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Infections, Accidents and Nursing Overtime in a Neonatal Intensive Care Unit

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The paper investigates the effects of nursing overtime on nosocomial infections and medical accidents in a neonatal intensive care unit (NICU). The literature lacks clear evidence on this issue and we conjecture that this may be due to empirical and methodological factors. We model the occurrences of both events using a sample of 3,979 neonates who represents over 84,846 observations (infant/days). We exploit an important change in workforce arrangement that was implemented in June 2012, and which aimed at reducing overtime hours to identify a causal impact between the latter and the two outcomes of interest. We contrast the results using a standard mixed-effects logit model with those of a semiparametric mixed-effects logit model. Contrary to the mixed-effects logit model, the semiparametric model unequivocally shows that both adverse events are impacted by nursing overtime as well as being highly sensitive to infant and NICU-related characteristics. Furthermore, the mixed-effects logit model is rejected in favour of the semiparametric one.

Keyword : Neonatal health outcomes, nursing overtime, parametric and semiparametric mixed-effects logit models.

1. Introduction

An important literature documents the effects of neonatal health on a wide range of adult outcomes such as wages, cognitive skills and human capital accumulation (Black et al., 2007; Oreopoulos et al., 2008; Currie et al., 2010; Figlio et al., 2014; Bharadwaj et al., 2018). Neonatal health is commonly proxied by birth weight or gestational age, as both are highly (and spatially) correlated (Neelon et al., 2014). Indeed, both preterm (<37 weeks gestation) and low birth weight infants (< 2500 grams) are more likely to develop neurologic, pulmonary, and gross motor impairments than full-term infants (Behrman and Butler, 2007), and are at higher risk of mortality within one year and up to age 17 (Paneth, 1995; Behrman and Butler, 2007).

Most preterm and low birth weight infants are admitted to a neonatal intensive care unit (NICU) upon birth. Frail newborns are at higher risk of contracting a nosocomial infection (Freeman et al., 1990; Vain et al., 2012) which results in increased morbidity and mortality, prolonged lengths of stay, and increased medical costs (Polin et al., 2012).[1] And because they require more care, are more vulnerable to medical incidents such as erroneous medication administration or feeding and equipment malfunctioning (Beltempo et al., 2017a). The onset of nosocomial infections and the occurrence of medical incidents may have adverse health effects that can potentially exacerbate health and socioeconomic problems into

[1]Neonates are at high risk of acquiring health care-associated infections because of impaired host-defence mechanisms, limited amounts of protective endogenous flora on skin and mucosal surfaces at time of birth, reduced barrier function of their skin, use of invasive procedures and devices, and frequent exposure to broad-spectrum antibiotic agents.

adulthood. Understanding the mechanisms that lead to these adverse events may help reduce the private and societal costs of poor neonatal health as well as contribute to cost containment (Evans and Kim, 2006; Russell et al., 2007; Mistry et al., 2009).

Neonatal intensive care units must contend with ever-changing caseloads, patient mix and unplanned admissions (Tucker et al. (1999)). Workforce management is thus challenging and nursing overtime is often used to meet required nurse-to-patient ratios (Berney and Needleman (2005); Beltempo et al. (2016)). The increasing use of overtime hours as a labour-management strategy has become an important issue across NICUs in Canada (Canadian Association of Paediatric Health Care Centers, 2013; Fallah et al., 2011) and elsewhere (Griffiths et al. (2014)). This is because nursing overtime has been found to be deleterious to adult patients' health (Bae (2013); Haizhen (2014); Cimiotti et al. (2012); Dorrian et al. (2006); Trinkoff et al. (2011)). Yet, the literature linking nursing overtime and neonatal outcomes, in addition to being relatively scant, is inconclusive (see, *e.g.*, Bae and Favry, 2013; Sherenian et al., 2013). While nurse understaffing *per se* is associated with higher infections rates (Rogowski et al., 2013) and mortality (Watson et al., 2016), mandatory staffing (nurse/patient) has been found to have no impact on health outcomes (Evans and Kim, 2006; Sochalski et al., 2008; Cook et al., 2012).

Understaffing must be viewed in relation to capacity and case mix. Indeed, it is widely acknowledged that NICUs usually operate at or near capacity, if not beyond. Yet, economists have long questioned whether the availability of supply itself may directly lead to additional utilization (Freedman, 2016). In the words of Roemer (1961), "A built bed is a filled bed", or to paraphrase Carroll (2015), "If you build them, they will come". There is ample evidence that newborns at all birth weights are increasingly likely to be admitted to a NICU, which raises the possibility of overuse of neonatal intensive care in some not-at-risk or low-risk newborns (Grumbach, 2002; Goodman et al., 2002; Harrison and Goodman, 2015). Likewise, there is excessive regional variation in the proportion of newborns admitted to a NICU that cannot be explained by variations in birth weight or gestational age alone.[2] It has been suggested that in some cases C-section delivery could be the sole reason for admitting newborns to NICU/ICU, including for observation of low-risk births (Fallah et al., 2011). Admitting low-risk/low-need infants will artificially decrease the nurse/patient ratio while not necessarily jeopardizing the health status of those more in need of intensive care (Freedman, 2016).

Yet, the lack of clear evidence linking nursing overtime, utilization and patient health may also be due to methodological factors (Bae and Favry, 2013; Weinstein et al., 2008). Indeed, most studies use cross-sectional data and contrast health outcomes stemming from heterogeneous units and/or hospitals.[3] Such analyses are likely to omit important unobserved patient characteristics and unit-specific

[2]For instance, in Canada the proportion of newborns admitted to a NICU/ICU between 2006–2009 ranged from 5.3% in the Province of Québec to 24.5% in the Province of New-Brunswick. In addition, the proportion of stays that lasted less than 24 hours varied from 9.8% in the Province of Prince-Edward Island to as much as 39.7% in the Province of Alberta (Fallah et al., 2011).

[3]Yet, see Mújica-Mota et al. (2020) for a recent analysis which accounts for heterogeneous causal effects of neonatal care on mortality.

work arrangements. As for NICUs, given that the mix of neonatologists, fellows, residents, nurse practitioners, *etc.* varies greatly across hospitals, singling out the contributions of nursing overtime and utilization on health outcomes is clearly a difficult task. This difficulty is compounded by the fact that the association between the former and the latter is perhaps not a linear cause-effect relationship (Hugonnet et al., 2006).

In this paper, we focus on the CHU de Québec NICU, a tertiary/quaternary referral centre with a 51-bed capacity that tends to a population of 1.7 million over a territory of 452,600 km^2 surrounding Québec City, Canada. We study the daily occurrences of health care associated infections and medical incidents/accidents (henceforth HCAI and MA, respectively) among all neonates admitted to the NICU between April 2008 and March 2013. Daily exposure to overtime and regular hours of work, as well as numerous individual and NICU-specific covariates are used to model the onset of the latter two outcomes. We also exploit an important change in workforce arrangement that was implemented in June 2012 and which aimed at reducing overtime hours. Management thus hired 15 full-time registered nurses and converted 10% of existing positions from 8-hour to 12-hour shifts which were exempted of additional overtime hours (Beltempo et al., 2016). This mandated change is used to identify a causal impact between the latter and the two outcomes of interest. We use both a standard mixed-effects logit model and a flexible semiparametric mixed-effects logit model to quantify the links between the main variables of interest and the two outcomes. The nonparametric components of the model allow to unearth potentially highly non-linear relationships in overtime, regular hours of work and birth weight, and is well suited to measure the sensitivity of the outcomes to the new workforce arrangement.

Section 2 presents the data. Section 3 outlines the empirical strategy about the estimation of parametric and semiparametric mixed-effects logit models. Section 4 presents the estimation the results while section 5 concludes.

2. Data and Institutional Arrangement

2.1. The NICU

The CHU de Québec NICU is a Level-III referral center with a 51 bed capacity.[4] Nurse staffing is determined before each shift according to patient acuity, planned admissions, and elective procedures/tests. When nurses are deemed in shortage, management initially turns to available off-duty nurses. Next, a pool of floating nurses is relied upon. Finally, it resorts to voluntary and mandatory overtime if necessary. Overtime is defined as all hours worked beyond the regular work schedule.[5]

Daily administrative data on overtime and regular hours of work, daily patient census and number of admissions were collected using the local administrative database *Logibec*. This latter is used to manage work shifts and pay schedules. The information on regular hours and overtime is thus quite precise. Information on HCAI was drawn from the infectious disease database *TDR* while information

[4] CHU: Centre Hospitalier Universitaire (*University Hospital Centre*).

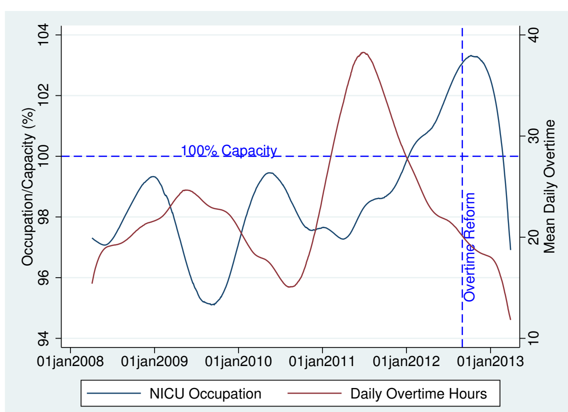
[5] Overtime occurs whenever a nurse either starts her shift earlier than planned or finishes later than scheduled. Working beyond 16 consecutive hours per day is forbidden.

on MA was retrieved from the *Gesrisk* database.[6]

Figure 1 below exhibits the smoothed daily variations in occupancy rates and overtime hours over our entire sample period (April 2008–March 2013). Occupancy rates are expressed in percentage relative to capacity (51 beds). They vary between 72% (35 filled beds) and 113% (58 filled beds). The NICU operates above capacity 41% of the time. Yet this occurs more frequently after the change in the overtime regime implemented by management in June 2012 (vertical dashed line). Indeed, prior to the implementation of the new policy, the NICU operated above capacity 35% of the time. The proportion increased to 71% in the aftermath. This is clearly depicted in the figure.

Overtime hours follow the opposite path. Prior to the implementation of the new regime, average daily overtime hours amounted to 23.6. In the months that followed, it decreased to 18.6. The implementation of the policy occurred at a time when occupancy was relatively high and overtime hours relatively low. Recall

Figure 1: Smoothed Daily Occupation Rates and Overtime Hours



[6] Reporting the information on the timing as well as the type of MA is mandatory.

from our discussion above that some have noted that infants at all birth weights are increasingly likely to be admitted to a NICU (Harrison and Goodman, 2015). If this it the case, then the health status at admission should be inversely related to the occupancy rates. Indeed, as available beds become fewer, management will naturally prioritize high-risk infants. Figure 2 below investigates this issue. The figure reports the (smoothed) average weight and weight/gestational age at admission by occupancy rates. It also distinguishes between pre and post reform periods.[7]

Figure 2: Weight and Weight/Gestational Age at Admission, by Occupancy Rate

According to the figure, prior to the reform both the weight and weight/gestational age were relatively independent of the occupancy up until a rate of 102%-103%. Above this rate, infants admitted to the NICU had slightly poorer health. Indeed, the average weight is roughly 100 grams lower and the weight/age ratio less by two units between occupancy rates of 102% and 110%.[8] On the other

[7]The figures depict local polynomial regressions for occupancy rates above 94%. The NICU operates at or above this rate 80% of the time. There are too few observations at lower rates to make valid statistical inference.

[8]3,322 infants were admitted prior to the reform, and only 657 in the aftermath.

hand, infants admitted in the post-reform period have both a greater average birth weight (132 grams) and birth weight/gestational age ratio (3 units). Both differences are highly statistically significant. As in the pre-reform period, the health status exhibits an inverse relation with the occupancy rate. Above 102%, the birth weight and the birth weight/gestational age ratio decrease at the same rate as those admitted prior to the reform. The negative relation between health status and occupancy lends credence to the claim that NICUs may have an incentive to operate at capacity and thus admit low-risk/low-need infants to that end (Freedman, 2016). [9]

2.2. Patient Characteristics and Health Outcomes

Patient characteristics are drawn from the hospital clinical database. The latter includes information on gestational age, birth weight, sex, Apgar score, multiple pregnancies, type of delivery, *etc.* All newborns admitted during the study period were included conditional on having spent at least four days in the NICU. If an infant had more than one episode of bacteremia, these were considered separate events if they occurred more than 14 days apart. The date of the infection was determined as that at which the blood culture was obtained.

The total number of infants admitted in the NICU over our sample period is 7,383. Of those, 3,404 were omitted since their stay was shorter than four days. The motivation for excluding short spells is twofold. First, HCAIs occur when-

[9] The unit operated above capacity 35.5% of days in the pre-reform period (Average capacity = 98.4) and more than 75.3% in the post-reform period (Average capacity = 103.4.) The difference is highly statistically significant.

ever a pathogenic organism can be isolated in blood or a cerebrospinal fluid culture. Such cultures usually require at least two to three days to be conclusive. Second, the exact timeline of events that leads to HCAIs is still not well defined in the literature (Polin et al., 2012). Studies focusing on adult and pediatric units suggest that low nurse-to-patient ratios and extensive overtime over a 3-day period may trigger the onset of HCAIs (Cimiotti et al., 2006; Beltempo et al., 2017a). In line with this literature, overtime hours on any given day was thus defined as a moving average computed over the preceding 3-day period when the analysis focuses on HCAIs. Such a moving average can only be computed for spells lasting at least 4 days. When analyzing medical accidents, on the other hand, we use daily exposure to overtime hours.

The final sample consists of 3,979 neonates which represents over 84,846 infant/days over the sample period. Table 1 provides descriptive statistics of the main variables used in the model. The first column focuses on infants who did not contract a HCAI or experience a MA. The next two columns focus on the subsample of infants who experienced a MA and contracted a HCAI, respectively. Not surprisingly, the table highlights the link between poor health and adverse events. Indeed, infants who experienced a MA or a HCAI had both a lower gestational age and a lower birth weight. They also had a lower Apgar score, were more likely to have been delivered by C-Section, and were more likely to be the mother's first childbirth. The next two lines focus on the Diagnosis Related Group (DRG) at admission. Our data contain 113 distinct DRG codes. These are categorised as surgical or medical. Infants who experienced a MA or a HCAI were much more likely to have been admitted following a surgical intervention. The next line reports the severity index of the DRG code which takes values between 1 and 4 (1=mild, 2=moderate, 3=severe, 4=extreme). Not surprisingly, accident and infection-free neonates had a low or moderately severe condition at entry. Those who did experience a MA or a HCAI were deemed severely or extremely ill at admission. Not surprisingly, their poor health translates into lengthy hospitalisation spells. The last line of the table reports the proportion of infants whose spell occurred during or after the implementation of the overtime reform.

The next panel of the table focuses on the average daily characteristics of the NICU by outcome subsamples. The only two noteworthy features concerns the hours of work. Indeed, infants who contracted a HCAI or experienced a MA were exposed to slightly more overtime and regular hours of work than otherwise. This is true despite the fact that there were on average no more admissions into the unit, nor was the occupancy rate greater than usual.

The last panel of the table provides a detailed account of the two outcome variables. Overall, 3,513 infants in our sample had an MA or HCAI-free stay in the unit. On the other hand, 300 infants (7.54%) experienced 389 MA events, and 240 of them (6.03%) contracted over 272 HCAIs. From the NICU's point of view, the probability of observing an MA or a HCAI in any given day was 21.35% and 14.92%, respectively. This translates into 0.458% and 0.321% when computed daily and per neonate.

The above discussion highlights the fact that the link between nursing overtime, case mix, and capacity is a complex one. The tables and figures provide at best weak *prima facie* evidence that the adverse events may be loosely related to hours of work. Yet the influence of other variables needs to be netted out in order to determine the precise link between work schedules and outcomes, if any. In what follows, we briefly sketch the standard mixed-effects logit model and the semiparametric mixed-effects logit model and highlight their distinctive features.

3. Empirical Strategy

As stated in the introduction, the literature linking nursing overtime and neonatal outcomes is inconclusive. Several factors may contribute to this indeterminacy. First, most analyses are conducted within a cross-sectional framework wherein all variables are averaged over individual spell lengths. Consequently, important unobserved patient characteristics cannot be accounted for. Likewise, work arrangements change daily – and across work shifts – so that newborns are exposed to considerable variations in overtime hours and nurse-to-patient ratios, say, during their stay in the unit. Averaging over over individual spells may thus hinder the identification of potential causal links. Second, it is highly likely that the causal links, if any, are non-linear: increasing overtime hours need not have the same effects at low and high levels. Assuming linearity and using spell-smoothed variables may be too constraining to identify causal links between important outcomes and unit/individual-specific factors.

Our analysis focuses on daily occurrences of HCAI and MA. Entry and exit dates vary across newborns and so does the length of stay. Such unbalanced panel data is customarily analysed using the so-called mixed-effects logit model. This standard specification allows for individual unobserved heterogeneity through the use of a random intercept and (possibly) random slopes. We briefly sketch this estimator in what follows. We then sketch the semiparametric logit model and highlight its distinctive features.

3.1. The Standard Parametric Mixed-Effects Logit Model

Consider the probability that the binary outcome (MA or HCAI), y_{it}, for newborn i occurs on its t-th day in the NICU. The unbalanced sample is composed of N infants $(i = 1, ..., N)$ each observed during T_i days $(t = 1, ..., T_i)$. Let y be the $(NT \times 1)$ vector of the y_{it} probabilities with $NT = \sum_{i=1}^{N} T_i$. Consider the following logistic model:

$$y \mid \beta, u \sim \text{Bernoulli}\left(\text{logit}^{-1}\left(X^R\beta^R + Z^R u^R + X^G\beta^G\right)\right), \tag{1}$$

where $y \sim \text{Bernoulli}\,(p)$ is shorthand for the elements of y having independent Bernoulli distributions with parameters corresponding to those in $p(\cdot)$, and $\text{logit}^{-1}(x)$ is shorthand for the logistic distribution, *i.e.* $e^x/(1+e^x)$. Let X^R be a $(NT \times q^R)$ matrix of control variables. Further, let X^G $(NT \times q^G)$ include regular and overtime hours of work as well as birth weight.[10] The matrix is associated with the constant slopes vector β^G. $X^R_{it,1}$ is the intercept and $X^R_{it,j}$, $2 \leq j \leq q^R$ include the other control variables. The random intercept is equal to $(\beta^R_1 + u^R_{i,1})$ and the

[10]The three variables will be modelled non-parametrically in what follows. This specification is based on the results of a generalised mixed-effects regression tree model (GMERT) using the same database as in Beltempo et al. (2020).

constant slope coefficients for variables $X_{i,2},...,X_{i,q^R}$ are $(\beta_1^R,...,\beta_{q^R}^R)$.[11] Finally, $u_{i,1}^R \sim N(0,\sigma_{u1}^2)$ are the individual-specific effects which are assumed to be identically and independently normally distributed.

The specification in equation (1) corresponds to the standard mixed-effects logit model also called random effects logit model. To investigate potential non-linearities between the outcomes, y, and the variables of interest, X^G, we may introduce additional quadratic and cubic terms:

$$y \mid \beta,u \sim \text{Bernoulli}\left(\text{logit}^{-1}\left(X^R\beta^R + Z^R u^R + X^G\beta^G\right)\right) \tag{1a}$$

$$y \mid \beta,u \sim \text{Bernoulli}\left(\text{logit}^{-1}\left(X^R\beta^R + Z^R u^R + X^G\beta^G + X^{2,G}\beta_2^G\right)\right) \tag{1b}$$

$$y \mid \beta,u \sim \text{Bernoulli}\left(\text{logit}^{-1}\left(X^R\beta^R + Z^R u^R + X^G\beta^G + X^{2,G}\beta_2^G + X^{3,G}\beta_3^G\right)\right), \tag{1c}$$

where $X^{j,G}$, $j = 2,3$ are the X^G variables raised to power j. The inclusion of the $X^{j,G}$ variables allows to capture the fact that the changes in the log odds ratios may increase or decrease rapidly at high or low values of $X^{j,G}$.

3.2. The Semiparametric Mixed-Effects Logit Model

Over the last decades, increased attention has been devoted to semiparametric and nonparametric regression models for estimation and forecasting purposes in different areas such as biostatistics, medicine, epidemiology, economics, *etc.* (see *e.g.* Ruppert et al. (2003), Yatchew (2003) and Horowitz (2012)). The interest

[11]In this specific case, Z^R is a $(NT \times N)$ matrix of submatrices $Z_i^R = I_N \otimes \iota_{T_i}$ where I_N is an identity matrix, ι_{T_i} is a vector of ones of dimension T_i and $\otimes$ denotes the kronecker product.

in nonparametric models stems from the fact that they do not impose any functional form between the outcome variables and the covariates. However, in high-dimensional models the variance of the parameter estimates increases rapidly due to the so-called "curse of dimensionality". In addition, nonparametric models rapidly become prohibitively time consuming as the number of covariates increases. Semiparametric specifications arguably combine the best features of the parametric and nonparametric models: they are easily interpretable and provide a fair representation of real-life data. However, semiparametric models require larger sample sizes than parametric models as the data must provide both the structure of the model as well as the model estimates *per se*. Importantly, it has been shown that if the link function between the outcome and the covariates is misspecified, the semiparametric models perform better in terms of fit and prediction than standard parametric models (see for instance Mahmoud et al. (2016) and Mahmoud (2021)).

The semiparametric model can be written in a similar fashion to the parametric specification in equation (1). Consider the following mixed-effects logistic model:

$$y \mid \beta, u \sim \text{Bernoulli}\left(\text{logit}^{-1}\left(X^R\beta^R + Z^R u^R + f\left(X^G\right)\right)\right). \tag{2}$$

The only distinctive feature of this specification concerns the third argument in the inverse logit function. Indeed, the expression $X^G\beta^G$ in the linear specification (1a) has been replaced by $f(X^G)$.[12] This semiparametric additive function is given

[12]Note that for both the standard mixed-effects logit and semiparametric mixed-effects logit models all the slope parameters can be made random. As reported in the supplementary material,

by

$$f\left(X^G\right) = X^G\beta^G + Z^G u^G = \sum_{l=1}^{L} X_l^G \beta_l^G + \sum_{l=1}^{L} Z_l^G u_l^G. \tag{3}$$

The matrix X^G and parameter vector β^G are as previously defined. The $(NT \times L)$ matrix X^G contains the L covariates that are not included in X^R. The $(NT \times q^L)$ matrix Z^G matrix, with $q^L = \sum_l^L q_l^G$, contains the spline basis functions of the L covariates using q_l^G knots, and u^G are the corresponding spline coefficient vectors.

Although the nonlinear panel data literature provides examples of either parametric logit models with random coefficients (for instance Moon et al. (2017)) and semiparametric logit models (Lewbel, 2000; Honoré and Lewbel, 2002; Ruppert et al., 2003), examples of models that encompass both features are scarce. This is perhaps because they are computationally prohibitive or may not behave properly when using estimation standard MCMC Bayesian techniques such as Gibbs sampling. Fortunately, Lee (2016) and Lee and Wand (2016) have proposed to use a mean field variational Bayes approximation method (henceforth MFVB) to estimate such models. MFVB consists in a set of tools which provide a good approximation of the posterior distributions of the parameters. Because the posterior distribution is approximated, MFVB is much faster than traditional Bayesian methods and can afford to tackle large models such as ours.[13]

we estimated semiparametric logit models with random intercept and slopes and semiparametric logit models with random intercept and constant slopes. Using a Wald test to discriminate between the two, we could not reject the semiparametric logit model with random intercept and constant slopes. For the sake of brevity and clarity, we only report results on the latter.

[13]See the supplementary material for details on the semiparametric logit model with random coefficients, the estimation method and the relevant algorithms. The convexity properties of the MFVB algorithm guarantees quick convergence to at least a local optimum.

4. Estimation Results

4.1. Standard Mixed-Effects Logit Model

4.1.1. Medical Accidents

The parameter estimates of the standard mixed-effects logit model are reported in Table 2. The three columns correspond to the specifications in equations (1a)–(1c), respectively. The top panel of the table reports the parameters associated with individual characteristics while the bottom panel focuses on those associated with the NICU characteristics which include the variables in X^G (regular and overtime hours of work and birth weight).

The estimates of the birth characteristics are quite consistent across all three specifications. Thus it is found that having contracted a nosocomial infection (`Prior Infection`) reduces the risk of a MA. This is presumably due to the fact that infected neonates require more care and are more closely monitored. `Gestational Age` is positively related to the occurrence of a MA except in the linear specification. This result is *a priori* somewhat surprising. Yet, since we are controlling for birth weight, a longer gestational age may in fact be associated with a poorer health status. In other words, lower weight-for-age infants may require more care or handling which may result in an increased likelihood of MA. Whether the infant was admitted in the NICU at birth or transferred from another unit or hospital (`Birth vs Transfert`) has no impact on the occurrence of a MA. The same applies to the `Sex` of the infant, whether delivery occurred through a `C-Section`, and whether the mother gave birth to `Twins`. Not surprisingly, a high `Apgar Score` reduces the occurrence of a MA. Finally, neonates who were admitted to the NICU following a `Surgical` intervention and those whose status was deemed very highly severe conditional on their `DRG` code are much more likely to experience a MA.

The previous parameter estimates relate to factors that are neonate-specific. Conditional on these, the next panel focuses on unit-specific factors. As argued previously, daily variations in `Unit Occupancy` and `Admissions` fluctuate randomly. When measuring their impact, it is implicitly assumed that all infants are exposed to the same "dose" of both factors. According to the parameter estimates, only `Occupancy` has a statistically significant, albeit very small and negative, effect. This result is consistent with those of Beltempo et al. (2017b) using similar data but a different estimation strategy, and for which unit occupancy was found to have no or very little impact on MAs. Recall that the province-wide `Overtime Reform` that was implemented in June 2012 involved hiring 15 full-time registered nurses and in converting 10% of existing positions from 8-hour to 12-hour shifts that were exempted from overtime hours. Over the whole sample period, this has resulted in approximately 7 fewer daily overtime hours and 35 additional regular hours. According to the parameter estimates of all three specifications, the new mix of work shifts has resulted in additional, not fewer, MAs despite the fact that infants admitted in the post-reform period had on average larger Weight/Age ratios.

From management's point of view, the main variables of interest are `Daily Overtime Hours` and `Daily Regular Hours`. As stressed earlier, the literature linking nursing time and neonatal outcomes is unfortunately inconclusive (Bae and Favry, 2013; Beltempo et al., 2018; Sherenian et al., 2013). According to the linear specification, both variables are positively related to the occurrence of a MA. Yet, adding quadratic or cubic terms yields somewhat conflicting results. Indeed, while `Daily Overtime Hours` remains statistically significant across all three specifications, `Daily Regular Hours` is marginally significant in the quadratic specification and becomes non-significant in the cubic specification despite the fact that none of the quadratic nor the cubic parameter estimates are statistically significant themselves. Another inconsistency arises when we focus on the parameters estimates associated with `Birth Weight`. Indeed, according to the linear specification, this variable has no impact on MA, nor does `Gestational Age` for that matter. This is somewhat surprising. On the other hand, the quadratic and cubic specifications conclude that both variables are important determinants of MAs. Simple likelihood-ratio tests reject the linear specification in favour of the latter two. On the other hand, the test can not discriminate between the quadratic and cubic specifications.

4.1.2. Health Care Associated Infections

The results of Table 2 provide robust evidence according to which nursing overtime increases the likelihood of MAs in the NICU. As with MAs, the literature linking work schedules and HCAIs is inconclusive (Beltempo et al., 2017a; Haley and Bregman, 1982; Hugonnet et al., 2006). Table 3 reports the parameter estimates obtained from fitting the same three specifications as above to the occurrence of HCAIs. Contrary to the previous table, few individual characteristics (save for birth weight) and none of the NICU characteristics have a statistically significant impact on the probability of observing a HCAI even when allowing for nonlinearity (Hugonnet et al., 2006). According to the table, neonates who experienced a MA are less likely to eventually contract a nosocomial infection presumably because they receive more attentive care. In addition, neonates who are admitted following a surgical intervention are more likely to experience a MA while those who have a low DRG severity index at admission less so.

4.1.3. MA and HCAI odds-ratios

The sensitivity of the probability of observing a MA or a HCAI relative to the policy variables of the model is best illustrated through the odds-ratios as reported in Table 4. The first part of each panel reports the ORs following an increase of one unit in the relevant variables. The second part reports the ORs computed between the 10^{th} and 50^{th} percentiles of the latter while the last part computes them between the 90^{th} and 50^{th} percentiles. Recall from Table 2 that the statistical significance of the parameter estimates associated with `Overtime Hours` and `Regular Hours` of the MA model varied across specifications. In the linear model, both were significant. As shown in the first part of Table 4, all three specifications yield essentially the same OR and their confidence interval do not include 1. These ORs correspond to those provided by all standard statistical software. Yet, if we compute the same ORs between the 10^{th} and 50^{th} percentiles, then they are all well below unity and vary somewhat across specifications. The quadratic and the cubic specifications yield similar ORs and both are smaller than that of the linear specification.[14] The converse holds when they are computed between the

[14]See the supplementary material for the derivation of the ORs and their confidence intervals in the standard mixed-effects logit model with polynomial covariates.

90^{th} and the 50^{th}percentiles: The ORs are all larger than one and also vary across specifications. The second panel of the table focuses on the ORs of the HCAI specification. As reported in Table 3, none of the parameter estimates associated with either `Daily Regular Hours` or `Daily Overtime Hours` are statistically significant. Not surprisingly, all the confidence intervals include 1, irrespective of the points at which they are computed, and vary little across specifications.

From a policy perspective, our results indicate that the probability of observing a MA in a NICU is related to the level of daily working hours, and in particular to overtime hours. On the other hand, our data do not allow to establish such a link between working hours and HCAIs, at least when using a mixed-effects logistic model.

4.2. Semiparametric Mixed-Effects Logit Model

4.2.1. Medical Accidents

The parameter estimates of the MA model are reported in Table 5. The table is divided into three sections. The first reports the parameters β^R, the second one focuses on β^G, and the third reports the panel-level variance component, $\sigma^2_{u^R}$. The table also reports the associated odds ratios as well as their 95% confidence intervals.[15,16]

According to Table 5, most parameter estimates of the birth and NICU characteristics are of similar magnitude to those obtained using the mixed-effects logit

[15]Since the model is estimated through a Bayesian approach, strictly speaking we should use "posterior means" and "posterior standard deviation" whenever we write "parameters" and "standard deviations" in what follows.

[16]Strictly speaking, we should write "credible intervals" instead of "confidence intervals".

model. All the parameter estimates that were found to be statistically significant in the latter model are likewise significant in the semiparametric model. In addition, it is now found that `Gestational Age`, `C-Section` deliveries and `Twin Births` also impact the probability of experiencing a MA while in the NICU.

Columns 3–6 of the table report the odds-ratios of the X^R variables, their standard deviation as well as their 95% confidence intervals. When the event $y_{it} = 1$ is rare as in our case, then the odds-ratios are approximately equivalent to the relative risks.[17] According to Table 5, the lowest odds ratios concern `DRG Severity` (OR $\in$ [0.35–0.68]), `Prior Infection` (OR = 0.59) and `Apgar Score` (OR = 0.76), while the highest odds ratios relate to `Gestational Age` (OR = 1.06), `Overtime Reform` (OR = 1.29) and `Surgical vs Medical` (OR = 1.41). Thus the probability that a MA occurs on any given day and for any given infant varies greatly with the conditioning variables at both the infant and the NICU levels. For instance, infants who contracted a `Prior Infection` in the NICU are 41% less likely to experience a MA. On the other hand, infants admitted after the `Overtime Reform` are 29% more likely to do so.

We further investigate the links between hours of work and MA in the next panel of the table where we report the fixed parameters β^G of the semiparametric additive function $f\left(X^G\right)$ in (3). According to these, `Daily Overtime` and `Daily Regular` hours of work have a positive and statistically significant effect on MA and are both of similar magnitude as what was obtained using the linear specifica-

[17]The relative risk is the ratio of the probability of the outcome with the risk factor ($X_j^R = b$) to the probability of the outcome with the risk factor ($X_j^R = a$).

tion of the mixed-effects logit model. Contrary to the latter model, `Birth Weight` is now also found to significantly impact the probability of observing a MA.

The main benefit of using a semiparametric model is its ability to yield varying and potentially non-linear odds-ratios for each variable in X^G.[18] Figure 3a draws the odds-ratios associated with `Overtime Hours` conditional on the 90^{th} percentile of `Regular Hours` (=584) and three different percentiles (10^{th}=800, 50^{th}=1,640 and 90^{th}=3,325) of `Birth Weight` along with their pointwise 95% credible sets. The figure exhibits three interesting features. First, as we move along the horizontal, which spans the entire domain of `Overtime Hours`, the odds-ratios increase twofold and are always above one. Second, for any given level of `Overtime Hours`, the odds-ratio is highly sensitive to the weight of the newborn. Finally, the credible sets are relatively narrow and never overlap. The situation that is depicted in the figure is one in which the occupancy rate is presumably relatively high given the assumed number of `Regular Hours`. According to the figure, thus, the 800g newborn is twice as likely to experience a MA than the 3,325g one, and the gap increases with overtime hours.

The model can be used to illustrate the complex interactions between the main policy variables and hence the difficult task management faces in order to prevent adverse events (Hugonnet et al., 2006). Figure 4 depicts two-dimensional contour plots for different combinations of X^G variables, conditional on a given value of a third one. Thus, Figure 4a shows the sensitivity of the odds-ratio for different

[18]See the supplementary material for the derivation of the ORs and their pointwise 95% credible sets.

combinations of `Daily Regular Hours` and `Daily Overtime Hours` for neonates at the 10^{th} percentile of `Birth Weight` (800 grams). For such low weight infants, the odds ratios increase rapidly from 1 to over 7 or 8, depending on the combination of regular and overtime hours. The figure also illustrates the trade-offs between regular and overtime hours. For a given odds-ratio, an increase in regular hours must be linearly compensated for by less overtime hours. Figure 4b plots the odds-ratios for various combinations of `Birth Weight` and `Daily Overtime Hours`, conditional on the 90^{th} of `Daily Regular Hours` (584 hours). The contour surfaces are non-linear and the odds-ratios peak at values of `Birth Weight` below 1,000 grams. The probability of observing a MA for infants of mean weight is much less sensitive to `Daily Overtime Hours`. Finally, Figure 4c reports the odds-ratios between `Daily Regular Hours` and `Birth Weight`, conditional on the 90^{th} value of `Daily Overtime Hours` (53 hours). Once again, the odds-ratios are non-linear. The probability of observing a MA increases rapidly with regular hours of work but mostly so for low birth weight infants.

Figures 4a–4c highlight the fact that the occurrence of a medical accident is related to the work hours in the NICU. They also underline the fact that low birth weight infants are most at risk of experiencing such adverse events.[19]

[19]Figures A1–A12 of the supplementary material reports the conditional contours plots of the odds ratios of the probability of MA conditional of the couple (`Daily Regular Hours`, `Daily Overtime Hours`) for 3 percentiles of `Birth Weight` (10, 50, 90), of the couple (`Daily Regular Hours`, `Birth Weight`) for 3 percentiles of `Daily Overtime Hours` (10, 50, 90), and of the couple (`Daily Overtime Hours`, `Birth Weight`) for 3 percentiles of `Daily Regular Hours` (10, 50, 90).

4.2.2. Health Care Associated Infections

The parameter estimates of the HCAI model are reported in Table 6 whose setup is identical to the previous one. HCAIs have been much more investigated in the literature than MA presumably because nosocomial infections are likely to have long term health and socio-economic consequences (Bharadwaj et al., 2018). As stated earlier, netting out the impact of work hours on HCAIs is a difficult task. This is perhaps why the literature is inconclusive on this issue (Bae and Favry, 2013; Weinstein et al., 2008).

As was the case with the MA model, the MFVB parameter estimates in Table 6 are very similar to those of the standard mixed-effects logit model reported in Table 3. The main difference between the two models lies in the precision of the parameter estimates. Recall from Table 3 that few birth characteristics and none of the NICU characteristics were found to be statistically significant. According to the semiparametric model, on the other hand, most are found to impact significantly the probability of observing a HCAI. Thus, `Gestational Age`, `Birth vs Transfer` and `C-Section` deliveries all bear the expected *a priori* sign and are statistically significant. In addition, `Overtime Hours` and `Birth Weight` and also found to impact the probability of observing a HCAI in a statistically significant manner.

According to Table 6, neonates admitted to the NICU at birth rather than being transferred from the nursery are 32% more likely to contract a nosocomial infection. `C-Section` births are also associated with a much lower probability of infection. Recall that many have suggested that `C-Section` delivery could be the sole reason for admitting otherwise healthy infants to the NICU (Fallah et al., 2011). Our result is consistent with this conjecture, and with an odds-ratio of 0.82, the effect is sizeable. The reason for admission (`Surgical` *vs* `Medical`, OR=1.36) and the `DRG-Severity` at admission (OR $\in$ $[0.09, 0.84]$), not surprisingly, are very strong predictors of HCAIs.

The only NICU-specific factor which impacts the probability of observing a HCAI is `Daily Admissions` (OR=1.04), although the effect is relatively small. This is in line with the findings of Beltempo et al. (2017a) using other data and a simple logistic regression and which found `Daily Admissions` to have little or no impact on the occurrence of a HCAI. Interestingly, the `Overtime Reform` has had no impact on the probability of observing a HCAI, unlike what was found above for MAs.

We next investigate the sensitivity of observing a HCAI in Figure 3b by plotting the odds-ratios with respect to `Overtime Hours` conditional on the 90^{th} percentile of `Regular Hours` (=584) and three percentiles (10^{th}=800, 50^{th}=1,640 and 90^{th}=3,325) of `Birth Weight` along with their pointwise credible sets. According to the figure, at the median value of `Overtime Hours` the odds-ratio of observing a HCAI is equal to either 0.6, 1.0, or 1.4 according to whether the newborn weights 3,325g, 1,640g or 800g, respectively. In addition, as we move along the `Overtime Hours` axis the gaps between the curves increase further and beyond 90 hours, all odds-ratios are greater than one, irrespective of weight.

The sensitivity of the odds-ratios is further investigated in Figures 5a–5c which depict the contour plots for the same combinations of variables as in Figures 4a–4c. Figure 5a focuses on `Regular Hours` and `Overtime Hours` for neonates at the 10^{th} percentile of `Birth Weight`. Recall from Table 6 that the parameter estimate of `Regular Hours` is not statistically significant. This translates into contour plots that are vertical with respect to the latter, *i.e.* there are no trade-offs between `Regular Hours` and `Overtime Hours` in determining work schedules that minimise the occurrences of HCAIs. Yet, as shown in the figure the odds-ratios are very sensitive to increases in `Daily Overtime Hours`, and mostly so above 60 hours (see also Figure 3b).

Indeed, increasing the number of `Daily Overtime Hours` from 60 to 120 translates into a threefold increase in the odds-ratios. Figure 5b depicts the contour plot between `Birth Weight` and `Daily Overtime Hours`, conditional on the 90^{th} percentile of `Regular Hours` (584 hours). The contour surfaces are non-linear and the odds-ratios peak at values of `Birth Weight` below 1,000 grams. Infants above the sample mean of 2,400 grams are much less sensitive to overtime hours. Indeed, increasing the `Daily Overtime Hours` from 60 to 120 increases the odd-ratios from 1 to 1.5. Finally, Figure 5c reports the odds-ratios between `Regular Hours` and `Birth Weight`, conditional on the 90^{th} percentile of `Overtime Hours` (53 hours). Since the parameter estimate associated with `Regular Hours` is not statistically significant, the risk of contracting a nosocomial infection increases considerably as birth weight decreases, regardless of `Regular Hours`.[20]

[20] Figures A13–A24 of the supplementary material provides conditional contour plots of the odds ratios of the probability of HCAI for the couple (`Daily Regular Hours`, `Daily Overtime Hours`) for 3 percentiles of `Birth Weight` (10, 50, 90), for the couple (`Daily Regular Hours`, `Birth Weight`) for 3 percentiles of `Daily Overtime Hours` (10, 50, 90) and for the couple (`Daily Overtime Hours`, `Birth Weight`) for 3 percentiles of `Daily Regular Hours` (10, 50, 90).

5. Conclusion

Most preterm and low birth weight infants are admitted to a neonatal intensive care unit (NICU) upon birth. Frail newborns are at higher risk of contracting a nosocomial infection and are more vulnerable to medical incidents such as erroneous medication administration or feeding and equipment malfunctioning.

NICUs are complex entities that are challenging from a managerial point of view. Unplanned admissions, random patient mixes, ever-changing caseloads, *etc.* require a particularly flexible workforce. In order to meet to meet required nurse-to-patient ratios management often relies on nursing overtime. The literature linking nursing overtime and neonatal outcomes, in addition to being relatively scant, is inconclusive. We conjecture that the lack of clear evidence linking nursing overtime and adverse events may also be due to methodological factors. In this paper, we focus on a single tertiary NICU with a 51-bed capacity. We study the daily occurrences of health care associated infections and medical incidents/accidents among all neonates admitted to the NICU between April 2008 and March 2013. Daily exposure to overtime and regular hours of work, as well as numerous individual and NICU-specific covariates are used to model the onset of the latter two outcomes.

Our empirical strategy starts by using a standard mixed-effects logit model to investigate the probability of observing each outcome separately, conditional on an extensive set of individual and NICU-specific variables. We also estimate quadratic and cubic specifications in hours of work and infant birth weight to help unearth potential nonlinearities. While the quadratic and the cubic specifications statistically reject the linear specification, hours of work (overtime and regular) are only found to impact the occurrence of medical accidents. As with the previous literature, the data cannot identify any causal link between hours of work and nosocomial infections. Next, we investigate the same outcomes using a flexible semiparametric mixed-effects logit model. This approach is seldom used in health economics due to its heavy computational burden. Fortunately, it can easily be estimated with the MFVB approximation method. The non-parametric components allow to compute highly flexible odds-ratios between them. Contrary to the mixed-effects logit model, the semiparametric model provides clear evidence that the occurrence of medical accidents as well as the onset of nosocomial infections are intimately related to nursing overtime. This is because the model yields considerably more precise parameter estimates than the parametric logit model. Furthermore, when tested against the parametric specifications (linear, quadratic, cubic) using a series Vuong's tests for non-nested models, the latter are clearly rejected in favour of the semiparametric mixed-effects logit models for both the MA and HCAI models.[21,22]

[21]See the supplementary material for the test results.

[22]The estimated area under the ROC curve (AUC) for accidents (resp. infection) is 0.635 (resp. 0.665) (see the supplementary material). With extremely rare events, though, these measures should be viewed with caution. Imbalanced class distribution in many practical datasets greatly hampers the detection of rare events. Some have shown that the AUC values obtained with logistic regression on rare events were far from the AUC value of 0.75 (standard for clinical tests) (see Hegelich (2016)). Some authors have proposed to develop frameworks for learning healthcare data with imbalanced distribution *via* incorporating different rebalancing strategies such as logistic regressions combined with synthetic minority oversampling techniques (SMOTE), which produces best detection results for rare events (see for instance Zhao et al. (2018), Fujiwara et al. (2020), Wang (2020)). Introducing this SMOTE method into semiparametric mixed-effects logit models requires complex developments that we leave aside for future research.

Importantly, the sensitivity of the two outcomes is shown to vary greatly with the mix of regular and overtime hours, as well as with the infant's birth weight. Thus infants at, or above, average birth weight and who are exposed to little overtime are at low risk of contracting a nosocomial infection. On the other hand, low birth infants who are exposed to numerous overtime hours are considerably more at risk. It is thus conceivable that the inconclusiveness of the literature may partly be due to the fact that standard regression models focus on mean point estimates. Allowing for more flexibility in the model is perhaps better suited to unearth subtle non-linear relationships between adverse events and important policy variables.

Table 1: Sample Means and Standard Deviations

Variable	Accident Infection/ No	Accident Yes	Infection Yes
	NEONATES AT ADMISSION		
Sex (Female=1)(%)	44.37	47.33	43.75
	(0.49)	(0.50)	(0.50)
Gestational Age	35.27	32.00	29.72
	(3.49)	(5.02)	(4.25)
Weight (Grams)	2511.57	1885.13	1433.58
	(848.43)	(1048.06)	(845.84)
Apgar $>$ 7 at 5 Min. (%)	88.50	70.00	64.17
	(31.90)	(45.90)	(48.05)
C-Section (%)	40.68	55.67	64.17
	(49.13)	(49.76)	(48.05)
First Birth (%)	74.21	79.33	86.67
	(43.75)	(40.55)	(34.06)
DRG Surgical *vs* Medical (%)	6.97	34.67	33.75
	(25.47)	(47.67)	(47.38)
DRG Severity Index (1 – 4)			
Low	25.76	5.51	0.73
Medium	40.34	16.53	9.85
High	24.48	28.57	32.12
Very High	9.40	49.39	57.30
Length of stay (Days)	18.98	64.99	75.30
	(19.32)	(50.61)	(48.91)
Overtime Reform	16.73	22.08	16.00
	(37.20)	(40.71)	(35.48)
	NICU (1,822 DAYS)		
Daily Admissions	4.37	4.33	4.55
	(2.29)	(2.30)	(2.36)
Bed Occupancy	50.37	50.72	50.71
	(3.33)	(3.48)	(3.07)
Daily Regular Hours	519.82	535.15	522.35
	(49.92)	(45.46)	(50.50)
Daily Overtime Hours	22.70	26.77	26.53
	(20.74)	(21.62)	(21.84)
	OUTCOMES		
Number of Events (Infants)	3,513	389 [300]†	272 [240]†
Infant Frequency (%)		7.54	6.03
Daily Frequency (%)		21.35	14.92
Daily/Infant Frequency (%)		0.458	0.321

† The number between brackets represents the number of neonates involved in the events.

Table 2: Probability of MA. Standard Mixed-Effects Logit Model

Coeff.	Linear	Quadratic	Cubic
Intercept	-6.7028**	-14.8305	3.5210
Birth Characteristics:			
Prior Infection	-0.5064**	-0.5448**	-0.5640**
Gestational Age	0.0356	0.0695**	0.0660**
Birth *vs* Transfer	-0.1247	-0.0378	-0.0159
Sex (Female=1)	0.0638	0.0587	0.0432
C-section	-0.0205	-0.0873	-0.1074
Twins	-0.1017	-0.0662	-0.0193
Apgar Score	-0.2889**	-0.2730**	-0.2756**
DRG Surgical *vs* Medical	0.3925**	0.3740**	0.3275**
DRG Severity (Omitted: Very High)			
Low	-1.0872**	-1.0224 **	-1.0101**
Medium	-1.1556**	-1.0766**	-1.0390**
High	-0.4266**	-0.3710**	-0.3412**
NICU Characteristics:			
Occupancy	-0.0345*	-0.0448**	-0.0449**
Daily Admissions	-0.0029	-0.0011	-0.0016
Overtime Reform (June 2012)	0.2707*	0.3161**	0.3160**
Daily Overtime Hours	6.82E-03**	1.95E-02**	2.64E-02**
Daily Regular Hours	4.68E-03**	3.61E-02*	-6.42E-02
Birth Weight	-1.06E-04	-9.98E-04**	-2.42E-03**
(Daily Overtime Hours)^2		-1.53E-04**	-3.45E-04
(Daily Regular Hours)^2		-2.96E-05	1.61E-04
(Birth Weight)^2		1.64E-07**	8.42E-07**
(Daily Overtime Hours)^3			1.31E-06
(Daily Regular Hours)^3			-1.20E-07
(Birth Weight)^3			-9.28E-11*
σ_u^2	0.2348	0.2086	0.1909
Likelihood-Ratio Test: χ^2(df, p-value)			
Linear vs Quadratic	13.96 (3, 0.003)		
Quadratic vs Cubic		5.25 (3, 0.154)	
Linear vs Cubic	19.21 (6, 0.004)		

** p-value < 0.05; * p-value < 0.10.

Table 3: Probability of HCAI. Standard Mixed-Effects Logit Model

Coeff.	Linear	Quadratic	Cubic
Intercept	-4.9943**	-4.4977	-4.0987
Birth Characteristics:			
Prior Accident	-0.4531**	-0.4537**	-0.4562**
Gestational Age	-0.0216	-0.0010	1.24E-05
Birth *vs* Transfer	0.2466	0.3196	0.3127
Sex (Female=1)	-0.0126	-0.0199	-0.0159
C-section	-0.1850	-0.2407	-0.2339
Twins	0.0509	0.0859	0.0735
Apgar Score	-0.0434	-0.0299	-0.0300
DRG Surgical *vs* Medical	0.3117**	0.2835**	0.2977**
DRG Severity (Omitted: Very High)			
Low	-2.4178**	-2.3738**	-2.3718**
Medium	-1.1585**	-1.0960**	-1.1070**
High	-0.1917	-0.1507	-0.1600
NICU Characteristics:			
Occupancy	0.0075	0.0067	0.0065
Daily Admissions	0.0379	0.0385	0.0386
Overtime Reform (June 2012)	-0.0534	-0.0395	-0.0413
Daily Overtime Hours	3.19E-03	7.46E-03	6.59E-03
Daily Regular Hours	9.97E-05	-1.92E-03	-5.50E-03
Birth Weight	-2.99E-04	-1.02E-03**	-6.42E-04
(Daily Overtime Hours)^2		-5.39E-05	-2.82E-05
(Daily Regular Hours)^2		1.84E-06	8.57E-06
(Birth Weight)^2		1.53E-07**	-3.29E-08
(Daily Overtime Hours)^3			-1.82E-07
(Daily Regular Hours)^3			-4.13E-09
(Birth Weight)^3			2.53E-11
σ_u^2	1.13E-05	1.18E-05	1.14E-05
Likelihood-Ratio Test: χ^2(df, p-value)			
Linear vs Quadratic	3.67 (3, 0.299)		
Quadratic vs Cubic		0.36 (3, 0.948)	
Linear vs Cubic		4.03 (6, 0.672)	

** p-value < 0.05; * p-value < 0.10.

Table 4: Odds Ratios and their 95% Confidence Intervals, Linear, Quadratic and Cubic Standard Mixed-Effects Logit Models

	LINEAR			QUADRATIC			CUBIC		
MA	OR	Inf 95%	Sup 95%	OR	Inf 95%	Sup 95%	OR	Inf 95%	Sup 95%
overtime hours (+1 unit)	1.0068	1.0022	1.0115	1.0141	1.0058	1.0224	1.0153	1.0062	1.0245
regular hours (+1 unit)	1.0047	1.0023	1.0071	1.0051	1.0026	1.0076	1.0056	1.0017	1.0096
overtime hours (d10)	0.8971	0.8330	0.9662	0.7681	0.6518	0.9052	0.7251	0.5683	0.9250
regular hours (d10)	0.7276	0.6194	0.8548	0.6164	0.4700	0.8083	0.6231	0.4773	0.8133
overtime hours (d90)	1.2703	1.0787	1.4959	1.3593	1.1351	1.6278	1.2985	1.0276	1.6408
regular hours (d90)	1.3320	1.1520	1.5401	1.2239	1.0206	1.4676	1.2399	1.0095	1.5229

	LINEAR			QUADRATIC			CUBIC		
HCAI	OR	Inf 95%	Sup 95%	OR	Inf 95%	Sup 95%	OR	Inf 95%	Sup 95%
overtime hours (+1 unit)	1.0032	0.9976	1.0088	1.0055	0.9963	1.0148	1.0054	0.9954	1.0155
regular hours (+1 unit)	1.0001	0.9975	1.0027	1.0000	0.9974	1.0026	1.0001	0.9958	1.0043
overtime hours (d10)	0.9505	0.8691	1.0395	0.9030	0.7489	1.0887	0.9092	0.6874	1.2027
regular hours (d10)	0.9933	0.8320	1.1858	1.0085	0.7939	1.2811	1.0057	0.7783	1.2995
overtime hours (d90)	1.1183	0.9181	1.3621	1.1371	0.9260	1.3963	1.1453	0.8623	1.5212
regular hours (d90)	1.0061	0.8576	1.1804	1.0070	0.8029	1.2629	1.0117	0.8001	1.2794

median of overtime hours (resp. regular hours and birth weight): 17.67 (resp. 522.92 and 1640).
decile 10 of overtime hours (resp. regular hours and birth weight): 1.75 (resp. 455 and 800).
decile 90 of overtime hours (resp. regular hours and birth weight): 52.75 (resp. 584.15 and 3325).

Table 5: Probability of MA. Semiparametric Mixed-Effects Logit Model

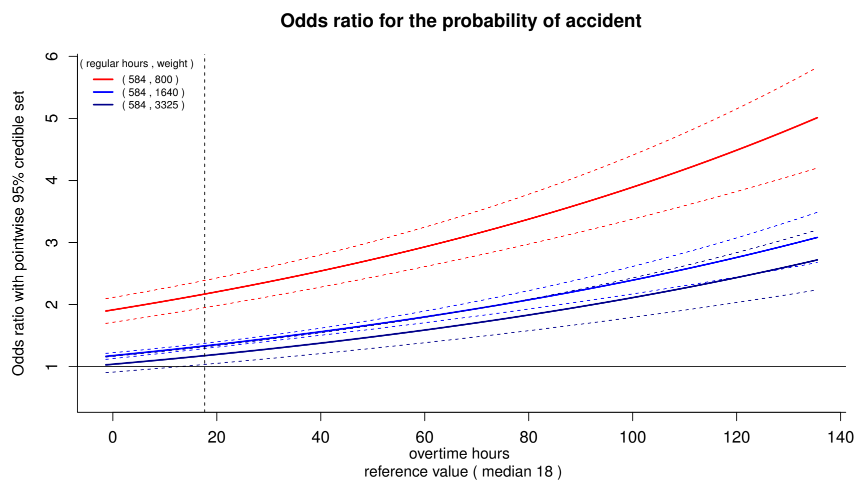
	Coeff.	Sd	Odds ratio	Sd	min 95% CI	max 95% CI
Constant coefficients: β^R						
Intercept	-7.50897	0.29623				
Birth Characteristics:						
Prior Infection	-0.51989	0.03463	0.59459	0.02059	0.55557	0.63634
Gestational Age	0.05979	0.00669	1.06161	0.00710	1.04778	1.07563
Birth *vs* Transfer	-0.04083	0.03693	0.95999	0.03545	0.89297	1.03205
Sex (Female=1)	0.02381	0.02342	1.02409	0.02398	0.97815	1.07219
C-Section	-0.07949	0.02967	0.92359	0.02740	0.87141	0.97889
Twins	-0.06311	0.03019	0.93884	0.02834	0.88490	0.99607
Apgar Score	-0.26775	0.02968	0.76510	0.02271	0.72186	0.81093
DRG Surgical *vs* Medical	0.34348	0.02979	1.40985	0.04200	1.32988	1.49462
DRG Severity (Omitted: Very High)						
Low	-1.04717	0.05334	0.35093	0.01872	0.31610	0.38961
Medium	-1.09140	0.03689	0.33575	0.01239	0.31233	0.36092
High	-0.38154	0.03155	0.68281	0.02155	0.64186	0.72637
NICU Characteristics:						
Occupancy	-0.03526	0.00422	0.96535	0.00408	0.95739	0.97338
Daily Admissions	-0.00305	0.00529	0.99696	0.00528	0.98667	1.00736
Overtime Reform (June 2012)	0.25988	0.03390	1.29678	0.04397	1.21340	1.38588
Constant coefficients β^G of semi-parametric function $f(X^G)$:						
Daily Overtime Hours	0.00708	0.00058				
Daily Regular Hours	0.00492	0.00026				
Birth Weight	-0.00012	0.00004				
$\sigma^2_{u^R}$	0.00119					

Table 6: Probability of HCAI. Semiparametric Mixed-Effects Logit Model

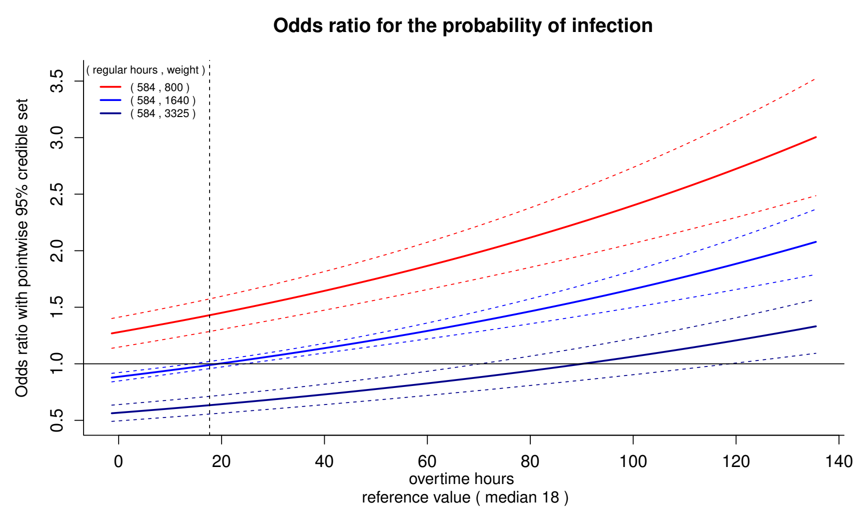
	Coeff.	Sd	Odds ratio	Sd	min 95% CI	max 95% CI
Constant coefficients: β^R						
Intercept	-4.87680	0.30249				
Birth Characteristics:						
Prior Accident	-0.46634	0.03171	0.62729	0.01989	0.58949	0.66752
Gestational Age	-0.01492	0.00698	0.98519	0.00688	0.97181	0.99876
Birth *vs* Transfer	0.27763	0.03910	1.31999	0.05162	1.22260	1.42514
Sex (Female=1)	-0.01500	0.02427	0.98512	0.02390	0.93936	1.03310
C-section	-0.20297	0.03066	0.81631	0.02503	0.76870	0.86686
Twins	0.05863	0.03064	1.06039	0.03249	0.99858	1.12602
Apgar Score	-0.03327	0.03035	0.96727	0.02935	0.91142	1.02655
DRG Surgical *vs* Medical	0.30544	0.03098	1.35723	0.04204	1.27727	1.44218
DRG Severity (Omitted: Very High)						
Low	-2.31153	0.05936	0.09911	0.00588	0.08822	0.11134
Medium	-1.13585	0.03878	0.32115	0.01245	0.29765	0.34651
High	-0.17249	0.03265	0.84157	0.02748	0.78940	0.89718
NICU Characteristics:						
Occupancy	-0.00313	0.00438	0.99688	0.00437	0.98835	1.00548
Daily Admissions	0.03458	0.00547	1.03519	0.00566	1.02415	1.04635
Overtime Reform (June 2012)	-0.00098	0.03598	0.99902	0.03595	0.93100	1.07202
Constant coefficients β^G of semi-parametric function $f(X^G)$:						
Daily Overtime Hours†	0.00631	0.00060				
Daily Regular Hours†	-0.00002	0.00027				
Birth Weight	-0.00023	0.00004				
$\sigma^2_{u^R}$	0.00124					

†Hours of work are computed as 3-day moving averages.

Figure 3: Odds Ratios for Medical Accidents and Infection.

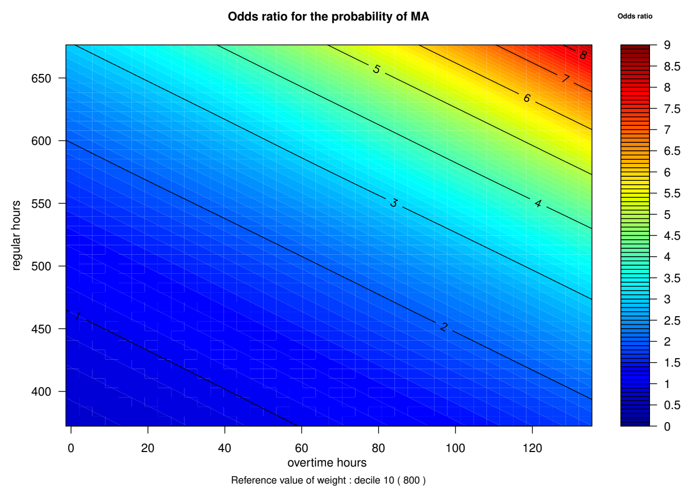


(a)

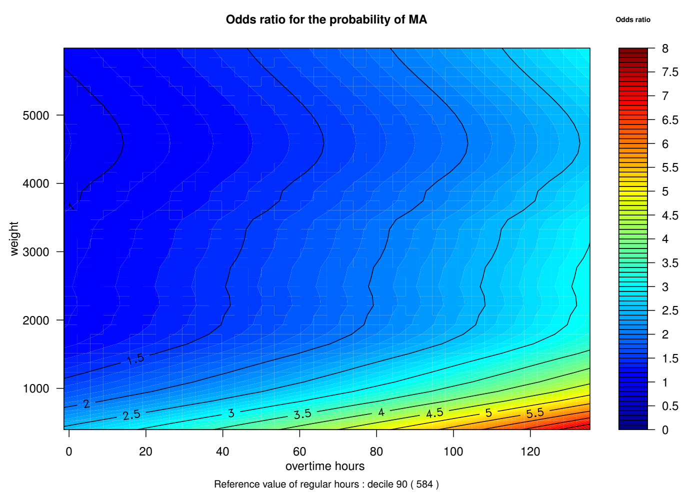


(b)

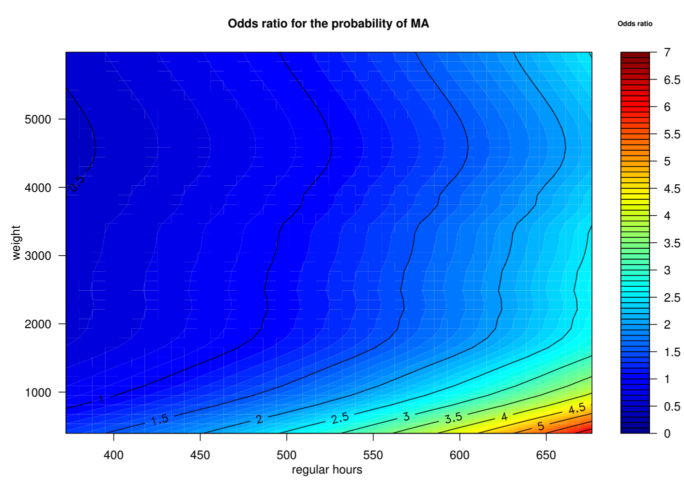
Figure 4: Contour Plots of Odds-Ratios for Medical Accidents.



(a) Regular *vs* Overtime Hours (Birth Weight: Percentile 10)

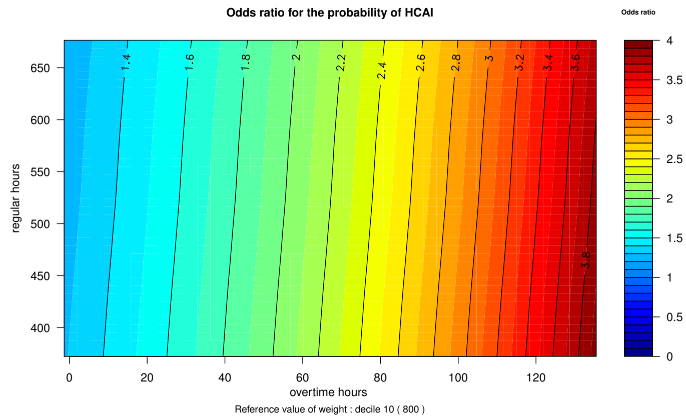


(b) Birth Weight *vs* Overtime Hours (Regular Hours: Percentile 90)

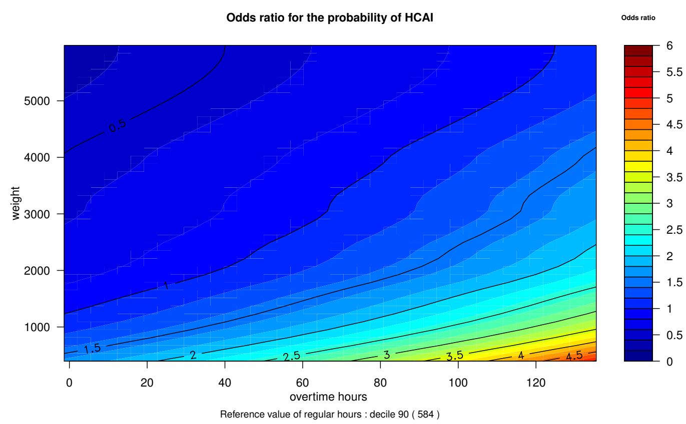


(c) Birth Weight *vs* Regular Hours (Overtime Hours: Percentile 90)

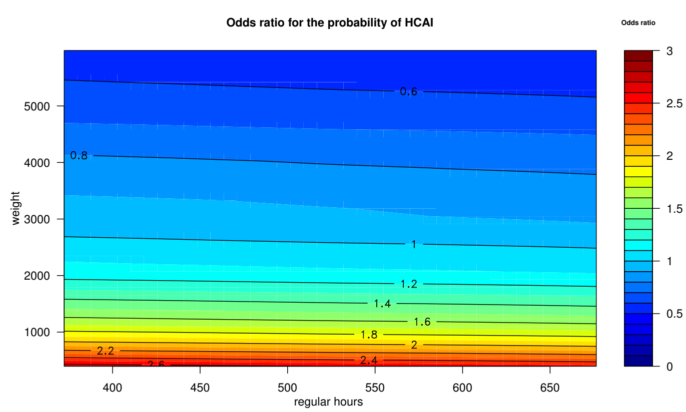
Figure 5: Contour Plots of Odds-Ratios for Health Care Associated Infections.



(a) Regular and Overtime hours (Birth Weight: Percentile 10)



(b) Birth Weight *vs* Overtime Hours (Regular Hours: Percentile 90)



(c) Birth Weight *vs* Regular Hours (Overtime Hours: Percentile 90)

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