Information Sharing in the Presence of Promotions in a Supply Chain
ISF 2018

Patrick Saoud & Nikolaos Kourentzes & John E. Boylan

Lancaster University

June 20, 2018

Marketing Analytics & Forecasting

Lancaster University Management School

CMAF

Table of Contents

CMAF

Motivation and Research Question

The aim of this research is to study whether sharing information between Supply Chain members is beneficial when the product is promoted, and which type of information should be shared in that case.

Promotions

- With the increase in competition, promotions are used more and more often to attract customers.
- When promotions are set, customers tend to buy more in that period.
- With the frequency of promotions and the difficulty in forecasting it, promotional forecasting is an interesting topic, as it can benefit many companies.
- Many models exist to represent promotional demand (see for e.g. Trapero et al., 2014; Huang et al., 2014).
- The effect of Promotions on the Supply Chain is important, yet not studied enough.

CMAF

The Bullwhip Effect

Definition

The Bullwhip Effect is defined as the amplification of demand variance along the supply chain.

- This results in higher costs and inefficient allocation of resources for all the members of the network (Lee et al., 1997; Metters, 1997).
- Demand is translated into orders, which the former usually more variable than the latter (see next slide).

CMAF

Bullwhip Effect

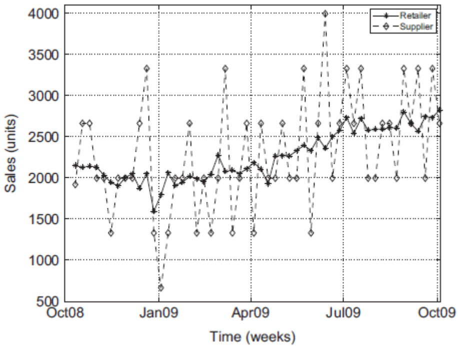

Figure: Example of the Bullwhip (Trapero et al., 2012)

Information Sharing: a Possible Solution to the Bullwhip

- Supply chain members exchange information. In this case, the manufacturer obtains access to customer demand.
- Information Sharing is not viewed as a universal solution, with conflicting results emerging in the literature(Ali et al., 2012; Babai et al., 2013, 2016; Trapero et al., 2012),
- From a theoretical perspective, the benefits of IS depend on the demand process and parameters (Babai et al., 2016).
- From an empirical point, Information Sharing is beneficial to the Manufacturer(Trapero et al., 2012; Cui et al., 2015).
- These results do not include promotional demands!

CMAF

Information Sharing

- While Information sharing appears in many studies, it is easier said than done.
- The benefits are not shared symmetrically between the entities.
- Setting it up is costly.
- Asymmetric Incentives.
- Many different platforms for sharing information.
- Bottomline: The benefits of Information Sharing should outweigh its costs.

CMAF

Promotions and the Bullwhip Effect

- Cited as one of the four original sources for the Bullwhip Lee et al. (1997).
- Since demand is more variable during promotions, it is only natural that it will cause an amplification of orders as well.
- Not much research is done on this topic (O'Donnell et al., 2009; Trapero et al., 2014).
- What about Information Sharing and promotions?

CMAF

Information Sharing with Promotions

- With promotions involved, there is now an additional source of information that can be shared, which is whether the promotion is running or not.
- The purpose of our research is to establish which information to share, how to use that information, and the possible benefits of each stream of information.
- Not many studies include both promotions and information sharing.
- Iyer and Ye (2000) studies sharing promotional data from an analytical framework, and shows that this reduces costs.
- Cui et al. (2015) also studies data that contain promotions, but they only study POS data sharing.
- Where does this research fit in?

CMAF

Different Types of Information Sharing

We study 5 different types of possible information sharing

Information Sharing Type	Demand Used	Exogenous Inputs
No Information Sharing (NIS)	Retailer Orders	None
Point of Sales Information Sharing (POS)	Customer Demand	None
Promotional Information Sharing (PIS)	Retailer Orders	Promotions
Full Information Sharing (FIS)	Customer Demand	Promotions
Exogenous Information Sharing (XIS)	Retailer Orders	Promotions, Lagged Customer Demand

Figure: Different types of Information Sharing

These will be studied via simulation.

CMAF

Why a Simulation?

We use a simulation with synthetic data to test our research question. The simulation is beneficial since:

- Results are hard to track analytically.
- Full data on a real supply chain is hard to obtain.
- Full Control of Demand (Process and Parameters)
- Full Control of the Supply Chain (No human intervention in the replenishment decision, design and complexity...)
- Full Control of the Promotional Impact and Frequency.

CMAF

Data Generating Processes

Demand

In order to represent demand, we use processes from the ARIMAX family, where the X component denotes the vector of occurrences of promotions.

More specifically, three types of demand are used:

- ARX(1): $y_t = \mu + \phi y_{t-1} + \varepsilon_t + a.P_t$
- MAX(1): $y_t = \mu + \varepsilon_t + \theta \varepsilon_{t-1} + a.P_t$
- IMAX(1,1): $y_t = \mu + y_{t-1} + \varepsilon_t + \theta \epsilon_{t-1} + a.P_t$

where a is the lift effect (Initial Level multiplied by elasticity), μ the level, P_t is a binary coding whether the promotion occurs at period t, ε is an i.i.d noise term. We assume the relation between the variables is linear, i.e. a log-log model.

CMAF

Data Generating Process

- To have more realistic promotional settings, we extract the values of promotional elasticity and frequency from (Huang et al., 2014).
- Three values of elasticity (lift effect) are used: Low (113%), Medium (187%) and High (335%).

CMAF

Supply Chain Design

- A two tier supply chain is designed, with one manufacturer and one retailer. This model has featured in many papers (see for e.g. Ali et al., 2012; Trapero et al., 2012)

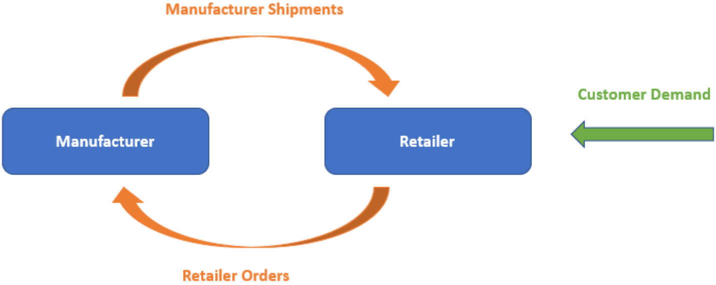

Figure: Dyadic Supply Chain

Data Partition

Each series contains 400 observations

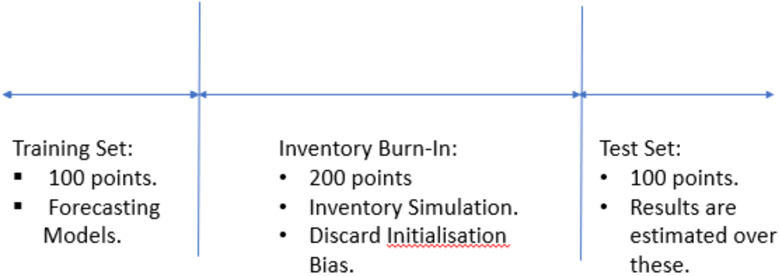

Figure: Data Split.

Simulation Details

- Since demand is an ARIMA with exogenous, the forecasting models for all entities in the Supply Chain are ARIMA with exogenous inputs. The model order and parameters are estimated by minimizing the AIC ($auto.arima$ function from the $forecast$ package in R).
- Using a rolling origin scheme, forecasts are produced for one to L-steps-ahead, and then aggregated to produce lead-time forecasts.
- A periodic (R, S) Inventory Policy is implemented, with the review period R set to 1.
- Unmet demand is backordered to the next period.

CMAF

Simulation Details

- 3 Process Types.
- 3 Values of Elasticity.
- 3 values for the horizon $(L + R)$: $\{1, 3 ,5\}$.
- 3 Cycle-Service Levels: $\{90\%, 95\%, 99\%\}$.
- Inventory backorders (b) and holding (h) costs are based on the fill rate approximation $\frac{b}{b+h}$.

CMAF

Results

- To gain insights from our simulation, we track the forecasting performance of the different types of Information Sharing for the Manufacturer.
- This is not sufficient as there is no clear relationship between accuracy and costs (Ali et al., 2012).
- Therefore,we also measure the inventory costs for the Manufacturer.
- Given that we are assessing the impact of different types of sharing information, we do not present raw results, but ratios with respect to No Information Sharing.
- Can we use the Bullwhip Effect Measure (Chen et al., 2000)?

CMAF

Accuracy Results

- The Mean Squared Error (MSE) is used.
- It is the input fed to the Safety Stock calculations.
- Since we are not comparing across products, it can be employed to determine the forecasting accuracy.
- Since the Manufacturer always face retailer's orders, the error term is defined as:

$$\text{Error}_{IS,t} = \text{Retailer Order}_t - \text{Forecast}_{IS,t} \tag{1}$$

- The result is in the form of:

$$\frac{\text{MSE}_{IS}}{\text{MSE}_{NIS}} \tag{2}$$

Accuracy Results

Elasticity	1.13			1.87			3.35		
	AR(1)	MA(1)	IMA(1,1)	AR(1)	MA(1)	IMA(1,1)	AR(1)	MA(1)	IMA(1,1)
NIS	1	1	1	1	1	1	1	<u>1</u>	1
POS	0.89	0.61	3.04	1.63	1.88	1.41	1.12	1.53	3.55
PIS	<u>0.53</u>	<u>0.30</u>	<u>0.19</u>	0.89	1.97	<u>0.35</u>	0.88	1.53	0.46
FIS	0.59	0.42	0.19	<u>0.86</u>	1.13	0.36	<u>0.83</u>	1.02	<u>0.45</u>
XIS	1.27	1.52	0.79	1.62	3.87	0.90	1.32	3.11	0.88

Figure: Manufacturer MSE Ratios

In most cases, information sharing increases the accuracy of our forecasts.

Cost Results

- We look at Total Inventory Cost of the Manufacturer.
- Total Cost = Holding Cost + Backorder Cost.
- Again, we look at ratios with respect to the NIS scenario.

CMAF

Cost Results

Elasticity	1.13			1.87			3.35		
	AR(1)	MA(1)	IMA(1,1)	AR(1)	MA(1)	IMA(1,1)	AR(1)	MA(1)	IMA(1,1)
NIS	1	1	1	1	1	1	**1**	1	1
POS	0.88	**0.78**	0.90	1.03	**0.94**	**0.74**	1.13	**0.97**	0.75
PIS	0.90	1.01	1.07	1.05	1.05	0.76	1.10	1.16	0.79
FIS	0.84	0.98	**0.86**	1.05	1.06	0.76	1.23	1.16	0.75
XIS	**0.83**	0.94	2.39	1.22	1.42	1.77	1.17	1.38	**0.64**

Figure: Manufacturer Cost Ratios

Cost Results

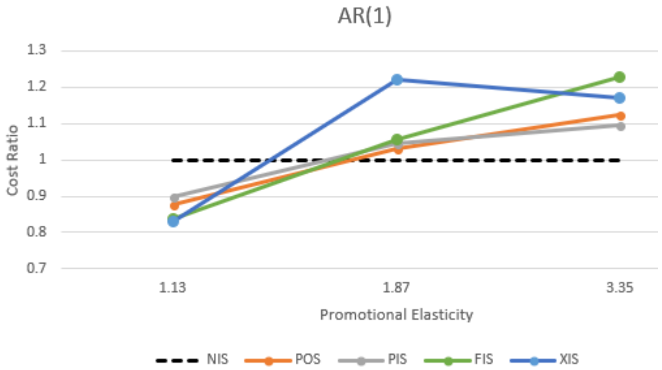

Figure: AR(1) Manufacturer Cost Ratios

Cost Results

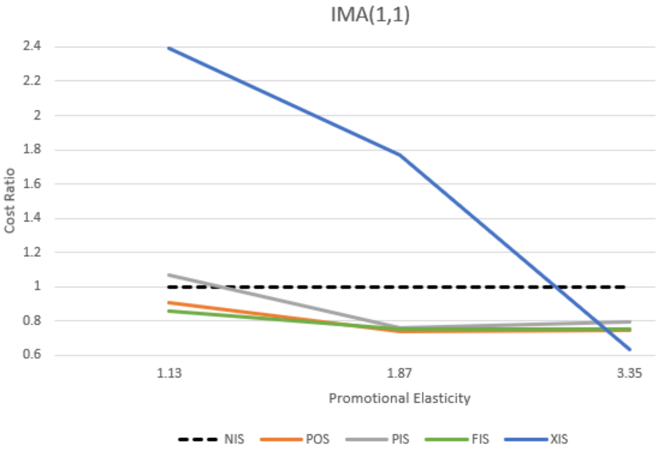

Figure: IMA(1,1) Manufacturer Cost Ratios

Summary

- The aim of this study is to investigate which information should be shared in a promotional setting.
- From an accuracy perspective, Information Sharing reduces the MSE.
- From a cost perspective, Information Sharing is beneficial, but this depends on the process and the elasticity parameter.
- More work should be done to better study the effect of the elasticity, process and demand parameters.
- The accuracy impact of different error metrics will be examined.
- The impact of the promotional elasticity on the fill rate will be studied as well.
- The results still need to be validated on real life data.

Questions

Ali, M. M., Boylan, J. E., Syntetos, A. A., 2012. Forecast errors and inventory performance under forecast information sharing. International Journal of Forecasting 28 (4), 830 – 841, special Section: Election Forecasting in Neglected Democracies. URL http://www.sciencedirect.com/science/article/pii/S016920701100015X

Babai, M., Ali, M., Boylan, J., Syntetos, A., 2013. Forecasting and inventory performance in a two-stage supply chain with arima(0,1,1) demand: Theory and empirical analysis. International Journal of Production Economics 143 (2), 463 – 471, focusing on Inventories: Research and Applications. URL http://www.sciencedirect.com/science/article/pii/S0925527311003902

Babai, M., Boylan, J., Syntetos, A., Ali, M., 2016. Reduction of the value of information sharing as demand becomes strongly auto-correlated. International Journal of Production Economics

181, 130 – 135, sI: ISIR 2014.
URL http://www.sciencedirect.com/science/article/pii/S0925527315001462

Chen, F., Drezner, Z., Ryan, J. K., Simchi-Levi, D., 2000. Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information. Management science 46 (3), 436–443.

Cui, R., Allon, G., Bassamboo, A., Van Mieghem, J. A., 2015. Information sharing in supply chains: An empirical and theoretical valuation. Management Science 61 (11), 2803–2824.

Huang, T., Fildes, R., Soopramanien, D., 2014. The value of competitive information in forecasting fmcg retail product sales and the variable selection problem. European Journal of Operational Research 237 (2), 738–748.

Iyer, A. V., Ye, J., 2000. Assessing the value of information sharing in a promotional retail environment. Manufacturing & Service

CMAF

Operations Management 2 (2), 128–143.
URL https://doi.org/10.1287/msom.2.2.128.12350

Lee, H. L., Padmanabhan, V., Whang, S., 1997. Information distortion in a supply chain: the bullwhip effect. Management science 50 (12_supplement), 1875–1886.

Metters, R., 1997. Quantifying the bullwhip effect in supply chains. Journal of Operations Management 15, 89–100.

O'Donnell, T., Humphreys, P., McIvor, R., Maguire, L., 2009. Reducing the negative effect of sales promotions in supply chains using genetic algorithms. Expert Systems with Applications 36 (4), 7827–7837.

Trapero, J. R., Kourentzes, N., Fildes, R., 2012. Impact of information exchange on supplier forecasting performance. Omega 40, 738–747.

Trapero, J. R., Kourentzes, N., Fildes, R., 2014. On the

Identification of Sales Forecasting Models in the Presence of Promotions. Journal of the Operational Research Society, 1–9.

CMAF