows. In section 2, we summarize the literature on health effects of working conditions, sleep, and shift work. In section 3, we outline the theoretical framework and put forth our testable hypothesis, and in section 4, we delineate the institutional framework. In section 5, we present our data and sample, and we provide descriptive statistics on all nurses as well as our sample of nurses employed at public hospitals. In section 6, we describe our estimation and identification strategies; in section 7, we show and discuss our results. We end by summarizing our findings and identifying areas for future research in section 8.

2 Background Literature

In this section, we summarize the literature on health effects of working conditions, sleep, and shift work.

2.1 Health and Cumulative Exposure to Demanding Work Characteristics

Health interacts with income, education, and employment. Better health enables individuals to get better educated, get and retain a job, and generate higher income. In turn, better education, employment, and higher income can protect health. Yet, Case and A.Deaton (2005) suggest that wear and tear by work is another driver of health disparities between manual and non-manual workers. This suggestion sparked research that addresses the important question of whether job characteristics drive health disparities, which is necessary to provide suggestions for areas that policies should target to reduce the impact of adverse working conditions. In particular, this literature tries to answer whether the cumulative effects of several years of wear and tear by work lead to faster health deterioration and even more substantial health disparities over time. This idea is pursued in several studies examining the cumulative effects of work characteristics on different health outcomes.

Lakdawalla and Philipson (2007) represents the first study to examine the cumulative effects of on-the-job exercise and BMI and find that physically demanding jobs reduce BMI. Fletcher et al. (2011) formalized Lakdawalla and Philipson (2007)'s approach by deriving an econometrics model specification from Grossman's human capital model. Using a 5 years measure for cumulative exposure to physical and environmental demands, Fletcher et al. (2011) find that health declines for individuals having worse work conditions, particularly for women and older workers. Nicholas et al. (2020) extend the approach in Fletcher et al. (2011) but applied to life time exposure rather than 5 years of exposure. Nicholas et al. (2020) find that routine manual work increases Social Security Disability Insurance (SSDI) and worse health. Ravesteijn et al. (2018) regress health on lagged occupational stressors, lagged health and other covariates. They extrapolate year-to-year estimates to cumulative effects by letting health effects of shocks to occupational stressors decay using the estimated coefficient of lagged health. Ravesteijn et al. (2018) find that physical strain and low job control affect health negatively and increasingly so with age.

A common approach in this literature is to link job demands with average scores by job group from surveys or expert ratings to panel data with health and other important variables. Such expert ratings include the Dictionary of Occupation Titles (DOT) (Lakdawalla and Philipson, 2007; Fletcher et al., 2011) and the Occupational Information Network (O*NET) (Nicholas et al., 2020) while surveys include the German Qualification and Career Survey (GQCS) Ravesteijn et al. (2018).

A common challenge in these studies is how to deal with endogenous selection because health may determine the occupations that subjects choose. Some studies focusing solely on the health effects of lagged working conditions are, in some cases, able to find instruments (Cottini and Lucifora, 2013; Belloni et al., 2022, e.g.). However, the problem is exacerbated in studies that consider cumulative effects since health and occupational choices interact period by period. Fletcher et al. (2011) strategy retrospective self-assess health at age 16 to mitigate self-selection. Nicholas et al. (2020) use a similar strategy but also add controls for family socioeconomic status, which they also argue can influence later life health and job choice. Ravesteijn et al. (2018) use job switches to identify variation job exposures, arguing that job switches are random after conditioning on individual fixed effects, lagged health and other relevant time-varying characteristics. Nicholas et al. (2020). A common limitation of these studies, also recognized by the authors, is that they rely on the conditional independence assumption, i.e. job choice/switches are statistically independent of health conditional on the observables and time-constant observables in fixed

effects specification. The weakness in these designs is that it is impossible to confirm that all relevant variables are included. Our design has similar limitations. Another limitation is that these strategies do not address the ongoing interaction between health and occupational stressors in the measurement period of cumulative exposure. For example, initial health may well capture selection effects on the first observed occupational stressors, e.g. in $t-5$, but a health shock in $t-4$ can affect occupational stressors in $t-3$, which initial health cannot capture. In this paper, we reduce such potential biases using Marginal Structural Models.

2.2 Sleep and Mental Health

Sleep research shows that sleep is important for emotional processing (Walker and van der Helm, 2009; Menz et al., 2016; Tempesta et al., 2018). First, sleep reduction impairs the ability to form and retain neutral and positive memories, whereas negative memories are less affected. In one experiment, subjects (sleep-deprived vs. control) learned words with negative, neutral and positive words, which they had to recall in a subsequent session after a learning session. The sleep-deprived group had more difficulties remembering the positive and neutral words, but their memory of negative words was comparable to that of the control group (Walker and van der Helm, 2009). Theoretically, this bias skews a person's perceived life history as being dominated by negative events, even if objectively, it is more balanced with positive and neutral experiences. Second, sleep regulates the learning ability of what to fear and what not to fear. Thus, sleep deprivation can impair the ability to consolidate danger and safety stimuli. This has been demonstrated in experiments (e.g. Menz et al., 2016; Goldstein and Walker, 2014), where subjects are exposed to stimuli (pictures) that can be linked to (mild electrical) shocks. Results indicate that sleep-deprived are less able to discriminate whether certain pictures (stimuli) are linked to shocks when they do a similar test with the same pictures on another day. A concern raised in the sleep research literature is, therefore, whether sleep deprivation can generate dysfunctional and persistent fear, which in turn can cause and maintain anxiety disorders (Tempesta et al., 2018). Third, sleep deprivation is linked to social isolation and loneliness. Ben Simon and Walker (2018) find that sleep-deprived persons perceive themselves as lonelier and are less desirable to engage with socially, as rated by an independent panel.

In sum, sleep deprivation can distort emotional processing and thereby result in an over-representation of negative memories, dysfunctional fear responses to non-dangerous stimuli, feelings of loneliness, and a lack of desire for social engagement. This reveals the potential mechanism between sleep deprivation as a risk factor for adverse mental health outcomes.

2.3 Shift Work and Mental Health

Evidence from several meta-analyses and systematic reviews supports a link between shift work and adverse mental health. In a meta-analysis of longitudinal studies, Torquati et al. (2019) find that shift workers had a 30 pct. higher risk of poor mental health, anxiety and depression symptoms relative to non-shift workers across seven included studies. In a meta-analysis of cross-sectional studies (18), cohort studies (5), one prospective study and one case-study report, D'Oliveira and Anagnostopoulos (2021) find that shift work increases depressive symptoms and anxiety. In Zhao et al. (2019)'s systematic review and meta-analysis, including ten cross-sectional studies, 22 longitudinal studies, and one including both, corroborate this evidence. They conclude that irregular and unpredictable work is associated with poorer mental health. Interestingly, they find less evidence for an association between night/evening work and poorer mental health. These results are perhaps not too surprising given that it is well-known that

many adverse mental health outcomes co-occur with sleep problems, which puts into question whether sleep problems cause adverse mental health, whether it is the other way around or perhaps, whether the relationship is bidirectional (Walker and van der Helm, 2009). Scott et al. (2021)'s meta-analysis of 65 randomized controlled trials shows that improving sleep quality improves mental health, which shows that sleep can affect mental health (although it does not preclude the existence of an effect in the opposite direction).

The existing literature has three important limitations. Firstly, it relies on self-reported outcome measures. This is the case for all meta-analyses reviewed. We have identified two studies that employ objective health measures. Albertsen et al. (2022) use psychotropic prescription medicine and psychiatric hospitalization treatment due to mood, anxiety or stress-related disease as outcomes. They find a positive association between night shift work and the former outcome but no association with the latter outcome, concluding that night shift work is not an important predictor for adverse mental health. Hall et al. (2019) also use prescriptions for psychotropic medication as an outcome. They detect no effect of night shift work. Existing evidence should be corroborated by additional analyses relying on such objective measures. Secondly, the literature lacks assessments of the relationship between cumulative exposure to night shift work and mental health. Instead, it has been focused on the impact of short-term exposure. As argued above, if the effects are growing in exposure, examining the impacts of cumulative rather than short-term exposure is more relevant. Finally, the epidemiological literature is largely susceptible to misclassification bias. Studies assess exposure at baseline and then consider differences in outcomes during a follow-up period. Hence, they generally ignore the fact that subjects can and do change occupations or work arrangements within the same job over time. With our study, we address these limitations by leveraging objective health measures, assessing effects of cumulative exposure, and identifying daily working conditions at the individual level.

3 Theoretical Framework

In this section, we describe the theoretical framework for our analysis. Based on this, we put forth a testable hypothesis for the mental health effects of cumulative exposure to night shift work.

3.1 The Grossman Model

Our theoretical framework departs from the Grossman model, which links individuals' current and past health decisions to their health in any given period of their life (Grossman, 1972). Health is considered a stock, implying that past decisions affect current health, and current decisions affect future health. Beginning life with an initial stock, individuals' health increases with positive investments but depreciates with age and negative investments (Bhattacharya et al., 2014).

The model departs from the assumption that an individual's utility in a period t is a function of its level of health H_t and a home good Z_t, representing everything else that provides utility:

$$U_t = U(H_t, Z_t).$$

Individuals are time-constrained; they have 24 hours per day, which they can spend working T^W (to finance goods that will increase H_t and Z_t), playing T^Z (to increase Z_t), improving their health T^H (to increase H_t), or being sick T^S. Time spent working, playing, and improving health is utility enhancing (i.e., productive), while time spent being sick is utility reducing (i.e., unproductive). Individuals do not voluntarily choose to spend time being sick; it solely depends on their health status. Hence, better health enhances utility through two channels: directly as an input in the utility function and indirectly through more productive time.

Health is produced by a combination of time and market goods. An individual's health in a period t is a function of the past period's health H_{t-1}, the rate of health depreciation due to aging γ, time spend improving health T_t^H, and market inputs into health M_t (e.g., exercising equipment):

$$H_t = H(H_{t-1}(1-\gamma), T_t^H, M_t). \tag{3.1}$$

Hence, health enhances utility through a third channel, namely as a capital affecting future health. With time, H_t falls until reaching its minimum level $H_t = H_{min}$ at which point the individual dies, implying that the length of their life span is endogenous. Following Fletcher et al. (2011), we rewrite the health production function (3.1) such that health in period t is a linear function of initial health H_0 as well as investments into health through time T_t^H and market inputs M_t:

$$H_t = \gamma^t H_0 + \sum_{k=1}^{t} \gamma^{k-1}(T_k^H + M_k).$$

We can split investments into positive (i.e., health improving, e.g., exercising) I_t and negative (i.e., health reducing, e.g., smoking) E_t investments:

$$H_t = \gamma^t H_0 + \sum_{k=1}^{t} \gamma^{k-1}(I_k - E_k). \tag{3.2}$$

With this version of the health production function at hand, we can translate the theoretical framework from the Grossman model to our setting and formulate predictions for the mental health effects of

cumulative exposure to night shift work.

3.2 Hypotheses

Working night shifts affect sleep, and sleep can affect health production and utility (well-being) through three channels. First, sleep is an input in the production of health and, thereby, an indirect input in the utility function. Adequate sleep improves physical and mental health because it is a restorative process of memory consolidation and maintenance of the immune system (Caldwell, 2024). Hence, enough and good quality sleep can increase individuals' level of health in a given period H_t. Second, sleeping can be considered time spent improving health T^H, which enhances utility. In addition, time spent sleeping can vary in productiveness. Interrupted sleep is lower quality than continuous sleep because it disrupts the body's sleep cycles (Wilckens et al., 2014; Someren et al., 2015). Therefore, eight hours of continuous rather than interrupted sleep is more productive. Third, sleep influences future health through its impact on current health. Receiving more and higher quality sleep today improves individuals' health throughout the rest of their lives because it strengthens their health capital.

Working night shifts adversely affects nurses' sleeping patterns, causing deprivation of late-night sleep where REM (Rapid Eye Movement) sleep is more abundant (Kecklund and Axelsson, 2016). REM sleep is important for emotional processing, so nurses with less REM sleep have higher exposure to miscalibrated emotional processing, increasing the risk of adverse mental health outcomes.

According to the Grossman model, working night shifts in a given year will thus impair nurses' health in the short-term by reducing their level of health and productive time spent sleeping. With health being a stock, this will carry over to worsened health in the long-term through a lower health capital stock. Working night shifts over a longer period of time will exacerbate these adverse health effects. Having a lower health capital stock after one year results in more time spent being sick, further lowering their productive time and thus their health capital. The consequence of these negative feedback mechanisms is faster deterioration of health.

Based on this, we formulate the following a testable hypothesis:

H_0 **:** An additional year of being a night shift worker will impair nurses' mental health.

This hypothesis assesses the marginal effect of exposure to night shift work. We will describe the formal tests of the hypothesis in section 6.1 and present the results in section 7.

4 Institutional Framework

Nurses' work schedules must meet a list of regulations put forth by the European Union, the Ministry of Employment, and the collective agreements between representative unions of nurses and public hospitals. In this section, we present the set of regulations that are central to comprehending the institutional framework of our analysis.

4.1 Working Hours

One part of the regulations concerns working hours. In a seven-day period, nurses can work a maximum of 48 hours (including overtime) on average over four months. Within a 24-hour period, working hours during nights cannot exceed eight on average over four months. If night work involves hazards, a shift cannot be longer than eight hours. There can be deviations from these working hour rules if they are agreed upon locally between employers and employees.[3] Night workers are entitled to a free health assessment, and if experiencing health issues proven to be caused by night shift work, they should be transferred to day work whenever possible.[4] Nurses are compensated for performing shifts during non-standard working hours. The compensation rates are decided locally between employers and employees or follow the standard rates put forth in the collective agreements. Table A.9 shows the compensation rates for working hours during evening, night, weekends, and public holidays for the period 2005-2021 as listed in the collective agreements. The rates vary from 27% for evenings to 50% for public holidays but have otherwise remained roughly constant during the period 2005-2021. In particular, night shift work is compensated at a rate of 30.5-32.5%. Nurses can redeem the compensation as a supplement to their hourly wage or as time off.[5] Hence, nurses working more night shifts should either earn a higher wage income, have more free time, or work fewer shifts relative to nurses working fewer or no night shifts.

4.2 Shift Schedule Arrangements

A second part relates to shift schedule arrangements. Nurses' schedules should be available at least four weeks in advance. They are informed about changes to the schedule at least 24 hours in advance. Otherwise, they will receive hourly monetary compensation for the rescheduled working hours. The schedule contains one weekly long off-duty period of 55-64 hours or two short off-duty periods of at least 35 hours (or 32 hours if rest time between shifts is set locally to 8 instead of 11 hours).

Overtime work (i.e. working hours that are not planned) should be communicated to the nurses within 24 hours. Otherwise, they receive monetary compensation per incident of untimely announcements. Nurses are rewarded for overtime work either through a 50% wage supplement or a 50% off-duty time. If overtime work happens between two planned shifts and results in less than 11 (or 8 depending on the locally set rest time) hours of rest in between shifts, nurses are entitled to paid rest until they have reached 8 hours of rest.

Nurses can take on voluntary extra work, defined in the collective agreements as work that cannot be performed within the regulations, e.g., overtime work. Voluntary extra work mostly involves planned, non-acute activities bounded by time or a defined task. It is predominantly taken on in case of long waiting lists, extraordinary sickness absence, or other situations of imbalance between health care personnel and

[3] European Union and EUR-lex (2003); European Commision (2003)

[4] Amtsrådforeningen et al. (1995)

[5] Regionernes Lønnings- og Takstnævn et al. (2021)

tasks to avoid relying on temporary workers. Nurses' compensation for their voluntary extra work is agreed upon locally between the employers and employees.

Apart from the regulations mentioned above, there are no official guidelines on the composition of schedules regarding shift types. Notably, there is no set maximum for the number of night shifts within a certain time period. Instead, hospitals may make local recommendations on the composition of shift schedules. Examples can be minimizing night work, working a maximum of 2-4 night shifts in a row, or having clockwise rotation in shifts (day-evening-night instead of night-evening-day).[6]

4.3 Rest and Off-Duty Periods

A third part is about off-duty periods. Nurses must have at least 11 hours of rest between shifts.[7] The rest time can be reduced to 8 hours twice in one week but not on two consecutive days.[8] Over a seven-day period, nurses should have 24 consecutive hours of rest, preferably on a Sunday. Once a month, this off-duty day can be postponed such that there are 12 days between two off-duty days. If a shift is longer than six hours, nurses are entitled to a break during the shift.[9]

[6] Regionernes Lønnings- og Takstnævn et al. (2018)
[7] European Commision (2003)
[8] Amtsrådforeningen et al. (2003)
[9] Amtsrådforeningen et al. (1995)

5 Data and Descriptive Statistics

In this section, we first describe our data and define our estimation sample of a graduation cohort of nurses. We then characterize our estimation sample of nurses employed at public hospitals.

5.1 Data

5.1.1 Data sources

We combine daily payroll data from the Danish Work Hour Database (DWDH) with yearly administrative data on demographic and socioeconomic characteristics and healthcare utilization using personal identification numbers from Statistics Denmark and the Danish Health Agency (see table Table A.1 for more detail).

We link these data at the individual level to the DWDH, a unique database containing rich and high-frequency employment-related data on all nurses employed at public hospitals. It allows us to track all nurses' paid activities at the minute level, including shift starting and ending times, sickness absence, leave, and vacation.

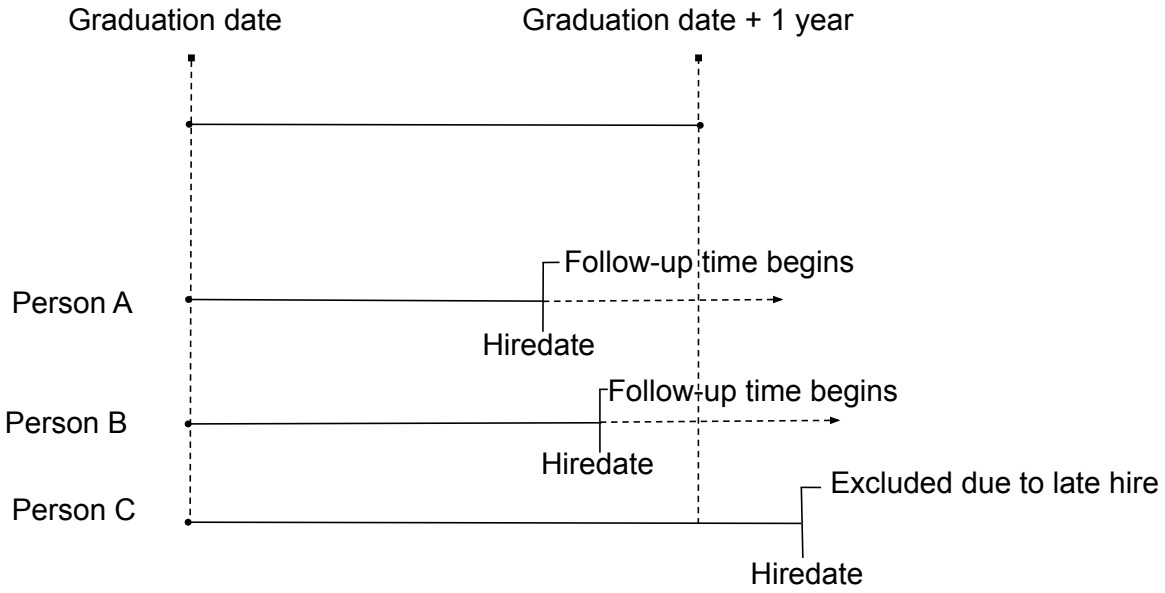
5.1.2 Sample

Our sample consists of all individuals completing a bachelor's degree in nursing in 2009-2015, who are hired at a public hospital within one year of graduation. By focusing on graduate nurses, we minimize the impact of exposure to night work before the period where we can assess their exposure.Figure 5.1 depicts this initial selection process. We make two restrictions. First, we focus on nurses working full-time (at least 900 hours, approximately 120 shifts) during their first year of employment. This restriction makes nurses' exposure to work intensity more similar. Second, we exclude nurses redeeming prescriptions for mental health medication (psycholeptic or psychoanaleptic medication) within five years prior to their hospital hire to reduce the impact of early life differences in present health, which otherwise is important to control for Fletcher et al. (2011). The final sample consists of 3,524 nurses with rotating or permanent day, evening, and night shift work. We follow everyone for up to six years of employment or until they leave their job at the public hospital, work part-time, emigrate, or die. Censored nurses are not allowed to re-enter the sample after because we cannot measure their exposure to night work during the period in which they are censored. Section B.1.5 outlines how we estimate censoring weights and include these in our estimation regressions to account for changes in our sample composition generated by censoring.

5.1.3 Exposure to Night Shift Work

We acquire information on working hours from the DWHD, which contains payroll data with each shift's exact start and end time for all public hospital employees in Denmark from 2008 to 2020. We follow Garde et al. (2018) and define a night shift as ≥ 3 hours of work between 23:00 and 06:00. We define shifts falling outside of this time interval as non-night shifts. We normalize time to nurses' hire date and measure exposure and outcomes in years relative to this date. Figure 5.1 illustrates how this normalization is done. For each year since hire, we evaluate the number of night and non-night shifts nurses have worked. We then define nurses as night or non-night workers in a year based on the share of night shifts they have had. Specifically, we define nurses as night workers if they have $> 6.7\%$ night shifts during one year and non-night workers otherwise, again following Garde et al. (2018).

Figure 5.1: *Initial Sample Restriction and Normalization of Time*



Note: The figure depicts the initial sample restriction to nurses hired within one year of graduation. Graduation date denotes the date at which they complete a bachelor's degree in nursing. Hire date denotes the date of their first hire at a public hospital after graduating. The figure also illustrates how we normalize time to their date of hire. Each follow-up year thus measures years since their hire at a public hospital upon graduation.

5.1.4 Mental Health

We measure nurses' mental health status primarily based on their utilization of mental health medication. The National Patient Pharmaceutical Database contains detailed information on all prescription medication purchased at pharmacies in Denmark. We use redeemed prescriptions for psychotropic drugs, which are classified as psycholeptic (N05, e.g., antipsychotica, anxiolytica) and psychoanaleptic (N06, e.g., antidepressiva, psychostimulantia) drugs according to the Anatomical Therapeutic Chemical (ATC) Classification system. We examine extensive margin responses using an indicator for redeeming prescriptions for psychotropic drugs, and we analyze intensive margin responses using yearly redeemed dosages of psychotropic drugs based on WHO's Defined Daily Dose (DDD). This is a technical measurement that indicates the average daily maintenance dose for a drug and allows for effect evaluation on drug consumption. We secondarily measure nurses' mental health based on their yearly number of sick days. The DWHD contains information on shifts for which nurses have called in sick. A nurse's total number of sick days in a year is then calculated as the number of days between their first registered missed shift and their next regular shift. It is worth noting that sick days related to their children or other next of kin are classified differently, so our measure only includes nurses' own sick days.

5.1.5 Covariates

Nurses' mental health and tendency to work night shifts are likely affected by a range of health-related, demographic, and socioeconomic characteristics. Therefore, we include three groups of controls in our regressions. First, we adjust for nurses' history of redeemed prescriptions for psychotropic drugs (four years back in time), visits to psychiatrists or psychologists, and mental health-related hospitalizations. Second, we control for age, gender, origin, region of residence, partnership status, parental status, and age of the youngest child. Third, we adjust for sickness absence, annual working hours at the hospital, annual wage income, region of employment, and past night-worker status. Details on these controls are

outlined in Table A.2.

5.2 Descriptive Statistics

5.2.1 Demographic, Socioeconomic, and Health Characteristics

Table 5.1 shows descriptive statistics on our sample of an inception cohort of nurses characterized in section 5.1.2. Overall, the sample consists of relatively young females in their mid-20s who likely have a partner and are less likely to have children. In their first full year of employment at a public hospital, nurses work 18% night shifts, and 64% are night workers. Out of around 1500 annual working hours, they spend about 200 hours during night shifts. Nurses are sick around 12 days per year on average, a right-skewed distribution that includes longer sick spells. Notably, 2.5% of nurses redeem prescriptions for psychotropic medication, primarily driven by psychoanaleptic medication compared to psycholeptic medication. The average Defined Daily Dose (DDD) consumed is 3.6, of which the largest part is attributable to psychoanaleptic medication. Mental health-related hospital visits are rare, while visits to psychologists or psychiatrists are more common, with 3% of nurses having at least one visit per year.

Table A.8 shows descriptive statistics on all nurses employed at a public hospital during the period 2008-2020. In relation to the overall population of nurses employed at public hospitals, nurses in our sample are younger, less likely to have a family, and in a better mental health state. They earn a higher wage income because they work more, both overall and during the night. Yet, their sickness and pregnancy-related absence rates are comparable. Since we have selected an inception cohort of healthy nurses who work full-time and have not yet been exposed to night shift work, it is not surprising that nurses in our sample are not perfectly representative of the overall population of public hospital nurses. Table A.7 shows descriptive statistics on our estimation sample, including nurses who have prior mental health issues, are not hired within a year of graduation, or are censored during the follow-up period. Table A.7 shows descriptive statistics on our estimation sample, including nurses with prior mental health issues who are not hired within a year of graduation or are censored during the follow-up period. Compared to this group, nurses in our sample seem representative on all dimensions except their mental health state.

Table 5.1: *Summary Statistics on Estimation Sample*

Follow up year (years since hire)	−1		1	
Variable	Mean	SD	Mean	SD
Demographic characteristics				
Age	25.693	5.47	27.693	5.47
Female	0.95	0.217	0.95	0.217
Is Danish	0.888	0.315	0.889	0.314
Has partner	0.532	0.499	0.662	0.473
Has children	0.229	0.42	0.301	0.459
No. children	0.412	0.809	0.503	0.857
Youngest child aged 0-2	0.112	0.315	0.148	0.356
Youngest child aged 3-6	0.068	0.251	0.083	0.276
Youngest child aged 7-12	0.032	0.176	0.051	0.22
Youngest child aged 13-18	0.017	0.13	0.019	0.137

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Table 5.1 – continued from previous page

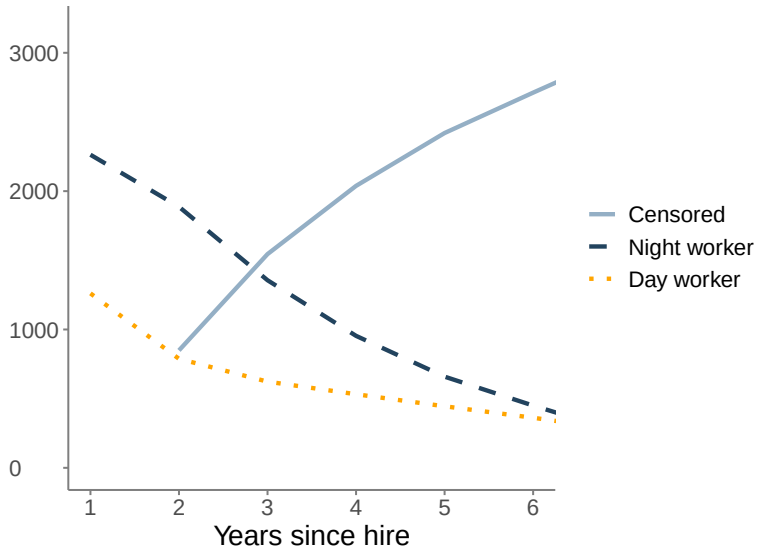
Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Lives in the Northern region	0.071	0.257	0.073	0.26
Lives in the Central region	0.264	0.441	0.253	0.435
Lives in the Southern region	0.173	0.378	0.179	0.383
Lives in the Capital region	0.341	0.474	0.373	0.484
Lives in the Zealand region	0.128	0.334	0.122	0.328
Health characteristics				
Any mental health medication	0	0	0.025	0.156
Any psycholeptic medication	0	0	0.011	0.103
Any psychoanaleptic medication	0	0	0.015	0.123
Mental health medication dose	0	0	3.573	45.362
Psycholeptic medication dose	0	0	0.901	34.064
Psychoanaleptic medication dose	0	0	2.673	29.922
Any hosp. visit for mood, anxiety, or stress-disorder	0.002	0.048	0.002	0.048
Any mental health related visit to hospital	0.006	0.075	0.005	0.069
Any psychiatrist or psychologist visit	0.026	0.159	0.029	0.168
Socioeconomic characteristics				
Wage income	48,443.901	53,469.711	316,579.232	52,425.833
Night worker	-	-	0.642	0.479
Working hours	-	-	1519.387	203.465
Working hours, night shifts	-	-	198.895	177.883
No. shifts	-	-	187.554	24.868
No. night shifts	-	-	33.69	21.147
No. quick returns	-	-	9.529	7.867
No. early starts	-	-	0.11	0.967
Sick	-	-	0.914	0.28
Sick days	-	-	11.975	16.092
On maternity leave or pregnant	-	-	0.083	0.276
Industry: Temp. empl. agencies	0.028	0.164	0	0
Industry: Hospitals	0.008	0.089	0.936	0.245
Industry: General practitioners	0.004	0.065	0	0
Industry: Other health care	0.014	0.117	0.005	0.073
Industry: Institutions	0.198	0.399	0.014	0.116
Industry: Home care	0.061	0.24	0.003	0.056
Unemployed	0.025	0.157	0.005	0.071
Out of the labor force	0.409	0.492	0.018	0.134
Individuals	3524			

Notes: 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, works full time during their first year of employment, and have not redeemed prescriptions for mental health medication (psycholeptic or psychoanaleptic) during the five years before employment. In the estimation sample, individuals are censored if they die, emigrate, works part-time or outside the region. The table shows statistics for the estimation sample excluding these censored individuals. Follow-up year refers to years since hire at the public hospital. Follow-up year 1 is the nurses' first full year of employment. A night shift is defined as ≥ 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.

5.2.2 Night and Non-Night Workers Over Time

Figure 5.2 shows the number of night and non-night working as well as censored nurses over time since their hire at a public hospital. After one year, our sample contains 3512 nurses, with 2.227 classified as night workers and 1.286 as non-night workers. Over time, group sizes of night and non-night workers converge and coincide six years after hire. The size of both groups declines over time, with the biggest absolute and relative decline happening among night workers. After two years, 856 have been censored (≈25). The number of censored increases monotonically, which is expected since it is an absorbing state.

Figure 5.2: *Composition of Sample Over Time*



Note: A night shift is defined as ≥ 3 hours of work between 23:00 and 06:00. Nurses are defined as night workers if they work > 6.7% night shifts and non-night workers otherwise. Censored nurses include emigrants, dead, part-time workers, and workers leaving the regions. Censoring is an absorbing state.

To add some context, Figure 5.3 shows that around 27% of all full-time nurses employed at public hospitals are classified as night workers in a given year. The share is fairly constant between 2008 and 2020. When we split the sample by age groups, it is evident that the share of night workers is larger among younger (40% among workers < 35) compared to middle-aged (25% among workers aged 35-50) and more senior workers (17% among worker 50+).

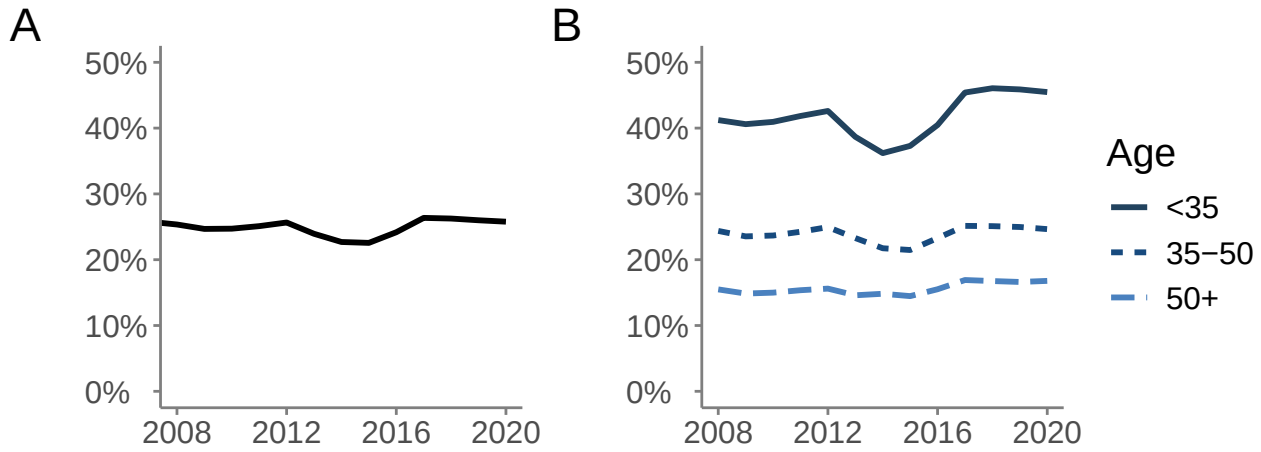
5.2.3 Shift Work Intensity

Figure 5.4 shows the distribution of night shift work intensity in the first year of employment among nurses in the estimation sample. Around 21% have less than 10 night shifts, and a negligible share has zero night shifts. More than half of nurses have between 10 and 50 night shifts; about 30% and 24% have 10-25 and 26-50 night shifts per year, respectively. The share of nurses with more night shifts declines for higher intensities.

5.2.4 Shift Starting Time and Duration

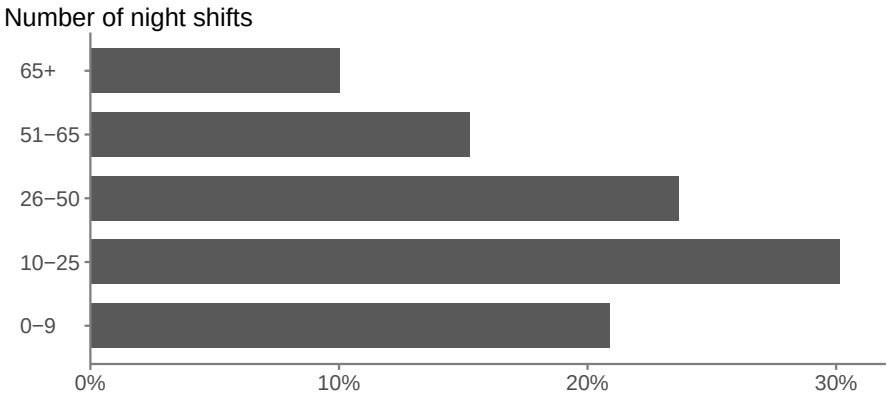
Figure 5.5 shows starting time and duration of shifts among nurses in our sample characterized in section 5.1.2. One noticeable pattern is an eight hour cycle of nurses replacing each other. Most shifts (≈42 pct.) start at 7 am (07:00) and last for 8-9 hours. Around 18% of all shifts start at 3 pm (15:00) and last 8-9

Figure 5.3: *Share of Night Workers Among Nurses, All and by Age Groups*



Note: Panel A displays the overall share of night workers among all nurses working full time at public hospitals between 2008 and 2020, and panel B splits the share by age group. A night shift is defined as ≥ 3 hours of work between 23:00 and 06:00. Nurses are defined as night workers if they work > 6.7% night shifts and non-night workers otherwise.

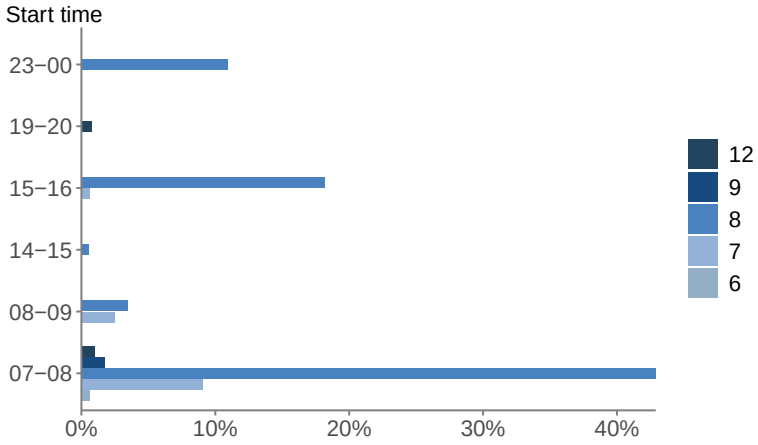
Figure 5.4: *Distribution of Shift Work Intensity*



Note: The figure shows nurses grouped by the intensity of night shift in their first year of employment. A night shift is defined as ≥ 3 hours of work between 23:00 and 06:00. Nurses are defined as night workers if they work > 6.7% night shifts and non-night workers otherwise.

hours, while 10% start at 11 pm (23:00) and last 8-9 hours. Another pattern visible from the figure is a 12 hour cycle of nurses replacing each other. Around 1% of shifts start at 7 am (07:00) and at 7 pm (19:00) and lasts for 12 hours. In total, the figure illustrates that nurses predominantly work eight hour shifts, mostly during standard working hours and otherwise in the evenings and nights.

Figure 5.5: *Start and Duration of Shifts*

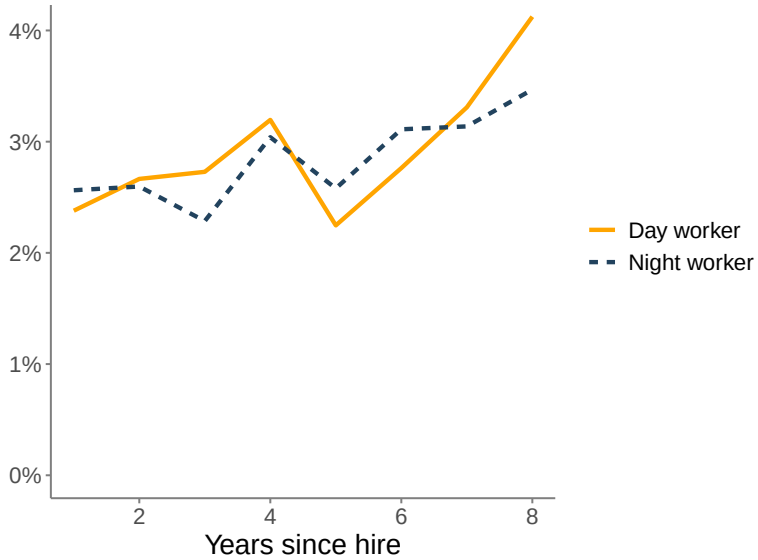


Note: This figure comprises 92 % of all start-duration combinations in a sample of nurses working full time during their first year of employment at a public hospital. The remaining combinations each represent less than 0.005%.

5.2.5 Nurses' Mental Health over Time

Figure 5.6 shows the share of night and non-night workers in our sample redeeming prescriptions for psychotropic medication over time since their hire at a public hospital. Nurses are classified as night and non-night workers each year. The share redeeming prescriptions for psychotropic medication is similar among night and non-night workers over time. One year after being hired at a public hospital, around 2.5% in each group take up medication, and the share steadily increases towards 4% eight years after initial hire. The similar shares of nurses with mental health issues among night and non-night workers over time may indicate that there is no added mental health impact of working night shifts. However, the depicted associations are purely correlational and does not take into account the interdependent relationship between night worker status and mental health.

Figure 5.6: *Mental Health over Time*



Note: The figure shows the share of nurses in our sample redeeming prescriptions for psychotropic (psycholeptic or psychoanaleptic) medication. A night shift is defined as ≥ 3 hours of work between 23:00 and 06:00. Nurses are defined as night workers if they work > 6.7% night shifts and non-night workers otherwise.

6 Empirical Framework

In this section, we describe our estimation and identification strategies. We first outline the traditional approach to estimating health effects of exposure to disadvantageous working conditions. We then define our alternative approach, the Marginal Structural Model, as well as the construction of exposure and censoring weights using Inverse Probability Weighting and Entropy Balancing. Finally, we discuss the identification strategies of the two approaches.

6.1 Estimation Strategy

Comparing the mental health of night to non-night shift worker leads to biased estimates due to endogeneity. First and most importantly, workers with better mental health are more likely to continue working night shifts, so a correlational study would indicate a positive mental health effect of night shift work. This endogenous selection is referred to in the literature as the healthy worker bias. Second, other factors, such as parenthood, likely influence both night shift work and mental health. Finally, if workers with worse mental health leave their jobs, the observed relation between exposure and health among the remaining workers becomes weaker, resulting in downward biased estimates, underestimating the true effect. Because of these endogeneity concerns, we would ideally estimate causal effects by randomizing night shifts among workers. As this is not feasible in our setting, we instead turn to econometric methods and leverage our high-quality data.

Our estimation strategy is threefold: We estimate the mental health effects of night shift work using a traditional approach as well as a sequential weighted matching approach using two different methods for computing sampling weights.

6.1.1 The Traditional Approach

The traditional approach to estimating health effects of exposure to working conditions is to regress current health on past health, exposure, and covariates. We start by following this approach and estimate the effect of past exposure to night work on nurses' mental health. We follow Fletcher et al. (2011) and model mental health of nurse i at time t as follows:

$$MH_{it} = \alpha + \sum_{k=t-6}^{t-1} \rho_k MH_{ik} + \beta^{trad} \sum_{l=t-6}^{t-1} E_{il} + \theta X_{it-1} + \epsilon_{it}, \tag{6.1}$$

where MH_{it} is an indicator for having mental health issues at time t; $\sum_{k=t-6}^{t-1} \rho_k MH_{ik}$ are indicators for having mental health issues at time $t-p$ through $t-1$; $\sum_{l=t-6}^{t-1} E_{il}$ is cumulative exposure to night work the past p years (between $t-6$ and $t-1$); X_{it-1} is a vector of control variables measured at time $t-1$; and ϵ_{it} is an idiosyncratic error term. We control for gender, age, origin, region of employment, partnership status, having children, age of the youngest child, working hours, wage income, sick days, as well as contacts with psychiatric hospitals, psychiatrists, and psychologists (see Table A.2 for a detailed description of covariates). Whereas Fletcher et al. (2011) control for initial health at age 16 and five years prior to exposure, we control for mental health in one to four years before evaluating effects because we believe it captures the relevant variation in mental health among exposed and unexposed, which is not caused by night work. We estimate equation (6.1) for up to six years of exposure history using a logistic regression, and we cluster our standard errors at the individual level.

The coefficient of interest β^{trad} measures the change in nurses' log odds of having mental health issues due to an additional year of exposure to night work. Testing our hypotheses put forth in section 3.2 amounts to testing

$$H_0 : \beta^{trad} \neq 1, \quad H_A : \beta^{trad} = 1.$$

Since we estimate (6.1) using logistic regression when evaluating extensive margin responses, we report results in odds ratios, so $\beta^{trad} = 1$ is equivalent to no mental health effect of night shift work. We evaluate the hypothesis in section 7.1.

6.1.2 The Sequentiel Weighted Matching Approach

An alternative approach to estimating the mental health effects of night shift work is sequential weighted matching, often dubbed Marginal Structural Models (MSM). It originates in the epidemiological literature (e.g. Robins et al., 2000), but it has since been applied in labour economics for evaluations of labour market programs (Lechner, 2009; Lechner and Miquel, 2010; Lechner and Wiehler, 2013; van den Berg and Vikström, 2022b) and highlighted in several reviews on treatment effects (Imbens and Wooldridge (2009), Roth et al. (2023)). Following this approach, we essentially weigh the groups of nurses exposed and unexposed to night shift work such that they, for all practical purposes, are identical except for their exposure. We then estimate the effects by comparing the mental health of the two groups the year after possible exposure to night shift work. For a detailed presentation of Marginal Structural Models, see Appendix section B.

To fix ideas, consider a static framework, where the aim is to estimate the treatment effects of lagged night-shift work on lead mental health. In the weighted matching approach, the idea is to balance the covariates of the two groups of night and non-night workers by weighting each observation such that they are similar and treatment is statistically independent of health history and background characteristics (i.e. the mean age in control and treatment is approximately the same, etc.). In the sequential weighted matching approach, we simply apply the static framework to each period; we estimate weights to balance treatment and control groups in each period. In addition to these exposure weights, we also estimate censoring weights. In each period, we censor nurses who work part-time (fewer than 900 registered working hours), leave public hospital employment, emigrate, or die. We do not allow censored nurses to re-enter the sample because we cannot assess their exposure to night shift work when they are not employed at public hospitals. We estimate censoring weights to account for systematic differences among censored in the groups of night and non-night workers. The weights applied to the sample are then the product of the cumulative products of the exposure and censoring weights. We use two methods for constructing exposure and censoring weights: Inverse Probability Weighting (IPW) and Entropy Balancing (EB).

Inverse Probability Weighting (IPW). The concept in IPW is to estimate propensity scores using, for example, logistic regression and then use the inverse propensities as weights (Robins et al., 2000). In this setting, we first estimate unconditional and conditional propensity scores for being a night worker in period t as respectively:

$$E_{it}^{uc} = \alpha + \phi E_{it-1} + \epsilon_{it}, \tag{6.2}$$

and

$$E_{it}^{c} = \alpha + \phi E_{it-1} + \sum_{k=t-3}^{t} \rho_k MH_{ik} + \theta^1 X_{it} + \theta^2 X_{it-1}^{L} + \epsilon_{it}, \tag{6.3}$$

where E_{it} is an indicator for nurse i being a nigher worker in period t; $\sum_{k=t-3}^{t-1} \rho_k MH_{ik}$ are indicators for

having mental health issues at time $t-3$ through t; and ϵ_{it} is an idiosyncratic error term. X_{it}^1 is a vector of control variables measured at time t including age, gender, origin, having children, age of youngest child as well as contacts with psychiatric hospitals, psychiatrists, and psychologists. X_{it-1}^2 is a vector of labor market control variables measured at time $t-1$ including region of residence, partnership status, exposure, working hours, wage income, and sick days. There are 2^{t-1} potentially different exposure histories. Some of these combinations are empty, and some have very few observations. Therefore, we use a parsimonious representation of exposure history to increase statistical power and model it simply as lagged exposure following (Neophytou et al., 2014).

We then construct IPW weights as the inverse of the estimated conditional propensity scores:

$$W_{it}^{IPW} = \frac{1}{\widehat{E}_{it}^{c}}, \tag{6.4}$$

where $\widehat{E}_{it}^{c}$ is the estimated conditional propensity score from (6.3). These weights can be unstable and thus lead to an estimator with a large variance. Since large unstabilised weights are probably due to the estimation process rather than underlying true probabilities (Stuart, 2010), we follow Hernán et al. (2002) and estimate the stabilized weights as:

$$SW_{it}^{IPW} = \frac{\widehat{E}_{it}^{uc}}{\widehat{E}_{it}^{c}}, \tag{6.5}$$

where $\widehat{E}_{it}^{uc}$ is the estimated unconditional propensity score from (6.2). We estimate two models for the propensity scores. First, we estimate nurses' propensity to be night workers in their first year of employment (follow-up year 1). Second, we estimate a pooled logistic regression over the follow-up years 2-6 to get a prediction equation for the propensity scores for being a night worker in these years. The only difference between the two models is that we include lagged exposure, annual wage income, working hours, and sickness absence in the second model. These variables relate to employment as a nurse at a public hospital and are irrelevant in adjusting for exposure selection in year 1.

To construct censoring weights, we first estimate the unconditional and conditional propensity scores for being censored in period $t+1$ as:

$$C_{it+1}^{uc} = \alpha + E_t + \epsilon_{it}, \tag{6.6}$$

and

$$C_{it+1}^{c} = \alpha + \sum_{k=t-3}^{t} \rho_k MH_{ik} + \theta X_{it} + \epsilon_{it}, \tag{6.7}$$

where C_{it+1} is an indicator for nurse i being censored in period $t+1$; E_{it} is an indicator for being a night worker; $\sum_{k=t-3}^{t-1} \rho_k MH_{ik}$ are indicators for having mental health issues at time $t-3$ through t; X_{it} is a vector of control variables measured at time t; and ϵ_{it} is an idiosyncratic error term. We control for age, gender, origin, region of residence, partnership status, having children, age of the youngest child, exposure, working hours, wage income, sick days as well as contacts with psychiatric hospitals, psychiatrists, and psychologists.

We then construct stabilized censoring IPW weights as the inverse of the estimated conditional

propensity score, scaled by the estimated unconditional propensity score:

$$CW_{it}^{IPW} = \frac{\widehat{C}_{it+1}^{uc}}{\widehat{C}_{it+1}^{c}}, \tag{6.8}$$

where $\widehat{C}_{it+1}^{uc}$ and $\widehat{C}_{it+1}^{c}$ are the estimated unconditional and conditional propensity scores from (6.6) and (6.7), respectively. We estimate eq. 6.6 and 6.7 pooled logistic regression over the follow-up years 1-6 to obtain a prediction equation for the censoring propensity scores.

Having estimated exposure and censoring weights, we compute the final weights as the product of the cumulative products of exposure and censoring weights:

$$FW_{i}^{IPW} = \prod_{t=1}^{6} SW_{it}^{IPW} \times \prod_{t=1}^{6} CW_{it}^{IPW}, \tag{6.9}$$

where $\prod_{t=1}^{6} SW_{it}^{IPW}$ and $\prod_{t=1}^{6} CW_{it}^{IPW}$ are the cumulative products of estimated exposure and censoring weights, respectively, for follow up years 1-6.

Entropy Balancing (EB). With Entropy Balancing, a method developed by Hainmueller (2012), the goal is to construct weights that balance covariates across the groups of exposed and unexposed, minimize the variability of weights, and reduce problems with extreme weights. Using propensity scores to jointly balance covariates has the important limitation that improving balance for some variables may reduce balance for other variables if the propensity score model is not correctly specified (Iacus et al., 2012). EB instead generates weights that enforce restrictions such that mean and potentially higher-order moments of variables in the control and treatment groups will be exactly the same. This important feature, its ability to minimize variability and extreme weights, its computational speed, and its easy implementation in Stata or R makes it an increasingly popular tool in economics and other disciplines.

The set of unit weights $W_t^{EB} = [w_{it}^{EB}, ..., w_{nt}^{EB}]$ are found by minimizing the entropy distance between W_t^{EB} and a vector of base weights $Q = [q_{it}, ..., q_{nt}]$ assigning equal weight to everyone within a group of n nurses (Hainmueller and Xu, 2013). Specifically, the entropy distance metric $H\left(w_t^{EB}\right)$ is minimized for each nurse i in period t, separately for night and non-night workers:

$$\min_{w_{it}^{EB}} H\left(w_t^{EB}\right) = \sum_{i} w_{it}^{EB} \log\left(w_{it}^{EB}/q_{it}\right), \tag{6.10}$$

subject to a balance, normalization, and non-negativity constraint given as respectively:

$$\sum_{i} w_{it}^{EB} c_{rit}\left(X_{it}\right) = m_r \quad \text{with} \quad r \in 1, ..., R \tag{6.11}$$

$$\sum_{i} w_{it}^{EB} = 1 \tag{6.12}$$

$$w_{it}^{EB} \geq 0 \quad \forall i \quad \text{such that} \quad E = e, \quad e \in [0, 1]. \tag{6.13}$$

The balance constraint in (6.11) says that upon weighting, the moment function of a specific covariate for one group $c_{rit}\left(X_{it}\right)$ should map directly into the r-th order moment of the same covariate in the other group. In our estimation, we restrict the first-order moment of the same covariates we in the prediction equation for estimating propensity scores. The non-negativity constraint in (6.13) and the normalization

constraint in (6.12) ensures that weights are non-negative and sum to one in each group.

To construct censoring weights, we estimate the set of unit weights $CW_t^{EB} = [cw_{it}^{EB}, ..., cw_{nt}^{EB}]$ by minimizing the distance metric $H(cw_t^{EB})$ for each nurse i in period t, separately for the night and non-night workers:

$$\min_{cw_{it}^{EB}} H\left(cw_t^{EB}\right) = \sum_i cw_{it}^{EB} \log\left(cw_{it}^{EB}/q_{it}\right), \tag{6.14}$$

subject to a balance, normalization, and non-negativity constraint given as respectively:

$$\sum_i cw_{it}^{EB} c_{rit}\left(X_{it}\right) = m_r \quad \text{with} \quad r \in 1, ..., R \tag{6.15}$$

$$\sum_i cw_{it}^{EB} = 1 \tag{6.16}$$

$$cw_{it}^{EB} \geq 0 \quad \forall i \quad \text{such that} \quad E = e, \quad e \in [0, 1]. \tag{6.17}$$

Having estimated exposure and censoring weights, we compute the final weights as the product of the cumulative products of exposure and censoring weights:

$$FW_i^{EB} = \prod_{t=1}^{6} w_{it}^{EB} \times \prod_{t=1}^{6} cw_{it}^{EB}, \tag{6.18}$$

where $\prod_{t=1}^{6} w_{it}^{EB}$ and $\prod_{t=1}^{6} cw_{it}^{EB}$ are the cumulative products of estimated exposure and censoring weights, respectively, for follow up years 1-6.

Estimation. After having constructed the final weights, we estimate the mental health effects of night shift work by reweighing the sample and running the following logistic regression:

$$MH_{it} = \alpha + \beta^{msm} \sum_{l=t-p}^{t-1} E_{il} + \epsilon_{it}, \tag{6.19}$$

where MH_{it} is an indicator for nurse i having mental health issues in period t; $\sum_{l=t-p}^{t-1} E_{il}$ is cumulative exposure to night work the past p years (between $t-p$ and $t-1$); and ϵ_{it} is an idiosyncratic error term. Since we have reweighted the sample to balance characteristics, we do not need to include a vector of covariates in (6.19). We estimate the model using Generalized Estimations Equation (GEE) estimator assuming an exchangeable correlation structure, i.e. all mental health responses within a nurse are equally correlated (Ford, 2023). Appendix section B.1.3 provides details on the GEE estimator. We model (6.19) using logistic and linear regressions for binary and continuous outcomes, respectively. We cluster standard errors at the individual level.

The coefficient of interest β^{msm} measures the change in nurses' probability of having mental health issues due to an additional year of exposure to night shift work. Testing our hypotheses put forth in section 3.2 amounts to testing

$$H_0 : \beta^{msm} \neq 1, \quad H_A : \beta^{msm} = 1.$$

Since we estimate (6.19) using logistic regression when evaluating extensive margin responses, we report results in odds ratios, so $\beta^{msm} = 1$ is equivalent to no mental health effect of night shift work. We evaluate the hypothesis in section 7.1.

6.2 Identification Strategy

We now turn to the discussion of the identification strategies of the traditional and sequentiel weighted matching approaches. As noted earlier, the approaches must address three issues: the healthy worker effect, confounding, and attrition.

6.2.1 The Traditional Approach

The traditional approach outlined in section 6.1.1 provides causal estimates of the mental health effects of night shift work under the assumption that exposure is random conditional on past mental health and observable characteristics. However, this assumption is unlikely to hold. First, the approach does not address the healthy worker effect. Controlling for lagged health and exposure does not preclude that nurses' mental health three years ago influenced their night shift work two years ago and vice versa. Second, the approach possibly suffers from confounding. It relies on prior mental health and other covariates capture any other variation in current mental health, not influenced by cumulative exposure to night shift work. Although we control for a wide range of characteristics, there may be some (potentially unobserved) factors impacting mental health, which we have not been able to include in the model. Finally, the approach does not account for attrition. If unhealthy workers leave their jobs, past health issues are underestimated. In conclusion, the traditional approach presumably produces biased estimates of β^{trad} due to endogenous selection, confounding, and attrition. Hence, the results may suggest that night shift work positively affects nurses' mental health. This concern is our reason for turning to the sequential weighted matching approach, which we expect to reduce bias in the estimates of the mental health effects of night shift work.

6.2.2 The Sequential Weighted Matching Approach

The SWM approach outlined in section 6.1.2 produces causal estimates of the mental health effects of night shift work under the Dynamic Conditional Independence Assumption; in each period, there is no unobserved confounding after controlling for observable characteristics and exposure history (i.e., after reweighing our sample). The assumption ensures that exposure is random, so any changes in mental health can be attributed to night shift work. It fails if observable or unobservable characteristics affect exposure systematically. Arguably, we do not observe all important information, so the share of nurses with unobserved subclinical or untreated mental health problems may be higher among non-night workers. In that case, our estimates will be downward biased due to the healthy worker effect. However, the advantage of weighted matching compared to controlling for covariates in a standard regression is that the latter cannot handle endogeneity in time dimensions when a feedback mechanism exists between health and exposure over time. In this setting, sequentially weighting the treatment and control groups can ensure that treatment is as good as randomized in each period and thus solve the endogeneity problem by accounting for time-varying confounding and exposure by eliminating endogenous feedback effects between health status and exposure. In particular, this ensures that the exposed group is not healthier than the unexposed group in each period, which otherwise causes a healthy worker bias. Hence, even if we do not have all relevant variables, we can better correct for part of the healthy worker effect relative to existing studies, which gives a less biased lower bound of the adverse effects of night work on mental health. Further, if we fail to account for other relevant factors besides health, the approach will produce biased estimates due to confounding. Yet, we have controlled for all (observable) characteristics, which we presume are important for predicting whether a nurse is a night worker. Finally, we explicitly address the

attrition issue. By applying censoring weights, we ensure that the characteristics of censored nurses are as well-represented in the sample as if they had not been censored. In conclusion, the sequential marginal weighting approach provides better opportunities to appropriately handle the endogeneity issues caused by the healthy worker effect, confounding, and attrition and produces significantly less biased estimates of the mental health effects of night shift work.

7 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 nurses who are not exposed to night shift work. 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.

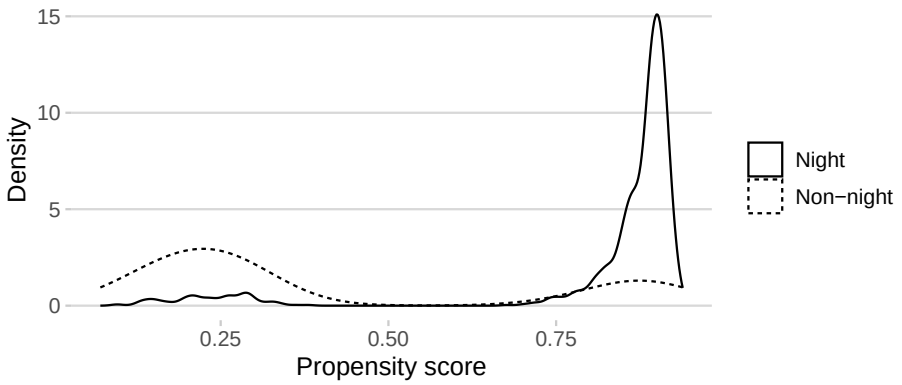
7.1 Assessing the Matching Procedures

7.1.1 Overlapping Propensity Scores

The overlap assumption says that any combination of variables in our sample generates a positive probability of being a night worker, independent of actual exposure. It implies that for all non-night workers, we can find a night worker with a similar propensity score, and vice versa. In practice, we want the propensity scores from the exposed and the unexposed groups to overlap since this implies regions where the two groups share comparable characteristics. We can thus easily assess overlap by plotting the distributions of propensity scores for the night and non-night workers and checking that there are no propensity scores at 0 or 1.

Figure 7.1 shows the propensity scores for the night and non-night workers, that is, the probability that they would be night workers, conditional on observable characteristics. The propensity score distributions are bimodal for both groups. Lagged work arrangements give rise to this bimodal distribution because nurses with night work at $t-1$ are much more likely to be night workers at time t. The propensity scores for nurses with non-night work at $t-1$ are distributed around the left peak, whereas those for nurses with night work at $t-1$ are distributed around the right peak. Importantly, there is an overlap of night and non-night workers' propensity scores around each peak, which shows that we have comparable observations in each group. Although the distributions differ in density across the propensity score, we can scale the populations to become more similar with inverse probability weighting because there is overlap in the propensity scores.

Figure 7.1: *Distribution of Propensity Scores among Night and Non-Night Workers*



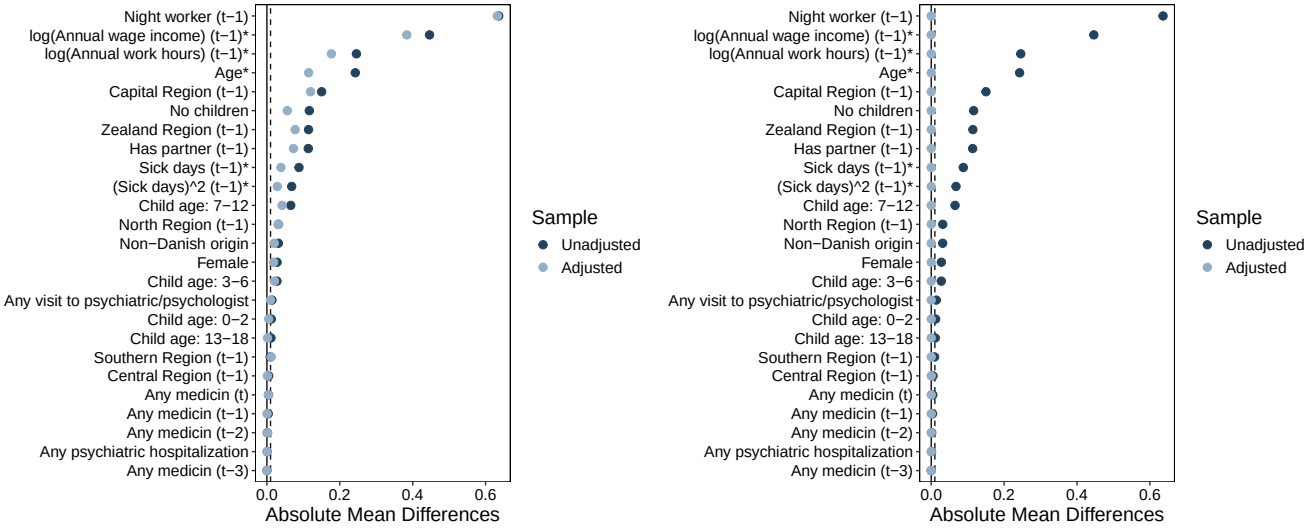
Note: Distribution of propensity scores among night and non-night workers. Propensity scores are estimated using the model specified in (6.3). We control for age, gender, origin, region of residence, partnership status, having children, age of youngest child, night work exposure, working hours, wage income, sick days as well as contacts with psychiatric hospitals, psychiatrists, and psychologists in the year before.

7.1.2 Covariate Balance

Our empirical strategy aims to construct two groups of nurses who are identical in all aspects except that one is exposed to an additional year of night shift work and the other is not. To do so, we balance the characteristics of nurses in each group to the extent that our data allows. More specifically, we weigh individuals in the groups of exposed and unexposed nurses according to their characteristics. Unexposed nurses who are less similar to exposed nurses are weighted up, and exposed nurses who are less similar to unexposed nurses are also weighted up, and vice versa. We can examine the balancing of characteristics before and after weighting the groups by looking at the difference in the average of each characteristic across the groups.

Figure 7.2: *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. * Indicate continuous variables where we show the standardized mean difference. The dark blue dots reflect differences before weighting the sample, and the light blue does illustrate differences after weighting the sample. Figure 7.2a shows the results of using the Inverse Probability Weighting method to weight the sample. Figure 7.2b presents the results of using the Entropy Balancing method to weight the sample.

Figure 7.2a shows the difference in average characteristics between exposed and unexposed nurses three years after initial hire at a public hospital. The darker and lighter blue dots represent differences before and after weighting the sample using the Inverse Probability Weighting (IPW) method, respectively. Surely, 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 exposure, 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 6.2.2. Therefore, we turn to entropy balancing to improve the balancing of characteristics across the groups.

Figure 7.2b shows the difference in average characteristics between exposed and unexposed nurses three years after initial hire at a public hospital. The darker and lighter blue dots represent differences before and after weighting the sample using the Entropy Balancing (EB) method, respectively. Clearly, the two groups' average characteristics are identical when we apply EB weights. This is because the EB procedure mechanically ensures that the average of characteristics is exactly identical across the

two groups. As similarity between the groups increases the validity of our identification strategy and thus minimizes bias in our estimation results, we prefer using Marginal Structural Models with Entropy Balancing when estimating the mental health effects of night shift work.

7.2 The Mental Health Effects of Night Shifts

7.2.1 Main Results

The main outcomes in our analysis are whether a nurse redeems prescriptions for psychotropic medication, the dose of these medications, and nurses' number of sick days. Table 7.1 shows the effect of night shift work on these three outcomes, estimated following the traditional approach or the sequential weighted matching approach with weights constructed using IPW or EB. Our main model pools data for up to six years of working as a nurse since graduation, depending on censoring during this period. The results for the extensive margin response in psychotropic medication from the traditional model suggest that night shift work protects mental health with an odds ratio of 0.91. This implies that an additional year of night shift work reduces the odds of redeeming prescriptions for psychotropic medication by 9%. The MSM estimates range from 1.12-1.24, suggesting that night shift work increases the odds by 12-24% with each additional year of night shift work. These results imply that a nurse with 5 years of night shift work has $5^{1.24} \approx 3$ times higher odds of redeeming prescription drugs than a nurse with 5 years of non-night shift work. These results show that it is important to account for the healthy worker effect since it alters the sign of our main parameter. Moreover, the results are statistically significant. Turning to the intensive margin, the traditional approach suggests night shift work protects mental health by decreasing DDD by $-.85$ each additional year of night shift work. In contrast, the MSM models suggest the opposite: DDD increases by $2-4$ with each additional year of night shift work. However, the results are not significant at a 5% level. For sickness absence, the results are mixed and insignificant, suggesting no clear relationship between cumulative night shift work and sickness absence.

We evaluate our hypothesis put forth in section 3.2 and formulated in section 6.1 based on the extensive margin responses to night shift work reported in Table 7.1. The table shows that we cannot rule out that $\beta^{trad} = 1$, so based on the traditional approach, we can therefore reject our H_0 stating that night shift work impairs mental health. However, the results from MSM using either IPW or EB to construct weights illustrate that we cannot rule out that $\beta^{msm} \neq 1$. Thus, based on results from our preferred estimations strategies, we cannot reject our H_0 that there are adverse mental health effects of night shift work.

In table 7.2, we estimate the SWM-model for any mental health issue where the cumulative years of exposure are modelled as a categorical variable. The estimates are more noisy than the parsimonious specification, where cumulative exposure is continuous but useful for illustrating how we can interpret our results. 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 increases the odds by a factor of 1.21-1.25[10], which is similar to the estimate 1.24 from the main results with a continuous specification of cumulative exposure.

[10] $2.56^{(1/5)} \approx 1.21$ and $2.45^{(1/4)} \approx 1.25$

Table 7.1: *Mental Health Effects of Cumulative Exposure to Night Shift Work*

			95% CI			
Model	e^{β}	t-statistic	Lower	Upper	Persons	Person-years
Any mental health issue						
Traditional	0.91	2.45	0.81	1.02	3513	11498
MSM-IPW	1.12	3.72	1.00	1.25	3513	11498
MSM-Ebal	1.24	4.41	1.01	1.52	3513	11498
Dose						
Traditional	-0.88	2.50	-1.97	0.21	3513	11498
MSM-IPW	1.79	2.03	-0.67	4.24	3513	11498
MSM-Ebal	4.09	2.90	-0.62	8.80	3513	11498
Sick days						
Traditional	-0.33	3.50	-0.67	0.02	3513	11498
MSM-IPW	0.10	0.15	-0.39	0.58	3513	11498
MSM-Ebal	-0.50	2.37	-1.14	0.14	3513	11498

Note: Traditional: Follows the traditional approach with outcome on the LHS and cumulative exposure and all covariates on the RHS as specified in (6.1). MSM-IPW: Marginal Structural Model using Inverse Probability Weighting where propensity scores are based on logistic regression. MSM-Ebal: Marginal Structural Model using balancing weights generated from entropy-balancing. The Marginal Structural Model is specified in (6.19). Weights are winzorised at the 1 and 99 percentile. Any mental health issue: The outcome variable is an indicator for redeeming prescriptions for psychotropic medication. Dose: The outcome variable is a continuous measure of psychotropic medication dose, measured using WHO's definition of Defined Daily Dose (DDD). Sick days: The outcome variable is the number of sick days. The extensive margin of mental health (any mental health issue) is modeled using logistic regression, while the intensive margin (dose) and sick days are modeled using linear regression.

7.2.2 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 4 to 5 years of night shift work. However, the effect on the extensive and intensive margin concerning mental health tends to increase if we consecutively add more follow-up years to the estimation sample. This pattern is what we see in table Table 7.3. Only after 5 years of follow-up did the odds ratio increase from 1.07 to 1.34 for mental health at the extensive margin and the effect of dose increase from 0.07 DDD to 2.75 DDD.[11] This suggests that the cumulative effects of an additional year also depend on how many years a person has previously been exposed. This indicates that our main results 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. Adding follow-up years consecutively to the sickness absence model does not reveal any discernible patterns. Rather, the results underscore that we do not find evidence suggesting that cumulative years of night shift work affect sickness absence.

7.3 Robustness Checks

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). This threshold allows for flexibility since subjects taking only a few night shifts a year do not necessarily consider themselves night workers. Nevertheless, we tested the sensitivity of our results to different thresholds.

[11] At follow-up year 1, the effect 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, 4 to 5 years etc.).

Table 7.2: *Extensive Margin Mental Health Effects of Cumulative Exposure to Night Shift Work with Categorical Instead of Continuous Exposure Assessment*

			95% CI	
Cumulative years with night shift work	e^{β}	t-statistic	Lower	Upper
Ref: 0 years				
1 year	0.84	0.56	0.53	1.32
2 years	1.55	1.68	0.80	3.01
3 years	1.05	0.01	0.46	2.43
4 years	2.45	2.96	0.88	6.79
5 years	2.56	3.24	0.92	7.09
6 years	1.06	0.01	0.33	3.39
Person-years	11498			
Persons	3513			

Note: Results from a Marginal Structural Model employing balancing weights generated with Entropy Balancing, estimated with GEE and modeled using logistic regression. The outcome variable is an indicator for redeeming prescriptions for psychotropic medication. Rather than utilizing a continuous measure of cumulative exposure to night work as in Table 7.1, we use indicator variables for cumulative years of exposure ranging from 1 to 6 years. Weights are winzorised at the 1 and 99 percentile.

The results are reported in Table 7.4. Lowering the threshold by a factor 0.5, the odds ratio increases from 1.24 to 1.3 but is still significant. Increasing the threshold by a factor 1.5 and 2 lowers the odds ratio to 1.17 and 1.18, respectively. For these estimates, the lower part of the 95%-confidence interval is just below 1, which indicates that the results are not statistically significant. 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. In either case, the results are qualitatively similar.

Compensating wage differentials theory predicts that jobs with worse working conditions are compensated with higher wages. However, suppose better working conditions are a normal good. In that case, demand for better working conditions should rise in income, which can explain why better working conditions and better wages can bundle together (Lavetti, 2023). While such an explanation is plausible across different occupations and seniority levels, compensating wage differentials due to night shifts are more likely to explain wage differentials in our design since nurses have the same seniority level at each follow-up year. Since wage differentials mechanically increase when night shift work increases, equivalized disposable income may better capture whether income effects alter the propensity to work night shifts. By adjusting weights using equivalized disposable income rather than wage income, the odds ratio only increases slightly to 1.28, which suggests that income effects do not play a significant role in selection.

We proceeded to test whether it was important to adjust for lagged night worker status by excluding it from the estimation of the weights. The odds ratio is more precise but otherwise identical to our main results. Lastly, we exclude working hours and wage income to examine whether they cushion the negative effects of night work on mental health. The odds ratio (1.22) is virtually identical to our preferred model (1.24), indicating that higher income and fewer work hours from night work do not cushion the adverse effect.

7.4 The Compensatory and Social Effects of Night Shifts

Does night shift work affect another outcome relevant to individuals' well-being, which can corroborate our results? To answer this, we study the impact on nurses' social life and their degree of compensation. In

Table 7.3: *Mental Health Effects of Cumulative Exposure to Night Shift Work Evaluated at Varying Follow Up Years*

			95% CI			
	e^{β}	t-statistic	Lower	Upper	Persons	Person-years
Any mental health issue						
Year 1	0.96	0.03	0.62	1.51	3524	3524
Year 2	0.98	0.03	0.77	1.24	3524	6199
Year 3	0.99	0.01	0.81	1.20	3524	8178
Year 4	1.07	0.35	0.86	1.32	3524	9664
Year 5	1.34	7.34	1.08	1.66	3524	10768
Year 6	1.30	7.28	1.07	1.57	3524	11580
Dose						
Year 1	-1.90	0.45	-7.42	3.63	3524	3524
Year 2	-0.99	0.63	-3.44	1.46	3524	6199
Year 3	-1.58	4.31	-3.07	-0.09	3524	8178
Year 4	0.07	0.35	-0.15	0.28	3524	9664
Year 5	2.75	2.30	-0.81	6.31	3524	10768
Year 6	4.27	3.14	-0.45	8.99	3524	11580
Sick days						
Year 1	0.27	0.08	-1.56	2.09	3524	3524
Year 2	-0.02	0.00	-1.01	0.98	3524	6199
Year 3	-0.31	0.74	-1.03	0.40	3524	8178
Year 4	0.07	0.35	-0.15	0.28	3524	9664
Year 5	-0.34	0.89	-1.03	0.36	3524	10768
Year 6	-0.51	2.64	-1.13	0.11	3524	11580

Note: Results from a Marginal Structural Model using balancing weights estimated with Entropy Balancing, estimated using GEE. Weights are winzorised at the 1 and 99 percentile. Any mental health issue: The outcome variable is an indicator for redeeming prescriptions for psychotropic medication. Dose: The outcome variable is a continuous measure of psychotropic medication dose, measured using WHO's definition of Defined Daily Dose (DDD). Sick days: The outcome variable is the number of sick days. The extensive margin of mental health (any mental health issue) is modeled using logistic regression, while the intensive margin (dose) and sick days are modeled using linear regression.

these analyses, we use our preferred specification, sequentially weighted matching with entropy balancing, to account for healthy worker bias and other relevant observables.

7.4.1 The Compensatory Effects of Night Shifts

The results reported in table Table 7.5 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 increases nurses' annual wage income by around 17,778 DKK, corresponding to yearly income growth of about 5% relative to nurses with an additional year of regular shift work. At the same time, an additional year of night shift work reduces annual working hours by around 26, corresponding to a yearly reduction in working hours of about 2%. This is also reflected in approximately 4 fewer shifts per year. Moreover, night-shift workers have approximately two more vacation days. Night workers also have 2.9 fewer returns to work within 24 hours and 2.5 fewer returns within 48 hours, which shows that night workers more often have longer rest periods. However, there is 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).

Table 7.4: *Extensive Margin Mental Health Effects of Cumulative Exposure to Night Shift Work, with Varying Night Worker Thresholds and Weight Adjustments*

			95% CI			
Model	e^{β}	t-statistic	Lower	Upper	Persons	Person-years
Night worker threshold						
6.7 pct. × 0.5	1.30	7.35	1.08	1.58	3513	11498
6.7 pct.	1.24	4.36	1.01	1.52	3513	11498
6.7 pct. × 1.5	1.17	3.15	0.98	1.39	3513	11498
6.7 pct. × 2	1.18	1.95	0.94	1.48	3513	11498
Weights adjusted for						
Equivalized disposable income†	1.28	5.44	1.04	1.57	3513	11498
Weights not adjusted for						
Lagged night worker status	1.24	8.77	1.07	1.42	3513	11498
Working hours and wage income	1.22	3.95	1.00	1.47	3513	11498

Note: Results from a Marginal Structural Model using balancing weights estimated with Entropy Balancing, estimated with GEE and modeled using logistic regression. Weights are winzorised at the 1 and 99 percentile. 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 unless stated otherwise in the table. †Equivalized disposable income (actual) replaces log(annual income).

7.4.2 The Social Effects of Night Shifts

Night shift work may affect nurses' social life. On the one hand, working odd hours means having odd leisure hours, which can make it difficult to uphold social relationships and family activities, 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. In this part of our analysis, we examine how night shift work influences nurses' partnership status, fertility, and their tendency to work part-time or elsewhere than the public hospitals.

The results reported in table Table 7.5 show that night work reduces the odds by 19% of having a child the following year, and the results are statistically significant. The point estimate suggests that the odds of leaving the region are 10% lower for night workers, but the estimate is imprecise and not statistically significant. Moreover, no substantial evidence suggests that night work influences the odds of working part-time or having a partner the following year.

7.5 Discussion

Our analysis assumes that workers with better health capital are more likely to remain in jobs with higher exposure to night work. However, it is also possible that healthier workers prefer less health-demanding, non-night work arrangements. For instance, healthier nurses may engage in healthier behaviours—such as exercising regularly and maintaining a balanced diet—partly because they have lower discount rates and are less likely to engage in risky behaviours like smoking or excessive alcohol consumption. These characteristics could lead healthier nurses to sort more strongly into non-night work arrangements. We believe this does not substantially bias our results for several reasons. First, nurses undergo the same length of education, which can serve as a proxy for time preferences. This suggests that heterogeneity in time preferences within the nurse population is likely minimal. Second, our weighting procedure accounts for whether nurses with better or worse health tend to sort into or out of night work, though

Table 7.5: *Compensatory and Social Effects of Cumulative Exposure to Night Shift Work*

				95% CI (β)	
Model	α	e^{β}	t-statistic (β)	Lower	Upper
Compensatory					
Working hours	1469.81	-23.26	47.91	-29.84	-16.67
Off-duty hours	16.48	0.11	10.07	0.04	0.17
Quick returns	9.05	-0.22	2.23	-0.51	0.07
Returns within 24h	115.23	-2.58	32.67	-3.47	-1.70
Returns within 48h	118.46	-2.28	24.82	-3.17	-1.38
Shifts	184.99	-3.69	70.59	-4.55	-2.83
Vacation days	8.84	1.99	185.70	1.70	2.27
Wage income	304814.25	18430.91	229.92	16048.55	20813.27
Social (Odds ratio)					
Gets child(ren)	0.15	0.81	4.27	0.66	0.99
Has partner	2.34	1.05	1.35	0.97	1.13
Works part-time	0.06	1.06	0.50	0.91	1.24
Leaves region	0.00	0.90	1.05	0.74	1.10
Persons			3513		
Person-years			11498		

Note: Results from a Marginal Structural Model using balancing weights estimated with Entropy Balancing, estimated using GEE. 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. Social outcomes are evaluated at $t+1$, while compensatory outcomes are evaluated at t. Compensatory outcomes are modeled using linear regression, while social outcomes are modeled using logistic regression.

this adjustment is limited to observable characteristics. Importantly, our results reveal that healthier workers are more likely to remain in night-shift jobs, as evidenced by the reversal in the sign after adjusting for endogenous selection. Finally, while we cannot observe all health conditions contributing to health capital, it is unlikely that workers systematically use these unobserved conditions to sort into non-night work arrangements, as they would also remain unobservable to employers. In summary, it is implausible that our findings are significantly biased by healthier nurses leveraging their health capital to avoid night-shift work.

The legitimacy of our approach relies on the notion that matches on observables also match on unobservables that correlate with the observed variables. However, this approach can be problematic if some unobserved variables do not correlate with other observables but with the treatment and outcome variable (Stuart, 2010). Suppose we fail to observe health conditions crucial to the joint determination of night shift exposure and future mental health. Then, we cannot fully account for endogenous selection driven by the healthy worker effect. For instance, our model does not capture scenarios where nurses experiencing mild anxiety or depression symptoms transition to non-night work arrangements as a mitigation strategy. This limitation implies that our results may represent a lower bound of the true effect. Additionally, we adjust for income and work hours, which may mediate the effects of night shift work. Night workers often benefit from higher incomes and shorter average working hours, providing greater opportunities to invest in health capital—for example, by affording gym memberships or allocating additional leisure time to exercise. Adjusting for these factors may underestimate the direct effect of night shift work, suggesting it could be even larger than our findings indicate. Nevertheless, we estimate the

net effect of night shift work by incorporating income and work hours into our model, which is the policy-relevant effect, as Ravesteijn et al. (2018) argue. Moreover, other occupations with night shifts typically offer similar forms of compensation. Therefore, our findings provide a comprehensive measure of the overall impact of night shift work across comparable settings.

Our research design also rests on the stabilized unit value treatment assumption (SUTVA), which states that one subject's treatment should not affect another subject's outcome. In our framework, assigning night work to one nurse could potentially affect other nurses' mental health. For example, if night workers call in sick more often, it could put more pressure on other nurses in the same department. Moreover, ill-treated mental health issues can spill over to other nurses. However, this would require that the nurses in our sample work in the same department. The department should be relatively small so that any absence from sickness has to be covered by relatively few. Even so, our estimates do not suggest that night workers have higher sickness absences. While we show night work increases the risk of mental health issues, the proportion of nurses with mental health issues in our sample is still relatively small and if treated well, it is unlikely that these mental health issues spill over to over nurses in our sample.

Focusing on graduate nurses as a sample offers both strengths and limitations. Their relatively homogenous demographics, institutional settings, and education reduce variability stemming from differences in work arrangements and stressors across occupations. Furthermore, nurses' health education likely enhances their awareness of how night shift work affects their well-being, making them more proactive in addressing symptoms before they escalate into serious conditions.

However, nurses may differ systematically from the general population in ways that affect the external validity of the findings. For instance, nursing might disproportionately attract evening-oriented individuals, as morning-oriented people may avoid the irregular hours associated with the profession. If this is true, night shift work might impact nurses less than other populations. On the other hand, similar diurnal-type dynamics might exist in other night-shift-heavy professions, making the findings relevant beyond nursing. Finally, if sleep deprivation is the primary mechanism underlying the observed effects, the results are more likely to generalize across occupations, as sleep disruption is a common consequence of night shift work regardless of profession.

8 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 bias; 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 six years, combined with administrative data on prescriptions for psychotropic medications in Denmark.

We find that night shift work has sizable, adverse mental health effects. Nurses' odds of redeeming prescriptions for psychotropic medication increase by 12-24 pct. for each additional year of night work. Although not statistically significant, nurses also react on the intensive margin by increasing their medication dose. We present evidence suggesting that night shift work impairs mental health because of sleep deprivation rather than a lack of social life. Being a night worker does not change nurses' probability of having a family, working part-time, or leaving public hospital employment. Nurses are compensated for working night shifts because of its disadvantages, e.g., the inconvenience of working odd hours, influence on sleep and circadian rhythms, as well as physical health effects. We document nurses' compensation along several dimensions: increased earnings, off-duty time between shifts, and vacation days, as well as reduced working hours, shifts, and returns within 24 or 48 hours. In sum, night workers incur costs regarding their mental health and benefits in terms of earnings and work intensity. Whether the benefits outweigh the cost is yet to be determined and is beyond the scope of our paper.

We show that the traditional 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 that suggest that night shift work has a protective effect on mental health. Hence, using the traditional or SWM approach generates contrasting results. This demonstrates the importance of accounting for the healthy worker bias 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 bias, which we show is important because it changes the policy implications of our analysis.

Despite its contributions, our study has some notable limitations. First, night workers with mild symptoms of mental illness who transition to non-night workers are not captured as sick in our analysis, so our results represent a lower bound of the true mental health effect of night shift work. Second, our study measures the direct effect of night shift work on mental health, not considering any indirect effects through higher income and fewer working hours. Third, our sample of graduate nurses arguably reduces 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.

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. One policy implication is to increase compensation for night shift work. Earning a higher income and working fewer hours gives night workers more time to rest, reducing sleep deprivation and, thereby, adverse mental health effects. However, such a proposal seems ambitious, given recent negotiations of nurses' collective agreements. A more realistic proposition is to include explicit recommendations in the agreements to

recognise the mental health consequences of night shift work when constructing shift schedules. A second implication is to monitor night workers' mental health more closely than what has been done so far, potentially by making the voluntary health examinations mandatory and passing them a condition for working night shifts.

We recognize several directions for future research. First, while our approach adjusts for the healthy worker bias 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, we identify the direct effects of night shift work on mental health. Still, there may be indirect effects through the income and work intensity compensations, and future research should attempt to distinguish between the direct and indirect effects (VanderWeele, 2009; Coffman and Zhong, 2012). Third, our analysis examines the impact of being exposed to night work or not, and future research should investigate how the intensity of exposure matters for mental health. 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 Data and Sample

Table A.1: *Summary Statistics on Estimation Sample Incl. Censored, Nurses with Prior Mental Health Issues, and Graduate Nurses Not Hired within One Year*

Variable	**Description**
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
Packages	Number of packages redeemed
ATC	The Anatomical Therapeutic Chemical code, N06 and N05
Volume	The numerical volume of one package
Type of volume	Categorical, code for unit of measurement of volume
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	Starting date and time (hours and minutes) for activity
End date	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	
Referral date	Date of referral to the hospital
Admission date	Date of admission to the hospital
Discharge date	Date of discharge from the hospital
Diagnosis	Diagnosis related to hospital visit (coded following ICD-10)

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Table A.1 – continued from previous page

Variable	**Description**
	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.

Notes: The table the variables used in our analysis including the registries from which they are obtained.
Sources: Statistics Denmark (2024a), Statistics Denmark (2024c), Statistics Denmark (2024b), Statistics Denmark (2024h), Statistics Denmark (2024e), Statistics Denmark (2024d), Statistics Denmark (2024f), Statistics Denmark (2024g), DWHD, VNDS, SSSY

Table A.2: *Data Description for Selected Variables*

Variable	**Description**
Age (t)	Age in years
Female (t)	Indicator for being a female (based on social security number)
Has partner (t-1)	Indicator for having a partner (i.e., cohabiting or married)
Non-Danish origin (t)	Indicator for being of non-Danish origin (i.e., immigrant or descendant)
No children (t)	Number of children, conditional on having any children
Child age 0-2 (t)	Indicator for youngest child being 0-2 years old
Child age 3-6 (t)	Indicator for youngest child being 3-6 years old
Child age 7-12 (t)	Indicator for youngest child being 7-12 years old
Child age 13-18 (t)	Indicator for youngest child being 13-18 years old
Capital Region (t-1)	Indicator for living in the Capital Region
Zealand Region (t-1)	Indicator for living in the Zealand Region
Northern Region (t-1)	Indicator for living in the Northern Region
Central Region (t-1)	Indicator for living in the Central Region
Southern Region (t-1)	Indicator for living in the Southern Region
log(Annual wage income) (t-1)	Logarithm of 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.
log(Annual working hours) (t-1)	Logarithm of annual working hours at the public hospital
Night worker (t-1)	Indicator for being a night worker
Sick days (t-1)	Number of sick days
$(\text{Sick days})^2$ (t-1)	Number of sick days, squared
Any medicine (t)	Indicator for redeeming a prescription for psychotropic medication: psycholeptics (ATC N05) or psychoanaleptics (ATC N06) in t
Any medicine (t-1)	Indicator for redeeming a prescription for psychotropic medication: psycholeptics (ATC N05) or psychoanaleptics (ATC N06) in t-1
Any medicine (t-2)	Indicator for redeeming a prescription for psychotropic medication: psycholeptics (ATC N05) or psychoanaleptics (ATC N06) in t-2
Any medicine (t-3)	Indicator for redeeming a prescription for psychotropic medication: psycholeptics (ATC N05) or psychoanaleptics (ATC N06) in t-3
Any visit to psychiatrist / psychologist (t)	Indicator for visiting a psychiatrist or psychologist
Any mental health related hospital visit (t)	Indicator for having a mental health related hospital visit

Note: The table describes covariates used in 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-1. For the Entropy Balancing method, the covariates enter as the list of mean characteristics that should be equalized.

Table A.3: *Summary Statistics on Estimation Sample Incl. Censored Nurses*

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Demographic characteristics				

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Table A.3 – continued from previous page

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Female	0.951	0.217	0.951	0.217
Age	25.712	5.493	27.712	5.493
Is Danish	0.887	0.316	0.888	0.315
Has partner	0.539	0.499	0.665	0.472
Has children	0.232	0.422	0.31	0.462
No. children	0.418	0.815	0.517	0.867
Youngest child aged 0-2	0.112	0.316	0.156	0.363
Youngest child aged 3-6	0.07	0.255	0.083	0.276
Youngest child aged 7-12	0.032	0.177	0.051	0.219
Youngest child aged 13-18	0.018	0.131	0.019	0.137
North	0.074	0.261	0.075	0.264
Central	0.264	0.441	0.252	0.434
Southern	0.173	0.379	0.18	0.384
Capital	0.338	0.473	0.37	0.483
Zealand	0.129	0.336	0.123	0.329
Health characteristics				
Any mental health medication	0	0	0.026	0.158
Any psycholeptic medication	0	0	0.012	0.107
Any psychoanaleptic medication	0	0	0.016	0.124
Mental health medication dose	0	0	3.746	45.883
Psycholeptic medication dose	0	0	0.91	33.537
Psychoanaleptic medication dose	0	0	2.836	31.286
Any hosp. visit for mood, anxiety, or stress-disorder	0.002	0.047	0.002	0.05
Any mental health related visit to hospital	0.005	0.074	0.005	0.074
Any psychiatrist or psychologist visit	0.026	0.159	0.03	0.171
Socioeconomic characteristics				
Wage income	48417.55	53144.862	314136.399	55255.783
Night worker	0	0	0.621	0.485
Working hours	0	0	1485.401	275.482
Working hours, night shifts	0	0	193.485	177.533
No. shifts	0	0	183.421	33.658
No. night shifts	0	0	33.02	21.19
Share of night shifts	0	0	0.128	0.117
No. quick returns	-	-	9.292	7.854
No. early starts	0	0	0.107	0.951
Sick	0	0	0.905	0.293
Sick days	0	0	12.056	17.055
Sick periods	0	0	1.454	1.264
On maternity leave or pregnant	0	0	0.089	0.285
Temp. empl. agencies	0.028	0.164	-	-
Hospitals	0.008	0.087	0.936	0.245
General practitioners	0.004	0.064	-	-
Other health care	0.014	0.116	0.005	0.072
Institutions	0.2	0.4	0.014	0.116

Continued on next page

Table A.3 – continued from previous page

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Home care	0.061	0.24	0.003	0.057
Other industry	0.685	0.465	0.04	0.197
Employed elsewhere	0.53	0.499	0.001	0.037
Has secondary employment	-	-	0.003	0.055
Unemployed	0.026	0.159	0.005	0.072
Out of the labor force	0.409	0.492	0.018	0.131
Full time	0	0	0.967	0.18
Employed at public hospital	0	0	0.999	0.037
Part time	0	0	0.032	0.176
N	3649		3649	

Notes: 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, works full time during their first year of employment, and have not redeemed prescriptions for mental health medication (psycholeptic or psychoanaleptic) during the five years before employment. In the estimation sample, individuals are censored if they die, emigrate, work part time or outside the region. The table shows statistics for the estimation sample including these censored individuals. Follow up year refers to years since graduation. Follow up year 1 is the full year in which nurses are employed at the public hospitals.

Table A.4: *Summary Statistics on Estimation Sample Incl. Nurses w. Prior Mental Health Issues*

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Female	0.953	0.211	0.953	0.211
Age	26.029	5.785	28.029	5.785
Is Danish	0.892	0.31	0.893	0.309
Has partner	0.543	0.498	0.665	0.472
Has children	0.245	0.43	0.313	0.464
No. children	0.436	0.825	0.522	0.865
Youngest child aged 0-2	0.111	0.314	0.145	0.352
Youngest child aged 3-6	0.076	0.264	0.089	0.285
Youngest child aged 7-12	0.038	0.192	0.058	0.233
Youngest child aged 13-18	0.019	0.138	0.022	0.146
North	0.071	0.257	0.072	0.258
Central	0.264	0.441	0.251	0.434
Southern	0.172	0.378	0.181	0.385
Capital	0.339	0.474	0.369	0.483
Zealand	0.134	0.34	0.128	0.334
Any mental health medication	0.071	0.257	0.074	0.261
Any psycholeptic medication	0.027	0.163	0.023	0.149
Any psychoanaleptic medication	0.056	0.229	0.059	0.236
Mental health medication dose	21.2	111.119	20.732	112.462
Psycholeptic medication dose	1.091	16.186	1.807	38.588
Psychoanaleptic medication dose	20.109	106.986	18.925	102.339
Any hosp. visit for mood, anxiety, or stress-disorder	0.008	0.088	0.006	0.078
Any mental health related visit to hospital	0.016	0.124	0.009	0.094
Any psychiatrist or psychologist visit	0.051	0.221	0.048	0.214

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Table A.4 – continued from previous page

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Wage income	47286.365	53186.326	316590.558	51796.556
Night worker	0	0	0.637	0.481
Working hours	0	0	1511.944	205.143
Working hours, night shifts	0	0	197.989	180.857
No. shifts	0	0	186.611	25.088
No. night shifts	0	0	33.647	21.532
Share of night shifts	0	0	0.131	0.121
No. quick returns	-	-	9.387	7.821
No. early starts	0	0	0.107	0.924
Sick	0	0	0.922	0.268
Sick days	0	0	12.992	17.213
Sick periods	0	0	1.526	1.32
On maternity leave or pregnant	0	0	0.082	0.274
Temp. empl. agencies	0.028	0.164	-	-
Hospitals	0.008	0.088	0.932	0.251
General practitioners	0.004	0.062	0.001	0.035
Other health care	0.013	0.115	0.006	0.078
Institutions	0.195	0.396	0.015	0.122
Home care	0.06	0.238	0.004	0.06
Other industry	0.692	0.462	0.041	0.198
Employed elsewhere	0.517	0.5	0	0
Has secondary employment	-	-	0.003	0.056
Unemployed	0.027	0.161	0.006	0.076
Out of the labor force	0.424	0.494	0.019	0.136
Full time	0	0	1	0
Employed at public hospital	0	0	1	0
Part time	0	0	0	0
N	4118		4118	

Notes: 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 works full time during their first year of employment. In the estimation sample, we exclude individuals that have redeemed prescriptions for mental health medication (psycholeptic or psychoanaleptic) during the five years before employment. Moreover, individuals are censored if they die, emigrate, work part time or outside the region. The table shows statistics for the estimation sample excluding censored but including individuals who redeem prescriptions for mental health medication within the five years before employment. Follow up year refers to years since graduation. Follow up year 1 is the full year in which nurses are employed at the public hospitals.

Table A.5: *Summary Statistics on Estimation Sample Incl. Censored and Nurses w. Prior Mental Health Issues*

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Female	0.954	0.21	0.954	0.21
Age	26.039	5.794	28.039	5.794
Is Danish	0.892	0.311	0.893	0.309
Has partner	0.548	0.498	0.668	0.471
Has children	0.247	0.432	0.322	0.467

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Table A.5 – continued from previous page

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
No. children	0.441	0.829	0.535	0.872
Youngest child aged 0-2	0.112	0.315	0.153	0.36
Youngest child aged 3-6	0.077	0.267	0.09	0.286
Youngest child aged 7-12	0.039	0.193	0.058	0.233
Youngest child aged 13-18	0.019	0.138	0.022	0.146
North	0.073	0.26	0.073	0.26
Central	0.264	0.441	0.251	0.433
Southern	0.173	0.379	0.181	0.385
Capital	0.336	0.472	0.366	0.482
Zealand	0.135	0.341	0.128	0.335
Any mental health medication	0.074	0.261	0.076	0.264
Any psycholeptic medication	0.028	0.165	0.024	0.153
Any psychoanaleptic medication	0.058	0.233	0.06	0.238
Mental health medication dose	22.248	115.154	21.861	117.416
Psycholeptic medication dose	1.077	15.904	1.839	37.98
Psychoanaleptic medication dose	21.171	111.294	20.021	107.946
Any hosp. visit for mood, anxiety, or stress-disorder	0.008	0.088	0.006	0.079
Any mental health related visit to hospital	0.015	0.122	0.01	0.099
Any psychiatrist or psychologist visit	0.053	0.223	0.05	0.218
Wage income	47179.391	52872.176	314020.434	54916.086
Night worker	0	0	0.614	0.487
Working hours	0	0	1475.532	280.847
Working hours, night shifts	0	0	192.21	180.341
No. shifts	0	0	182.181	34.333
No. night shifts	0	0	32.937	21.56
Share of night shifts	0	0	0.128	0.12
No. quick returns	-	-	9.14	7.807
No. early starts	0	0	0.104	0.908
Sick	0	0	0.912	0.283
Sick days	0	0	13.162	18.915
Sick periods	0	0	1.511	1.326
On maternity leave or pregnant	0	0	0.088	0.283
Temp. empl. agencies	0.027	0.163	-	-
Hospitals	0.007	0.086	0.931	0.253
General practitioners	0.004	0.061	0.001	0.037
Other health care	0.013	0.114	0.006	0.078
Institutions	0.196	0.397	0.015	0.122
Home care	0.061	0.239	0.004	0.063
Other industry	0.692	0.462	0.041	0.199
Employed elsewhere	0.516	0.5	0.002	0.043
Has secondary employment	-	-	0.004	0.059
Unemployed	0.027	0.163	0.006	0.079
Out of the labor force	0.424	0.494	0.019	0.136
Full time	0	0	0.964	0.186

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Table A.5 – continued from previous page

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Employed at public hospital	0	0	0.998	0.043
Part time	0	0	0.034	0.182
N	4276		4276	

Notes: 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 works full time during their first year of employment. In the estimation sample, we exclude individuals that have redeemed prescriptions for mental health medication (psycholeptic or psychoanaleptic) during the five years before employment. Moreover, individuals are censored if they die, emigrate, work part time or outside the region. The table shows statistics for the estimation sample including censored as well as individuals who redeem prescriptions for mental health medication within the five years before employment. Follow up year refers to years since graduation. Follow up year 1 is the full year in which nurses are employed at the public hospitals.

Table A.6: *Summary Statistics on Censored Nurses*

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Female	0.968	0.175	0.968	0.175
Age	25.331	4.943	27.331	4.943
Is Danish	0.896	0.306	0.897	0.304
Has partner	0.594	0.491	0.725	0.447
Has children	0.219	0.413	0.348	0.476
No. children	0.373	0.764	0.566	0.883
Youngest child aged 0-2	0.116	0.32	0.222	0.416
Youngest child aged 3-6	0.067	0.25	0.073	0.26
Youngest child aged 7-12	0.023	0.149	0.038	0.191
Youngest child aged 13-18	0.013	0.114	0.015	0.121
North	0.081	0.273	0.08	0.271
Central	0.271	0.445	0.262	0.44
Southern	0.186	0.389	0.198	0.399
Capital	0.306	0.461	0.339	0.474
Zealand	0.132	0.338	0.121	0.326
Any mental health medication	0	0	0.02	0.141
Any psycholeptic medication	0	0	0.011	0.102
Any psychoanaleptic medication	0	0	0.011	0.106
Mental health medication dose	0	0	2.273	25.075
Psycholeptic medication dose	0	0	0.282	4.197
Psychoanaleptic medication dose	0	0	1.99	24.4
Any hosp. visit for mood, anxiety, or stress-disorder	-	-	-	-
Any mental health related visit to hospital	-	-	0.006	0.078
Any psychiatrist or psychologist visit	0.019	0.138	0.028	0.165
Wage income	50628.737	52694.758	305349.582	63107.194
Night worker	0	0	0.558	0.497
Working hours	0	0	1414.095	388.867
Working hours, night shifts	0	0	173.692	168.918
No. shifts	0	0	174.746	47.38
No. night shifts	0	0	30.423	20.398

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Table A.6 – continued from previous page

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Share of night shifts	0	0	0.117	0.109
No. quick returns	-	-	8.852	7.852
No. early starts	0	0	0.086	0.546
Sick	0	0	0.882	0.322
Sick days	0	0	11.508	18.587
Sick periods	0	0	1.414	1.264
On maternity leave or pregnant	0	0	0.147	0.355
Temp. empl. agencies	0.032	0.177	0	0
Hospitals	0.008	0.089	0.945	0.229
General practitioners	0.004	0.066	0	0
Other health care	0.013	0.114	-	-
Institutions	0.203	0.402	0.011	0.106
Home care	0.065	0.247	-	-
Other industry	0.674	0.469	0.039	0.193
Employed elsewhere	0.536	0.499	0.004	0.066
Has secondary employment	-	-	0.006	0.078
Unemployed	0.024	0.152	0.005	0.072
Out of the labor force	0.407	0.492	0.022	0.147
Full time	0	0	0.893	0.309
Employed at public hospital	0	0	0.996	0.066
Part time	0	0	0.103	0.304
N	1139		1139	

Notes: 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 works full time during their first year of employment. In the estimation sample, individuals are censored if they die, emigrate, work part time or outside the region. The table shows statistics for individuals in the estimation sample who are censored at one point during the follow up period. Follow up year refers to years since graduation. Follow up year 1 is the full year in which nurses are employed at the public hospitals.

Table A.7: *Summary Statistics on Estimation Sample Incl. Censored, Nurses with Prior Mental Health Issues, and Graduate Nurses Not Hired within One Year*

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Female	0.954	0.21	0.954	0.21
Age	26.203	5.916	28.039	5.794
Is Danish	0.878	0.327	0.893	0.309
Has partner	0.552	0.497	0.668	0.471
Has children	0.257	0.437	0.322	0.467
No. children	0.452	0.834	0.535	0.872
Youngest child aged 0-2	0.124	0.33	0.153	0.36
Youngest child aged 3-6	0.075	0.264	0.09	0.286
Youngest child aged 7-12	0.039	0.193	0.058	0.233
Youngest child aged 13-18	0.019	0.138	0.022	0.146
North	0.073	0.259	0.073	0.26
Central	0.259	0.438	0.251	0.433

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Table A.7 – continued from previous page

Follow up year	−1		1	
Variable	Mean	SD	Mean	SD
Southern	0.173	0.378	0.181	0.385
Capital	0.33	0.47	0.366	0.482
Zealand	0.135	0.341	0.128	0.335
Any mental health medication	0.077	0.266	0.076	0.264
Any psycholeptic medication	0.029	0.168	0.024	0.153
Any psychoanaleptic medication	0.06	0.238	0.06	0.238
Mental health medication dose	23.581	126.313	21.861	117.416
Psycholeptic medication dose	1.594	29.012	1.839	37.98
Psychoanaleptic medication dose	21.987	115.765	20.021	107.946
Any hosp. visit for mood, anxiety, or stress-disorder	0.007	0.084	0.006	0.079
Any mental health related visit to hospital	0.015	0.122	0.01	0.099
Any psychiatrist or psychologist visit	0.054	0.226	0.05	0.218
Wage income	45840.56	52750.793	314020.434	54916.086
Night worker	0	0	0.614	0.487
Working hours	0	0	1475.532	280.847
Working hours, night shifts	0	0	192.21	180.341
No. shifts	0	0	182.181	34.333
No. night shifts	0	0	32.937	21.56
Share of night shifts	0	0	0.128	0.12
No. quick returns	-	-	9.14	7.807
No. early starts	0	0	0.104	0.908
Sick	0	0	0.912	0.283
Sick days	0	0	13.162	18.915
Sick periods	0	0	1.511	1.326
On maternity leave or pregnant	0	0	0.088	0.283
Temp. empl. agencies	0.028	0.165	-	-
Hospitals	0.007	0.083	0.931	0.253
General practitioners	0.004	0.063	0.001	0.037
Other health care	0.013	0.111	0.006	0.078
Institutions	0.188	0.391	0.015	0.122
Home care	0.059	0.236	0.004	0.063
Other industry	0.701	0.458	0.041	0.199
Employed elsewhere	0.499	0.5	0.002	0.043
Has secondary employment	-	-	0.004	0.059
Unemployed	0.028	0.165	0.006	0.079
Out of the labor force	0.429	0.495	0.019	0.136
Full time	0	0	0.964	0.186
Employed at public hospital	0	0	0.998	0.043
Part time	0	0	0.034	0.182
N	4794		4276	

Notes: The table shows summary statistics on a sample of nurses graduating in 2009-2015. In the estimation sample, we exclude individuals that have redeemed prescriptions for mental health medication (psycholeptic or psychoanaleptic) during the five years before employment, are not hired at a public hospital within a year of graduation, and does not work full time during their first year of employment. Moreover, individuals are censored if they die, emigrate, work part time or outside the region. The table shows statistics for the estimation sample including censored as well as individuals who redeem prescriptions for mental health medication within the five years before employment, are not hired at a public hospital within a year of graduation, and does not work full time their first year of employment. Follow up year refers to years since graduation. Follow up year 1 is the full year in which nurses are employed at the public hospitals.

Table A.8: *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	43.025	43.532
Is Danish	0.942	0.939	0.931
Has partner	0.859	0.85	0.845
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
Mental health medication dose	27.813	28.691	27.007
Psycholeptic medication dose	4.819	4.017	3.883
Psychoanaleptic medication dose	22.994	24.673	23.124
Any hosp. visit for 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 psychologist or psychiatrist	0.034	0.045	0.040
Socioeconomic characteristics			
Wage income	305212.271	342835.672	369947.074
Working hours	1044.196	1103.992	1159.596
Working hours, night shifts	112.286	116.402	130.486
No. shifts	132.985	140.398	146.811
No. night shifts	25.091	24.679	26.657
Share of night shifts	0.107	0.111	0.111
No. quick returns	4.82	4.518	4.313
No. early starts	0.339	0.35	0.396
Night worker	0.25	0.257	0.266
Full time	0.675	0.722	0.741
Part time	0.325	0.278	0.259
Sick	0.781	0.769	0.734
Sick days	11.657	11.636	10.471
Sick periods	3.531	3.548	3.461
On maternity leave or pregnant	0.089	0.073	0.072
Works in the Northern region	0.108	0.112	0.105
Works in the Central region	0.239	0.233	0.231

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Table A.8 – continued from previous page

Variable	2008	2013	2018
Works in the Southern region	0.214	0.216	0.215
Works in the Zealand region	0.113	0.111	0.11
Works in the Capital region	0.326	0.328	0.338
Individuals	41791	42914	46970

Notes: The table shows summary statistics on nurses hired at a public hospital during the period from 2008 to 2018.

Table A.9: *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%

Notes: *Additional hourly wage or time off in lieu pr. hour worked in time-period. †Change from previous level implemented 1/4-2010.
Source: https://okportal.dk/

B Empirical Framework

B.1 Marginal Structural Models with Repeated Measures

B.1.1 Notation

MH_{it} denotes whether a person receives prescription medicine for a mental health condition. We suppress subject-specific notation and write MH_{it} as MH_t. Further, let Z be a vector of time-independent baseline covariates while X_t is a vector for time-varying covariates. Importantly, X_t includes MH_t. E_t denotes exposure at time t. Variables X_t are temporally before deciding E_{t+1}. Bars represent covariate history. Workers can have the exposure histories $\bar{E} = [E_1, ..., E_6]$, where E_t is equal to one if a worker is exposed to night work at time t. Further, $\bar{E}_t$ represents an exposure history through t. Similarly, $\bar{X} = [X_1, ..., X_6]$ denote covariate history. Note that Z is a subset of the variables in X_1. Workers can switch between night and non-night work. Therefore, there are 2^6 potential exposure histories. We use $\perp\!\!\!\perp$ to indicate statistical independence. Thus, $MH \perp\!\!\!\perp E \mid X$ means that mental health MH is conditionally independent of exposure E given covariates X.

B.1.2 Repearted Measures

In a controlled randomized trial, the treatment history is completely independent of potential outcomes. In this context, it translates into that the prior exposure history is independent of the counterfactual outcome:

$$MH_{\bar{e}(t+1)} \perp\!\!\!\perp \bar{E}_t \quad t = 1, ..., 6 \tag{B.1}$$

In this observational study, we must make a stronger assumption, namely that counterfactual outcomes, $MH_{\bar{e}(t+1)}$, are independent of exposure history, E_k, conditional on lagged exposure history, $\bar{E}_{k-1}$, and other observables, $\bar{X}_k$ for all $\bar{e}$ and $t \geq k$:

$$MH_{\bar{e}(t+1)} \perp\!\!\!\perp E_k \mid \bar{E}_{k-1}, \bar{X}_k \tag{B.2}$$

Which is the sequential conditional independence assumption. Thus, we treat the assignment mechanism (exposure) as randomized sequentially for each period, conditional on the observables $\bar{X}_k$ and lagged exposure history, $\bar{E}_{t-1}$. [12]

Under the sequential conditional independence assumption, we use a marginal structural model for repeated measures to estimate the cumulative effect of night shift work on mental health. Specifically,

[12] But why must we also condition on (lagged) exposure history? We aim to estimate the increase in risk for an additional year of night shift work. If we do not condition on lagged exposure history, then night workers in year t are more likely to have had larger cumulative exposure to night-shift work. In turn, mental health will no longer be statistically independent on night shift work, conditional on exposure history. If healthy workers are more likely to have more cumulative years of night shift work, the adverse effects of additional night shift work will be attenuated.

we follow Hernán et al. (2002) and model the mean of the counterfactual outcomes $MH_{\bar{e}t}$:

$$\mathbb{E}[MH_{\bar{e}(t+1)}] = g(\bar{e}_t, \boldsymbol{\theta}) \tag{B.3}$$

where $\boldsymbol{\theta}$ are parameters that we will estimate and g is a known function. Rather than modelling all 2^6 potential exposure histories, we specify the parsimonious does-response relationship using a linear logistic marginal structure model:

$$\log \mathbb{P}[MH_{\bar{e}(t+1)}] = \theta_0 + \theta_1 cum[\bar{e}_t], \tag{B.4}$$

Here $cum(\bar{e}) = \sum_{t=0}^{T} e_t$ is the cumulative exposure through baseline to the most recent follow-up year.

Assuming sequential conditional independence and overlap, i.e. $f[\bar{e}_{t-1}, \bar{x}_t] > 0 \implies f[\bar{e}_t \mid \bar{e}_{t-1}, \bar{x}_t] > 0$, we can asymptotically obtain an unbiased estimate of θ_1 by fitting the MSM model using the efficient GMM estimator, namely, the *generalized* estimations equations (GEE) estimator as advocated for pooled generalized linear models (e.g. Cameron and Trivedi, 2006; Wooldridge, 2010).

B.1.3 Estimation

In the GEE estimator, each worker has the estimated time-specific weight, and the estimator solves:

$$\sum_{i=1}^{N} \frac{\delta \mathbf{g}_i'(\boldsymbol{\theta})}{\delta \boldsymbol{\theta}} \Sigma_i^{-1} SW_i(\mathbf{MH}_i - \mathbf{g}_i(\boldsymbol{\theta})) \tag{B.5}$$

Where $\boldsymbol{MH}_i = (MH_{i1}, ..., MH_{iK+1})'$, $\boldsymbol{g}_i(\boldsymbol{\theta}) = (g(E_{i0}, \boldsymbol{\theta}), ..., g(\bar{E}_{iK}, \boldsymbol{\theta}))$', where $K+1$ is the last time that MH is measured. Σ_i is the working covariance matrix where we use the exchangeable matrix with $\Sigma_i \equiv \Sigma_i(\sigma)$ where $corr(MH_{it}, MH_{it}') = \alpha_i$ for all $t \neq t'$. SW_i is a diagonal matrix with weights SW_t for $t, ..., K$. We use the sandwich estimator to obtain panel-robust variance estimates, which are robust to misspecification of Σ_i (Cameron and Trivedi, 2006).

B.1.4 Estimating Weights

To estimate θ_1, we need to plug in an estimate for each worker's time-specific weight. We use two approaches: the inverse probability weights (IPW) using propensity scores from logistic regression (e.g. Robins et al., 2000) and weights generated employing entropy-balancing (Hainmueller, 2012).

IPW

A popular approach to estimate IPW is first to estimate propensity scores using logistic regression (Robins et al., 2000) and then use the inverse propensities as weights. In this setting, we estimate the propensity scores with logistic regression for the unstable weights W_{it}:

$$W_{it} = \frac{1}{\prod_{k=0}^{t} f[E_{ik} = e_{ik} \mid \bar{E}_{i(k-1)} = \bar{e}_{i(k-1)}, \bar{X}_{ik} = \bar{x}_{ik}]} \tag{B.6}$$

Plugging in these weights in eq. B.6 yield a consistent and asymptotically normal estimator of $\boldsymbol{\theta}$ (Hernán et al., 2002). There are 2^{t-1} potentially different exposure histories, $\bar{E}_{i(t-1)}$. Some of these combinations are empty, and some have very few observations. Therefore, we use a parsimonious representation of exposure history to increase statistical power and model it simply as lagged exposure following (Neophytou et al., 2014).

Moreover, the unstable weights can lead to an estimator with a large variance. Since large unstabilised weights are probably due to the estimation process rather than underlying true probabilities (Stuart, 2010), we follow Hernán et al. (2002) and estimate the subject-specific stabilized time weights as:

$$SW_{it} = \frac{\prod_{k=0}^{t} f[E_{ik} = e_{ik} | \bar{E}_{i(k-1)} = \bar{e}_{i(k-1)}]}{\prod_{k=0}^{t} f[E_{ik} = e_{ik} | \bar{E}_{i(k-1)} = \bar{e}_{i(k-1)}, \bar{X}_{ik} = \bar{x}_{ik}]} \tag{B.7}$$

We estimate two models for the propensity scores. First, we estimate the propensity of nurses to work night shifts the first year they start working in the regions. Second, we estimate a pooled logistic regression over the years 2-6 to get a prediction equation for the propensity scores for night shift work. The only difference between these models is that we include lagged night worker status, annual wage income, working hours, and sickness absence in the pooled logistic regression.

Intuitively, the inverse probability weights produce a pseudo-population where the exposure and control groups have similar characteristics. After weighting, adjusting for confounders is no longer necessary since the populations are the same in terms of other characteristics except exposure.

Entropy balancing

With propensity scores, we aim to balance covariates stochastically. This requires a fairly large sample and correct model specification. Yet, this can still result in low balance levels. Further, using propensity scores can counteract bias reduction in subsequent analysis when improving balance for some variables reduces balance for other covariates. Therefore, we also consider weights generated by entropy balancing developed by Hainmueller (2012). Entropy balancing generates weights that enforce restrictions such that mean and potentially higher moments of variables in the control and treatment will be exactly similar. At the same time, entropy balancing minimizes the variability of weights and reduces problems with extreme weights. Moreover, the algorithm is computationally very fast and easily implemented in Stata or R. These properties make entropy balancing an increasingly popular tool in economics and other disciplines.

B.1.5 Censoring with IPW and Entropy balancing

We censor part-time workers (fewer than 900 registered working hours) and workers leaving the regions and do not allow them to enter the sample again. We do not allow workers to enter the sample again because we cannot detect whether they work night shift when they no longer work in the regions. We use a weighting approach to account for censoring. We estimate the censoring weights with propensity scores derived from logistic regression and entropy balancing. Censoring is set to 0 for persons remaining in the sample, $C_t = 0$, and 1 for periods where the person is no longer in the sample. We only observe MH_{t+1} when $C_t = 0$. If the sequential conditional independence assumption holds for censoring:

$$MH_{\bar{e}t+1} \perp\!\!\!\perp C_{t+1} \mid \bar{C}_t \equiv 0, \bar{E}_t, \bar{X}_t \tag{B.8}$$

Then we can estimate still, asymptotically, get an unbiased estimate of $\boldsymbol{\theta}$ with weighted GEE estimator if we use the weights $SW^c_{it} \times SW^e_{it}$ (Hernán et al., 2002).

Censoring with IPW

Like the exposure weights, we estimate the censoring weights with IPW based on logistic regression with stabilised weights. Thus, to adjust for censoring, we estimate the predicted censoring weights SW^c_{it}:

$$SW^c_{it} = \frac{\prod_{k=0}^{t} f[C_{ik+1} = 0 | \bar{C}_{ik} = 0, \bar{E}_{ik} = \bar{e}_{it}]}{\prod_{k=0}^{t} f[C_{ik+1} = 0 | \bar{C}_{ik} = 0, \bar{E}_{ik} = \bar{e}_{ik}, \bar{X}_t = \bar{x}_{ik}]} \tag{B.9}$$

In year 0, we set all weights to 1 since the sample is restricted to persons hired for at least one year. We estimate a single pooled logistic regression conditional on the same covariates used for estimating IPW for exposure for the follow-up years > 0.

Censoring with Entropy Balancing

The approach to generating censoring weights with entropy balancing is similar to the approach we use to generate weights that balance the sample to exposure, except that we replace leaded exposure with leaded censoring. Similarly to the weights we generate with the inverse propensity scores, we multiply the exposure weights with the censoring weights to get the final weights.