Demand Forecasting Using Sell-through Data

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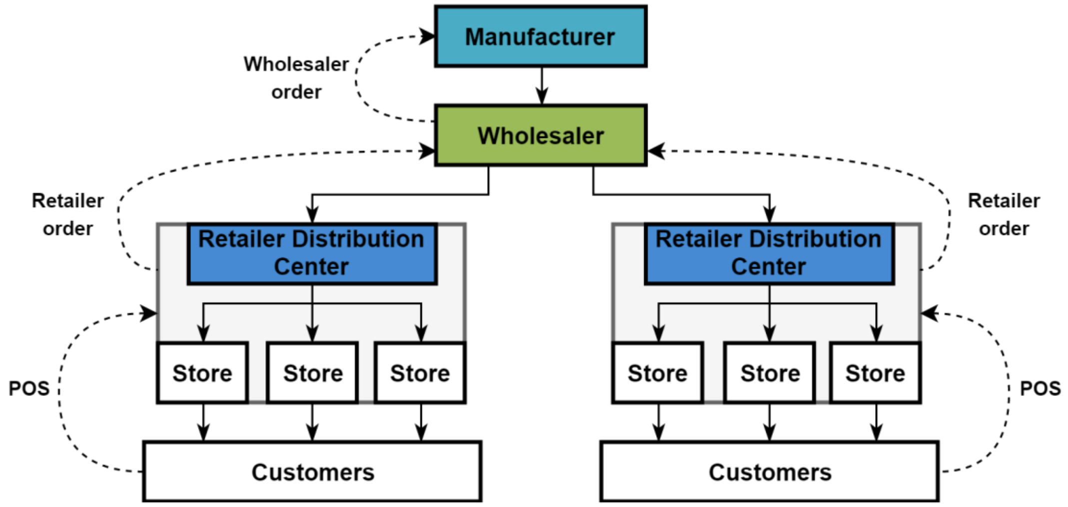
Supply chain planning & forecasting

- Supply chain planning (SCP): “the forward-looking process of coordinating assets to optimize the delivery of goods, services and information from supplier to customer, balancing supply and [forecasted] demand” (Gartner Inc., 2019)
  - Strategic: Network design
  - Tactical: Sales and operations planning
  - **Operational: Planning and scheduling**
- Goal SCP = max(service levels) & min(inventory costs)
- Critical input = **accurate demand forecasts**

Operational demand forecasting (I)

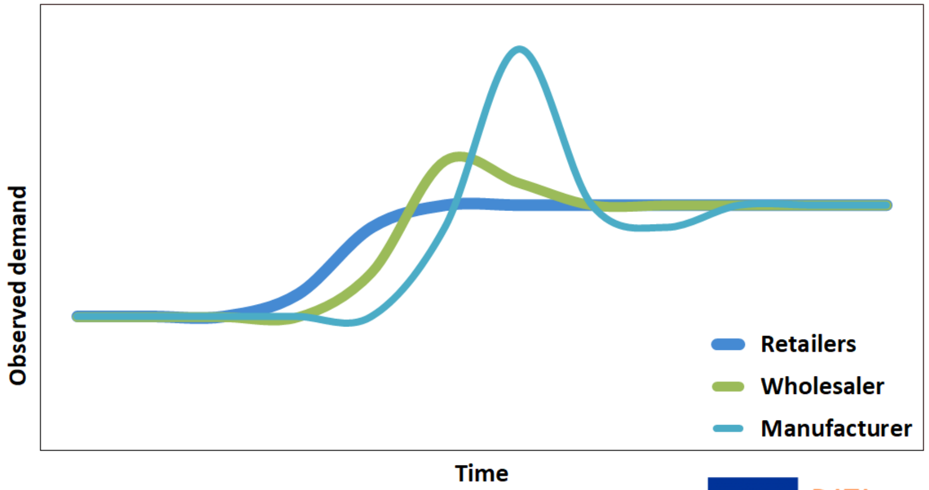
Traditional demand forecasting

- Univariate time series modeling techniques
- Manufacturer uses data on incoming wholesaler demand = distorted version of customer demand



Bullwhip effect

- Demand information becomes increasingly altered and volatile moving upstream in the supply chain
- Can lead to poor forecasts and supply chain inefficiencies
- Four major causes of the BWE: (i) **demand signal processing**, (ii) order batching, (iii) rationing and shortage gaming, and (iv) price fluctuations and promotions



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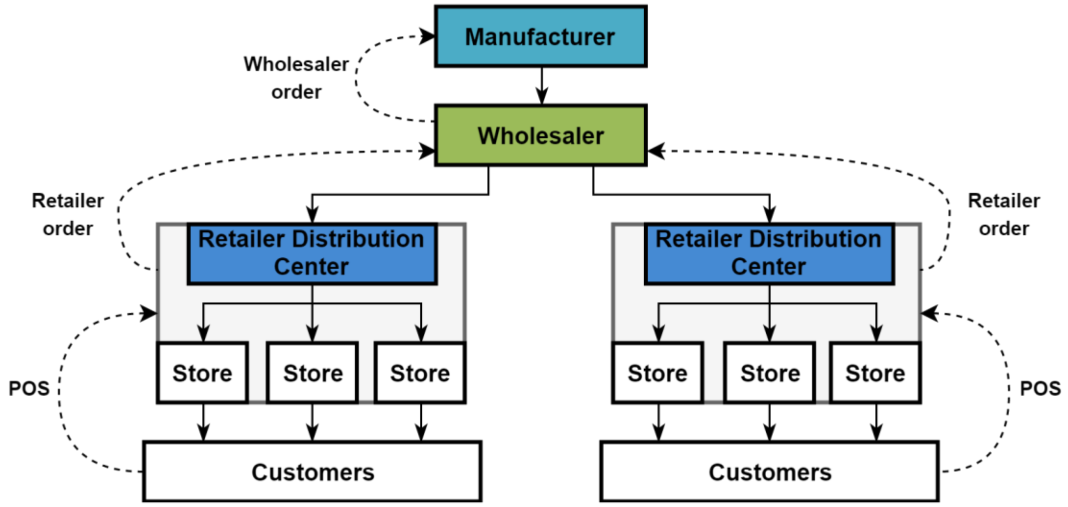
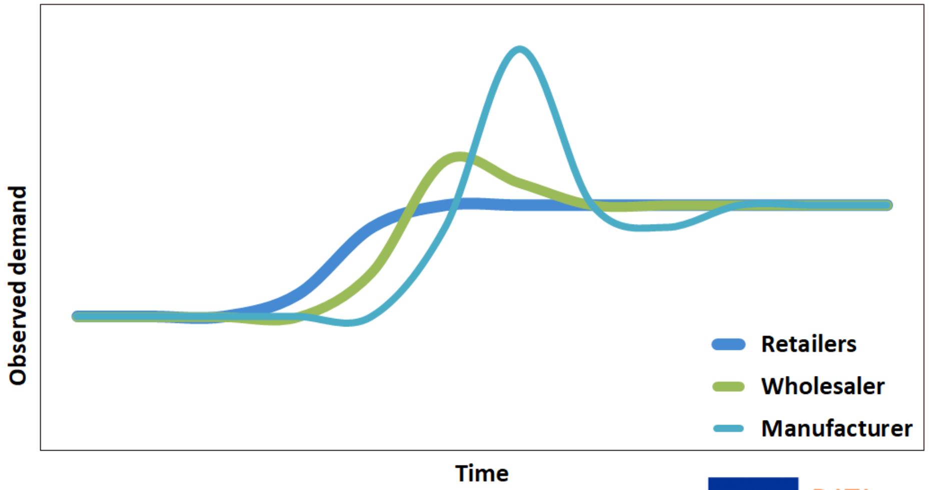
Operational demand forecasting (II)

Possible solution to counter the bullwhip effect

- “One remedy [...] is to make demand data at a downstream site available to the upstream site” – Lee et al. (1997)
- Use downstream data – from the manufacturer’s perspective in multi-echelon supply chain:
  - *Point-of-sale data*: product-related data that is directly available to the retailers
  - *Sell-through data*: product-related data that is directly available to the wholesaler = already a distorted picture of customer demand





Empirical studies on use of downstream data

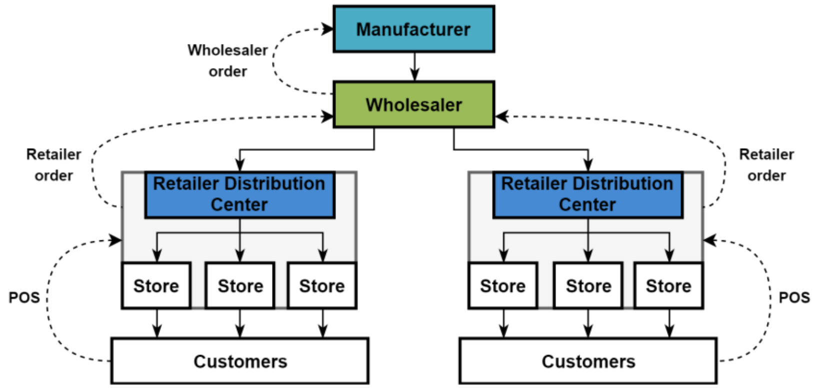
Author(s) Year	Context	Forecast horizons	Type of downstream data	Modeling techniques	Modeling approach
Hanssens, 1998	High-Tech	1	POS	ECM	Integration
P. Byrne & Heavey, 2006	Industrial	1	POS	Simulation & TS	Substitution
Hosoda et al., 2008	Retail	1	POS	TS	Substitution
Kelepouris et al., 2008	Retail	1	POS	Simulation & TS	Substitution
Williams & Waller, 2010	Retail	4, 13 & 26	POS	TS	Substitution
Williams & Waller, 2011	Retail	1-13	POS	TS & hierarchical	Substitution
Trapero et al., 2012	Retail	1	POS	TS, TSX & NN	Integration
Williams et al., 2014	Retail	1-6	POS	TS & VECM	Both
Hartzel & Wood, 2017	Retail	1	POS	NN	Integration
Our study	**Pharma**	**1-5**	**Sell-through**	**TS, TSX & ML**	**Both**

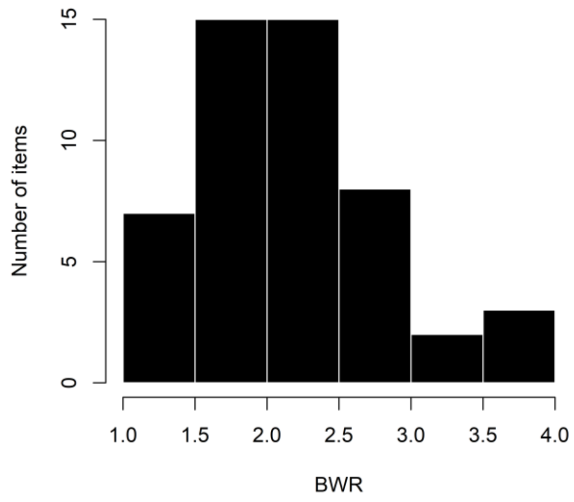
Modeling approaches:

- **Substitution approach** = substituting the directly observed prior demand by downstream demand
- **Integration approach** = integrate directly observed prior demand and downstream data

Case study: data & bullwhip

- US drug manufacturer operating in multi-echelon supply chain
- Weekly data collected from Jan 2014 until Oct 2018
- 50 items
  - 205 observations on average
  - Only 3.7% of zero wholesaler demand observations on average
- Data sources
  - **Prior shipments to wholesalers** = proxy for wholesaler demand
  - **Sell-through data**
    - Wholesaler sales = proxy for retailer demand
    - Ending inventory positions @ wholesaler
    - Open order quantities = total quantity wholesaler expected to receive for the reporting period that was not delivered
- One- to five-step ahead weekly forecasts
- Bullwhip ratio: $\mathrm{BWR} = \dfrac{\sigma_{\text{Manufacturer}} / \mu_{\text{Manufacturer}}}{\sigma_{\text{Wholesaler}} / \mu_{\text{Wholesaler}}}$





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Modeling – Forecasting methods & inputs

Class	Method	Time series		Features		
		Manufacturer shipments	Wholesaler sales	Seasonal dummies	Sell-through information	AR terms & trend
No information sharing (NIS)	ETS	✔		✔		
	ARIMA	✔		✔		
Information sharing (IS) Substitution	ETS-W		✔	✔		
	ARIMA-W		✔	✔		
Information sharing (IS) Integration – TS	ETSX	✔		✔	✔	
	ARIMAX	✔		✔	✔	
Information sharing (IS) Integration – ML	LASSO			✔	✔	✔
	MLP			✔	✔	✔
	SVR			✔	✔	✔
	RF			✔	✔	✔

- **Unconditional forecasting setup** → forecasting model is reformulated for each forecast horizon *h*
    - Sell-through data: (maximum) 10 lags for *wholesaler sales* and *wholesaler inventory*, and 1 lag for *open order quantities* for *h*=1
    - AR terms: 10 (forecasted) lags
- Variable selection for TS methods – forward stepwise selection
- ML methods – hyperparameter specification via grid search and 3X10-fold cross-validation

Evaluation

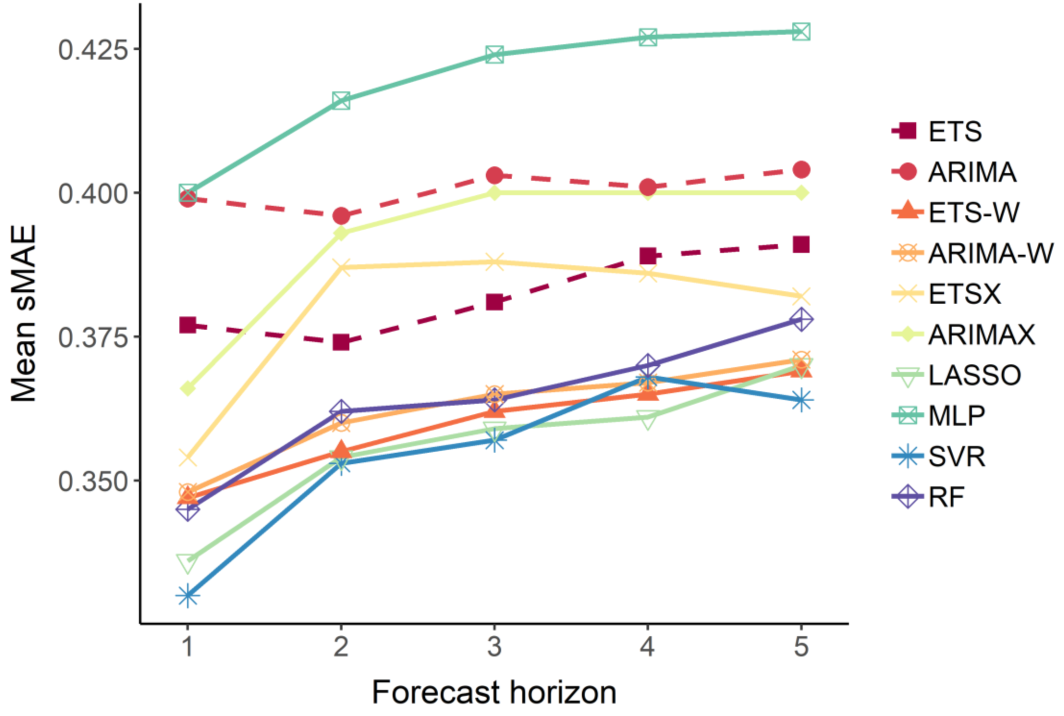
- One- to five-step ahead out-of-sample forecasts
- Train 70% - Test 30%
- Rolling origin evaluation
- Forecast accuracy (Petropoulos & Kourentzes, 2015)
  - scaled Absolute Errors (with *n* the number of observations in in-sample period):

$$sAE_t = \frac{|y_t - f_t|}{n^{-1}\sum_{i=1}^{n} y_t}$$

  - scaled Mean Absolute Error (sMAE): for each SKU, scaled Absolute Errors are averaged across all periods in the out-of-sample test set

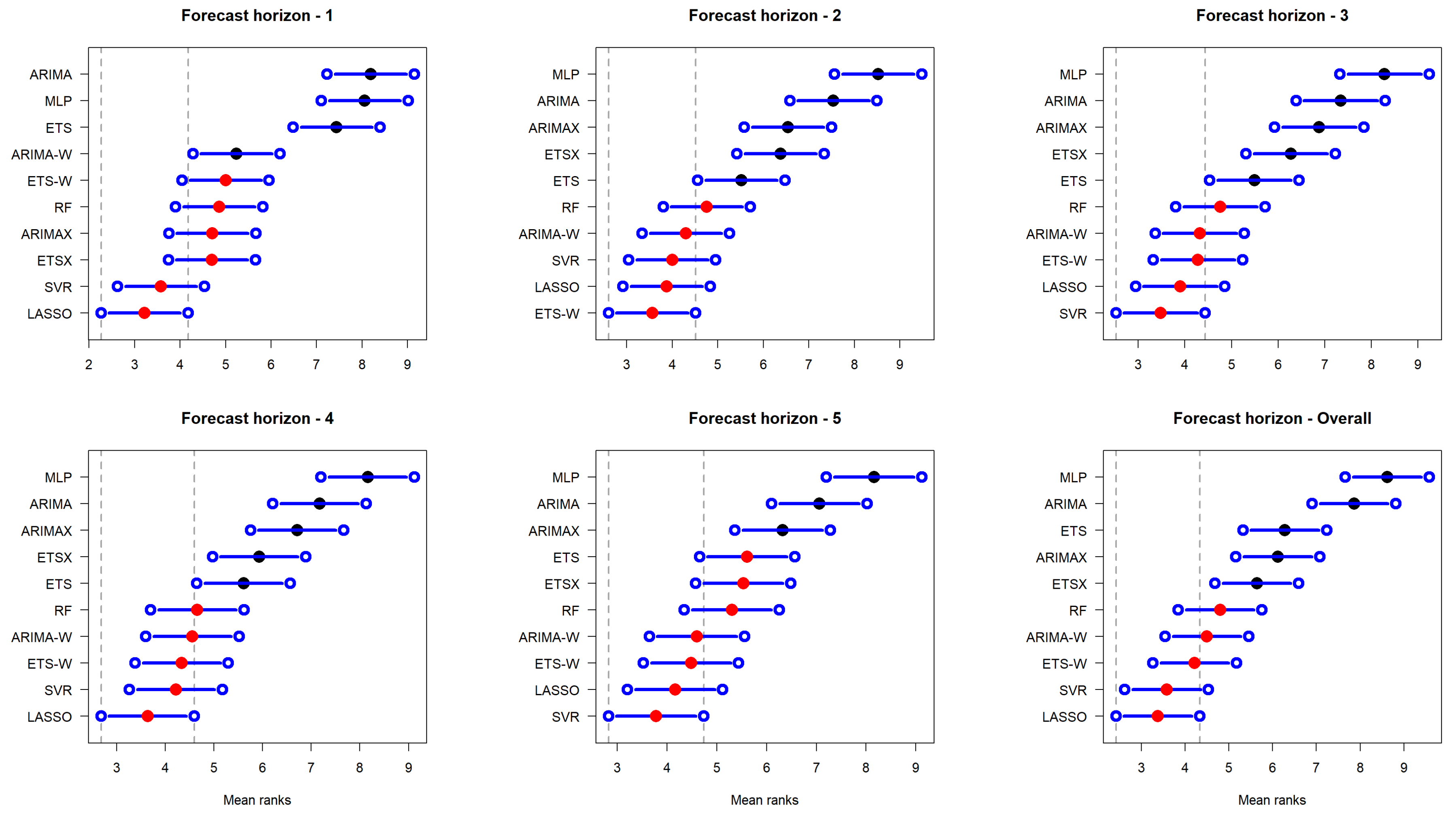
Mean sMAE

Forecast horizon	1	2	3	4	5	Overall
Best NIS	ETS	ETS	ETS	ETS	ETS	ETS
Mean sMAE	0.377	0.374	0.381	0.389	0.391	0.382
Best IS	SVR	SVR	SVR	LASSO	SVR	SVR
Mean sMAE	0.330	0.353	0.357	0.361	0.364	0.355
% improvement	**+12.5%**	**+5.6%**	**+6.3%**	**+7.2%**	**+6.9%**	**+7.1%**



- ETS outperforms ARIMA
- Best methods = IS methods (LASSO, SVR, RF, ETS-W and ARIMA-W)
  - Horizon 1 – LASSO and SVR
  - Horizons *h* > 1 – ETS-W, ARIMA-W and RF converge to LASSO and SVR
    → value of wholesaler inventory for *h* > 1?
- ETSX and ARIMAX show improvement for *h* = 1 but not for longer forecast horizons
- Poor performance of MLP
- SVR and LASSO perform quite similar
  → nonlinear relations not essential in this case

Multiple comparisons with the best (sMAE)



95% confidence level

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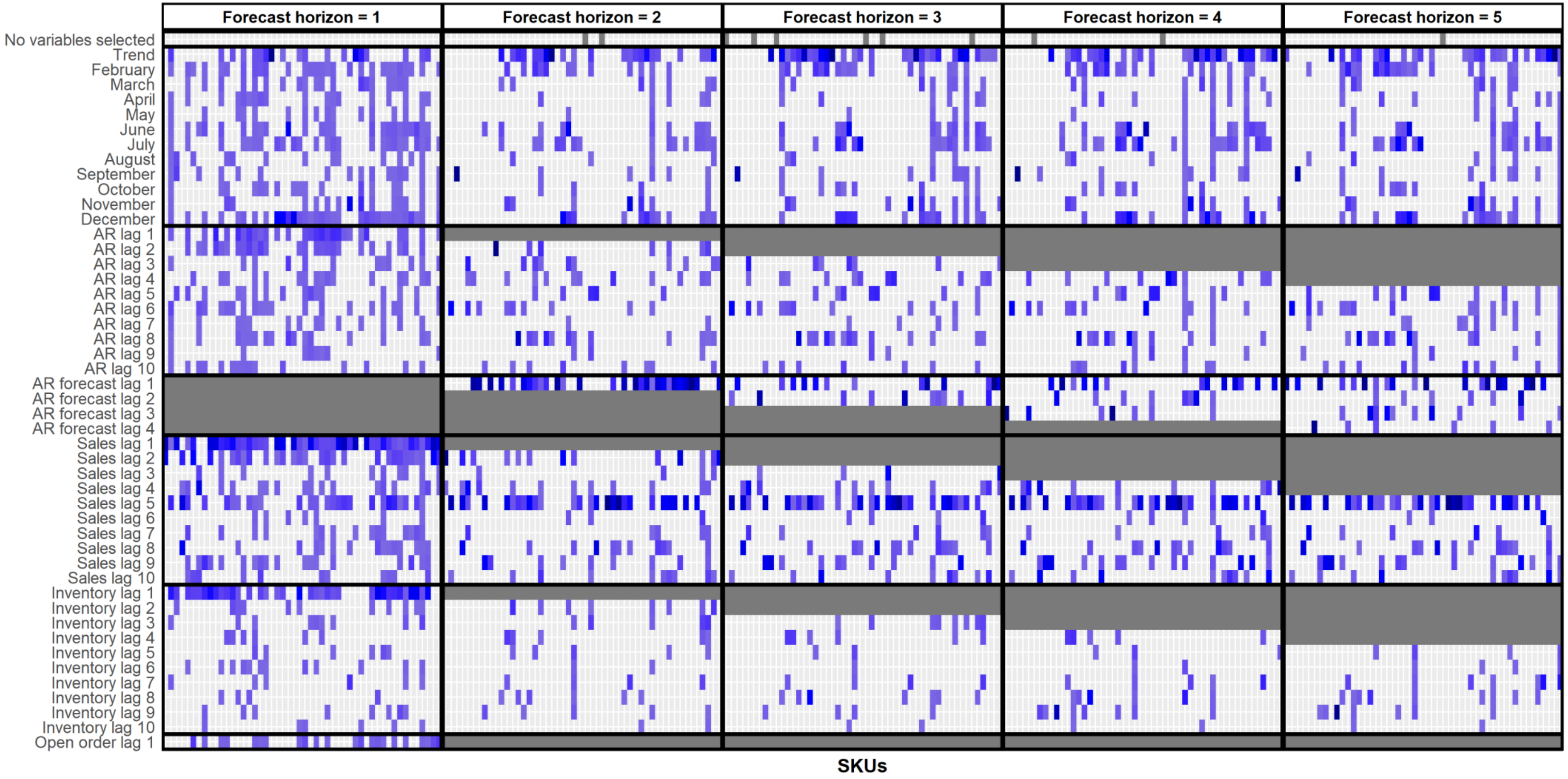
Variable importance analysis – LASSO



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Conclusions & future research

- **Conclusions**
  - We provide **empirical evidence of the value of sell-through data** to increase short-term forecast accuracy at manufacturer level → indirect evidence that its use allows to **mitigate the impact of the bullwhip effect**
  - The results point to **LASSO and SVR** as best methods and provide evidence of an increase in forecast accuracy for **all horizons considered**
  - The largest increase in accuracy is observed for **one-step ahead forecasts** → short delivery lead times in case study
  - Potential accuracy gains in other multi-echelon supply chains may depend on the characteristics of the involved supply chain, and more specifically on the **prevailing delivery lead times**

- **Future research**
  - Overarching study which takes into account both sources of downstream information: POS and sell-through data

Thank you

Q&A

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