# Decomposition of contextual information for forecast adjustments

Anna Sroginis, Robert Fildes, Nikolaos Kourentzes

Lancaster University

17th June 2019

Marketing Analytics and Forecasting

Lancaster University Management School

# Human role in forecasting

- Demand forecasting at the core of behavioural operations:
  - In retailing, manufacturing and services;
  - Delivered through a forecasting support system (FSS);
  - Handled by demand planners/forecasters.

# Human role in forecasting

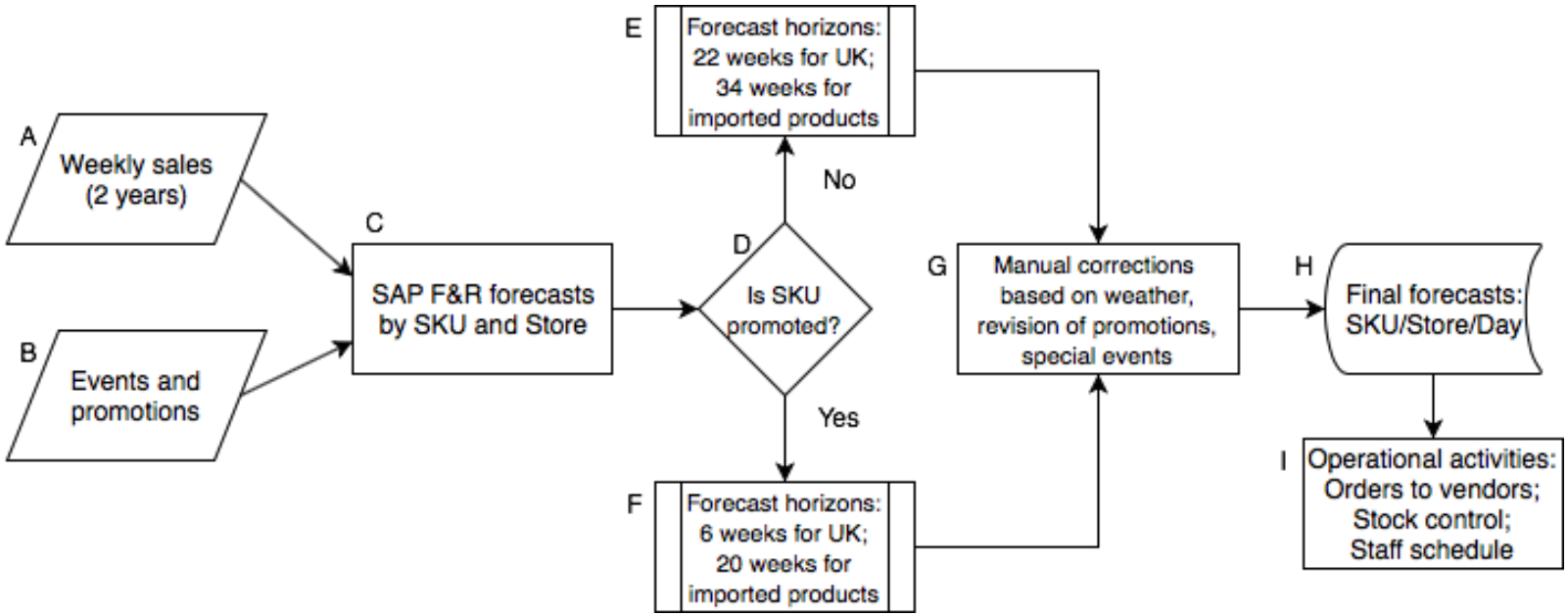
- Demand forecasting at the core of behavioural operations:
  - In retailing, manufacturing and services;
  - Delivered through a forecasting support system (FSS);
  - Handled by demand planners/forecasters.
- We know a lot about the algorithms:
  - New methods (e.g. machine learning).

# Human role in forecasting

- Demand forecasting at the core of behavioural operations:
  - In retailing, manufacturing and services;
  - Delivered through a forecasting support system (FSS);
  - Handled by demand planners/forecasters.
- We know a lot about the algorithms:
  - New methods (e.g. machine learning).
- But almost nothing about how these methods are used
  - Human input from choosing software to amending parameters.

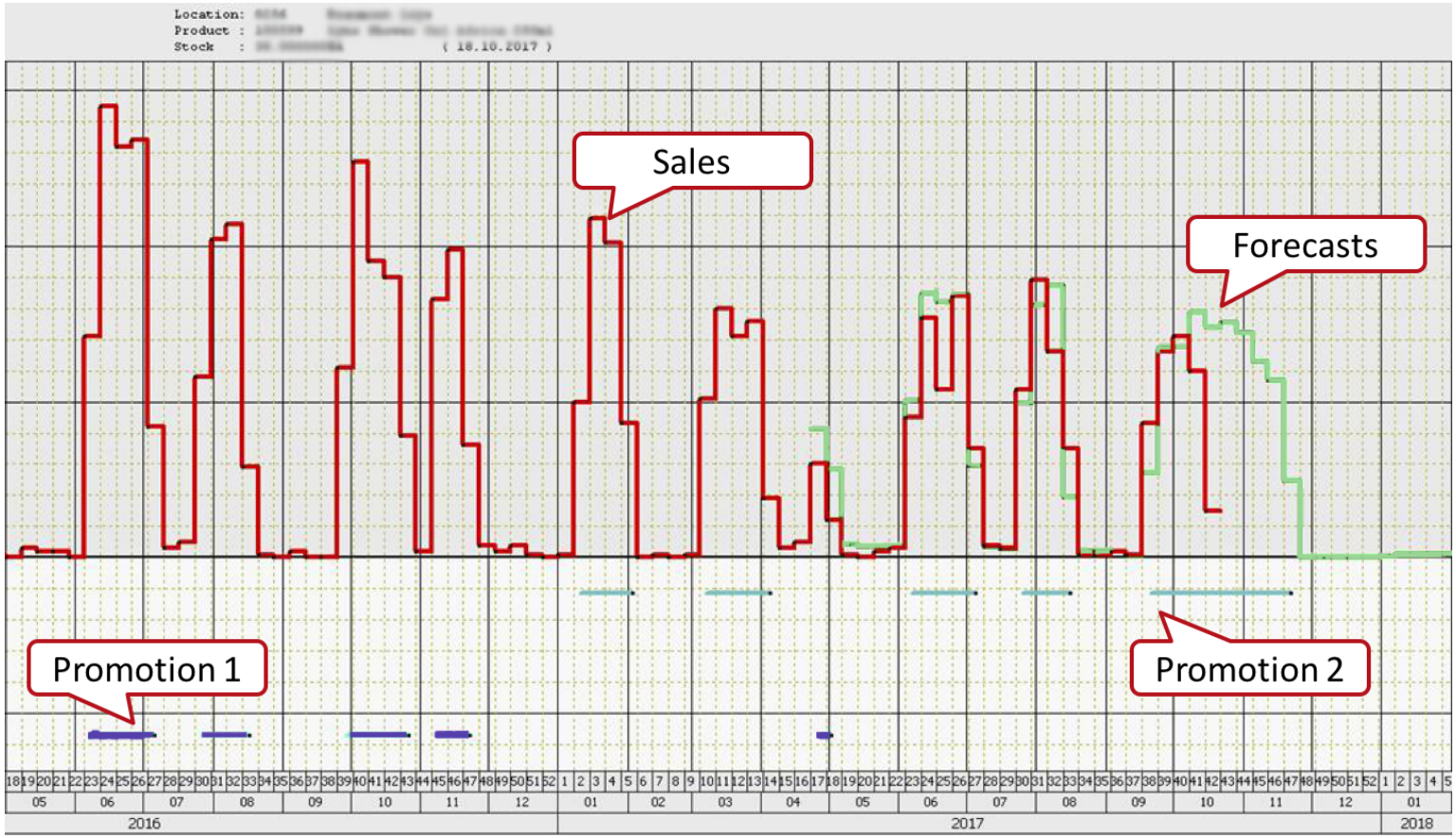
**Our objective:** to understand how forecasting algorithms are used in FSS and to propose improvements

# Forecasting process: a case study




- UK-based retailer with 50k SKUs and 400 stores
- 2 years of sales and 10 types of promotions
- Statistical model in the SAP F&R includes promotional dummies
- Around 60% of all SKUs are being adjusted due to seasonal events, promotions and weather

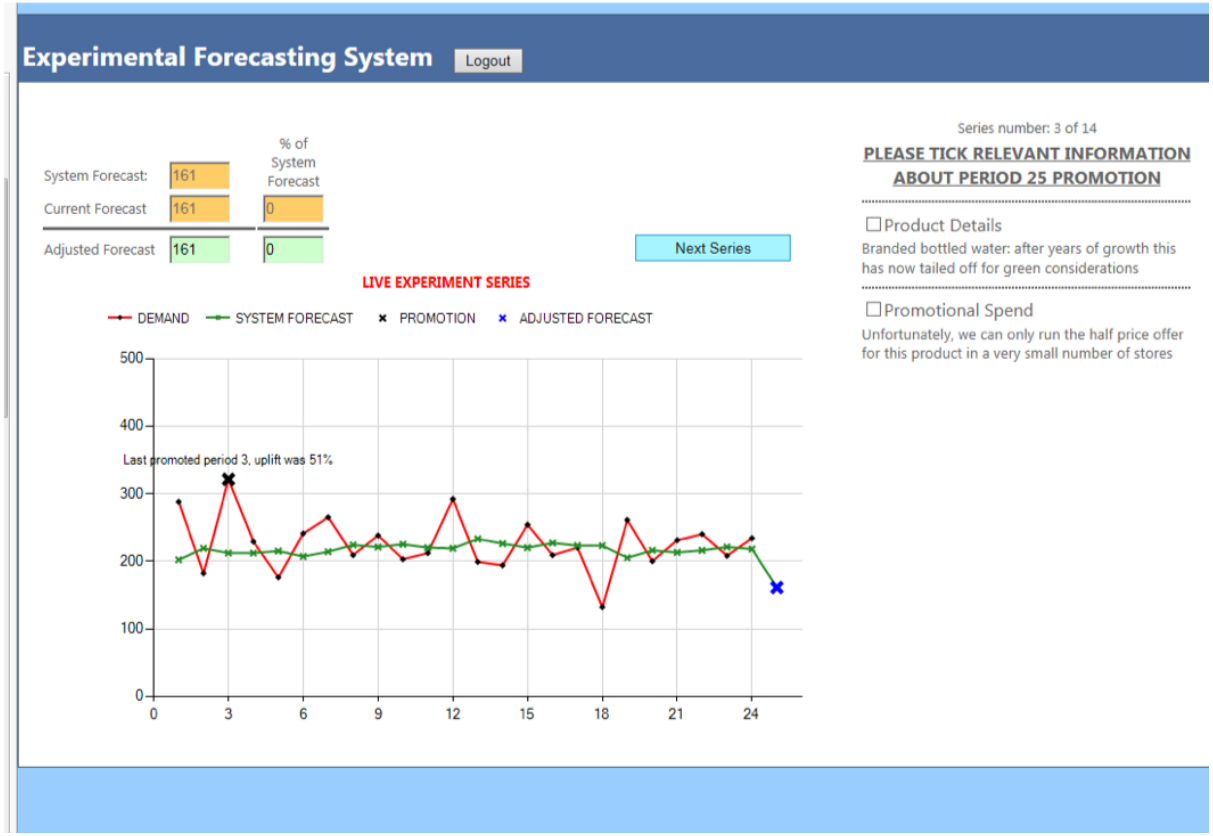
# Interface used in practice




Contextual information is handled outside of the system

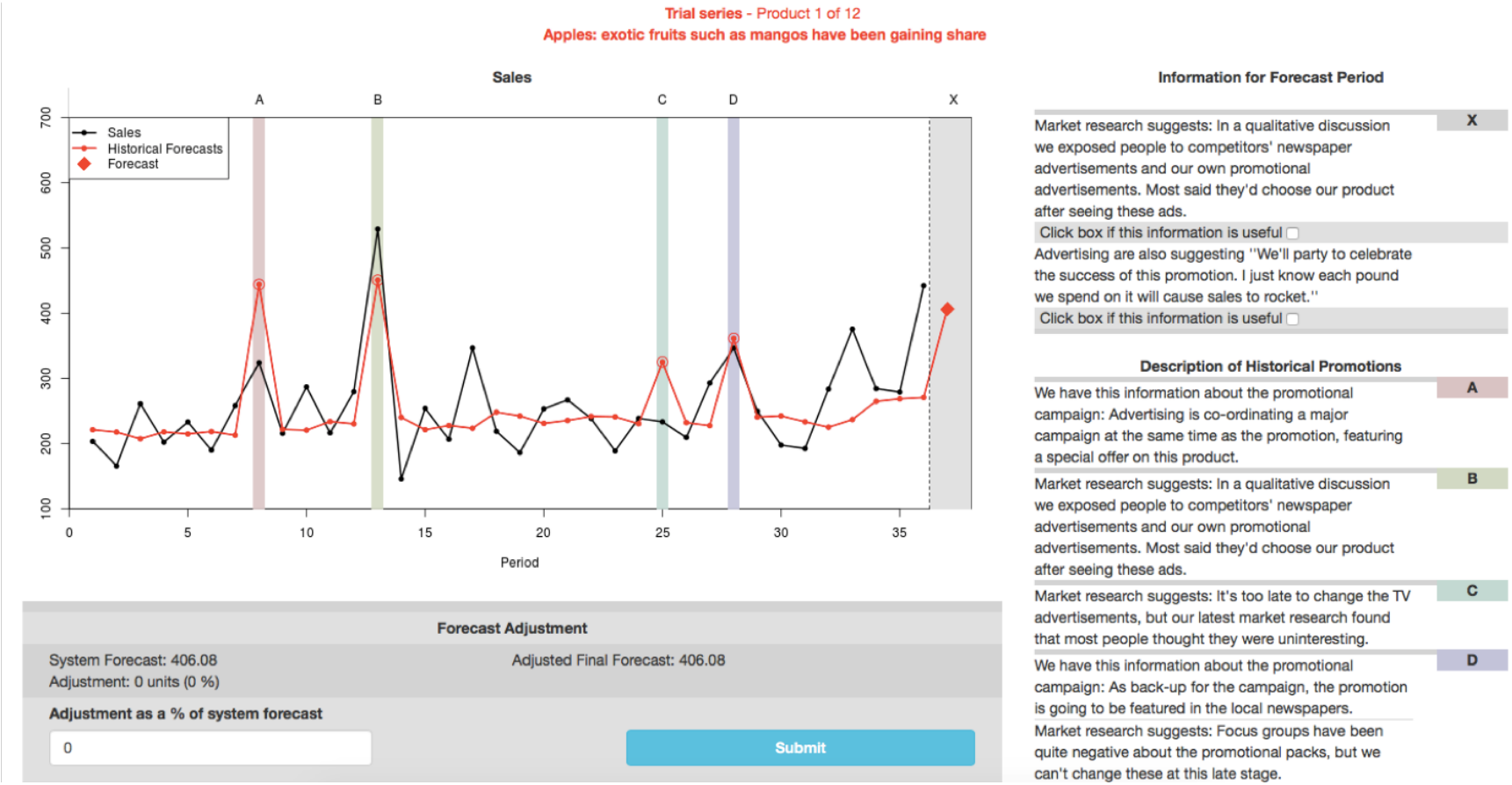
# The null case-experiment by Fildes et al. (2018)

Use and misuse of information in supply chain forecasting of promotion effects (IJF, 2018): *"participants were distracted from the 50% base rate by the previous promotion uplift and by the reasons given, despite this information having either no or unknown diagnosticity."*



# Our previous experiments

- What is the effect of contextual information on adjustments?
- Baseline forecasts vs statistical model with promotional effects



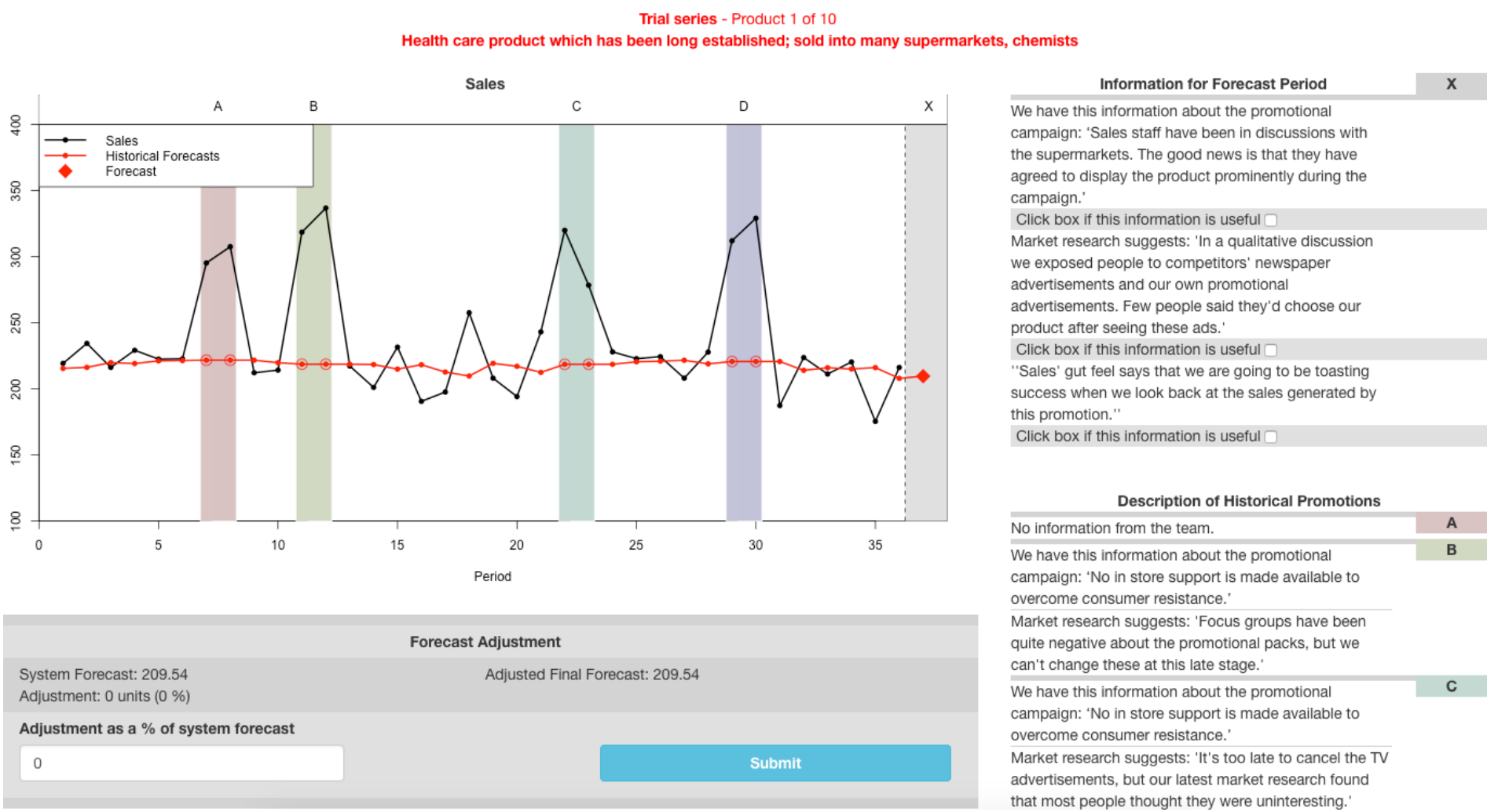
# Decomposition approach

## Decomposition of information

a strategy to split the task into smaller parts (sub-problems) in order to reduce cognitive load, which could enhance the forecasting process (Armstrong et al., 1975; Wright and Goodwin, 1993)

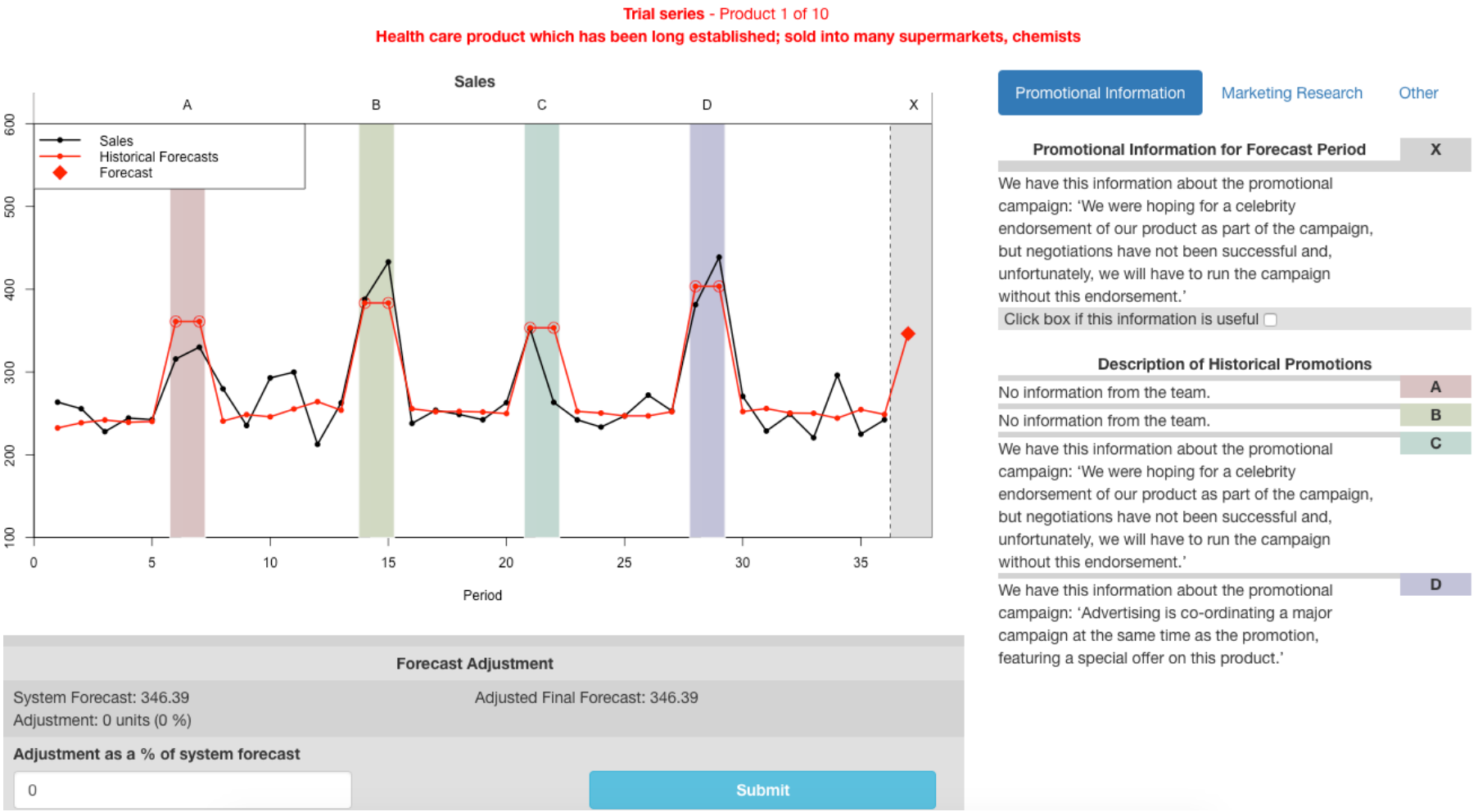
- Decomposition of judgments about trend/seasonality components (Edmundson, 1990);
- Presenting information selectively and sequentially in FSS improves accuracy (Webby et al., 2005): not substantially when the amount of information to be process increases (from 4 to 8 pieces).

# Experimental setting




- Control group with possible information overload;
- Baseline forecasts vs Statistical promotional model

# Experimental setting




- Decomposed contextual information;
- Baseline forecasts vs Statistical promotional model

# Hypotheses

- H1: Adjustments to statistical forecasts in a case of information decomposition will deviate from a control group.
- H2: Users revise their adjustments when they see new pieces of soft information.
- H3: Any type of decomposition will influence the magnitude of anchoring (e.g. last promotional uplift, current statistical forecast).

# Implementation of the experiment

- We assume that the average uplift for promotional periods is 50%;
- Promotional, marketing and hypothetical information for the upcoming period is provided;
  - Hype and marketing information do NOT have predictive value for forecasters;
  - Promotional information is diagnostic;
- Baseline statistical forecast is SES(0.2);
- 2-period promotions: 4 historical + 1 upcoming

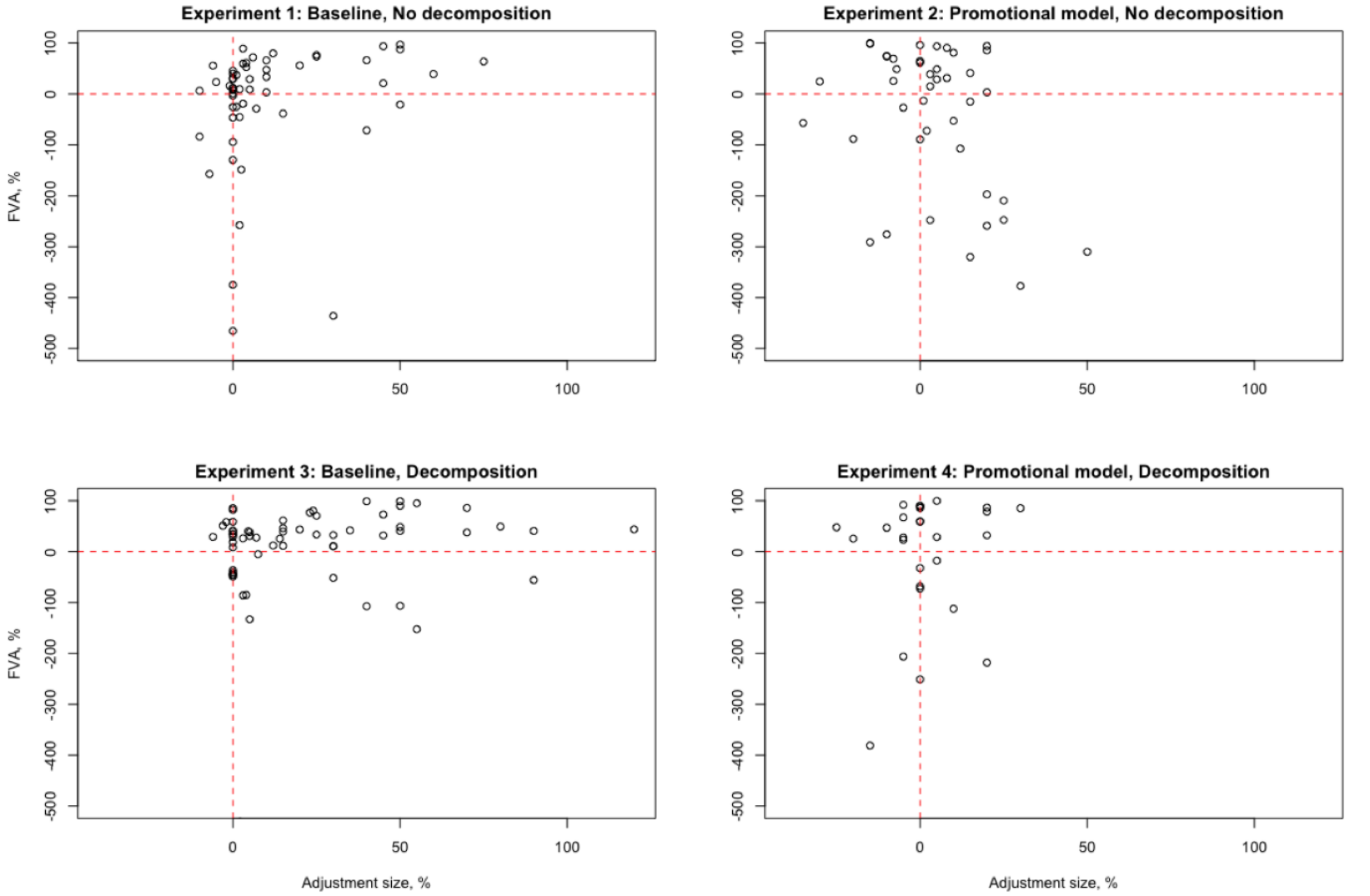
# Descriptive statistics

- Trial run: 25 people (mainly students);
- Between subjects;
- Repeated measures data: 200 observations

Table 1: Descriptive statistics.

| | Overall | Experiment type | | | |
|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 |
| Statistical forecast | | Baseline | Promotional | Baseline | Promotional |
| Decomposition | | No | No | Yes | Yes |
| Participants | 25 | 7 | 6 | 8 | 4 |
| Adjustment size | X | 11.38% | 3,08% | 22.57% | 0.09% |
| Adjusted cases | X | 73% | 93% | 73% | 72% |
| FVA | X | 4.7% | -2.73% | 6.12% | 1.59% |

# Accuracy


Experiment 1: Baseline, No decomposition
Experiment 2: Promotional model, No decomposition
Experiment 3: Baseline, Decomposition
Experiment 4: Promotional model, Decomposition
FVA, %
Adjustment size, %
100
0
-100
-200
-300
-400
-500
0
50
100

# Conclusions

- Given the role of human judgment in forecasting, how can we help a forecaster to deal with a flow of contextual information?
  - To filter and use it;
  - To evaluate forecast value added.
- Using a decomposition approach to contextual information, we find more consistent results.

Next steps:

1. To gamify the experiment;
2. To promote it online in order to get more participants;
3. To analyse adjustments and value added using regression modelling.

# Thank you for your attention!

Any questions?

Anna Sroginis, PhD student
a.sroginis@lancaster.ac.uk

Marketing Analytics and Forecasting

Lancaster University Management School

Armstrong, J. S., Denniston, W. B., Gordon, M. M., 1975. The use of the decomposition principle in making judgments. Organizational Behavior and Human Performance 14 (2), 257–263.

Edmundson, R. H., 1990. Decomposition; a strategy for judgemental forecasting. Journal of Forecasting 9 (4), 305–314.

Webby, R., O'Connor, M., Edmundson, B., 2005. Forecasting support systems for the incorporation of event information: An empirical investigation. International Journal of Forecasting 21 (3), 411–423.

Wright, G., Goodwin, P., 1993. Improving judgmental time series forecasting: A review of the guidance provided by research. International Journal of Forecasting 9, 147–161.