Interpreting information in judgmental forecasting

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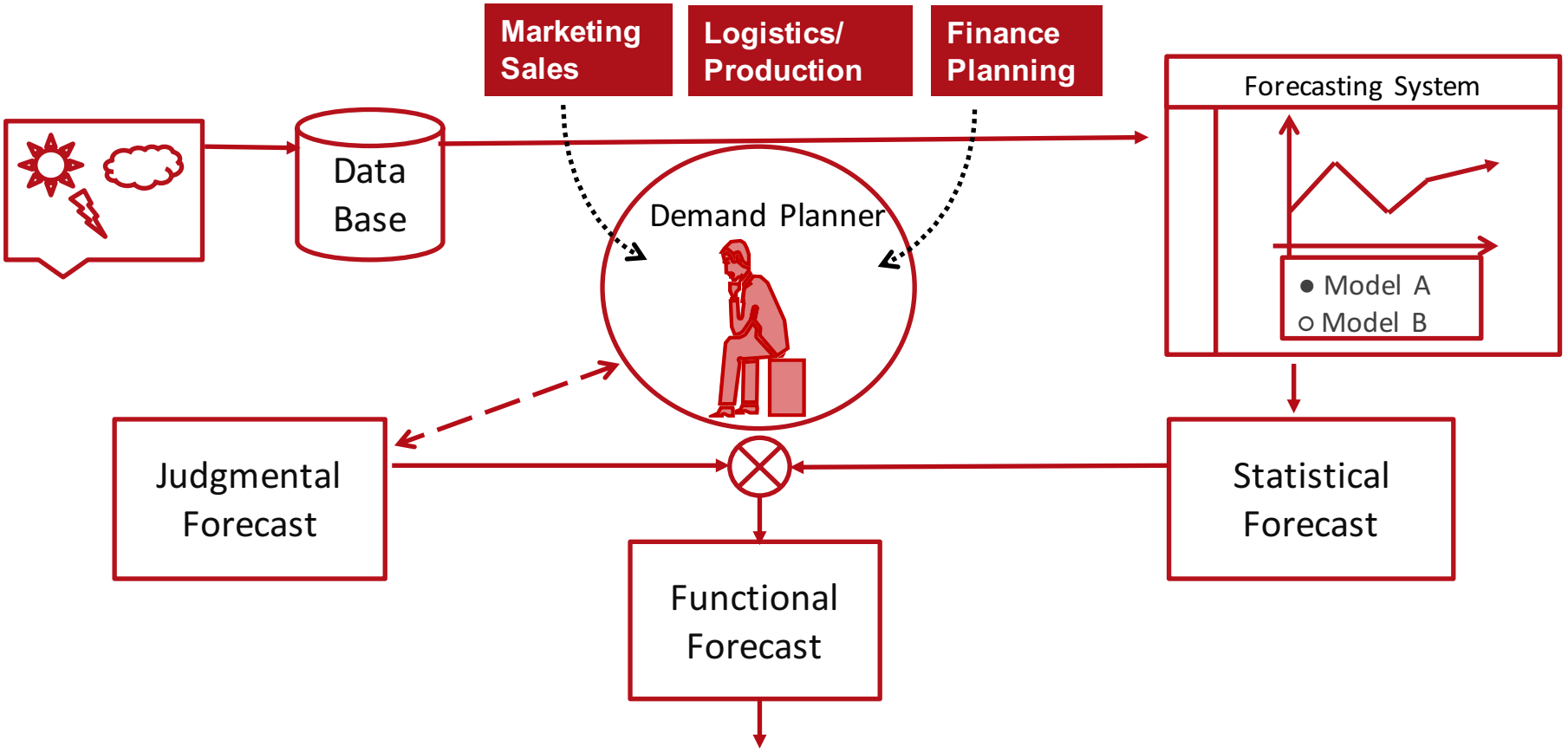
Agenda

- Introduction:
  - Forecasting process in S&OP with a case study example
  - Why judgmental adjustments?
- Forecasting issues:
  - Judgments
  - The main reason for using judgment
- Experiments: incorporating domain knowledge
- Our Experiment: setting and hypotheses
- Modelling results and discussion
- Future plans

Forecasting process in S&OP



The process (Sales and Operations Planning):

- Statistical forecast
- Information from sales, market research, planning and logistics, finance
- Incorporated into a final forecast
- Judgment is a key component for integration

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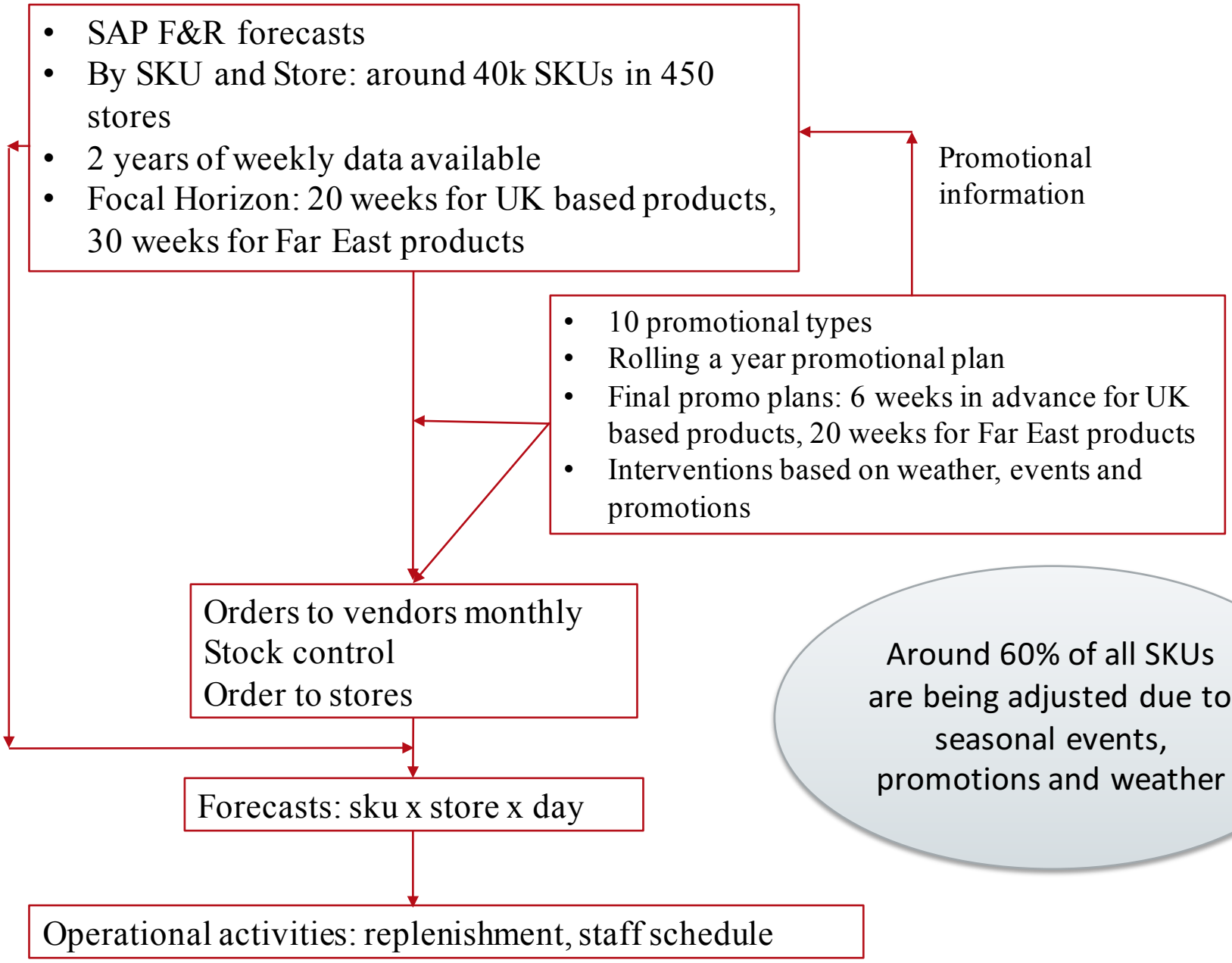
Forecasting process: a case study



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Why judgmental adjustments?

Table 1: Survey studies of methods used in practice

Method	Study				Average
	A	B	C	D	
Judgment alone	30%	25%	24%	14%	23%
Statistical methods exclusively	29%	25%	32%	30%	29%
Average statistical & judgment	41%	17%	–	19%	18%
Adjusted statistical forecast		33%	44%	37%	38%
Sample size	240	149	59	42	

A: Sanders and Manrodt (2003); B: Fildes and Goodwin (2007); C: Weller and Crone (2012); D: Fildes and Petropoulos (2015).

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Forecasting issues

- We know that there are many heuristics and biases (e.g. anchoring, overconfidence, illusion of control) (Tversky and Kahneman, 1974; Kahneman, 2012)
- One of the main reasons for adjusting sales forecasts in practice is promotional and advertising activities (Fildes and Goodwin, 2007)
- Several features of promotions are needed to be considered:
  - a length and frequency of promotional period,
  - possible lag and lead effects;
  - a main method for forecasting:
    - judgment (Trapero et al., 2013)
    - multivariate statistical models (Trapero et al., 2015)
    - VAR models (Hanssens et al., 1990).

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Experiments: incorporating domain knowledge

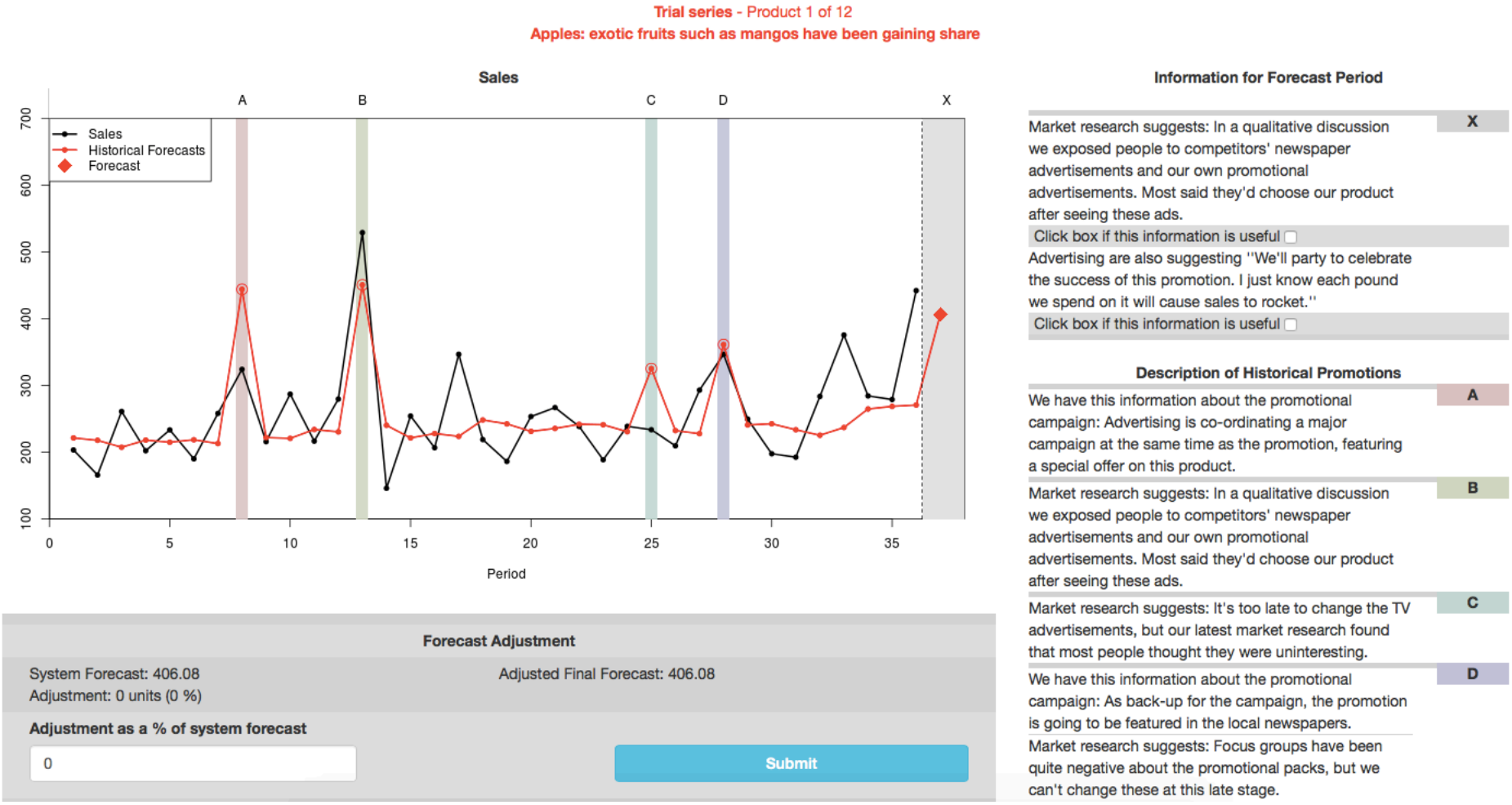
Study	Domain information	Results
A	Marketing, production and sales information	• The relatively larger adjustments - greater average improvements in accuracy, the smaller adjustments often damaged it. • General bias towards optimism
B	Promotions	May enhance the forecast accuracy when the adjustment size is not too large
C	Expertise knowledge	• Comparing three methods of expert knowledge elicitation (adjustments, 50%-50% and divide-and-conquer), judgmental adjustments show higher improvements in accuracy. • Only negative adjustments led to an improvement in accuracy
D	Promotional, marketing, weather	Participants • Underestimate promotional uplifts • Misweight relevant information

A: Fildes et al. (2009); **B:** Trapero et al. (2013); **C:** Alvarado-Valencia et al. (2017); **D:** Fildes et al. (2018)

Experimental setting

Research question:

What is the effect of contextual information of unknown diagnosticity on human adjustments during promotional periods*?*



FSS screenshot

Design features

- We assume that the average uplift for promotional periods is 50%
- Promotional, marketing and hypothetical information for the upcoming period is provided:
  - "Our spending on this campaign is only 20% of our normal spend" (Promo)
  - "The promotion is supported by a complimentary trial offer in store to overcome consumer resistance" (Promo)
  - "Based on market research, the Marketing Manager suggests there will be a positive reaction to the promotion campaign" (Market)
  - "Focus groups were excited by the benefits of the promotion" (Market)
  - "Sales has no doubts at all. ''We've got a winning promotion formula here" (Hype)
- Hype and marketing information have unknown diagnosticity for forecasters, while promotional information was relevant in cases when Enhanced time series were provided
- 4 past promotions, each of them lasts for only one period

*Thanks to Prof Paul Goodwin for the contribution

Hypotheses

- **H1:** Providing forecasters with additional qualitative information with unknown diagnosticity influences their adjustments.
  - H1a: Presenting contextual information about **past promotions**
  - H1b: Additional qualitative statements about **the upcoming period**
- **H2:** Forecasters accept statistical forecasts with integrated promotional effects in the presence of contextual information.
- **H3:** The final forecast accuracy is effected when contextual information of unknown diagnosticity is presented.

Participants

- Students who completed 'Business Forecasting' module with one lecture about judgmental forecasting
- The experiment was an voluntary exercise
- Different incentives: private tokens for participation, one-two prizes for the best performance and just verbal encouragement (no difference in performance was identified)

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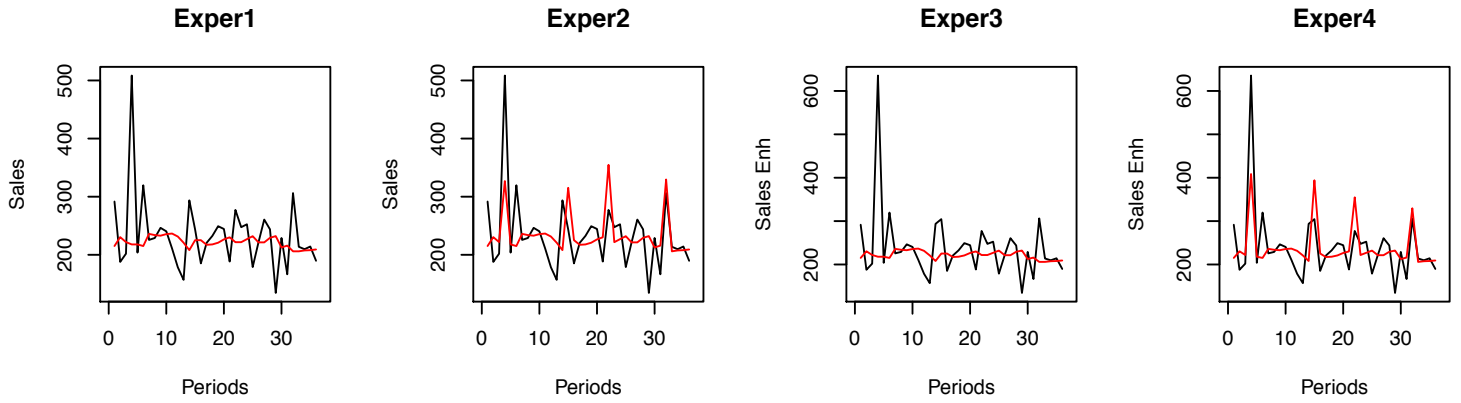
Implementation of the experiment

	Exper1	Exper2	Exper3	Exper4
Historical Demand	Not Enhanced		Enhanced*	
Stat forecast	Baseline*	Including promo	Baseline	Including promo
Anchor	50%	0%	50%	0%
Example				

Data Generating Process: $Sales_t = PromoEffect_t^{c_t} \cdot (\alpha Sales_{t-1} + (1-\alpha) BaseSales_{t-1}) \cdot \varepsilon_t$

*Enhanced demand have +25% uplift in cases of promotions with a positive contextual information

*Baseline statistical forecast is SES(0.2)

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Descriptive statistics

Table 3: Descriptive statistics

	Mean	Experiment type			
		1	2	3	4
Time Series		Not Enhanced	Not Enhanced	Enhanced	Enhanced
Statistical forecast		Baseline	with Promotions	Baseline	with Promotions
Participants	88	17	24	26	21
Adjustments (%)	12.75	16.08	1.42	29.01	2.88
Initial MAPE (%)	22.46	29.89	12.22	35.32	12.22
Final MAPE (%)	20.04	23.92	16.72	24.37	15.33
FVA (%)	2.42	5.97	-4.50	10.95	-3.11

*FVA (Forecast Value Added) = Initial MAPE – Final MAPE

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MultiLevel modelling

- Includes fixed and random effects:
  - Fixed effects: conventional effects in linear regression
  - Mixed effects: give random intercept/slope to uncontrolled grouping variable

- Random effects:
  - Time series (ts)
  - Three groups of students: Undergraduate/Masters 2016 or 2017

- Dependent variables:
  - Relative adjustments in logarithms
  - FVA, where FVA (Forecast Value Added) = Statistical MAPE – Final MAPE (after adjustments)

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Variables to consider

Technical part (quantitative)	Contextual information (qualitative)
Last promotional effect	Promotional, marketing information for the forecasting period
Current statistical forecast	Hype for the forecasting period
Low/high data noise	Promotional, marketing information for past promotions
Average promotional effect	
Last actual	

Other: order of time series, experiment type, expert prior estimates, usefulness of presented qualitative information, timer

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Log-log model

		Estimate	Standard Error
Fixed effects			
	Intercept	0.5446	0.4955
H2	Exper2	-0.5909	0.2886
H2	Exper3	0.1038	0.0164
H2	Exper4	-0.5498	0.2883
H1	Marketing reasons useful	-0.0366	0.0178
H1	Hype useful	0.0432	0.0180
H1	Promo reasons useful, positive	0.0708	0.0180
H1	Market reasons useful, positive	0.1092	0.0270
	Expert prior	0.0170	0.0064
	Last promotional uplift	0.2212	0.0864
	Current forecast	-0.2303	0.0518
	Current forecast, Exper 1 and 3	-0.1060	0.0513
	Low noise, Exper 1 and 3	0.0628	0.0282

Random effects	Standard Deviation
Participant group (intercept)	0.0101
Time series (intercept)	0.0589
Residual	0.1620

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Problem: Information overload

Ignoring contextual information about past promotions?

Possible information overload due to complexity of the interface?

How can we check that?

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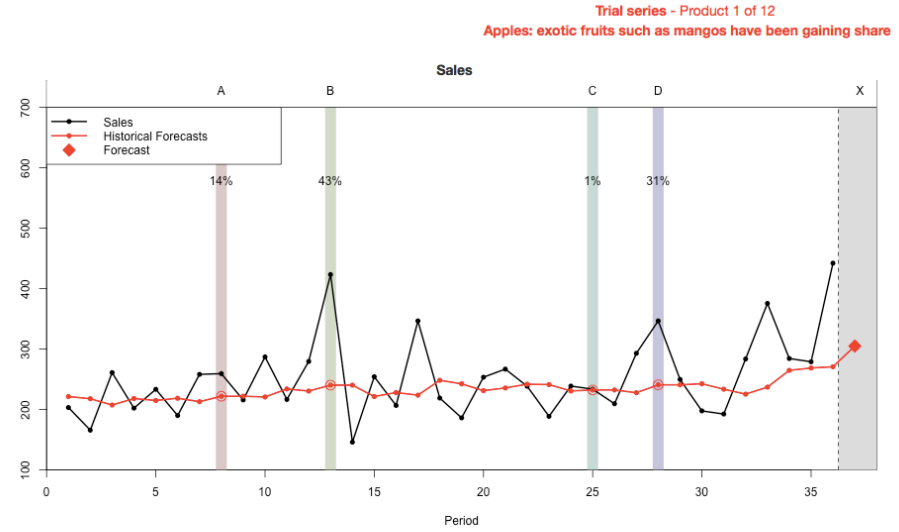
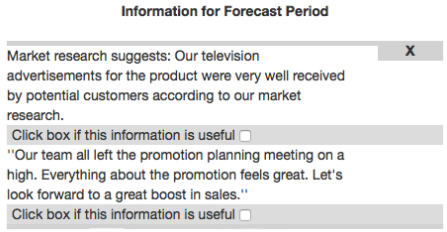
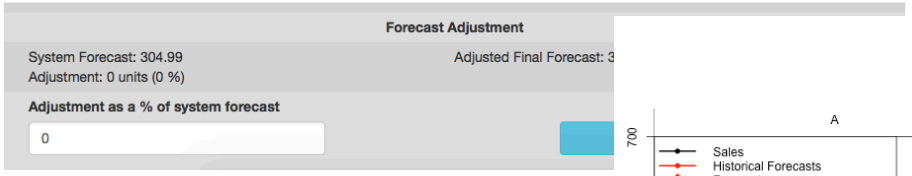
Simplified experiments

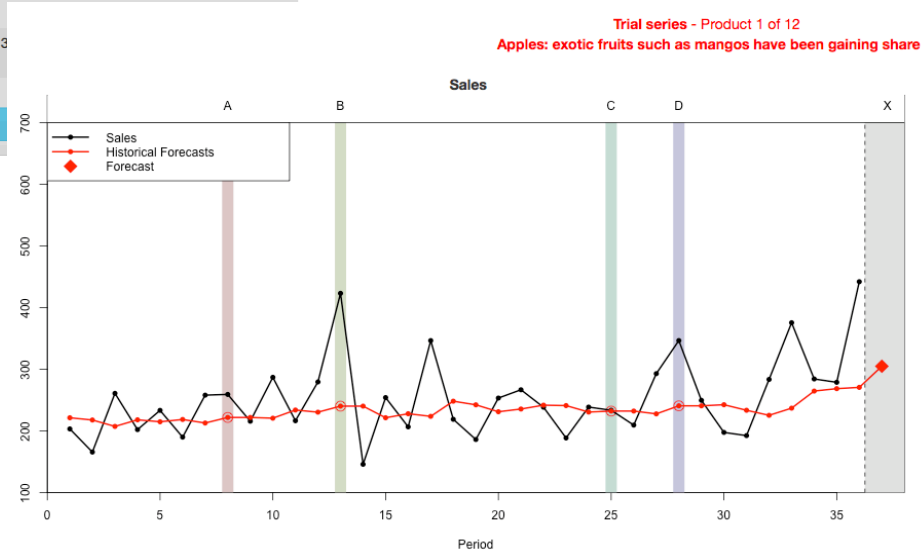


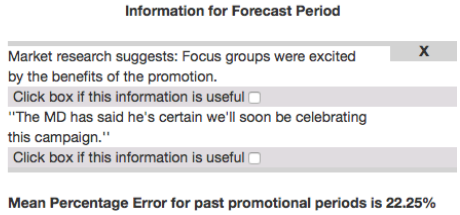


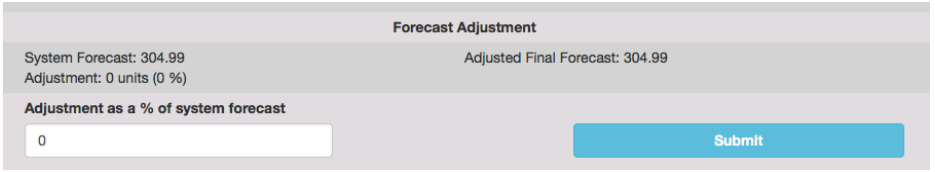
Without additional information about past promotions



With only one statement about past forecasts performance during promotions







Comparison of 'Full' and 'Simplified' models

H4: Simplifying the experiment setting will provide more accurate adjustments.

However, the real forecasting process is typically much more complex.

Table 8: Mixed effects model for full and simplified experiments

Fixed effects	Coefficient		p-value	
	Full	Simplified	Full	Simplified
Intercept	0.5661	0.9677	0.2913	0.0898.
Exper2	-0.5979	-1.3242	0.0393*	0.0173*
Exper3	0.1040	**-0.0011**	0.0000***	**0.9763**
Exper4	-0.5567	-1.3412	0.0547.	0.0163
Promo reasons useful	-0.0063	**0.1014**	0.7163	**0.0046****
Market reasons useful	-0.0360	-0.0869	0.0455*	0.0234*
Hype useful	0.0431	**-0.0253**	0.0169*	**0.5223**
Promo reasons useful, positive	0.0770	**-0.0600**	0.0016**	**0.1293**
Market reasons useful, positive	0.1089	0.1640	0.0000***	0.0053**
Expert prior	0.0170	0.0550	0.0085**	0.0002***
Last promotional uplift	0.2193	0.2345	0.0311*	0.0378*
Current forecasts	-0.2307	-0.2160	0.0000***	0.0162 *
Current forecasts, Exper 1 and 3	-0.1073	-0.2235	0.0373*	0.0226*
Low noise, Exper 1 and 3	0.0626	0.0281	0.0275*	0.5371
Split		0.0199		0.4879

Signif. codes: 0 "***", 0.001 "**", 0.01 "*", 0.05 "."
R2 for fixed effects: 0.3369 for full and 0.3538 for simplified models

- When simplifying the experiment: participants get clearer picture and behave closer to optimality

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Conclusions

- In order to analyse how people react to different types of information, several experiments were conducted:
  1. With qualitative information for both the upcoming promotional period and past promotions
  2. Enhancing the general anchors aiming to overcome underestimation
  3. Without any contextual information about past periods
  4. With a diagnostic statement for past promotional performance

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Conclusions

- Main outcomes:
  - Participants tend to ignore contextual information about past promotions and react to given statements for the forecasting period:
    - Positive promotional, marketing and hype statements increase adjustments on average
  - We find preliminary evidence of information overload and misinterpretation of the information due to complexity of the interface
    - This is motivation for further research into judgmental adjustments in forecasting

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Next experiments

- Run an experiment when forecasters can choose the most preferable experimental outline (with or without contextual information)
- Develop a new behavioural experiment (based on the current one) considering a decomposition of adjustments:
  - RQ1: Can people weight contextual information in a correct way if this information provided sequentially?
  - RQ2: Does the final accuracy change dynamically over time?

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Thank you for your attention!
Questions?

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