

Dynamic Effects of Store Promotions on Conversion Fraction: Expanding Technology Applications with Innovative Analytics

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- Summary and contributions

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- ▶ Managers conduct marketing activities (e.g., price promotions, store-front signage).
- ▶ Effect of a price promotion on **store performance**.
- ▶ Decomposition of store performance (Lam *et al.*, 2001):



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Stochastic processes of interest:

number of visits,

- ▶ **number of conversions**, conditional on the **number of visits**, and
average ticket size, conditional on the **number of conversions**.

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$$\begin{aligned}\{\text{Store Sales}\} &= \{\text{Conversion Counts}\} \times \{\text{Average Ticket Size}\} \\ &= \{\text{Number of Visits}\} \times \{\text{Conversion Fraction}\} \times \{\text{Average Ticket Size}\}\end{aligned}$$

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- ▶ A promotion may affect differently each one of these components.

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 - ... ticket size (i.e., customers' expenditure)?
- A promotion may affect differently each one of these components.
- **Focus of this talk:** Effects of a promotion on
 - i) conversion counts and ii) conversion fractions, based on

$$\{\text{Conversion Counts}\} = \{\text{Number of Visits}\} \times \{\text{Conversion Fraction}\}$$

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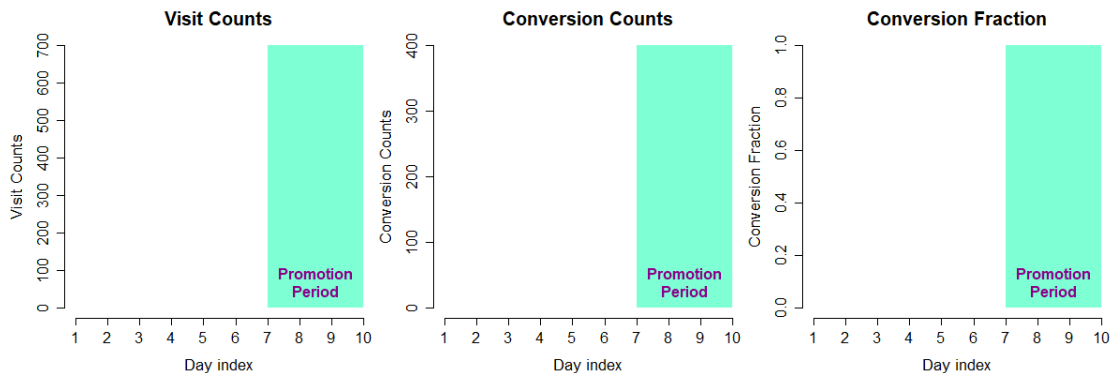
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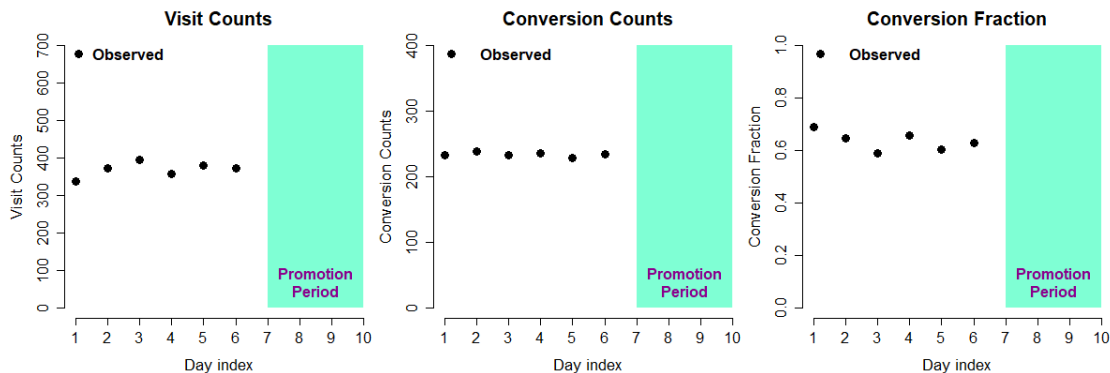
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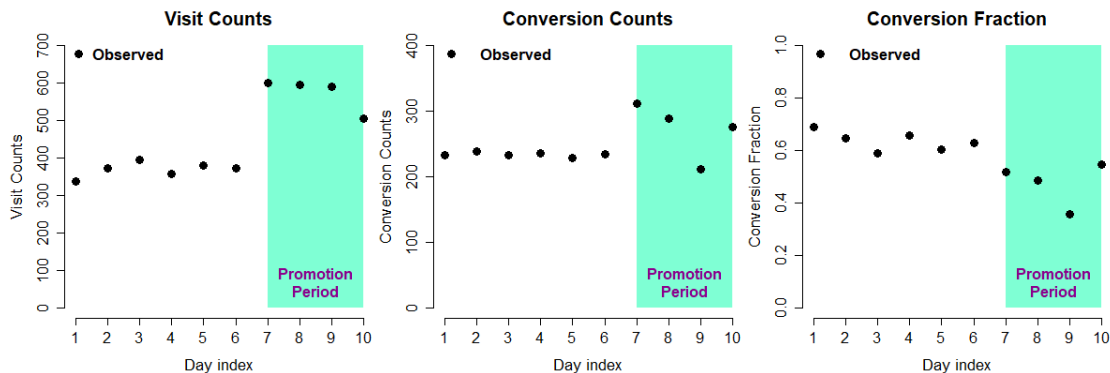
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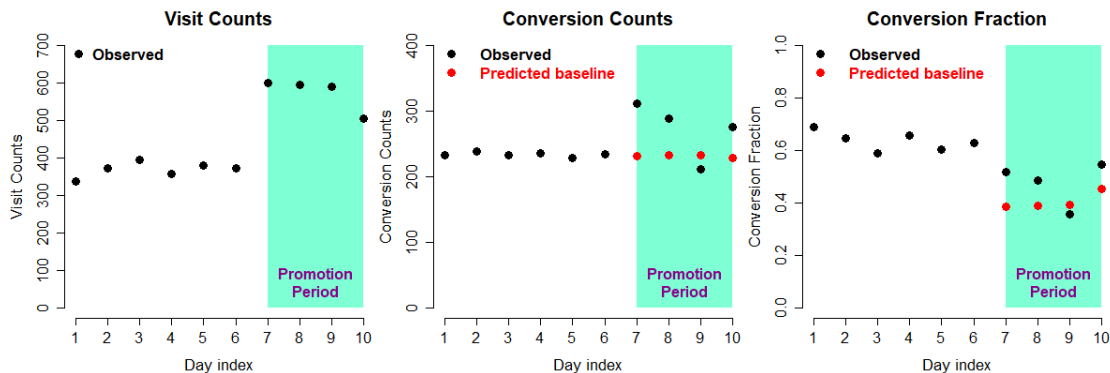
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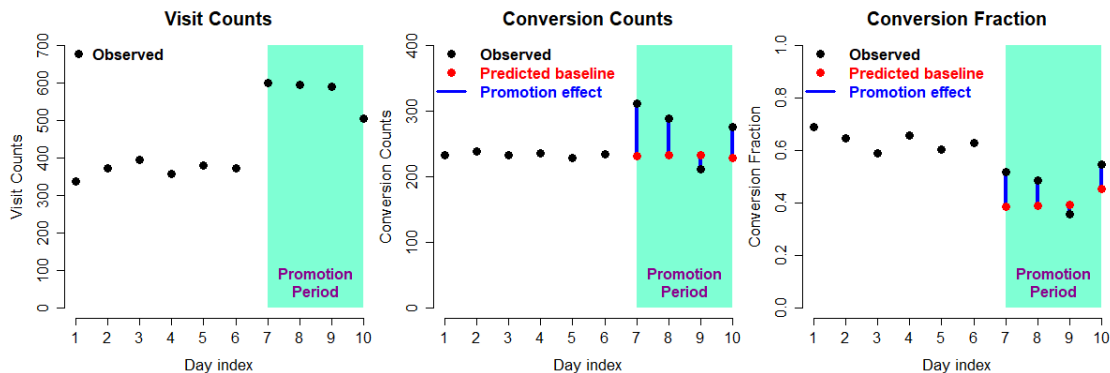
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- ▶ How can one measure the promotion effect on
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- ⇒ Measure each store performance component **relative to its corresponding baseline** (Abraham and Lodish, 1990).

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i) conversion counts and ii) conversion fractions?
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- ▶ **Main challenge:** Baselines for these store performance components are not available.

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- ▶ How can one measure the promotion effect on
i) conversion counts and ii) conversion fractions?
⇒ Measure each store performance component **relative to its corresponding baseline** (Abraham and Lodish, 1990).
- ▶ **Main challenge:** Baselines for these store performance components are not available.
- ▶ **Obstacles along the way:** How does one...
 - ▶ ...build these baselines?
 - ▶ ...predict the promotion effect (**and its variability**) on these store performance components in any specific time-band within a day?

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Advantages of our approach relative to prior research

Prior literature	Our research
Doyle and Saunders (1985): pointwise estimation of lag and lead effects of marketing-mix variables on aggregated sales and profits.	
Lam <i>et al.</i> (2001): attraction, conversion, and spending effects of marketing actions on aggregated store performance on each day using “marketing action” covariates. Ando (2008): Bayesian space-state modeling approach to examine effects of marketing actions on aggregated sales relatives to a baseline using “marketing action” covariates.	
Perdikaki <i>et al.</i> (2012): pointwise estimation of the effect of store traffic on aggregated conversion fraction on each day.	

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Doyle and Saunders (1985): pointwise estimation of lag and lead effects of marketing-mix variables on aggregated sales and profits.	Predictions of promotion effects and their uncertainty during the promotion period. More refined assessment of predicted promotion effects.
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Perdikaki <i>et al.</i> (2012): pointwise estimation of the effect of store traffic on aggregated conversion fraction on each day.	Predictions of promotion effects and their uncertainty on conversion fraction, during the promotion period. More refined assessment of predicted promotion effects.

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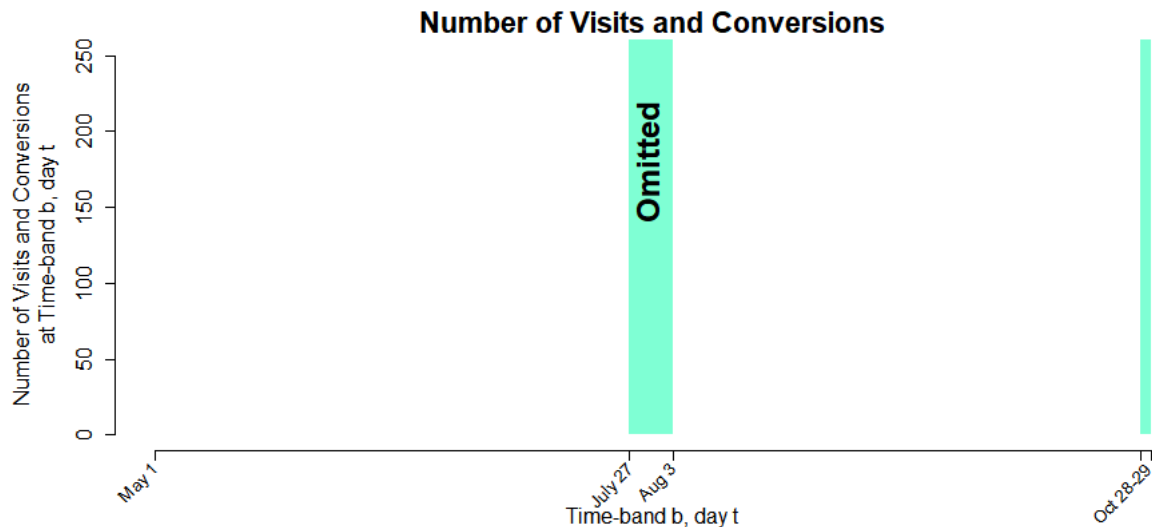
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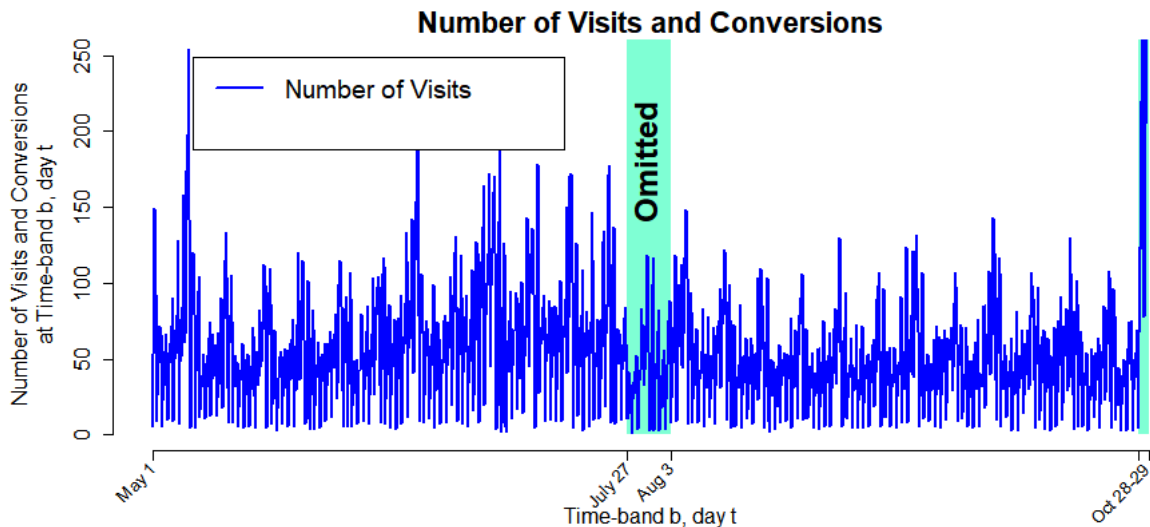
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An application: an initial description



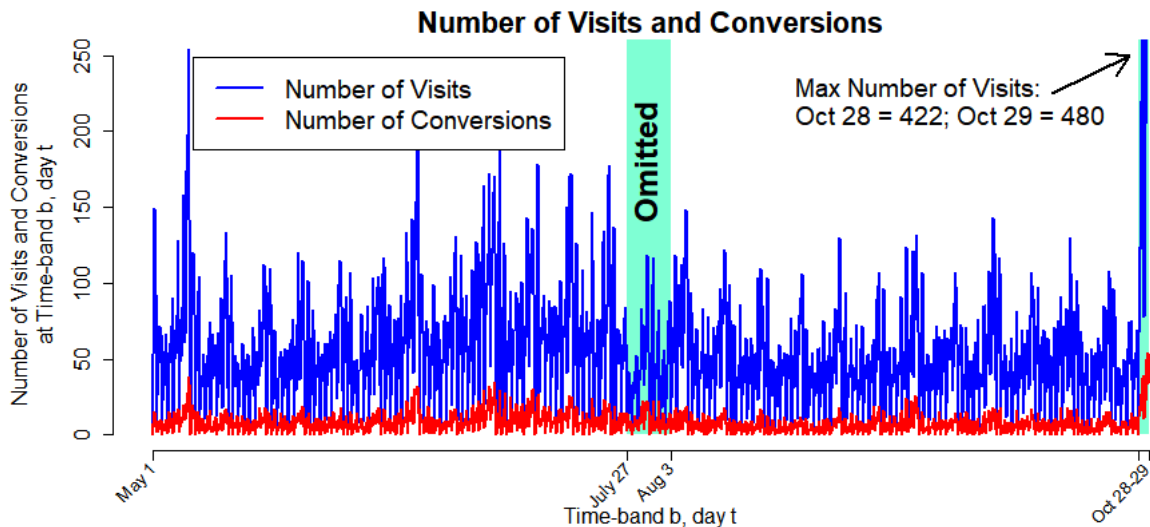
Source: FollowUp-Chile, from sensors placed at the store entrance and from cash registers.

An application: an initial description



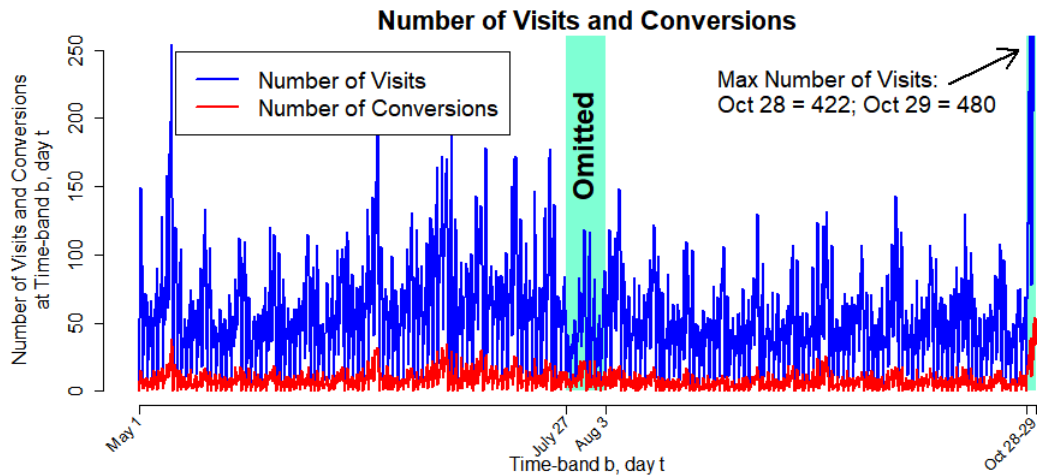
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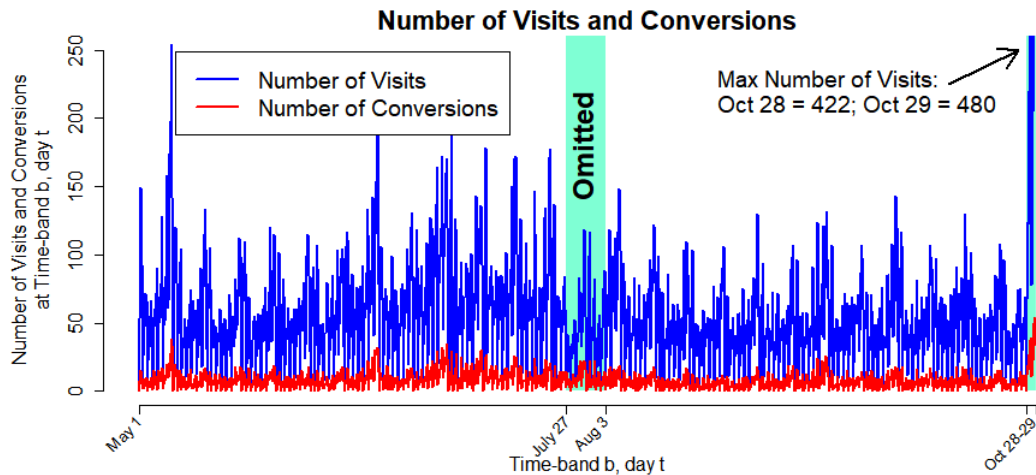


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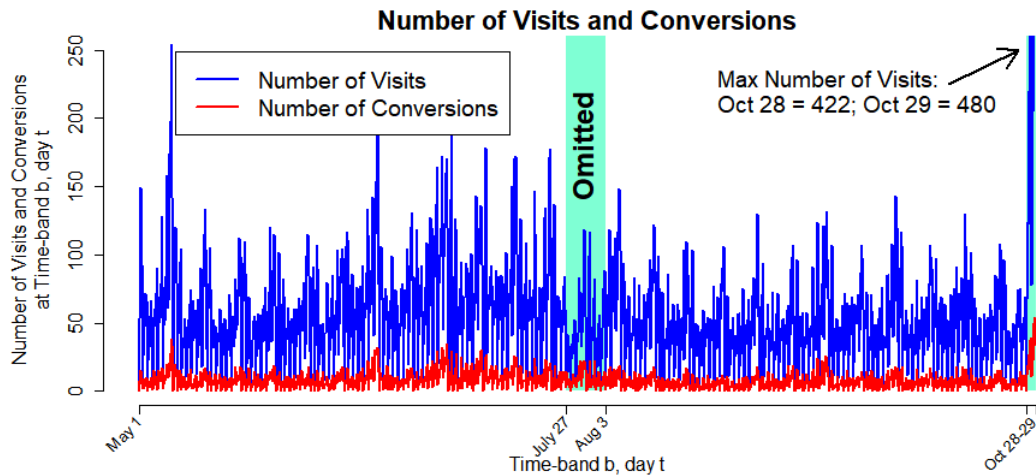


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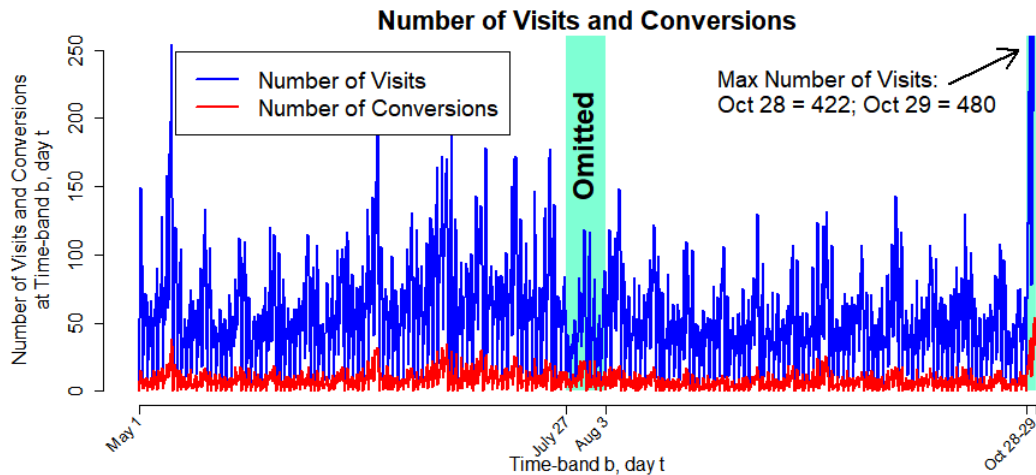
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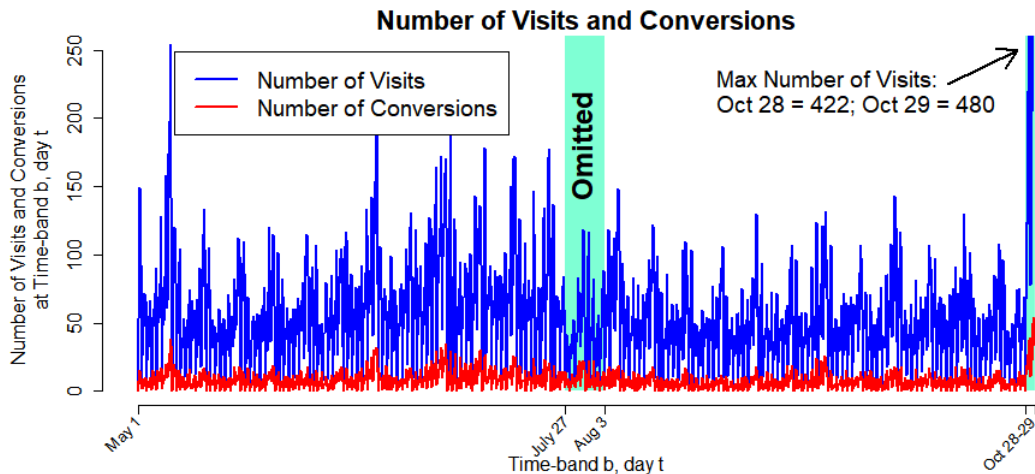
- ▶ Study period: May 1, 2016, to Oct 29, 2016 (i.e., 182 days for the analysis).
- ▶ t : day index, $t \in \{1, \dots, 182\}$, where
 - ▶ **Pre-promotion period**: from May 1 to Oct 27, $t \in \{1, \dots, 180\}$
 - ▶ **Promotion period**: Oct 28 and Oct 29, $t \in \{181, 182\}$

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- ▶ We excluded from the analysis days from July 27 to Aug 3 because of sensor malfunction.

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- ▶ We excluded from the analysis days from July 27 to Aug 3 because of sensor malfunction.
- ▶ b : time-band index in a day.

This application uses 11 one-hour time-bands per day:

[10:00; 11:00), [11:00; 12:00), [13:00; 14:00), ..., [20:00; 21:00).

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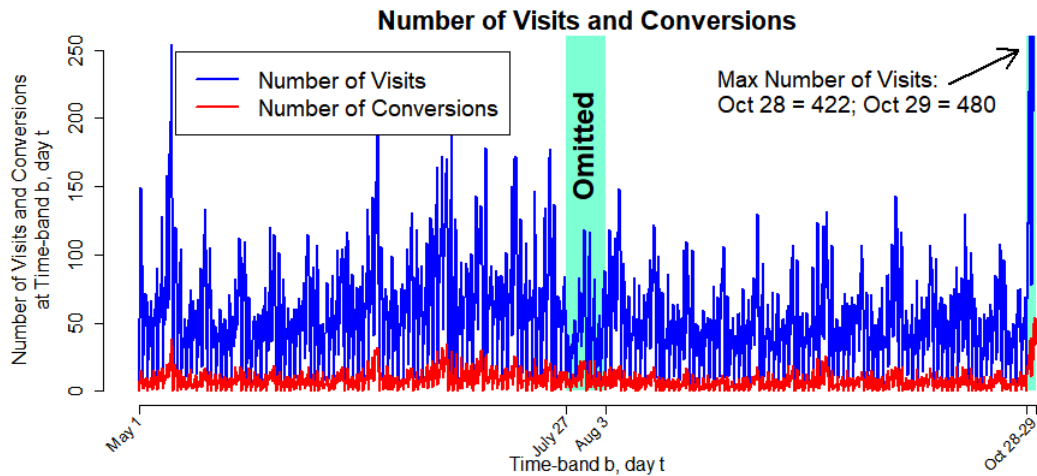
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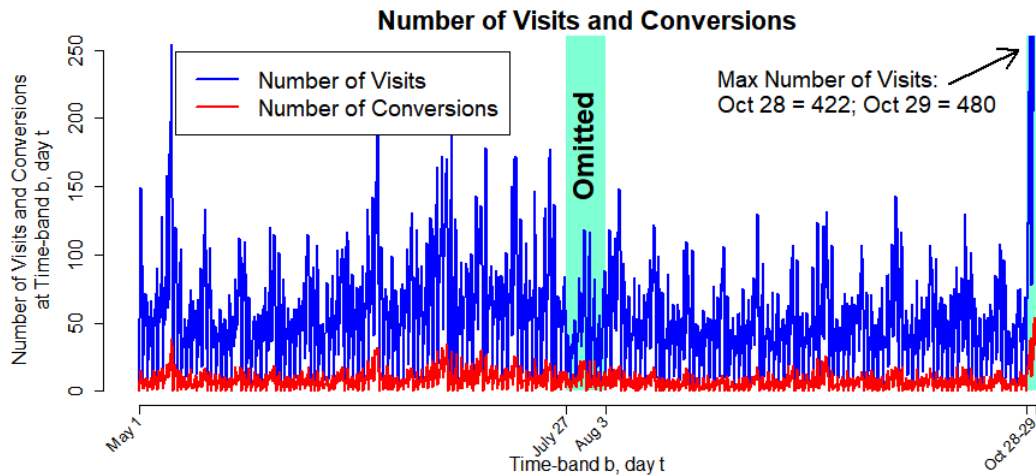
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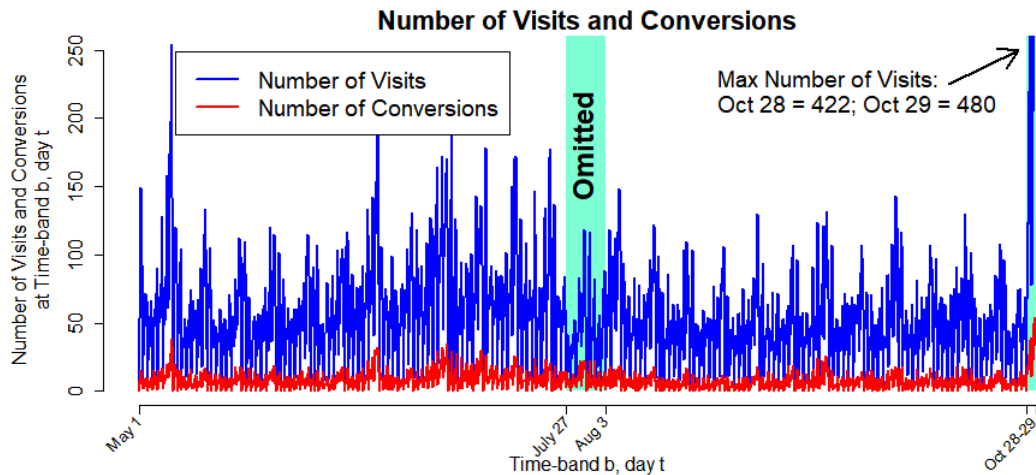
The Model



For the time-band b on the day t ,

- ▶ $v_{t,b}$: number of visits,
- ▶ $c_{t,b}$: number of conversions and
- ▶ $p_{t,b} = c_{t,b}/v_{t,b}$: conversion fraction.

The Model



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$c_{t,b} | \{v_{t,b}, p_{t,b}^{(c)}\} \sim \text{Binomial}(v_{t,b}; p_{t,b}^{(c)})^1$ with

$$\text{logit}(p_{t,b}^{(c)}) = \beta_0^{(c)} + \beta_1^{(c)} \cdot \mathbf{x}_{t,b}^{(c)}.$$

The Approach

The Approach

- ▶ Use data outside the promotion period to build a counterfactual prediction baseline for each time-band during the promotion.

For the time-band b on day $t \in \{181, 182\}$,

- ▶ $v_{t,b}$: observed visit counts,
- ▶ $\hat{c}_{t,b}$: pointwise prediction of $c_{t,b}$, conditional on $v_{t,b}$, and
- ▶ $\hat{p}_{t,b} = \hat{c}_{t,b}/v_{t,b}$: pointwise prediction of $p_{t,b}$.

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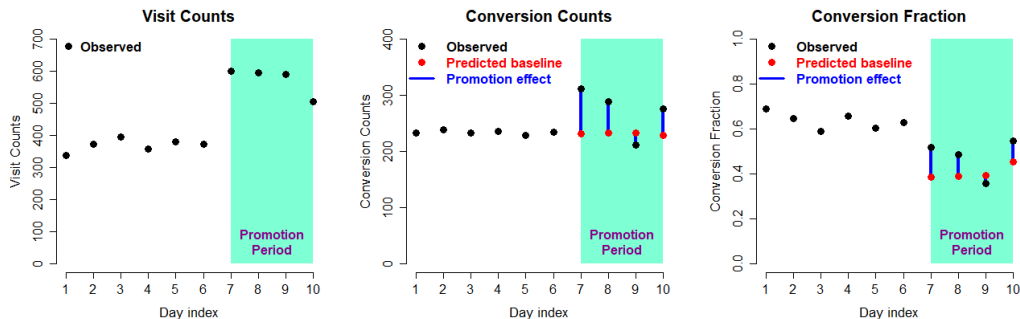
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 - $\hat{p}_{t,b} = \hat{c}_{t,b}/v_{t,b}$: pointwise prediction of $p_{t,b}$.
- Compare each observation to its corresponding prediction baseline to evaluate the effect of a promotion on conversion counts and conversion fraction at each time-band.

For time-band b of day $t \in \{181, 182\}$,

- $c_{t,b} - \hat{c}_{t,b}$: promotion effect on the **conversion counts** and
- $p_{t,b} - \hat{p}_{t,b}$: promotion effect on **conversion fraction**.



The Approach

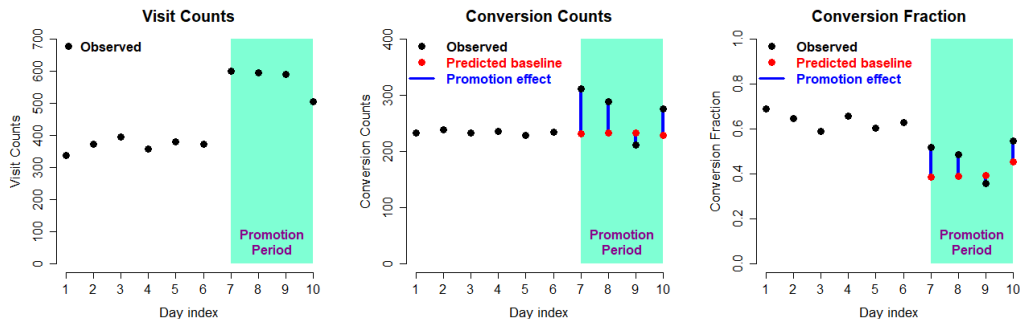
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For time-band b of day $t \in \{181, 182\}$,

- $c_{t,b} - \hat{c}_{t,b}$: promotion effect on the **conversion counts** and
- $p_{t,b} - \hat{p}_{t,b}$: promotion effect on **conversion fraction**.



- Study the variability of the effect of a promotion on each of these components through the prediction distribution.

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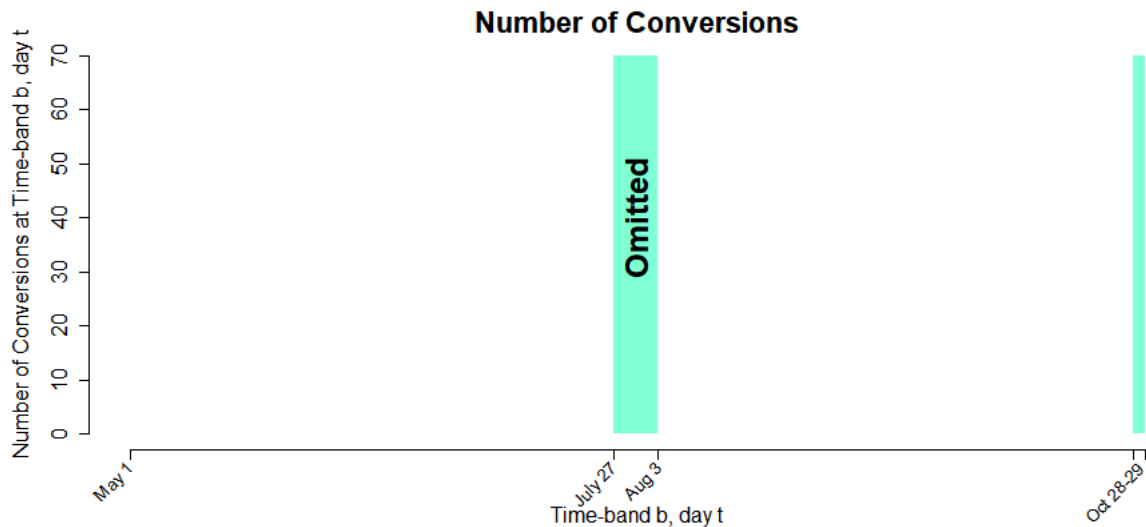
For each time-band b of day t , with $b \geq 1$, the estimated model for conversion counts, conditionally on visit counts, is

$$c_{t,b} | \{v_{t,b}; \hat{p}_{t,b}^{(c)}\} \sim \text{Binomial}(v_{t,b}; \hat{p}_{t,b}^{(c)}),$$

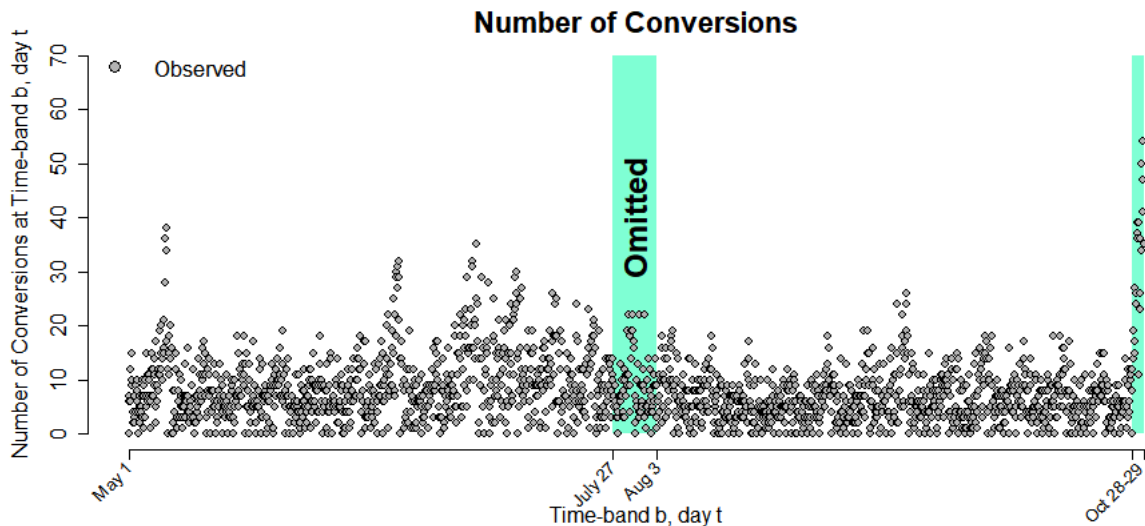
where $\text{logit}(\hat{p}_{t,b}^{(c)})$ is a function of

- ▶ 0/1-dummy variables for
 - ▶ the one-hour time-band of a day (TB):
[10:00; 11:00), [11:00; 12:00), [13:00; 14:00), ..., [20:00; 21:00),
 - ▶ the day of a week (D): **monday**, ..., **sunday**,
 - ▶ the week of a month (W): **1st**, ..., **6th**,
 - ▶ the month of a year (M): **may**, ..., **october**,
- ▶ TB $\times$ D, and W $\times$ M.

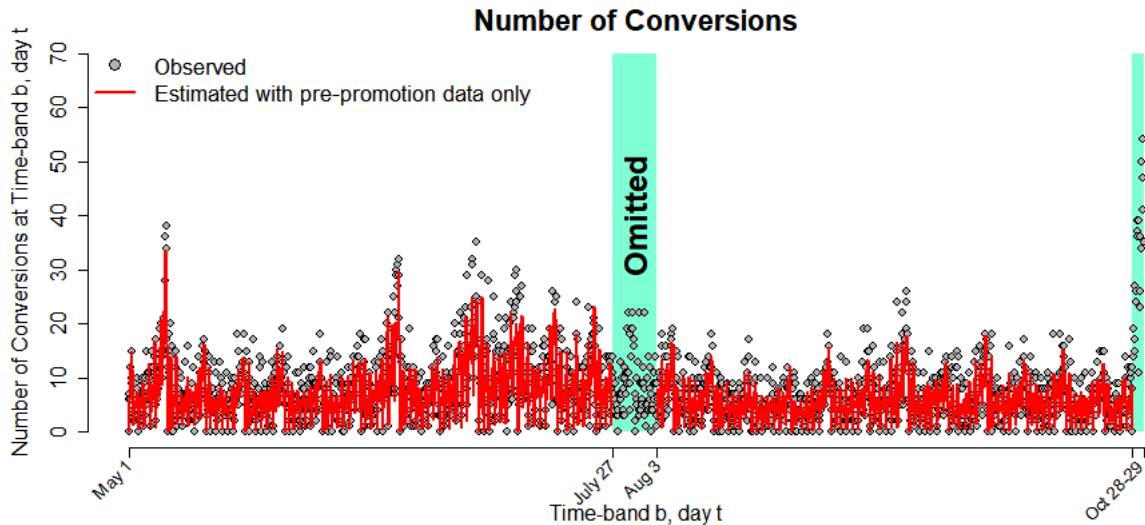
Observed, estimated, and pointwise prediction of
conversion counts ($c_{t,b}$)



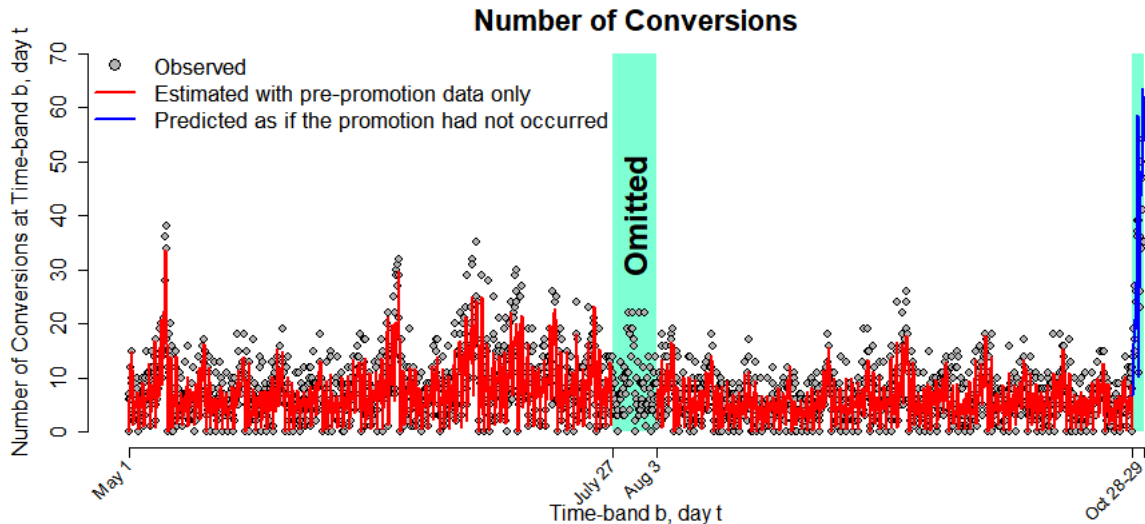
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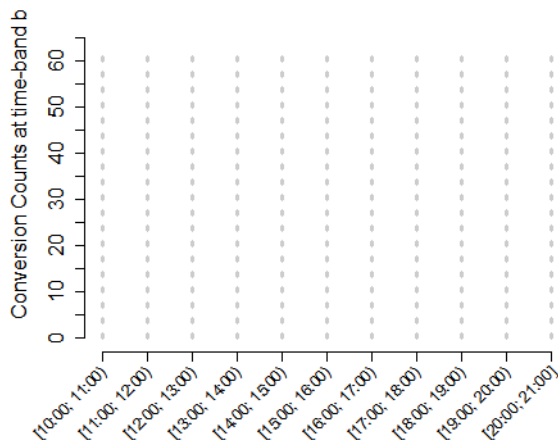


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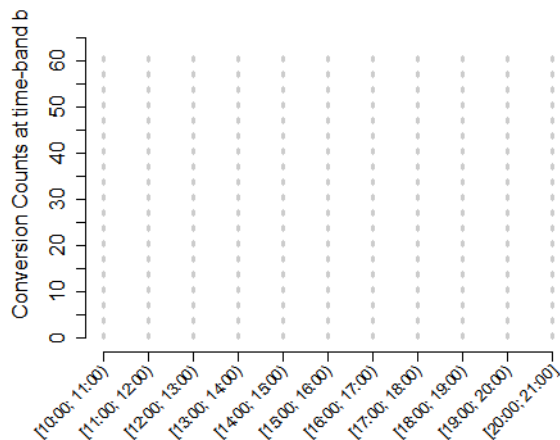


Observed and pointwise prediction of
conversion counts ($c_{t,b}$) during the promotion

Conversion Counts in Oct 28

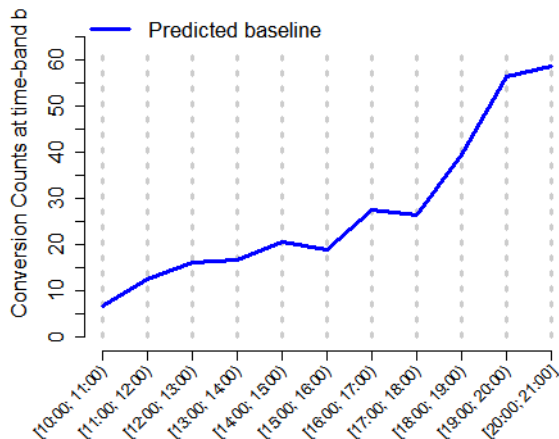


Conversion Counts in Oct 29

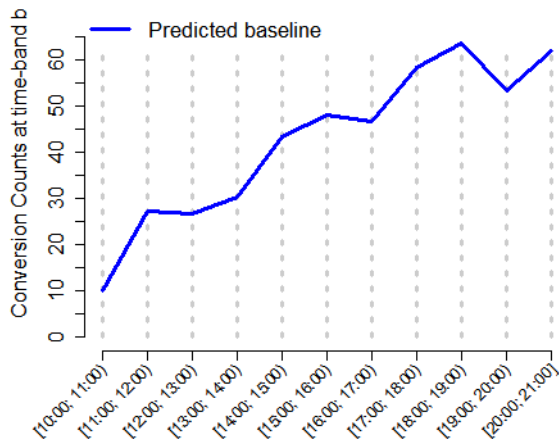


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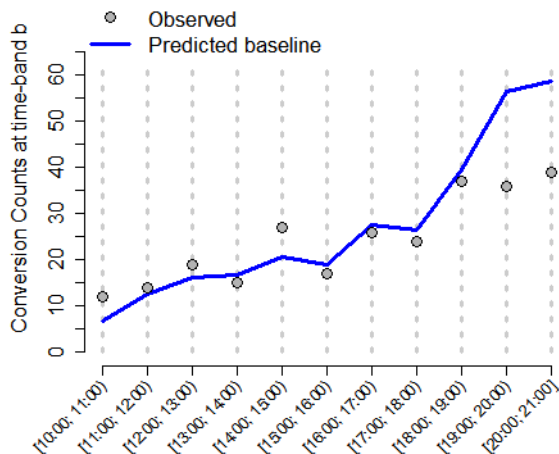


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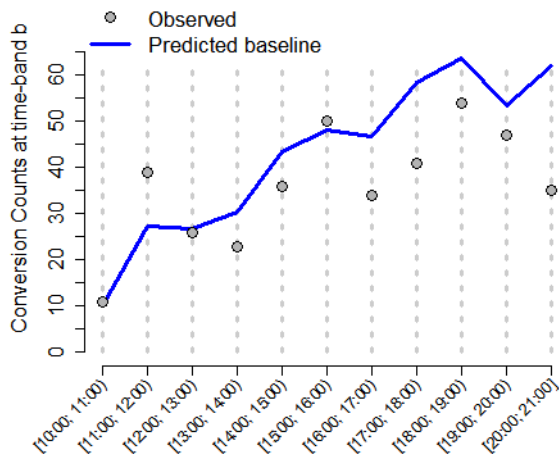


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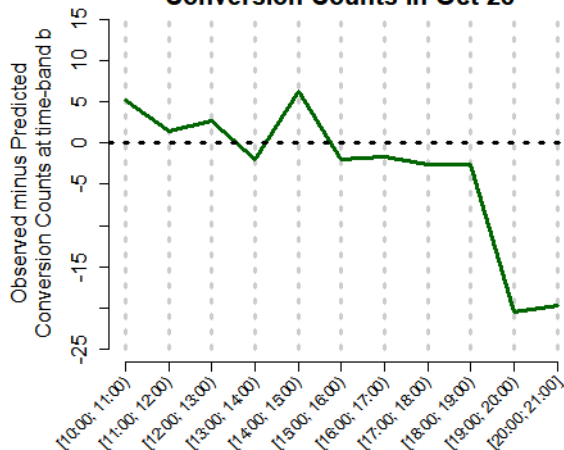


Conversion Counts in Oct 29

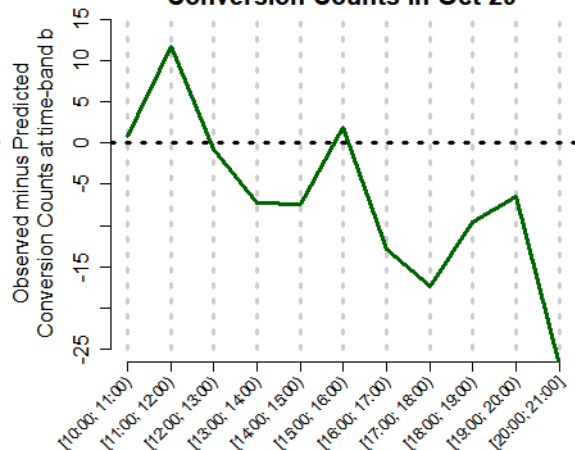


Predicted promotion **effects** on
conversion counts ($c_{t,b}$) during the promotion

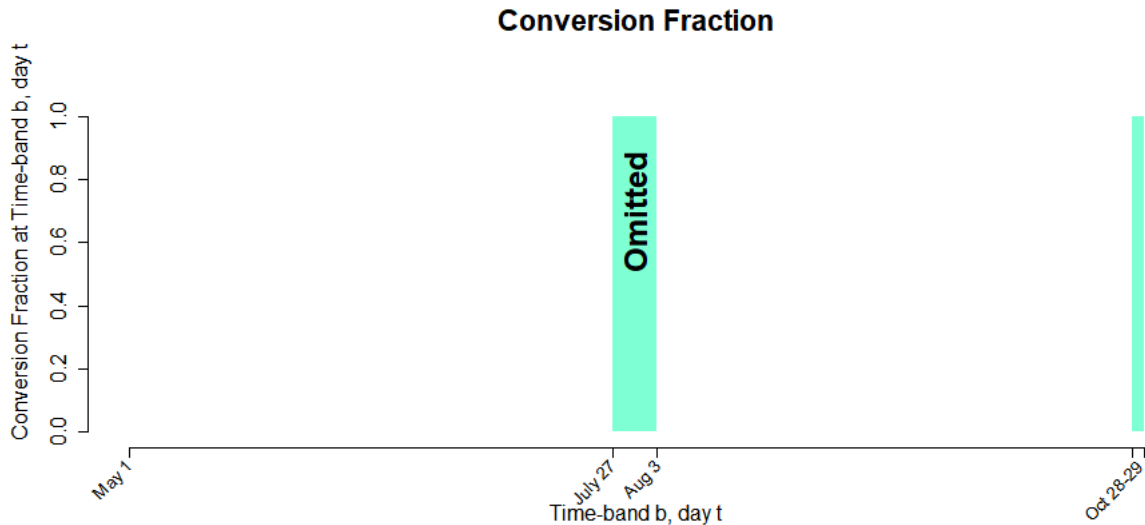
**Predicted Promotion Effect on
Conversion Counts in Oct 28**



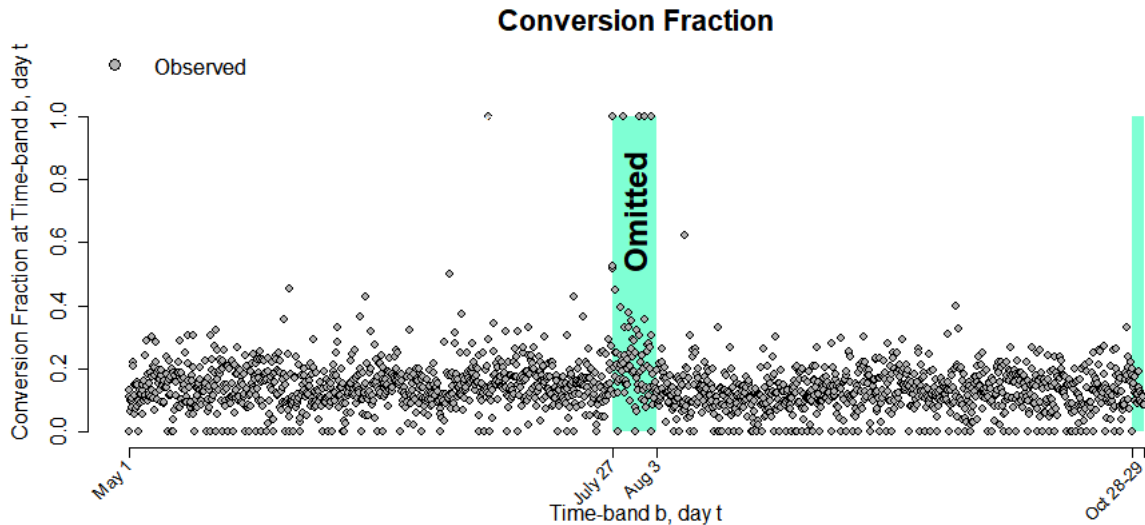
**Predicted Promotion Effect on
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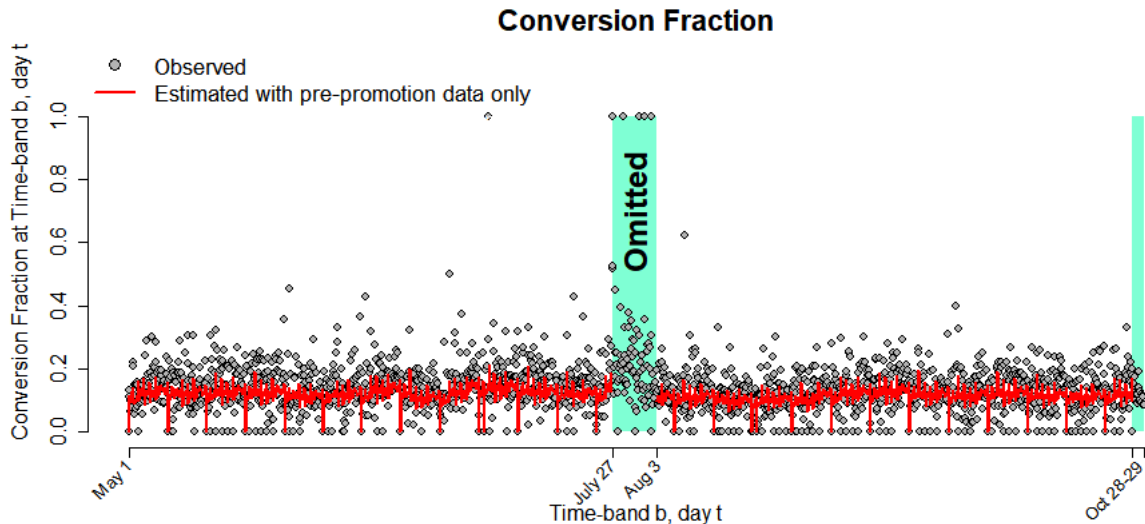
Observed, estimated, and pointwise prediction of conversion fractions ($p_{t,b}$)



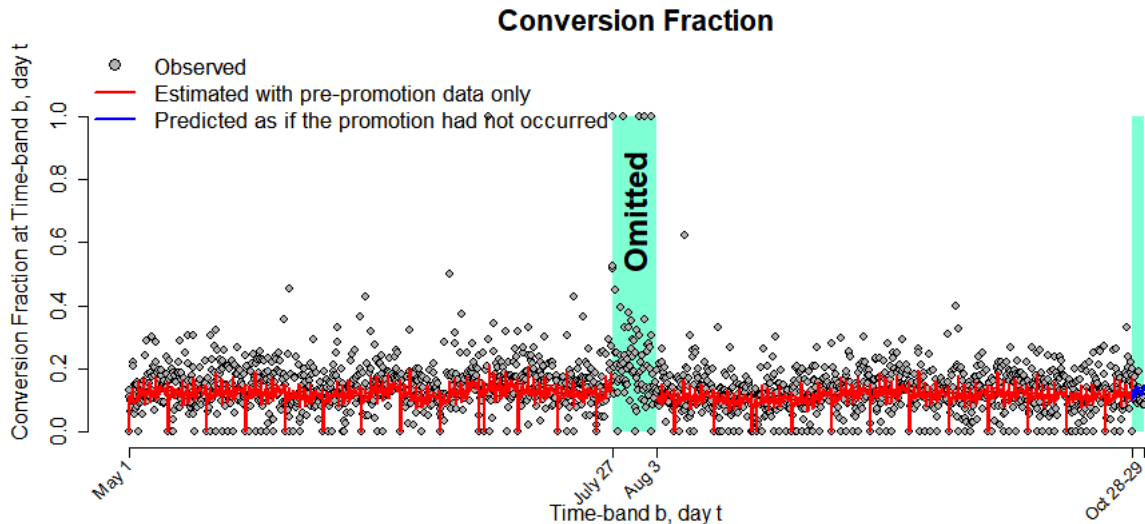
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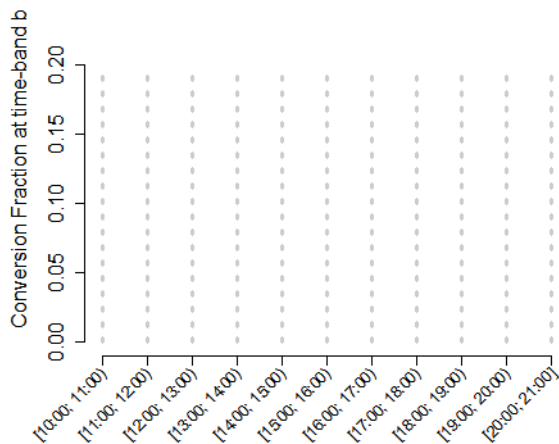


Observed, estimated, and pointwise prediction of
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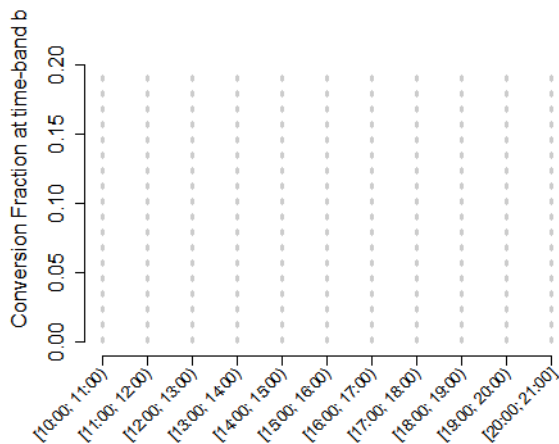


Observed and pointwise prediction of
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Conversion Fraction in Oct 28

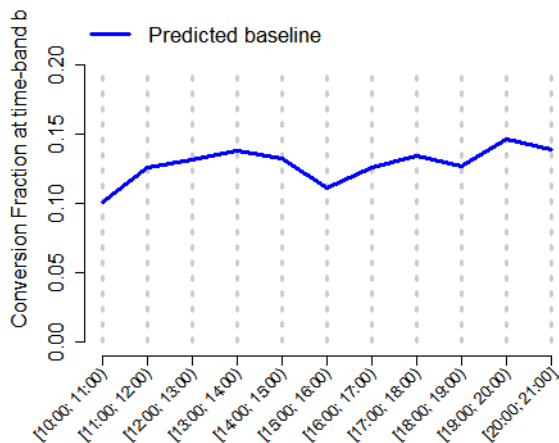


Conversion Fraction in Oct 29

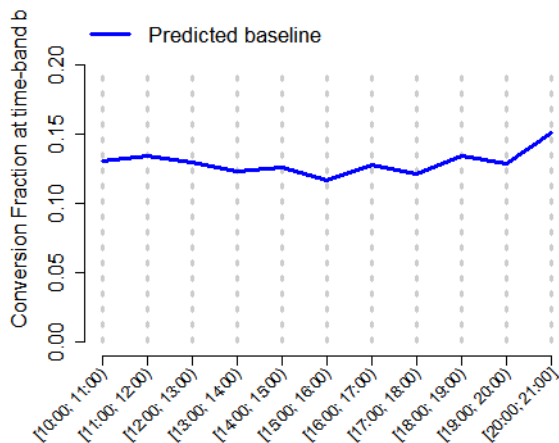


Observed and pointwise prediction of **conversion fractions** ($p_{t,b}$) during the promotion

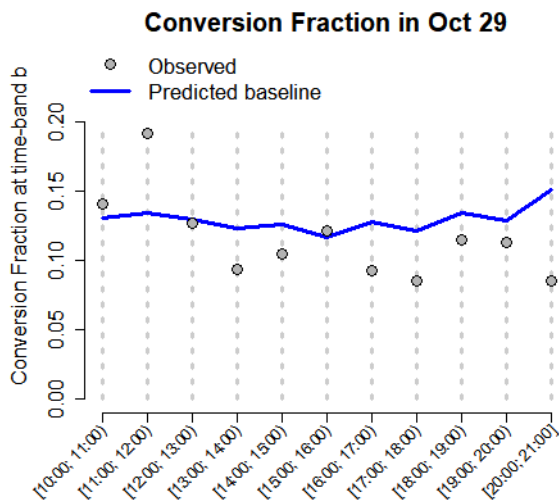
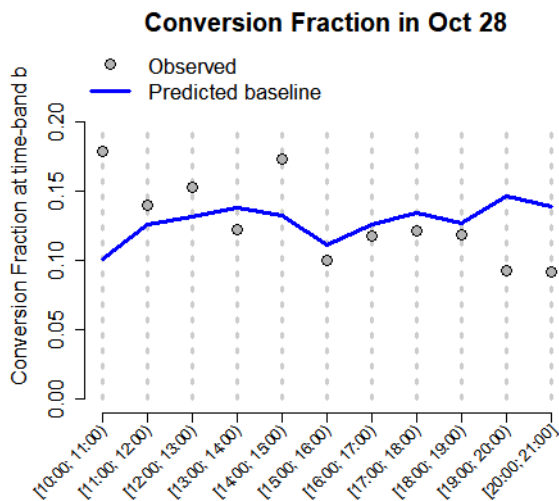
Conversion Fraction in Oct 28



Conversion Fraction in Oct 29

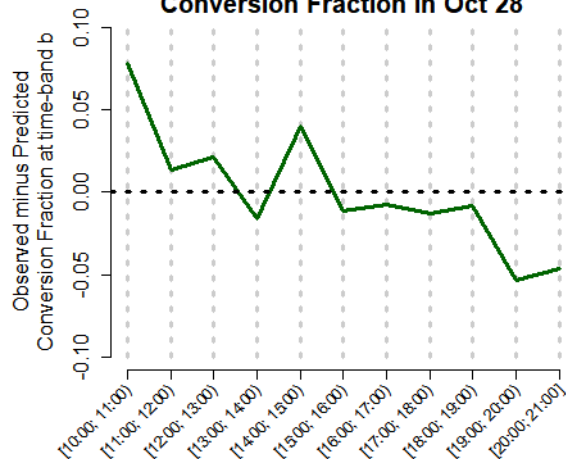


Observed and pointwise prediction of **conversion fractions** ($p_{t,b}$) during the promotion



Predicted promotion **effects** on
conversion fractions ($p_{t,b}$) during the promotion

**Predicted Promotion Effect on
Conversion Fraction in Oct 28**



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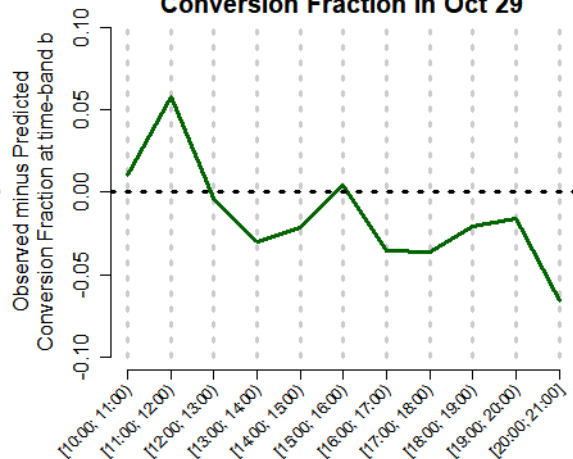


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Prediction distribution of the promotion effect

- ▶ **Important questions:** What is the variability of the promotion effect on
 - ▶ conversion counts, and
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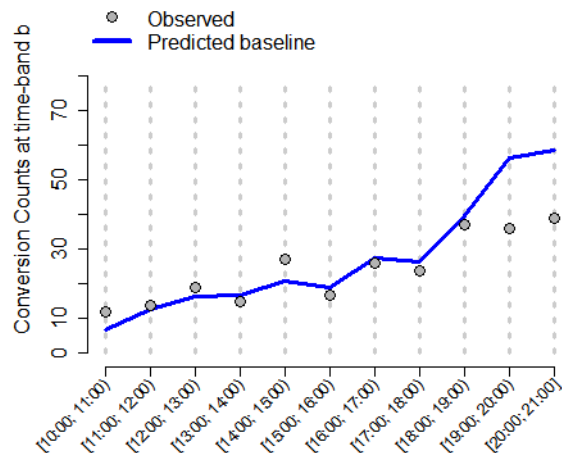
- ▶ **Important questions:** What is the variability of the promotion effect on
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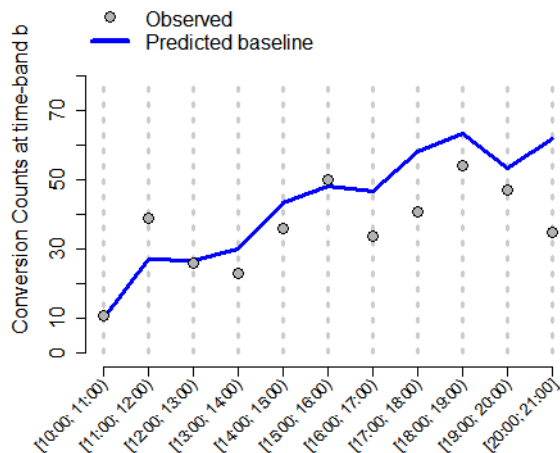
- ▶ **Important questions:** What is the variability of the promotion effect on
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 - ▶ conversion fractionsin a specific one-hour time-band?
- ▶ **Prediction distribution:** Distribution of the predicted effects of the promotion on conversion counts and conversion fractions.
- ▶ With bootstrap (Efron and Tibshirani, 1994), we use 10000 replicates to estimate prediction distribution.

Prediction distribution of **conversion counts** ($c_{t,b}$) during the promotion

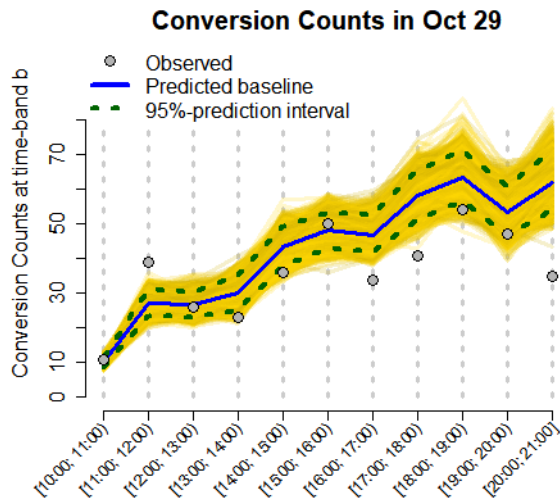
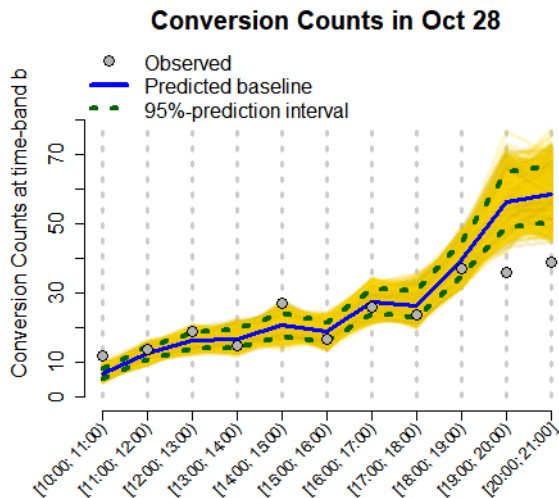
Conversion Counts in Oct 28



Conversion Counts in Oct 29



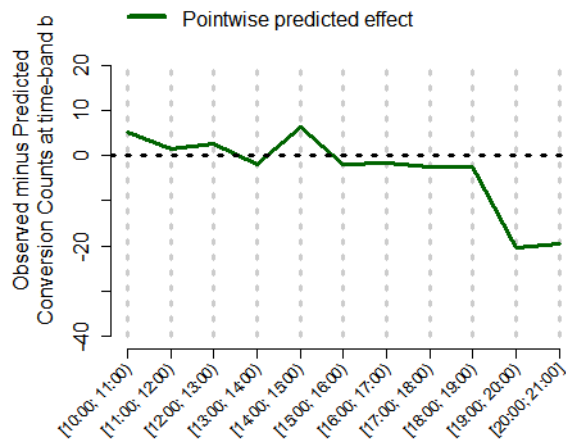
Prediction distribution of **conversion counts** ($c_{t,b}$) during the promotion



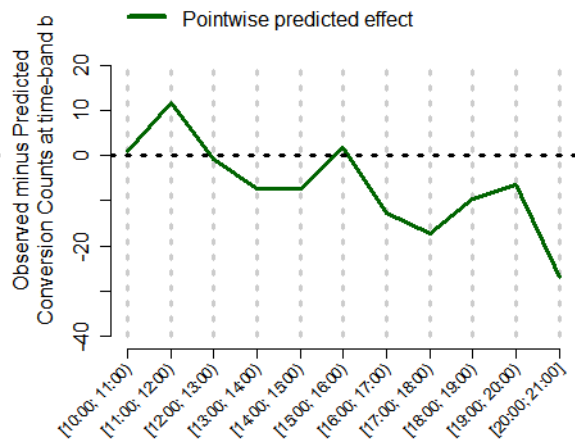
95 %-prediction intervals are based on 10000 bootstrap replicates.

Prediction distribution of the promotion **effect**
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**Predicted Promotion Effect on
Conversion Counts in Oct 28**

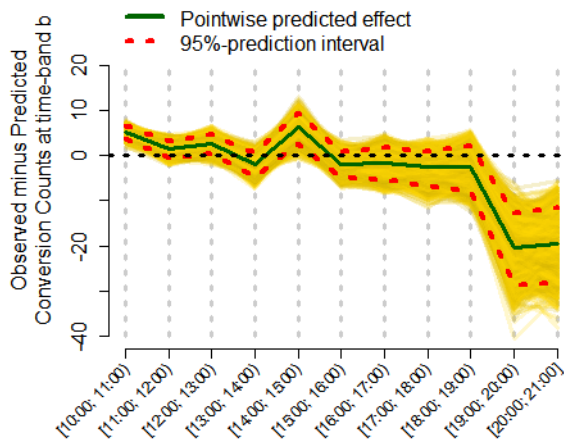


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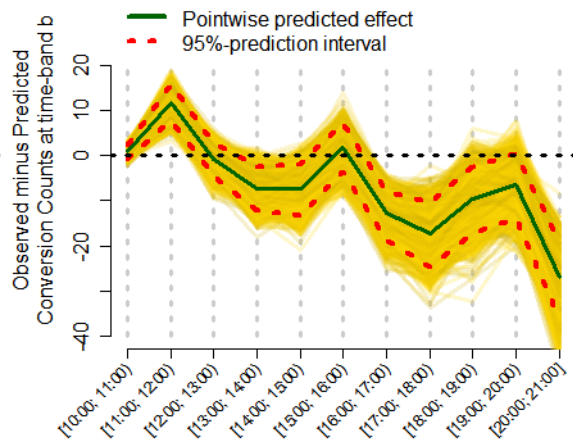


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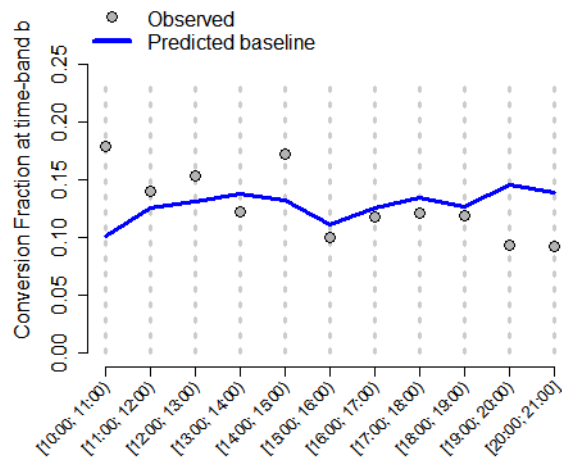
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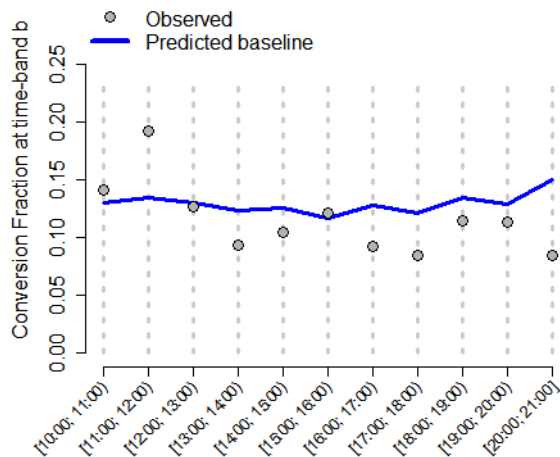
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Conversion Fraction in Oct 28

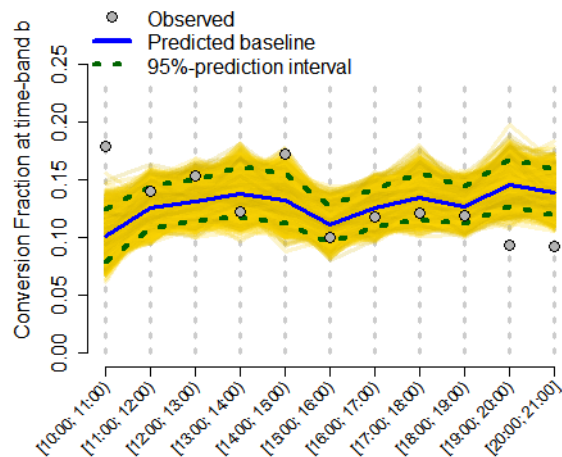


Conversion Fraction in Oct 29

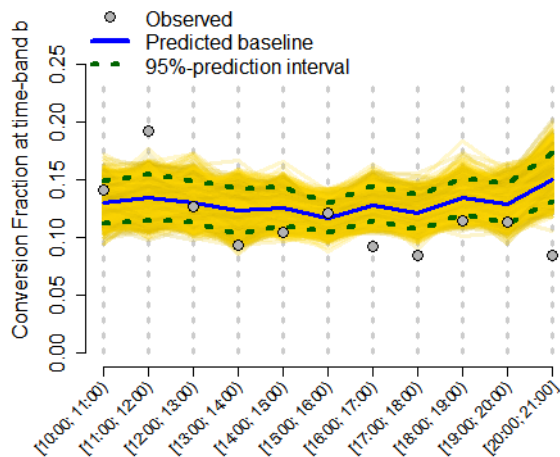


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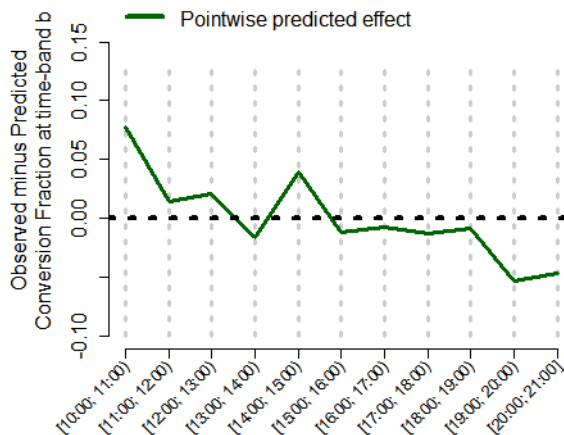
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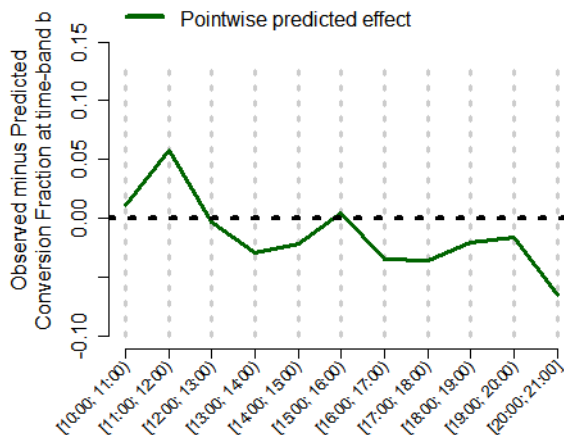
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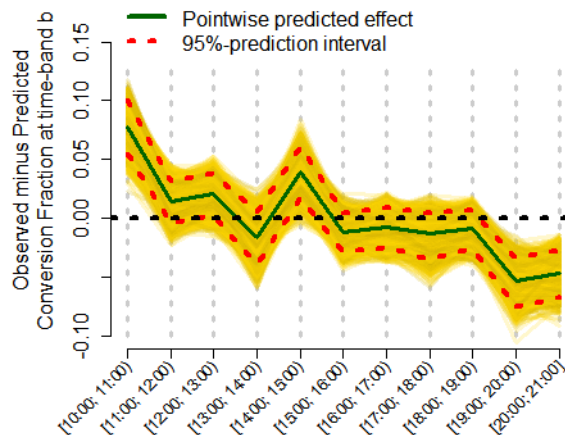


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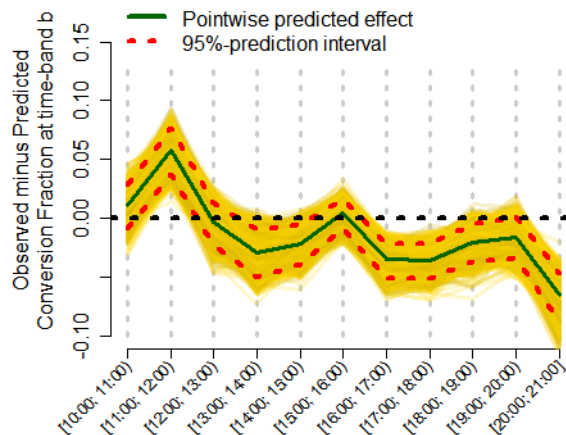


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 - ▶ provides valuable information for workforce management.

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- ▶ compare effectiveness of different marketing actions implemented at the same store (e.g., clearance promotions and in-store demonstrations), and to
- ▶ decompose the total effect of a marketing action on store performance components with customer-level data.



THANK YOU
for your
ATTENTION!

Dynamic Effects of Store Promotions on Conversion Fraction: Expanding Technology Applications with Innovative Analytics

FAPESP Thematic Project Workshop 2026, Sao Paulo, Brazil

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- ▶ Ando, Tomohiro (2008). Measuring the baseline sales and the promotion effect for incense products: a Bayesian state-space modeling approach, *Ann Inst Stat Math* 60:763-780.
- ▶ Doyle, P. & Saunders, J. (1986). Measuring the True Profitability of Sales Promotions, *The Journal of the Operational Research Society* 37 (10) 955-965.
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- ▶ Efron, B., & Tibshirani, R. J. (1994). *An introduction to the bootstrap*. CRC press.
- ▶ Epstein, L. D., Flores, A. A., Goodstein, R. C., & Milberg, S. J. (2016). A new approach to measuring retail promotion effectiveness: A case of store traffic. *Journal of Business Research*, 69(10), 4394-4402.
- ▶ Lam, Shun Yin, Mark Vandenbosch, John Hulland, & Michael Pearce (2001). Evaluating Promotions in Shopping Environments: Decomposing Sales Response into Attraction, Conversion, and Spending Effects, *Marketing Science* 20 (2) 194-215.
- ▶ Perdikaki, O., Kesavan, S., & Swaminathan, J. M. (2012). Effect of traffic on sales and conversion fraction of retail stores. *Manufacturing & Service Operations Management*, 14(1), 145-162.
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Appendix 1: Computing the number of visits per time-band

Appendix 2: Model diagnostics

Appendix 3: Statistical inference

Computing the number of visits per time-band

- ▶ We divide each day in the dataset into B time-bands of the same length.
- ▶ For each time-band b on day t , with $b \in \{1, 2, \dots, B\}$,
 - ▶ $A_{t,b}$: number of people who arrive to the store,
 - ▶ $E_{t,b}$: number of people who exit the store,
 - ▶ $c_{t,b}$: number of people who convert,
 - ▶ **$n_{t,b}$: number of visits**, i.e. the number of people who stay in the store during the time-band, and
 - ▶ $O_{t,b} = \max\{n_{t,b} - E_{t,b}; 0\}$: number of people who remain in the store at the end of the time-band.
- ▶ For each day t in the dataset, we observe $\{A_{t,b}\}$, $\{E_{t,b}\}$, and $\{c_{t,b}\}$, for all b . We use $\{A_{t,b}\}$, $\{E_{t,b}\}$, and $\{c_{t,b}\}$ to compute $\{n_{t,b}\}$ for all b .
- ▶ For each day t ,
 - ▶ $n_{t,b} \geq c_{t,b}$, for all $b \in \{1, 2, \dots, B\}$, and
 - ▶ nobody remains in the store at the end of the B -th time-band.
- ▶ Therefore, for all t , we use $n_{t,b} = \max\{c_{t,b}; \phi_{t,b}\}$ where

$$\phi_{t,b} = \begin{cases} A_{t,b} & \text{if } b = 1, \\ A_{t,b} + O_{t,b-1} & \text{if } b \in \{2, 3, \dots, B-1\}, \text{ and} \\ E_{t,b} & \text{if } b = B. \end{cases}$$

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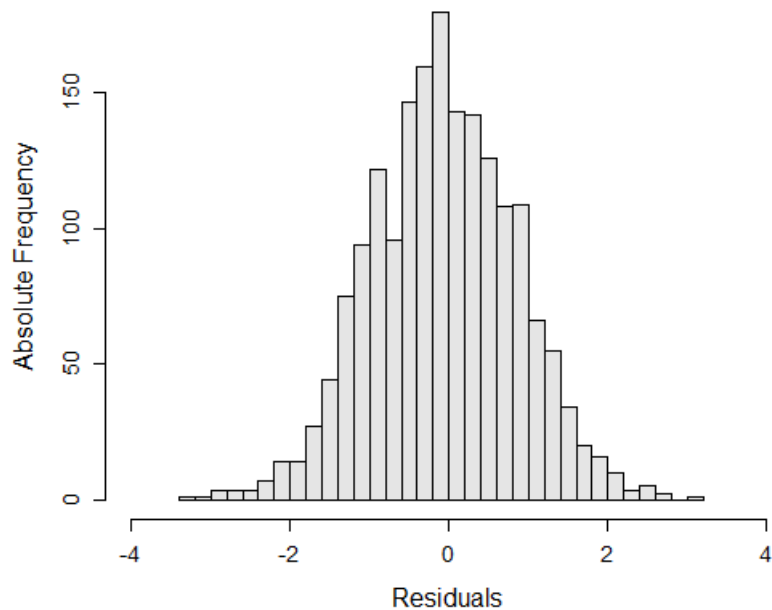
Appendix 3: Statistical inference

Model diagnostics

- ▶ For each store sales component, we use quantile residuals to check the adequacy of the respective model.
- ▶ If the model is adequate, quantile residuals are approximately distributed as standard normal (Dunn and Smyth, 1996).
- ▶ For each model, we examine
 - ▶ histogram of quantile residuals,
 - ▶ quantile-quantile (Q-Q) plot of quantile residuals,
 - ▶ estimated autocorrelation function of quantile residuals,
 - ▶ plot of quantile residuals vs fitted values,
 - ▶ histogram of quantile residuals per one-hour time-band on a day,
 - ▶ histogram of quantile residuals per day of the week,
 - ▶ histogram of quantile residuals per week of the month, and
 - ▶ histogram of quantile residuals per month of the year.

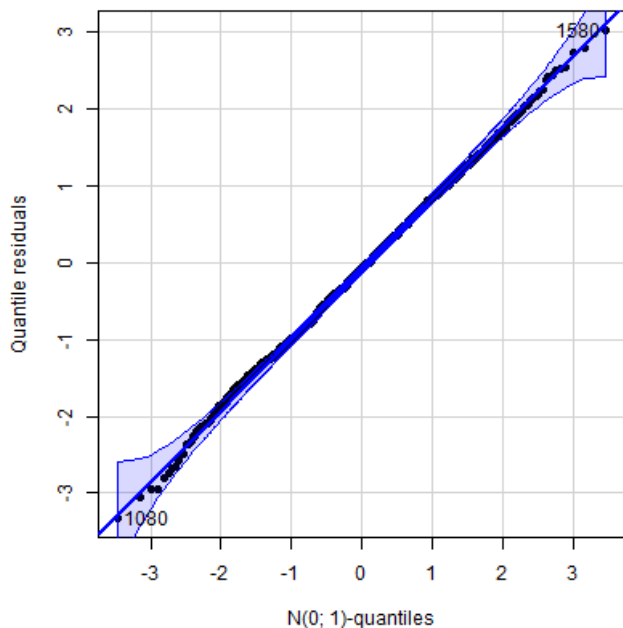
Diagnostics in the model for conversion counts

Histogram of quantile residuals



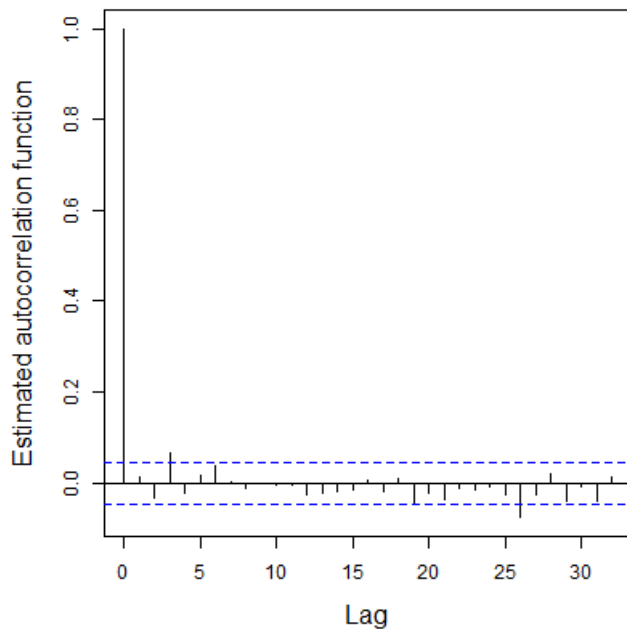
Diagnostics in the model for conversion counts

Quantile-quantile plot of quantile residuals (including a 95 %-confidence band)



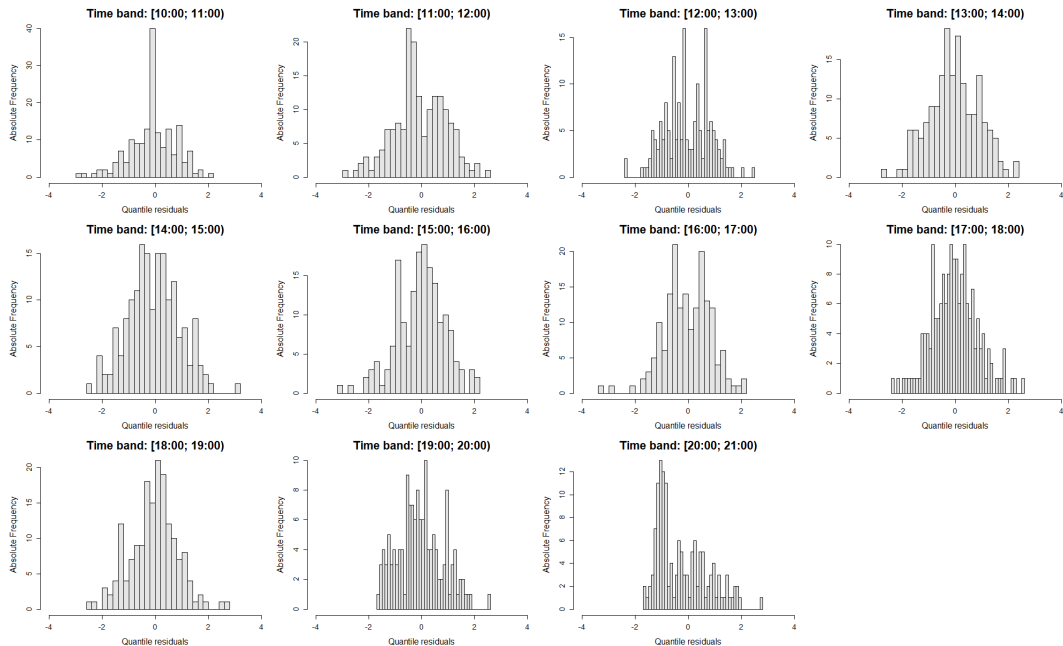
Diagnostics in the model for conversion counts

Estimated autocorrelation function of quantile residuals



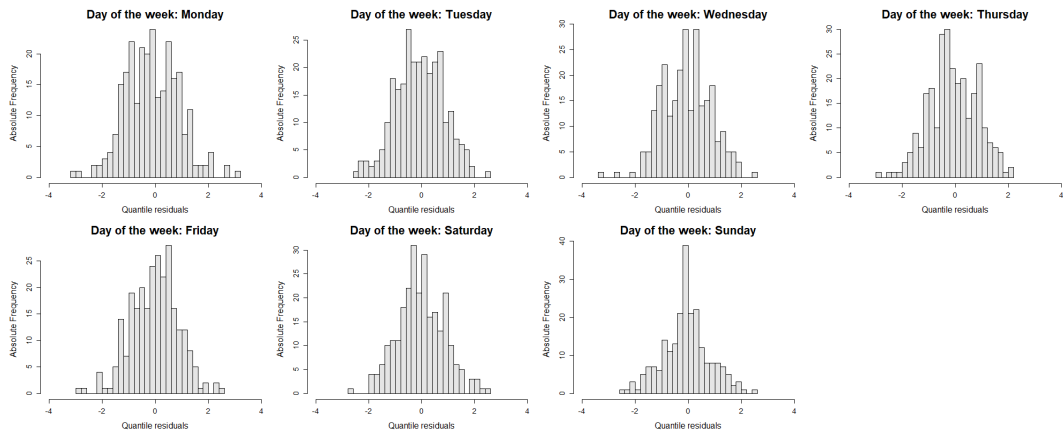
Diagnostics in the model for conversion counts

Histogram of quantile residuals per one-hour time-band on a day



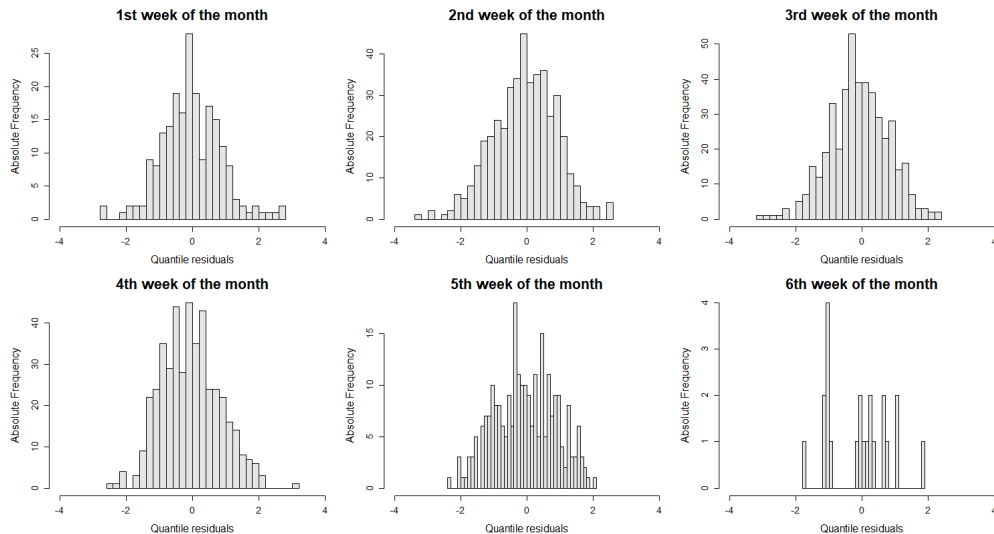
Diagnostics in the model for conversion counts

Histogram of quantile residuals per day of the week



Diagnostics in the model for conversion counts

Histogram of quantile residuals per week of the month



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Histogram of quantile residuals per month of the year

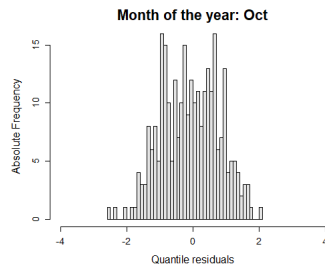
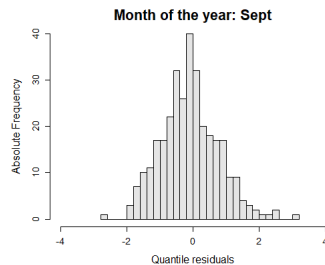
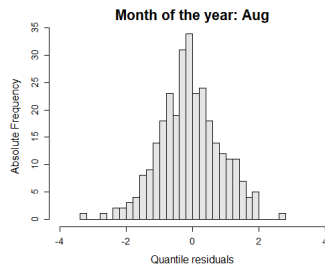
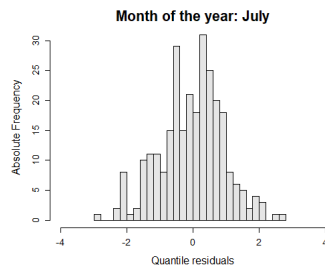
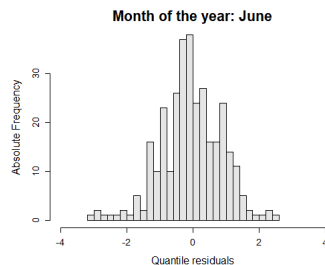
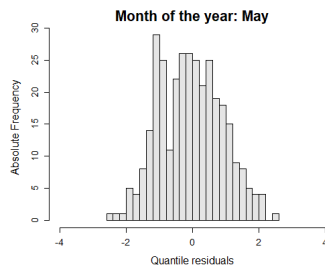


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Statistical inference

p -values based on likelihood-ratio tests

For $\text{logit}(p_{t,b}^{(c)})$ in $\text{Binomial}(v_{t,b}; p_{t,b}^{(c)})$

Variable	p-value
TB	1
D	1
W	1
M	1
TB×D	$2.259973 \cdot 10^{-6}$
W×M	0.003106045