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Service quality implications of extended periods of consecutive working days: An empirical study of neonatal intensive care nursing teams

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This supplementary material accompanies the paper "Service quality implications of extended periods of consecutive working days: An empirical study of neonatal intensive care nursing teams". It serves as reference material that provides further information on the analyses presented in the main paper. It complements the main paper and should not be read in isolation.

Section 1 supplements the robustness checks (presented in Section 6.3 of the main paper). It provides results from models with alternative time specifications (Section 1.1), tests the tenability of the proportionality assumption (Section 1.2) and the robustness of results towards changes in

the definition of 'high' and 'low' staffing levels (Section 1.3). Finally, it provides evidence that the results in the main paper are robust when we control for further patient characteristics and potential preferences of individual nurses for longer or shorter periods of consecutive working days (Section 1.4).

Section 2 clarifies the methodological procedure of our illustration of counterfactual effects of ACDW caps presented in Section 7 of the main paper. In Section 3, we provide the results of our IV estimation. Finally, in Section 4, we supplement the results of a potential ACDW tipping point.

1. Robustness Checks

1.1. Time specification

In the probit survival models, as presented in the main part of this paper, we include 28 time dummies and a linear time variable that captures potential effects of time after the first 28 days of stay. We do this to keep the model as parsimonious as possible. 28 time dummies capture all potential time effects for 91% of the patients, as only for 9% of the patients in the dataset it takes more than 28 days until feeding is changed to fully enteral. The maximum duration until feeding is changed to fully enteral is 133 days, and after 56 days, 99% of all patients have experienced the event. Therefore, we test whether results are robust to including 56 or 133 time dummies in our models. Further, we test linear, quadratic, and cubic time specifications with different numbers of time dummies. Table 1 provides coefficient estimates of regression models with the different time specifications. Estimation results are very similar, and the models with alternative time specifications are not sufficiently superior in terms of goodness-of-fit to justify the required number of additional time parameters.

Table 1 Coefficient Estimates – Variation of the Time Specification

Model	(1) Basic model	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ACDW	-0.082**	-0.088**	-0.071*	-0.073*	-0.079*	-0.082**	-0.079*	-0.082**	-0.079*	-0.083**	-0.079*	-0.079*
in nursing team	(0.031)	(0.029)	(0.029)	(0.030)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.032)	(0.031)	(0.031)
Low NPR	-0.115*	−0.102^{+}	−0.097^{+}	−0.098^{+}	-0.121*	-0.115*	-0.123*	-0.117*	-0.123*	-0.115*	-0.121*	-0.122*
	(0.055)	(0.053)	(0.056)	(0.059)	(0.056)	(0.055)	(0.056)	(0.056)	(0.056)	(0.055)	(0.056)	(0.056)
Complex patient	-0.509***	-0.380***	-0.475***	-0.498***	-0.511***	-0.509***	-0.511***	-0.508***	-0.511***	-0.509***	-0.511***	-0.510***
	(0.059)	(0.045)	(0.059)	(0.062)	(0.059)	(0.059)	(0.059)	(0.060)	(0.059)	(0.059)	(0.059)	(0.060)
Dummies for first days of stay	28	0	0	0	56	28	56	28	56	28	56	65
Time	-0.004	0.024***	0.103***	0.181***	0.014	0.018	0.711	-0.343	2.964	–	0.014	–
	(0.008)	(0.006)	(0.014)	(0.017)	(0.016)	(0.034)	(0.450)	(0.270)	(2.616)		0.016	
Time^2			-0.002***	-0.005***		-0.000	-0.006	0.007	-0.040			
			(0.000)	(0.001)		(0.000)	(0.004)	(0.005)	(0.038)			
Time^3				0.000***				-0.000	0.000			
				(0.000)				(0.000)	(0.000)			
NICU fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.711*	-1.544***	-2.159***	-2.620***	-2.119**	-1.202	−23.612^{+}	4.313	-71.796	-0.863***	-2.119**	-1.965***
	(0.328)	(0.069)	(0.126)	(0.135)	(0.796)	(0.743)	(13.420)	(4.157)	(58.641)	(0.149)	(0.796)	(0.325)
Log-Likelihood	-2458.509	-2703.005	-2605.149	-2560.508	-2449.128	-2458.289	-2445.533	-2456.902	-2445.291	-2458.713	-2449.128	-2440.998
Pseudo R^2	0.142	0.056	0.090	0.106	0.145	0.142	0.146	0.142	0.146	0.142	0.145	0.148
Patient-days	10,605	10,605	10,605	10,605	10,605	10,605	10,605	10,605	10,605	10,605	10,605	10,605
Number of patients	847	847	847	847	847	847	847	847	847	847	847	847
Number of NICUs	62	62	62	62	62	62	62	62	62	62	62	62

Notes. This table presents coefficient estimates from probit models with standard errors, clustered at NICU level, shown in parentheses. The time specification of Model (1) corresponds to the specification that we use in the models presented in the main part of the paper. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, $^{+}p < 0.1$. The ACDW variable has been demeaned to facilitate interpretation of the interaction effects.

1.2. Proportionality assumption

We examine the tenability of the proportionality assumption by checking whether a non-proportional (interaction-with-time) hazard function fits our data better than the main effects model, as presented in the main part of the paper. We test different functional forms for the interaction-with-time models and compare their deviance statistics (-2×log-likelihood) with that of the main effects model. The differences in deviance statistics are compared to a χ^2 distribution. Table 2 shows deviance statistics for the main effects hazard model that adheres to the proportionality assumption and for interaction-with-time models that do not.

First, we test whether the effect of ACDW differs across early and late phases. We create a dichotomous variable for 'period after day of stay x'. The values of this variable indicate whether a day of stay lies in the period after the first x days of stay. We create phase dummy variables and estimate models including dummy variables for phases after day 5, 7, 10, 12, 14, 17, 28, 34, and 56, as well as interactions of these dummies with the ACDW variable. We chose these time points because feeding was switched to fully enteral by day 12 for 50% of all patients, by day 17 for 75% of the patients, by day 28 for 90% of the patients, by day 34 for 95% of the patients, and by day 56 for 99% of the patients. As the differences between deviance statistics for these models and for the main effects model do not exceed the 1% critical value of a χ^2 distribution on two degrees of freedom (which is 9.210), we do not reject the null hypothesis that the effect does not differ between early and late phases.

Further, we compare deviance statistics for the main effects model and an interaction-with-time model, which allows the effect of ACDW to differ from day to day for the first 28 days. In this model, each of the dummies for the first 28 days of stay is interacted with the ACDW variable. The difference in deviance statistics is 24.2138, which by far does not exceed the critical values of a χ^2 distribution, not even the 10% critical value (which is 37.916 for 28 additional parameters). Also, coefficients of the interactions between the ACDW variable and dummies for the first 28 days of stay provide no indication of a linear change (decrease or increase) in the effect of ACDW over

time.

We conclude that the interaction-with-time models are not sufficiently superior in terms of goodness-of-fit for the required number of additional parameters to be justified. The test results do not provide us with any reason to assume that the proportionality assumption is violated. By testing these parsimonious functional forms for changing ACDW effects, we follow a routine recommended by Singer and Willett (2003). We do not use a model that allows the effect of ACDW to differ from day to day (beyond the first 28 days) because (i) theory does not point toward this kind of behavior and (ii) a model allowing such an effect would require too many parameters, as the dummies for each day of stay would have to be interacted with the ACDW variable.

Table 2 Deviance Statistics for Main Effects and Interaction-With-Time Models

	Goodness of fit: Deviance	Difference to deviance of main effects model
Main effects model	4917.0187	
Change in effect in period after day of stay x		
x= 5	4916.3858	0.6329
x= 7	4916.8726	0.1461
x= 10	4916.3607	0.6580
x= 12	4916.4770	0.5417
x= 14	4915.2424	1.7763
x= 17	4912.9236	4.0951
x= 28	4910.6622	6.3565
x= 34	4914.8178	2.2009
x= 56	4916.4727	0.5460
Daily change (for first 28 days of stay)	4892.8049	24.2138

Notes: This table shows deviance statistics for interaction-with-time models, which are compared to the deviance statistics of the main effects model. Note that, for 50% of all patients, feeding was switched to fully enteral after at most 12 days, for 75% after at most 17 days, for 90% after at most 28 days, for 95% of the patients after at most 34 days, and for 99% after at most 56 days.

1.3. Robustness of NPR tipping point

Using spline models, we found support for a 'NPR tipping point' and nonlinear workload effects. Workload was therefore measured as a binary variable ($LNPR_{it}$) which takes the value 1 if the NPR experienced by patient i on day t is below or equal to the NICU-specific 15$^{\text{th}}$ percentile of the NPR. To test whether our results are robust to changes in the chosen percentile, we replaced the NICU-specific 15$^{\text{th}}$ by the 10$^{\text{th}}$ or the 20$^{\text{th}}$ percentile and compared APE estimates between the models. Comparing the results of the main paper with estimation results of both models with different specifications of our NPR variable, we see that estimation results are very similar. Results are presented in table 3.

Table 3 APE Estimates of Daily Hazard of Event Occurrence – Regressions with NPR dummy specifications

Model NPR dummy specification	(1) ($\leq$ 10th percentile)	(2) ($\leq$ 15th percentile)	(3) ($\leq$ 20th percentile)
Hypothesis 1:			
ACDW in nursing team	-0.010**	-0.010**	-0.010**
	(0.004)	(0.004)	(0.004)
Log-Likelihood	-2,458.92	**-2,458.51**	-2,459.90
Hypothesis 2:			
ACDW when NPR is low	-0.018*	-0.020**	-0.014**
	(0.007)	(0.006)	(0.005)
ACDW when NPR is high	-0.008^{+}	-0.006	-0.009^{+}
	(0.004)	(0.005)	(0.005)
Difference	-0.010	-0.014*	-0.005
Log-Likelihood	-2,458.11	**-2,456.72**	-2,459.56
Hypothesis 3:			
ACDW for non-complex patients when NPR is high	0.000	0.004	-0.001
	(0.008)	(0.009)	(0.009)
ACDW for non-complex patients when NPR is low	-0.030*	-0.031*	-0.015
	(0.013)	(0.012)	(0.010)
Difference for non-complex patients	0.030*	0.036*	0.013
ACDW for complex patients when NPR is high	-0.013*	-0.012*	-0.012*
	(0.005)	(0.006)	(0.005)
ACDW for complex patients when NPR is low	-0.011	-0.013*	-0.014*
	(0.008)	(0.007)	(0.007)
Difference for complex patients	0.001	0.002	0.001
Log-Likelihood	-2,456.04	**-2,454.34**	-2,459.42

Notes: This table shows APEs based on estimates from linear probit models. Model (1), (2) and (3) summarize APE estimates using different specifications of our NPR variable, where workload is defined as below or equal to the NICU-specific 10$^{\text{th}}$ (Model 1), to the NICU-specific 15$^{\text{th}}$ (Model 2, as presented in the main paper) and to the NICU-specific 20$^{\text{th}}$ (Model 3) percentile of the NPR. The ACDW variable has been demeaned to facilitate interpretation of the interaction effects. Standard errors, clustered at NICU level, are shown in parentheses. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

1.4. Model specifications

The econometric specification in our main paper consists of several control variables which we believe might correlate with our dependent variable and independent variable. We did not use further patient-specific control variables as we do not have any theoretical arguments that these factors are correlated with our independent variable. Nevertheless, we checked whether our results might change when we include further patient characteristics as potential confounders in our model.

We discussed potential medical confounders with the NICU physician head of a participating university hospital. Based on this discussion, we then considered further patient control variables that are the most relevant key drivers for the development of VLBW patients regarding their nutrition: (1) a variable which takes the value 1 if the patient is discharged without having experienced any of the morbidities that are most relevant for the development of VLBW patients regarding their nutrition. This dummy takes the value 1 if the patient neither suffered from an Intraventricular Hemorrhage (IVH) stage >2, nor from Bronchopulmonary Dysplasia (BPD), nor got surgery for Necrotizing Enterocolitis (NEC) or for Focal Intestinal Perforation (FIP). IVH is a bleeding into the germinal matrix, ventricles or cerebral parenchyma, surrounded by the brain. It is a major complication of prematurity, stages >2 are clinically relevant. BPD is a term used to describe long-term breathing problems for preterm patients. It involves an abnormal development of the lung. In our study, the presence of BPD was defined as the requirement for supplemental oxygen at weeks 35+0 to 36+6 after birth. NEC is a gastrointestinal disease that involves infection and inflammation and causes damage and the death of cells in the intestine. FIP is a condition that describes the spontaneous intestinal perforation. (2) a variable according to the Clinical Risk Index for Babies (CRIB II) score, a validated measure of initial mortality risk and illness severity within the first hours of birth (Parry et al. 2003). The measure takes into account the birth weight, gestational age, body temperature, base excess, and sex of the patient. The scale ranges from 0 to 27, with better prognosis for lower scores and (3) we controlled for whether a patient was fed with

breast milk (mother or donor) or not during his or her stay with a dummy variable that takes the value 1 for patients who are fed with breast milk during the NICU stay. Finally, as presented in the main part of the paper, we additionally considered a control variable that captures potential preferences of individual nurses for longer or shorter periods of consecutive working days, which might confound the results.

Table 4 therefore presents two models: In model 1, we present the coefficient estimates for the daily hazard of event occurrence of the main model presented in the paper (Model 1, Table 2). In model 2, we present the coefficients for the specified model which incorporates the abovementioned control variables. Please note that the sample size is reduced, because information on morbidities is missing for some patients in our dataset. As a result, we find similar estimations as in the model we used in the main paper.

Table 4 Coefficient Estimates of Daily Hazard of Event Occurrence with specified model

Model:	Main model	Specified Model
ACDW in nursing team	-0.082**	-0.092**
	(0.031)	(0.034)
Low NPR ($\leq 15^{\text{th}}$ percentile)	-0.115*	-0.106
	(0.055)	(0.063)
Complex patient (birth weight $\leq$ median)	-0.509***	-0.161*
	(0.059)	(0.078)
No comorbidities at discharge		0.211*
		(0.086)
CRIB II		-0,062***
		(0.010)
Breast milk during stay		0.061
		(0.068)
Individual nurse preferences		-0.122
		(0.087)
Dummies for first 28 days of stay	Yes	Yes
Time (linear for day of stay > 28)	-0.004	-0.003
	(0.008)	(0.009)
NICU fixed effects	Yes	Yes
Constant	-0.711*	-0.227
	(0.328)	(0.393)
Log-Likelihood	-2458.51	-1981.06
Pseudo R^2	0.142	0.165
Patient-days	10,605	8,550
Number of patients	847	709
Number of NICUs	62	56

Notes: Standard errors in parentheses (clustered at NICU level)
$^{***}p < 0.001, ^{**}p < 0.01, \ ^{*}p < 0.05, ^{+}p < 0.1$

Table 5 Average Partial Effect Estimates with specified model

Model	Number of observations	(1)	(2)	(3)
Hypothesis 1:				
ACDW in nursing team	8,550	-0.012**		
		(0.0004)		
Hypothesis 2:				
ACDW when NPR is low (NPR $\leq$ 15th percentile)	2,647		-0.019**	
			(0.006)	
ACDW when NPR is high	5,903		-0.008	
			(0.005)	
Difference			-0.011	
Hypothesis 3:				
ACDW for non-complex patients when NPR is high	2,230			0.009
				(0.010)
ACDW for non-complex patients when NPR is low	1,008			-0.018^{+}
				(0.011)
Difference for non-complex patients				0.028*
ACDW for complex patients when NPR is high	3,673			-0.018**
				(0.007)
ACDW for complex patients when NPR is low	1,639			-0.020**
				(0.008)
Difference for complex patients				0.001

Notes: Standard errors in parentheses (clustered at NICU level)
$^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05, ^{+}p < 0.1$

2. Counterfactual effects of ACDW caps

For our counterfactual analyses, we compare the predicted duration until a certain percentage of the patients in our sample has experienced the event of interest, which is the changeover to full enteral feeding, between the baseline and counterfactual scenarios. This section describes how we calculate this outcome measure, following Singer and Willett (2003).

First, the predicted hazards for each patient-day, $\hat{h}_{it}$, are averaged over all patients who have not experienced the event by day of stay t. This yields the sample-average discrete-time hazard of event occurrence for each day of stay t, denoted by $\hat{h}_t$. Then, a survivor function that cumulates these day-by-day hazards is used to estimate, for each day t, the rate of patients who did not have their nutrition switched to fully enteral at the end of that day. The survivor function takes the following form:

$$\hat{S}_t = \hat{S}_{t-1}[1 - \hat{h}_t].$$

As the values of $\hat{S}_t$ provide the fraction of patients who have not experienced the event at the end of day t, $(1 - \hat{S}_t)$ provides the cumulative incidence, which is the fraction of patients who have experienced the event at the end of day t. Using the cumulative incidence, we calculate the number of days T until a certain fraction of the patients have experienced the event. The value of T for which the value of the estimated survivor function is 0.5 is the estimated median duration until feeding is switched to fully enteral. This is the point in time by which we estimate that half of the sample has experienced the event, and half has not. The estimated median duration until event occurrence is an outcome measure that is commonly used in survival analysis and calculated using the following formula:

$$\textit{Estimated median duration until event occurrence} = m + [\frac{\hat{S}_{t=m} - 0.5}{\hat{S}_{t=m} - \hat{S}_{t=m+1}}],$$

where m represents the day t on which the survivor function is just above 0.5, $\hat{S}_{t=m}$ is the value of the survivor function on that same day, and $\hat{S}_{t=m+1}$ is the value of the survivor function for the following day, when the value of the survivor function is below 0.5. Besides the estimated median

duration, we calculate the number of days after which 90% of the patients have experienced the event (with the same formula, but 0.5 is replaced by 0.9).

The standard errors for the estimates of $\hat{S}_t$ are calculated using Greenwood's approximation (see Singer and Willett 2003),

$$se(\hat{S}_t) = \hat{S}_t \sqrt{\sum \frac{\hat{h}_t}{n_t(1-\hat{h}_t)}},$$

where n_t is the number of patients who have not experienced the event by day t. 95% CI estimates are calculated using $\hat{S}_t \pm 1.96\ se(\hat{S}_t)$.

In order to obtain baseline estimates against which estimates from counterfactual analyses can be compared, we first estimate the predicted duration until the experience of the event based on the predicted baseline daily hazards of event occurrence, $\hat{h}_t$. Then, we estimate the predicted duration until the patients' feeding is changed to fully enteral based on the counterfactual predicted daily hazards of event occurrence, $\hat{h}_{1t}$.

3. IV estimation

To test for potential endogeneity of our independent variable ACWD, we used a control function approach according to Wooldridge (2015), where the continuous variable ACDW was regressed on the set of controls used in the main Model and 6 weekday dummies which served as instrumental variables (with Monday as the omitted variable). The estimates of this first stage regression are presented in table 6. The first stage residual was then used as an additional control variable for all IV models where we tested for potential endogeneity in the three main models (Table 2 of the main paper, Model 1-3). The estimates for the IV models are presented in table 7. Coefficients for the first stage stage residuals were all close to zero and highly insignificant (Model 1:-0.019, p=0.855; Model 2:-0.022, p=0.827; Model 3:-0,022, p=0.834), corresponding t-tests revealed no evidence of endogeneity.

Table 6 Control function approach: First stage regression

Model	(1)
Low NPR ($\leq 15^{\text{th}}$ percentile)	0.041**
	(0.015)
Complex patient (birth weight $\leq$ median)	-0.012
	(0.013)
Dummies for first 28 days of stay	Yes
Time (linear for day of stay > 28)	0.006**
	(0.002)
NICU fixed effects	Yes
Constant	-0.797***
	(0.081)
Tuesday	0.114***
	(0.021)
Wednesday	0.214***
	(0.021)
Thursday	0.240***
	(0.021)
Friday	0.248***
	(0.021)
Saturday	0.023
	(0.021)
Sunday	0.650***
	(0.021)
Patient-days	10,605
Number of patients	847
Number of NICUs	62

Notes: Standard errors in parentheses
$^{***}p < 0.001, ^{**}p < 0.01$, $^{*}p < 0.05, ^{+}p < 0.1$

Table 7 IV-models

Model	(1)	(2)	(3)
First stage residual	-0.019	-0.022	-0.022
	(0.102)	(0.102)	(0.107)
ACDW in nursing team	-0.066	-0.029	0.046
	(0.100)	(0.102)	(0.110)
Low NPR ($\leq 15^{\text{th}}$ percentile)	-0.116*	-0.110^{+}	-0.104
	(0.056)	(0.056)	(0.080)
Complex patient (birth weight $\leq$ median)	-0.508***	-0.508***	-0.505***
	(0.050)	(0.051)	(0.052)
ACDW x low NPR		-0.123*	-0.248*
		(0.061)	(0.099)
ACDW x complex patient			0.135^{+}
			(0.072)
Complex patient x low NPR			-0.008
			(0.099)
ACDW x complex patient x low NPR			0.223^{+}
			(0.135)
Dummies for first 28 days of stay	Yes	Yes	Yes
Time (linear for day of stay > 28)	-0.004	-0.004	-0.004
	(0.006)	(0.006)	(0.007)
NICU fixed effects	Yes	Yes	Yes
Constant	-0.702*	-0.690*	-0.712*
	(0.281)	(0.282)	(0.287)
Log-Likelihood	-2458.49	-2456.70	-2454.32
Pseudo R^2	0.142	0.142	0.143
Patient-days	10,605	10,605	10,605
Number of patients	847	847	847
Number of NICUs	62	62	62

Notes: Standard errors in parentheses using bootstrap to adjust for the two-step estimation.
$^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05, ^{+}p < 0.1$

Table 8 Average Partial Effect Estimates for IV-models

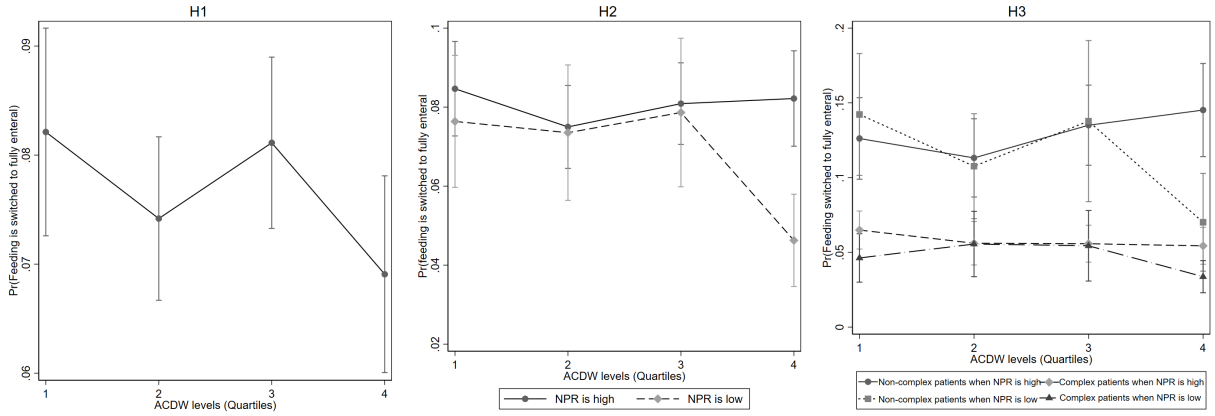
Model	Number of observations	(1)	(2)	(3)
Hypothesis 1:				
ACDW in nursing team	10,605	-0.008		
		(0.012)		
Hypothesis 2:				
ACDW when NPR is low (NPR $\leq$ 15th percentile)	3,151		-0.017	
			(0.013)	
ACDW when NPR is high	7,454		-0.004	
			(0.013)	
Difference			-0.014	
Hypothesis 3:				
ACDW for non-complex patients when NPR is high	2,691			0.008
				(0.017)
ACDW for non-complex patients when NPR is low	1,165			-0.029
				(0.018)
Difference for non-complex patients				0.036
ACDW for complex patients when NPR is high	4,763			-0.011
				(0.011)
ACDW for complex patients when NPR is low	1,986			-0.010
				(0.011)
Difference for complex patients				0.002

Notes: Standard errors in parentheses (clustered at NICU level)
$^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05, ^{+}p < 0.1$

4. ACDW tipping point

As described in the main paper, we re-estimated the primary models using quartiles of ACDW as categorical variables to explore whether the ADCW's impact increases significantly past a certain threshold ('tipping point') . The results, presented in Figure 1, show initial support for this hypothesis.

Figure 1 Predicted Daily Hazards of Event Occurrence by ACDW Quartile



Note: These graphs show the the predicted hazard of event occurrence by ACDW quartile, together with 95% confidence intervals. In Graph H1, the predicted hazards for different ACDW levels are averaged over all patient-days in the dataset. Graph H2 differentiates between days with high and days with low NPRs. Graph H3 differentiates between four classes: Complex patients when NPR is low (Complex, low NPR), Non-complex patients when NPR is low (Non-complex, low NPR), Complex patients when NPR is high (Complex, high NPR) and non-complex patients when NPR is high (Non-complex, high NPR).

References

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