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Demand forecasting in the presence of disruptions

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Agenda

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- Motivation
- Literature Review
- Gaps & Objective
- Shock Smoothing method
- Numerical Study & Real Data
- Conclusion

Motivation

- Forecast **demand during and after disruptions**
- Many existing models do not capture **changes in demand** well due to disruption
- Recent examples showed that retailers did not find **decision support systems** useful during times of disruption due to poor forecasts
- **Examples**:
  - Demand peaks for products such as flour and toilet paper as well as changes in demand patterns for many products during **Covid-19**
  - Delays at border and new rules imposed due to **Brexit** (59% fall in imports of oils and fats (Rowsell, 2022))
  - Increased demand for sunflower oil, wheat and maize during first months of **Russian invasion of Ukraine**

(Diqqiafrizal,2018)

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Literature Review

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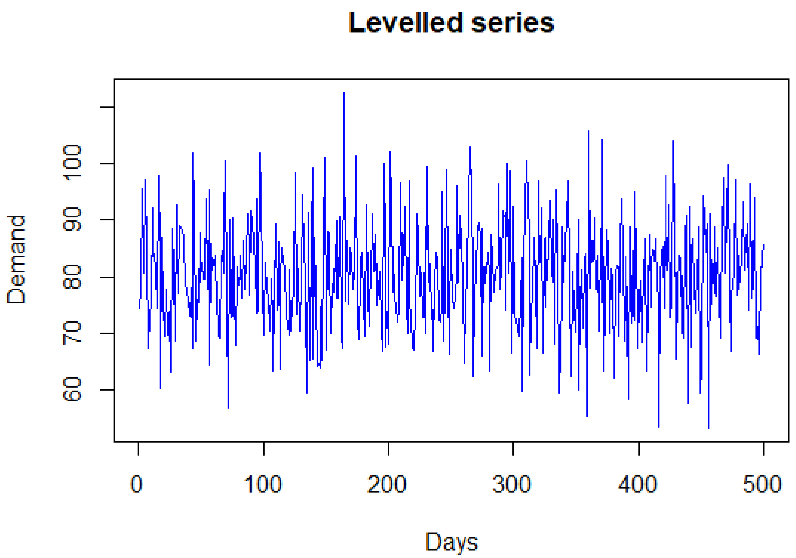
- **Retail forecasting** (Harrison and Stevens 1976, Fildes 1983, Fildes et al. 2022a, Fildes et al. 2022b, Makridakis et al, 2022, Hyndman and Rostami-Tabar 2024)
- **SC robustness and resilience** (Ivanov et al. 2016 , Ivanov et al. 2017, Chen et al. 2019, Hobbs 2020, El Baz and Ruel 2021, Hobbs 2021, Pereira et al. 2021)
- **Adaptive forecasting methods** (Trigg and Leach 1967, Shone 1967, Koehler et al. 2012)

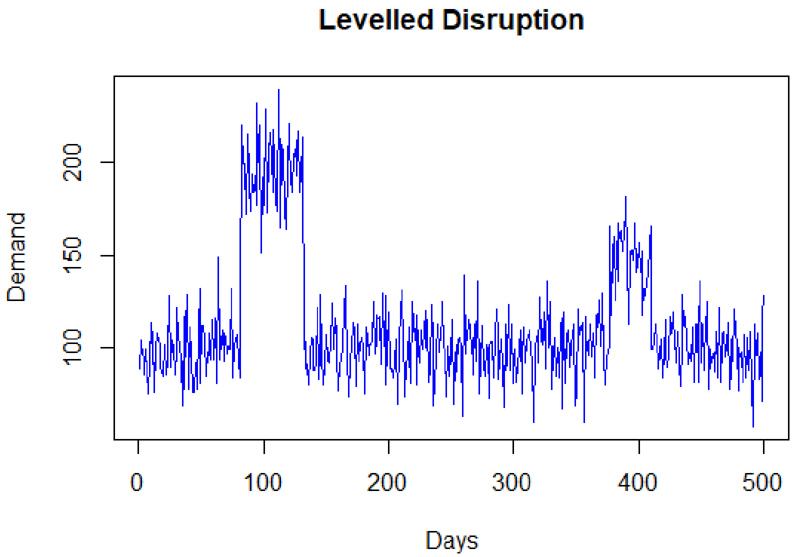
Limited research on quantitative forecasting models during disruptions in retailing (such as Hyndman and Rostami-Tabar 2024, Nikolopoulos et al. 2021).

"Although several approaches to the problem exist, the literature lacks recommendations and comparisons of alternative strategies for forecasting time series data influenced by interruptions such as the COVID-19 pandemic. " -
Hyndman and Rostami-Tabar 2024

Gaps & Objectives



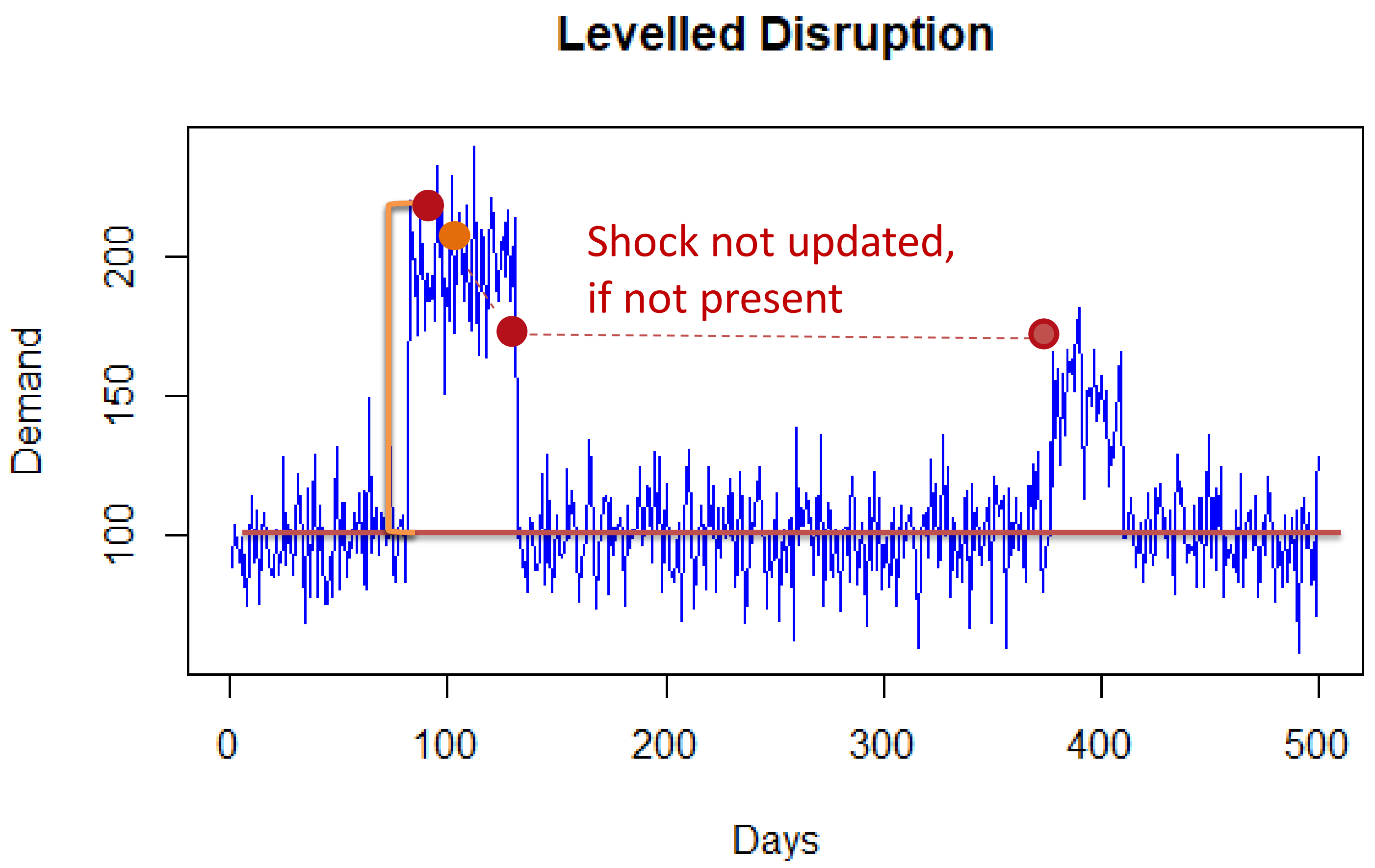
Standard vs. adaptive forecasting methods



Research objective: Identify suitable forecasting methods during disruptions

1. Evaluate performance of **standard and adaptive methods** in the presence of disruptions (e.g., methods built into commercial software solutions)
2. Develop **novel approach** that captures shock due to disruption

Shock Smoothing - Intuition



Shock Smoothing – State Space Equations

Forecast Equation : $\hat{y}_{t+1|t} = l_t + v_t\, u_{t+1}$

Level Equation : $l_t = l_{t-1} + \alpha\, \varepsilon_t$

Disruption/Shock Equation : $v_t = v_{t-1} + \delta u_t \varepsilon_t$

where,

l_t : estimate of the level at time t

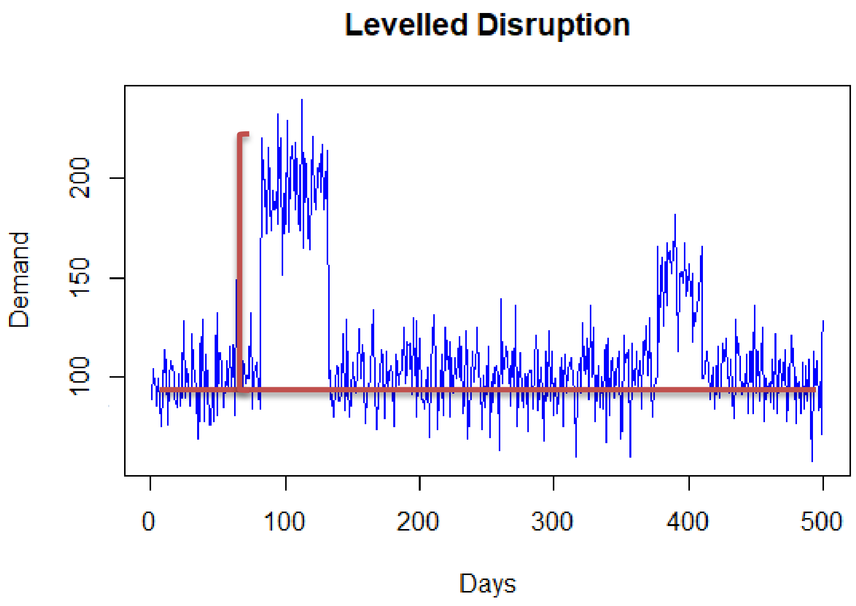
v_t : estimate of the disruption at time t (by how much)

u_t : disruption indicator variable (1: yes, 0: no)

α : smoothing parameter for the level ($0 \le \alpha \le 1$)

δ: smoothing parameter for the disruption (δ = 0 => no shock in series)

ε_t: error term



Numerical Study Design

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- Series fluctuates around a level
- Correlated/Uncorrelated demand
- Disruption
  - Causes structural break (level shift) in the series, lasting for several periods
  - Two disruptive events
  - May occur with different intensities (magnitude and variability)

Total 24 settings (12 correlated/12 uncorrelated)
100 series per setting
500 observations per case
70% Training set / 30% Test Set
6-step ahead forecasts
RMSSE as evaluation metrics
Evaluation pre/during/post second disruption

Numerical Study: Data Generation

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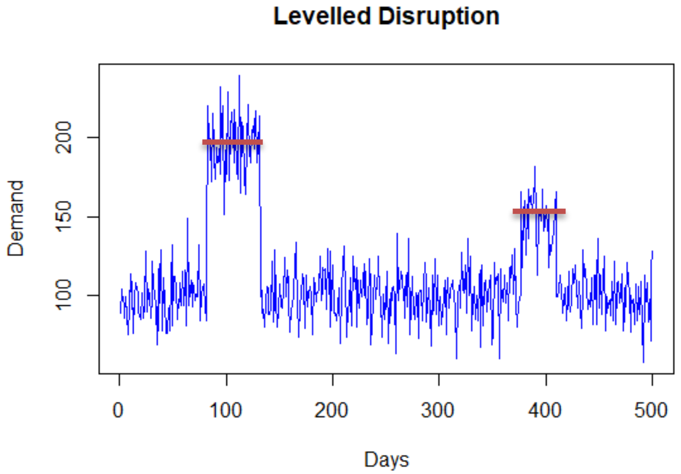
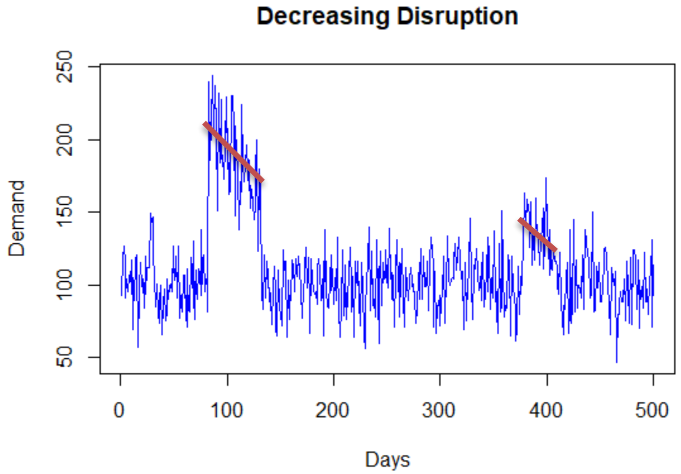
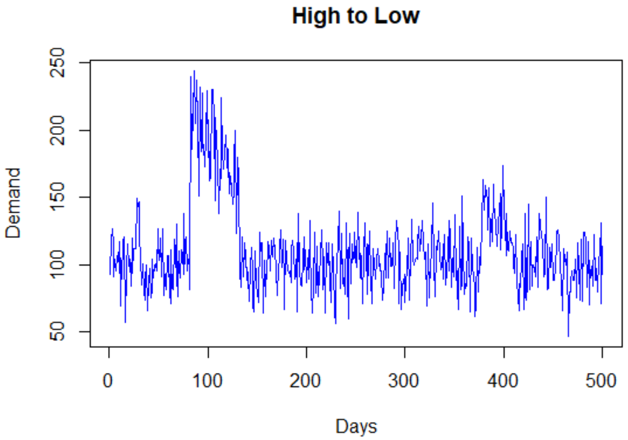
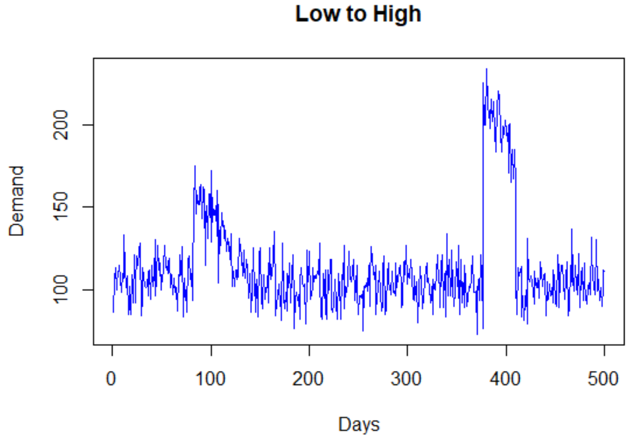
Patterns

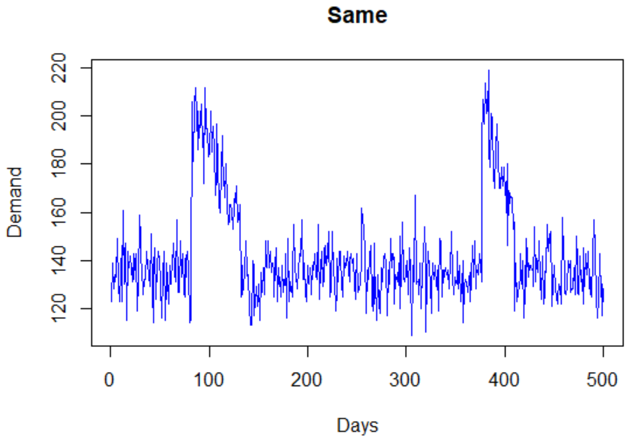




Intensities







Benchmark Methods

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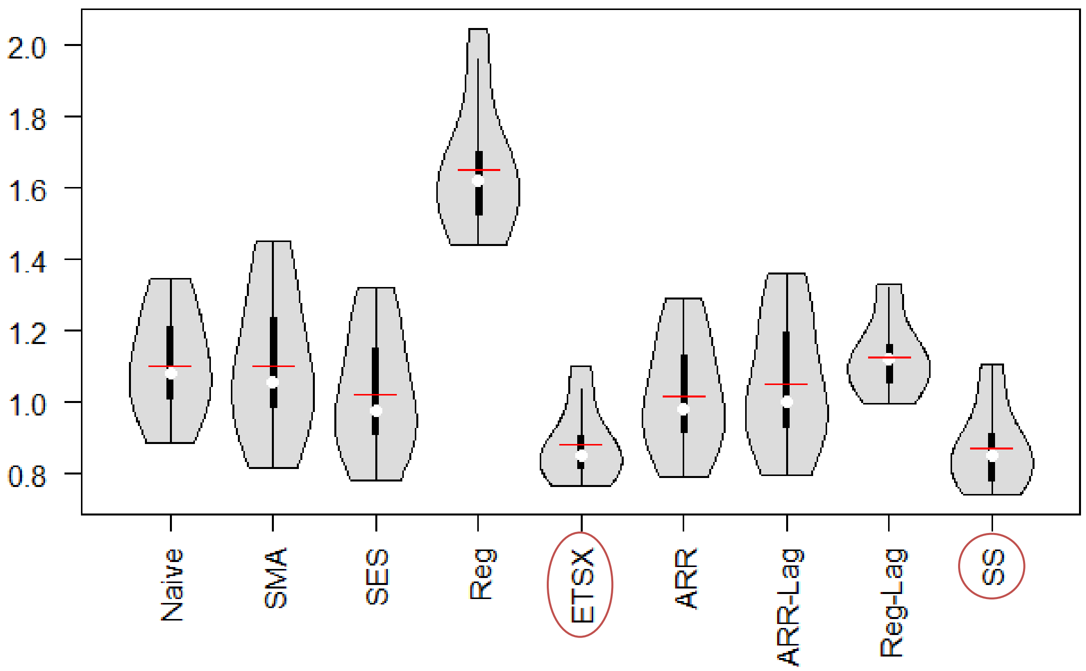
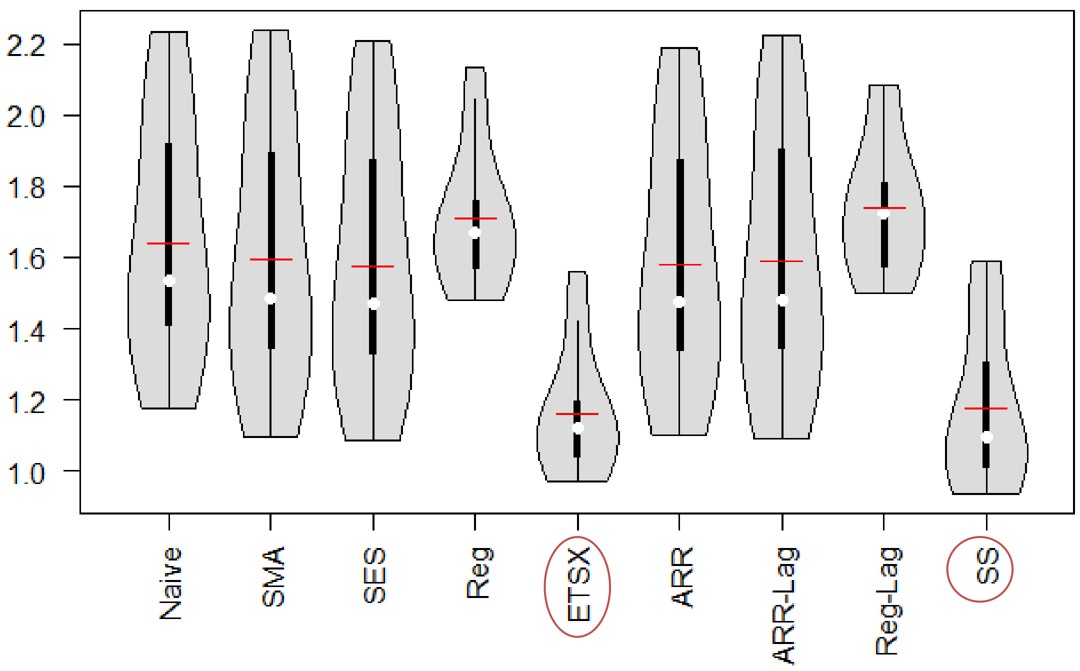
Methods	Relevance to SC disruption
Naïve (Hyndman R.J., & Athanasopoulos G. 2021)	Memory of 1 period
SMA (Hyndman R.J., & Athanasopoulos G. 2021)	Memory of k periods
SES(Brown, 1959)	Reacts depending on α
Adaptive **R**esponse **R**ate (Trigg and Leach, 1967)	Reacts depending on changes in α from the current period
Adaptive **R**esponse **R**ate_lagged (Shone, 1967)	Reacts depending on changes in α from the last period
Regression (Galton F., 1894)	Depends on unknown/known future variable
ETSX (Svetunkov I., 2023)	Depends on unknown/known future variable
Reg_lagged (Stanton, J.M., 2001)	Regression with lagged sales

Performance for correlated demand

RMSSE for h1

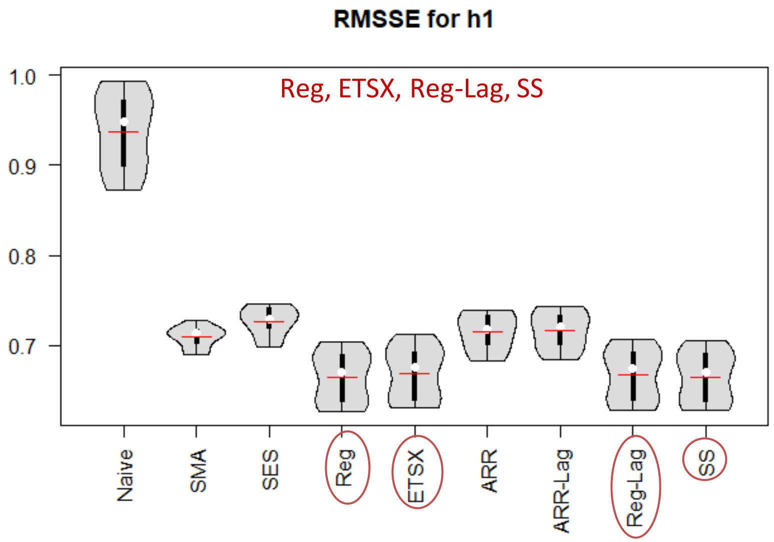


RMSSE for h6

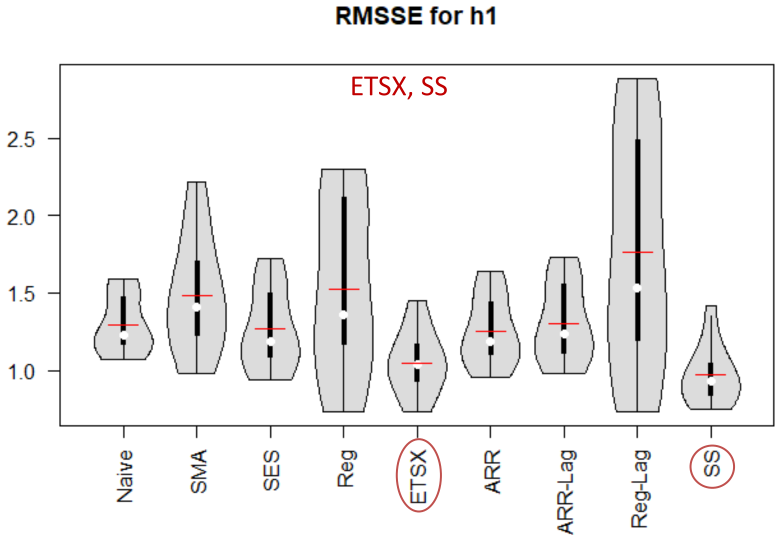


Comparison: Pre, during, post-disruption on uncorrelated demand

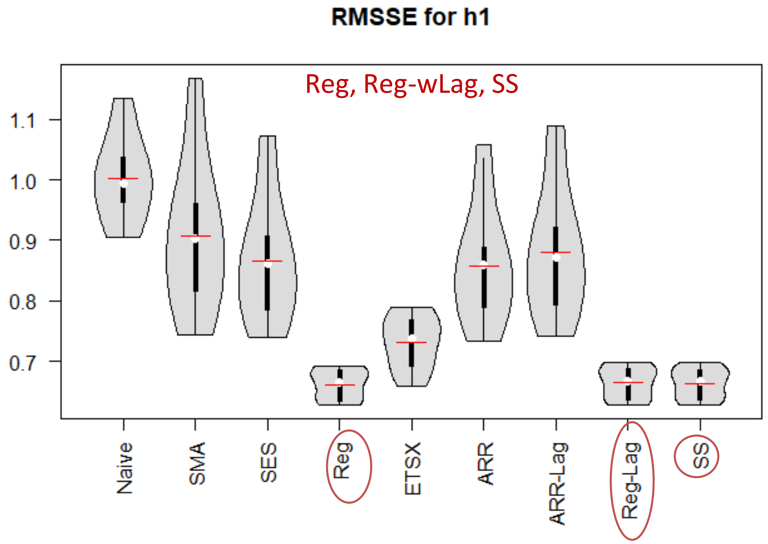
Pre-disruption



During-disruption



Post-disruption



Application on real data (RMSSE)

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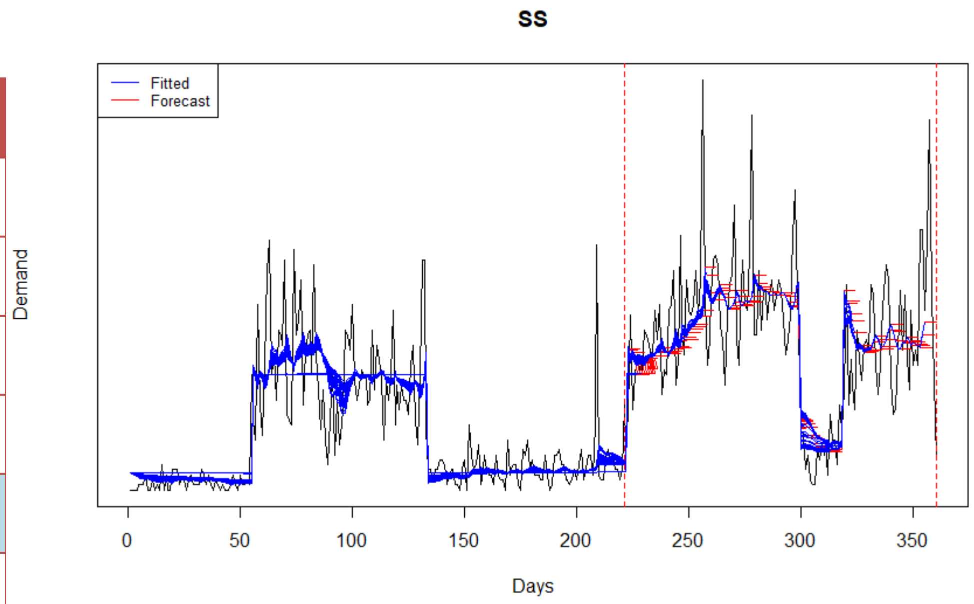
Methods	h1	h2	h3	h4	h5	h6
Naïve	1.782	1.971	2.071	2.172	2.249	2.359
SMA	1.689	1.805	1.884	1.981	2.038	2.094
SES	1.600	1.744	1.839	1.930	2.009	2.087
Regression	2.016	2.040	2.082	2.086	2.091	2.101
ETSX	1.507	1.579	1.627	1.666	1.680	1.711
Adaptive **R**esponse **R**ate	1.645	1.736	1.838	1.933	1.995	2.087
Adaptive **R**esponse **R**ate (with lagged alpha)	1.608	1.739	1.849	1.942	1.995	2.080
Regression (with lagged demand)	1.699	1.903	2.039	2.115	2.153	2.220
Shock **S**moother	1.454	1.520	1.579	1.619	1.631	1.670

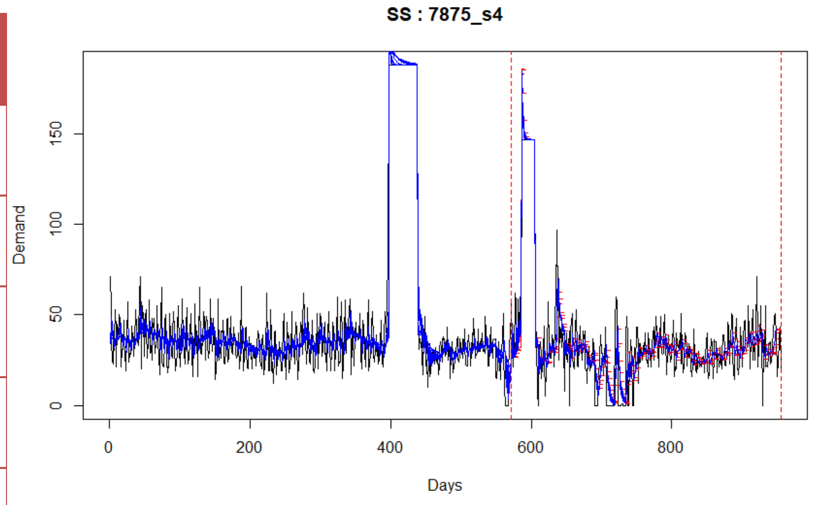


Key insights of real-data:

- 5 products
- Restaurant
- Jan 2021 - Feb 2022
- Forecast purpose:
  - Inventory management
  - Staff allocation

Application on real data (RMSSE)

Methods	h1	h2	h3	h4	h5	h6
Naïve	0.916	1.153	1.288	1.307	1.294	1.296
SMA	0.880	1.097	1.222	1.244	1.244	1.266
SES	0.881	1.088	1.196	1.212	1.214	1.254
Regression	1.221	1.229	1.238	1.248	1.258	1.269
ETSX	0.946	1.096	1.180	1.221	1.259	1.317
Adaptive **R**esponse **R**ate	0.922	1.045	1.122	1.170	1.218	1.279
Adaptive **R**esponse **R**ate (with lagged alpha)	0.890	1.042	1.127	1.159	1.191	1.251
Shock **S**moother	0.862	0.963	1.024	1.060	1.096	1.144



Key insights of real-data:

- 3 products * 10 stores
- Retail Data
- Nov. 2018 – Dec. 2021
- Forecast purpose:
  - Inventory management

Conclusion

Contribution

- Shock smoothing method **adjusts more quickly** and **on average, outperforms existing methods in most cases**
- Existing methods may **over-/underreact**
- **Decision support for retailers:** better forecasting decisions during disruptions, while also supporting them when there is no disruption present.

Future Research

- Extend to include **trend, seasonality and explanatory variables**
- Prediction **intervals**
- Support components selection via **information criteria**

Thank you for attending.
Any questions?

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