The Effect of Electrical Load Shedding on Pediatric Hospital Admissions in South Africa

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4 April 2019

Background

- South Africa faced repeated episodes of temporary power shutdowns in 2014-2015 (and currently again since 2018).
- Because the power supplier ESKOM was not able to satisfy the power demand, *load shedding* was implemented for several hours a day.
- Times and areas affected by load shedding have been communicated by ESKOM to the public on short notice (Twitter, homepages).

Case Reports from Red Cross Children's Hospital

- Because of load-shedding candles are used, little boy brushes teeth, pyjamas catch fire, burn wounds, wounds get infected...
- Mother creates temporary outdoor fireplace for cooking because of load-shedding, not much light, pan with hot fat placed in the dark, children play and one steps into the hot fat...

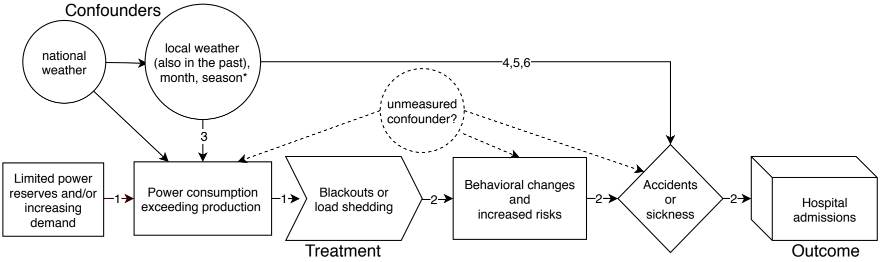
Objective

To evaluate whether load shedding has an effect on the number of hospital admissions at Red Cross Children's Hospital.

Data

- Study period: between 1 June 2014 and 31 May 2015.
- Outcome (Y): The number of unplanned admissions of children up to 13 years of age (by ICD-10 code).
- Intervention (A): Binary indicator whether load shedding was implemented on the same day (or any of the 2 preceding days).
  $\rightarrow$ Collected from Twitter and Facebook, verified later with data from the City of Cape Town (no co-operation from ESKOM).
- Confounders and other variables ($\mathbf{L}$), see DAG: current and past weather, season, month, week of payment, past admissions.
  $\rightarrow$ co-operation with South African Weather Service

DAG



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* Changes in weather conditions to more extremes like heat or cold lead to increasing demand by air conditioning or electric heaters and might directly influence health states.

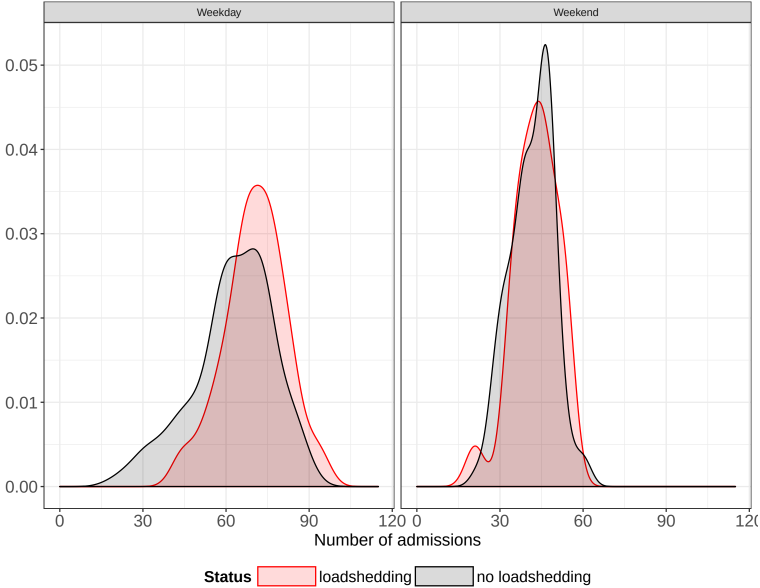
Analytical Approach

- Descriptives
- Quasi-Poisson regression
- Doubly robust causal inference

Descriptives (I)

- During the study period between June 2014 to May 2015, Cape Town experienced 72 days of load shedding, 48 during the week and 24 on the weekend.
- Load shedding started as soon as 11 June 2014, but many events (38) occurred in April/May 2015.
- The mean number of unscheduled admissions during the study period was about 57.
- On days of load shedding there were on average 61.3 admissions a day, and on days without there were about 56.7 admissions.

Descriptives (II)



Regression Analysis (I)

Large set of variables (> 40):

- weather: hours of sunshine (L^1), wind speed (L^2), humidity (L^3), pressure (L^4), precipitation (L^5), temperature (L^6) – on current day and past 2 days
- season: month (L_7), week of payment (L_8), and a seasonal (weekly) trend modeled via sine and cosine terms, i.e.

  $$\cos(\omega_k t) \quad \text{and} \quad \sin(\omega_k t) \quad \text{with} \quad \omega_k = \frac{2k\pi}{T}, \quad \text{with} \quad T = 7\,\text{days}$$

  i.e. $\cos(\omega_1 t) = L^9$, $\sin(\omega_1 t) = L^{10}$, $\cos(\omega_2 t) = L^{11}$, $\sin(\omega_2 t) = L^{12}$, $\cos(\omega_3 t) = L^{13}$, $\sin(\omega_3 t) = L^{14}$, $\cos(\omega_4 t) = L^{15}$, $\sin(\omega_4 t) = L^{16}$
- We also need to take past admissions (i.e. $Y_{i-\text{lag}}$, $\text{lag} \in \{1, 2, \ldots, 13, 14, 21, 28\}$) into account

Regression Analysis (II)

After limiting the number of variables (using model averaging[1]) to the most important ones (for computational feasibility), we use the following Quasi-Poisson model:

$$
\begin{aligned}
E(Y) \quad = \quad & \exp(\beta_0 + \underbrace{\beta_1 A}_{\text{load shedding}} + \underbrace{\mathbf{L}^* \boldsymbol{\beta}_2}_{\text{season}} \\
& \underbrace{+ f_1(Y_{i-1}) + f_2(Y_{i-3}) + f_3(Y_{i-7}) + f_4(Y_{i-9})}_{\text{past admissions}} \\
& \underbrace{\begin{array}{l} + f_5(L^1) + f_6(L^2) + f_7(L^5) \\ + f_8(L^3_{i-1}) + f_9(L^5_{i-1}) + f_{10}(L^6_{i-1}) + f_{11}(L^2_{i-2})) \end{array}}_{\text{(past) weather}}
\end{aligned}
$$

with $\mathbf{L}^* = (L^7, L^8, L^9, L^{10}, L^{11}, L^{12})$ being the seasonal trend.

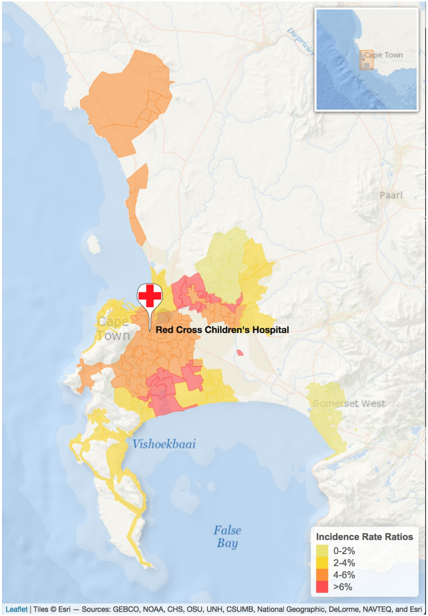
[1] see paper [1] for details

Regression Analysis (III)

	IRR	95% CI	VI
Main Result	**1.10**	**1.04;1.15**	
Weekday	1.12	1.07;1.18	
Weekend	1.01	0.91;1.11	
LS: same day	1.05	1.00;1.11	0.30
LS: 1 day prior	1.09	1.04;1.15	0.85
LS: 2 days prior	1.07	1.01;1.13	0.69
LS: 3 days prior	1.07	1.01;1.13	0.40
LS: 4 days prior	0.98	0.93;1.04	0.34
Surgical cases	1.08	1.00;1.16	
Medical cases	1.11	1.00;1.16	

→ see paper [1] for specific ICD-10 codes and diagnoses

Regression Analysis (IV)



Causal Approach, TMLE (I)

- Average Treatment Effect (ATE): "The difference in expected number of admissions per day had there been load shedding each day or on any of the preceding 2 days compared to if there had not been any load shedding".

$$\psi = E(Y^1) - E(Y^0),$$

- Estimate ψ with TMLE[2]. TMLE requires fitting of

  1. $E(Y|A, \mathbf{L})$ and
  2. $P(A = 1|\mathbf{L})$

  with regression models or machine learning, and also

  3. another regression that updates an initial estimate of ψ

[2] see Luque-Fernandez et al. [2] for a tutorial

Causal Approach, TMLE (II)

- TMLE is doubly robust
- This means that if *ONLY ONE* of the two models estimating

  1. $E(Y|A, \mathbf{L})$
  2. $P(A = 1|\mathbf{L})$

  are specified correctly, one can estimate the ATE consistently!
- If both are estimated consistently, one has an efficient estimator (smallest variance among respective class of estimators)
- Difficult to specify models correctly (we have > 40 variables) $\rightarrow$ use "super learning"

Causal Approach, TMLE (III)

1. Estimate $\bar{Q}^0(A, L) = E(Y|A = a, L = l)$ and set $A = 0$ and $A = 1$: to get the predictions

$$\begin{aligned}\hat{\bar{Q}}^0(1, L) &= \hat{E}(Y|A = 1, L) \quad \text{and} \\ \hat{\bar{Q}}^0(0, L) &= \hat{E}(Y|A = 0, L)\,.\end{aligned}$$

   For continuous outcomes, like “number of admissions”, use $Y^* = (Y - a)/(b - a)$.

2. Estimate $g^0(A|L) = P(A = 1|\mathbf{L})$ to get the predictions

$$\begin{aligned}\hat{g}^0(1|L) &= \hat{P}(A = 1|L) \quad \text{and} \\ \hat{g}^0(0|L) &= 1 - \hat{g}^0(1|L)\,.\end{aligned}$$

Causal Approach, TMLE (IV)

3. Estimate

$$\underbrace{\log\left(\frac{P(Y=1|A,L)}{1-P(Y=1|A,L)}\right)}_{\log(\bar{Q}^1(A,L)/[1-\bar{Q}^1(A,L)])} - \log\left(\frac{\hat{\bar{Q}}^0(A,L)}{1-\hat{\bar{Q}}^0(A,L)}\right) = \varepsilon\hat{H}(A,L)$$

with

$$\hat{H}(A,L) \quad = \quad \frac{I(A=1)}{\hat{g}^0(1|L)} - \frac{I(A=0)}{\hat{g}^0(0|L)}\,.$$

which is a regression (Quasi-Binomial, or logistic)

a) without intercept
b) with "*offset*" $\log(\bar{Q}^0(A,L)/[1-\bar{Q}^0(A,L)])$
c) and "clever covariate" $\hat{H}(A,L)$

Causal Approach, TMLE (V)

4. Estimate ATE as

$$\psi_{\text{ATE,TMLE}} = \frac{1}{n}\sum_{i=1}^{n}(\hat{\hat{Q}}_i^1(1, L_i) - \hat{\hat{Q}}_i^1(0, L_i))$$

- easy to calculate confidence intervals, appropriate to leave model specification to "machine learning".
- Results using same variables **L** as in Quasi-Poisson regression and using extensive machine learning:

	ATE	95% CI
TMLE	**6.50**	**5.12**; **7.87**
Linear Model	5.04	2.29; 7.80

Conclusion

- Load shedding, as implemented in RSA, is associated with an increase in hospital admissions of children, on the same day and up to two days following the power interruption.

- Under the assumption that the assumed DAG is correct, and that the modeling approach is appropriate, this effect (as estimated by the ATE) is causally interpretable.

Discussion

- Most accidents happen at night and at home; Capetonians have long daily commutes ($>$2 hours one-way) which could explain why load shedding affected admissions primarily during weekdays.
- Results on individual diagnoses were imprecise.
- Our results may indicate that poorer areas could be affected more heavily by load shedding than wealthier areas. However, wherever load shedding was not directly controlled by the city but ESKOM, data was unavailable.

Media

SOUTH AFRICA'S BIGGEST-SELLING SATURDAY NATIONAL NEWSPAPER

SATURDAY Star

R16.00 August 11 2018

Power cuts put children in danger

New research sheds light on load shedding risks

SHAUN SMILLIE

AS SOUTH Africans face the threat of more load shedding, a first-of-a-kind study has revealed the cost that planned blackouts are having on the health of children.

The research – to appear in the latest issue of the public health journal Epidemiology – examined the admissions of children at the Red Cross War Memorial Children's Hospital in Cape Town and found that during load shedding, paediatric admissions increased 10%.

The researchers, Christian Gehringer, Heinz Rode and Michael Schomaker, compared the number of admissions on the day of a load shedding and 48 hours after it to non-event days.

They further discovered that the admission increase linked to load

use the electric stove. Both incidents happened at night.

Gehringer decided to initiate the study while working at the Red Cross Children's Hospital. He said that doctors working in the burns unit had noticed admissions related to load shedding.

Rode, who works at the hospital, said that load shedding had contributed to the admission of children, not only to the burns unit but to other trauma units as well.

> In one case a boy was brushing his teeth when he was burnt by a candle

shedding in the week had to do with people finding it difficult to plan around the blackouts because of long commutes and work commitments.

The inability to plan properly led to more accidents. The study comes as Eskom warns of possible load shedding in the coming weeks because of striking workers. "The chances of load shedding this weekend are, however, low," said Eskom spokesperson Dikatso Mothae.

The authors concluded in their study that: "The association we measured is consistent with our hypothesis that failures of the power infrastructure increased risk to the children's health."

Gehringer believed that this was the tip of the iceberg.

DA spokesperson on health in Gauteng Jack Bloom said the study showed that load shedding was damaging more than just the economy.

YOU MUST BE KIDDING

WIN ALL AROU
Meet our cute
– and win a p

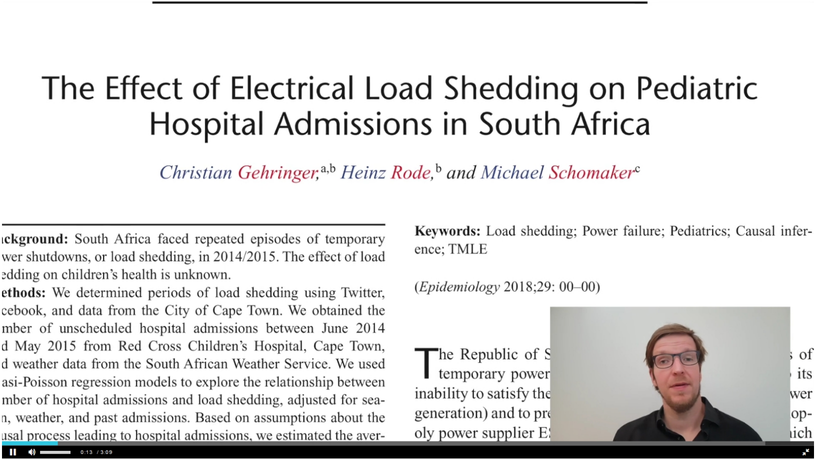
HYUNDAI 120:
Sensible, but not boring

TRAVELLE

PAARL:
The pearl of th

Video Abstract

On *Epidemiology* website:
`https://journals.lww.com/epidem/pages/videogallery.aspx?videoId=84&autoPlay=false`



The Effect of Electrical Load Shedding on Pediatric Hospital Admissions in South Africa

Christian Gehringer,[a,b] *Heinz Rode,*[b] *and Michael Schomaker*[c]

ıckground: South Africa faced repeated episodes of temporary wer shutdowns, or load shedding, in 2014/2015. The effect of load edding on children's health is unknown.
ethods: We determined periods of load shedding using Twitter, cebook, and data from the City of Cape Town. We obtained the mber of unscheduled hospital admissions between June 2014 d May 2015 from Red Cross Children's Hospital, Cape Town, d weather data from the South African Weather Service. We used asi-Poisson regression models to explore the relationship between mber of hospital admissions and load shedding, adjusted for sea- n, weather, and past admissions. Based on assumptions about the usal process leading to hospital admissions, we estimated the aver-

Keywords: Load shedding; Power failure; Pediatrics; Causal inference; TMLE

(*Epidemiology* 2018;29: 00–00)

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Appendix: Super Learning

1. First, split the data into blocks of equal size (i.e. ten blocks of 100 observations for a sample size of 1,000 units and the choice of 10-fold cross-validation) and fit each of the selected algorithms on the training set (i.e. on 9 out of the 10 blocks).
2. Then, predict the estimated probabilities of the outcome (Y) using the validation set (i.e. the remaining one block) for each algorithm.
3. Repeat steps 1 and 2 for each of the ten blocks. This yields predictions for all 1,000 observations for each learning algorithm.
4. Now, estimate the cross validated risk for each learning algorithm, that is a function of the true values of Y and the respective predictions, e.g.the (vector of the) squared differences.
5. Then, use non-negative least squares estimation to find the weighted linear combination of predictions (related to each learner) which predicts Y best. The weights sum up to one.
6. Then, use the weights to create a weighted prediction from the different learning algorithms applied to the complete data.