Supply chain forecasting when information is not shared

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HIGHLIGHTS

Supply chains where information is not shared are considered;

A Downstream Demand Strategy is evaluated;

Analytical expressions for that strategy are derived;

Real sales data from a major European supermarket is analysed;

Analytical results and an empirical strategy for performance improvement are presented.

Abstract

The operations management literature is abundant in discussions on the benefits of information sharing in supply chains. However, there are many supply chains where information may not be shared due to constraints such as compatibility of information systems, information quality, trust and confidentiality. Furthermore, a steady stream of papers has explored a phenomenon known as Downstream Demand Inference (DDI) where the upstream member in a supply chain can infer the downstream demand without the need for a formal information sharing mechanism. Recent research has shown that, under more realistic circumstances, DDI is not possible with optimal forecasting methods or Single Exponential Smoothing but is possible when supply chains use a Simple Moving Average (SMA) method. In this paper, we evaluate a simple DDI strategy based on SMA for supply chains where information cannot be shared. This strategy allows the upstream member in the supply chain to infer the consumer demand mathematically rather than it being shared. We compare the DDI strategy with the No Information Sharing (NIS) strategy and an optimal Forecast Information Sharing (FIS) strategy in the supply chain. The comparison is made analytically and by experimentation on real sales data from a major European supermarket located in Germany. We show that using the DDI strategy improves on NIS by reducing the Mean Square Error (MSE) of the forecasts, and cutting inventory costs in the supply chain.

Key Words: Supply chain management, Information sharing, Simple Moving Average, ARIMA, Downstream demand inference.

1. Introduction

The economic climate is becoming increasingly volatile. Having more information about the end consumer of products and services provides a critical means of reducing the uncertainty in future demand. Businesses are continually adopting new approaches to obtain and utilise this information in their planning.

These approaches require coordination of information sharing in the supply chains so that the relevant end-consumer data is passed to the upstream supply chain members (Ciancimino et al, 2012; Asgari et al, 2016). Advancements in information technology (IT) provide an efficient platform for such information to be transmitted in a speedy manner (Moskowitz et al, 2011; Cannella et al, 2013, Cannella et al, 2015). Supply chain visibility provides opportunities for managers not only to plan efficiently but also to react appropriately to the correct information. In recent years, there has been a greater tendency to use IT systems to make inventory, transportation and pricing decisions based on greater visibility of information. Sharing of information proves to be the backbone for various formal coordination initiatives such as Collaborative Planning, Forecasting and Replenishment (CPFR), Efficient Consumer Response (ECR) and Forecast Information Sharing (FIS).

Supply chains are becoming aware of the importance of such visibility. Many companies are sharing information on both sides of their supply chains to create a more collaborative environment. Examples in the retail industry include the introduction of information sharing platforms by two major retailers in the UK with their suppliers: Tesco's Knowledge Hub and the Save and Sustain of Asda. Angeline (2011) reported that collaboration between retailers and their suppliers contributed to a 260,000 tonne reduction in the amount of food and drink waste in the UK in 2010. In addition, GlobalNetXchange, a consortium of 30 companies including Unilever, Procter and Gamble and KimberlyClark have reported a 5%-20% reduction in inventory costs and an increase in off-the-shelf availability of 2%-12% following the launch of their CPFR programme (Terwiesch et al, 2005). Other empirical studies investigating benefits of sharing information have reported reductions in inventory levels up to 50% (Disney and Towill, 2002), reductions in inventory costs up to 40% (Ireland and Crum, 2006), and reductions in supply-chain costs by up to 40% (Boone and Ganeshan, 2008).

Notwithstanding the above success stories, the implementation of processes for effective information sharing is not widespread. About 84% of 111 companies surveyed by PRG

(E2Open, 2013) reported a formal supplier relationship management strategy in place. However, only one out of six of these companies were using those programmes. Similarly, interviews of 393 executives in a report by Butner (2010) revealed that more than half of the respondents have implemented practices aimed at improving information visibility. However, fewer than 20 percent were pursuing these practices extensively. The report also showed that only two-thirds of these organisations shared real time data with their supply chain partners. Similarly, Seifert (2003) reported two surveys on the assessment of the level of data sharing. The first, by CapGemini, of 16 retailers in Europe and North America, found that only 40% of the retailers shared shopper data with all of their suppliers. The second survey by Forrester Research of 89 retailers showed that 27% of retailers were sharing such data. In addition, the results from interviews carried out with 15 companies by Allred et al (2011) showed that high-level collaborations are rare and efforts to improve information sharing are seldom embraced holistically. The report by Butner (2010), mentioned earlier, ranks 'supply chain visibility' as one of the greatest management challenges. Shue et al (2006) have criticised the supply chain information sharing literature for presenting the idea of formal information sharing too simplistically, while not focussing on the bigger issues that hinder this inter-organisational collaboration. This provides the motivation for the research conducted in this paper where we evaluate a strategy to deal with supply chain demand management when information is not shared.

This new strategy is based on a recently discovered phenomenon known as Downstream Demand Inference (DDI). This applies to cases where the manufacturer is not aware of the demand process at the retailer. A stream of research has shown that the upstream member in the supply chain can infer the downstream demand without the need of a formal information sharing mechanism (e.g. Zhang, 2004; Gilbert, 2005). However, Ali and Boylan (2012) recently showed that, under a more practical setting, with less restrictive assumptions than those considered in previous research, DDI is not possible with optimal forecasting methods or Single Exponential Smoothing but is possible when supply chains use a Simple Moving Average (SMA) method. The Simple Moving Average, of length k, is defined as the average of the last k observations. It is not the optimal forecasting method for any Auto-Regressive Moving Average demand process (eg AR(1), MA(1)), but is a robust method that is often used in practice.

Hence, the strategy we evaluate for supply chains where information cannot be shared is based on the DDI approach using the SMA method. The performance of our strategy is measured by comparing the Mean Square Error (MSE) of the forecasts, and inventory cost of the DDI strategy with two other strategies: No Information Sharing (NIS) and Forecast Information Sharing (FIS). We define NIS as a strategy where the supply chain links do not share information formally and the forecasts are based simply on the orders received from the downstream supply chain member. On the other hand, an FIS strategy is where the supply chain links share consumer demand and hence the forecasts. A detailed description of the three strategies is presented in Section 3 of the paper.

Until now, there has been a lack of an analytical framework to allow comparison of DDI with the other two strategies (NIS and FIS) when using a Simple Moving Average forecasting method. The first contribution of this paper is to establish an expression for the Mean Square Error of the DDI approach, thus enabling a comparison across the three strategies when demand follows an autoregressive process of order one (AR(1)). The second contribution is to demonstrate that DDI is always dominated by FIS and that, beyond a certain 'break-point' of the autoregressive parameter of an AR(1) process, DDI dominates NIS in terms of Mean Square Error. The third contribution of the paper is to provide empirical evidence on the accuracy and stock control performance of the three strategies using data on almost two thousand products of a European supermarket. These results confirm the existence of a 'break-point' for DDI dominating NIS and demonstrate an overall benefit in forecasting accuracy by using DDI. However, it also shows that longer Simple Moving Averages are needed for this accuracy benefit to translate to improvements in stock control performance.

The remainder of the paper is organised as follows. Section 2 is dedicated to a review of the literature and is divided into two sub-sections: 'Information Sharing Inhibitors' and 'Downstream Demand Inference (DDI)'. In Section 3, we present the three demand management strategies and derive the Mean Square Error (MSE) associated with them for AR(1) demand processes. We numerically compare the performance of these strategies in Section 4, followed by an empirical investigation on the point of sale (POS) data of a European supermarket in Section 5. Finally, in Section 6, we present the conclusions and implications of the paper along with some natural avenues for further research.

2. Literature Review

2.1. Information Sharing Inhibitors

One of the most common blockages for information sharing discussed in the literature is the lack of availability of formal information systems. Research published by SCM World (Courtin, 2013) points out that many companies are held back by the huge investment costs and system implementation issues associated with formal collaborations to share information. A survey of 30 UK companies conducted by Frohlich (2002) shows three types of barriers to technology integration in supply chains: supplier-related, customer (manufacturer)-related and internal barriers. Cost is a major reason for resistance both by the suppliers and the customers and this often involves negotiation between the two parties involved in terms of the IT investment and customisation (Klein et al, 2007). Cost of the information systems is not only an issue in terms of the initial price but also in terms of implementation where time and monetary budgets are often exceeded by 50% - 100% (Fawcett et al, 2007). Companies involved also face internal organisational barriers for implementations as all organisations have a tendency to resist change.

Even when companies are able to successfully implement an Enterprise Resource Planning (ERP) system, sharing information may still be an issue. Successfully implemented systems in two companies may not 'talk' to each other. According to a market survey by Manhattan Associates (Greening, 2009): "*……. 85% of the respondent companies accepted that their information systems could be leveraged further to develop competitive advantage."* Although compatibility issues are being addressed by IT developments, sharing information is not just a technology related issue. Even when a company develops the required IT capability to share information, trust and commitment issues may negate this development (Mendelson, 2000). Managers make the ultimate decision on what information will be shared and with whom. Information will not be shared with a company which the managers do not trust, making mutual trust another major inhibitor of sharing information. These obstacles are not just inter-organisational. Within an organisation, company structures and cultures may militate against external collaborations (Fawcett et al, 2007; Allred et al, 2011).

The literature also explores cases where information sharing does not take place even when the supply chains have the required IT capability and when they trust their partners. There are two issues discussed in the literature for such non-information sharing strategies: information accuracy and information leakage. Information accuracy relates to error free information and supply chain managers may not trust the information being shared if they are unsure of its accuracy (and quality) (Forslund and Jonsson, 2009). On the other hand the issue of data leakage arises where there is a fear that information may be unintentionally leaked and acquired by competitors. For example, retailers can infer information about their competitors from the manufacturer's wholesale pricing strategy and from various other parameters from the manufacturer (Li and Zhang, 2008). Walmart had previously announced that it will no longer share its sales data with outside companies such as Information Resources, Inc and AC Nielsen due to fear of information leakage through these organisations (Hays, 2004).

2.2. Downstream Demand Inference

There has been an interesting debate in the Operations Management and Operational Research literature about a phenomenon known as Downstream Demand Inference (DDI). This is defined as an approach where the upstream member can mathematically infer the demand information from orders received from the downstream member and thus does not require a formal information sharing mechanism. Some papers (Graves, 1999; Raghunathan, 2001; Zhang, 2004; Gaur et al, 2005; Gilbert, 2005) argue that the orders from the downstream member to the upstream member already contain information about the consumer demand. Thus, these papers show that it is possible to obtain the consumer demand from the order history of the downstream member without having to share information with them. It is important to note that the supply chain models in this stream of research papers assume that the process and parameters of the consumer demand are known across the supply chain.

Ali and Boylan (2011) investigate the model assumptions in the above stream of research in view of their applications to the real world. They argue that it is highly unlikely that the supply chain members will share process and parameters of the demand but not the demand itself. By relaxing the above unrealistic assumptions, they evaluate DDI for a supply chain where the Minimum Mean Square Error (MMSE) optimal method is used for forecasting. The MMSE forecasting method is a method which minimises the Mean Squared Error (MSE). It is a common measure of estimation quality. Details about the MMSE forecasting follow in the next section (section 3). They conclude that under a more practical setting, with less restrictive assumptions, DDI is not possible with optimal forecasting methods. Their study shows that information in supply chains has to be shared via some formal information sharing mechanism rather than being deduced mathematically.

The feasibility of DDI relies upon whether the propagation of demand (from one stage to the other) is unique or not. In some cases, process propagation is unique: a unique demand process at the downstream member would translate into a given demand process faced at the upstream member. Or correspondingly, the demand faced at the upstream level can be traced back to one (unique) demand process. On the other hand, in some cases the propagation is not unique: various demand processes at the downstream member would translate into the same demand process at the manufacturer, in which case the retailer demand cannot be inferred by the manufacturer. For further details, the reader is referred to Ali and Boylan (2011).

Ali and Boylan (2012) extend the stream of research discussed above work by considering two non-optimal forecasting methods: Single Exponential Smoothing (SES) and Simple Moving Averages (SMA). In terms of SES, the paper concludes that, similar to the MMSE optimal method, DDI is not possible. Hence, a formal information system is required to facilitate demand information sharing for SES. On the other hand, DDI is found to be possible in the case of SMA. Thus, if the retailer in a supply chain uses SMA, the next upstream link can mathematically infer the retailer's consumer demand without the need to formally share this information. Although Ali and Boylan (2012) showed that the DDI strategy under SMA is feasible, they did not consider the practical aspects of the implementation of the strategy. This paper builds on the concept of feasibility of DDI under SMA, and evaluates its application in situations where formal information exchange is not possible even though there may be a willingness to share information from both parties.

The SMA forecasting method is the arithmetic mean of the N most recent observations. Every forecasting period, the newest observation is included and the oldest is dropped out. The choice of SMA is quite rational from a practitioner's perspective as well. The review of various surveys carried out by Ali and Boylan (2012) shows that SMA was ranked as the top choice in most surveys conducted to ascertain the usage, familiarity and satisfaction of forecasting methods among practitioners. In terms of accuracy, the empirical results from the M1 competition showed that the SMA method was less accurate than Single Exponential Smoothing but the difference in accuracy diminishes as the forecasting horizon lengthens (Makridakis et al, 1982). However, applications of SMA methods are limited because the method should not be applied to demand patterns that have strong seasonality and/or trend.

3. Supply Chain Strategies and Analytical Investigation

In this paper, we consider a two-stage supply chain having one upstream member, e.g. a manufacturer, and one downstream member, e.g. a retailer. The upstream and downstream members may be other than a manufacturer and a retailer, e.g. warehouse and distributor, but this does not affect the results. We consider three demand management strategies for the supply chain. The first demand management strategy is one where the supply chains have a No Information Sharing (NIS) strategy. This takes place when information cannot be shared in the supply chain, which, in our case, means that the manufacturer is not aware of the demand or the forecast of the retailer. The manufacturer would thus base its planning on the orders received from the retailer. We assume that, in this strategy, both the supply chain links use the minimum mean square error (MMSE) forecasting method.

The second demand management strategy, DDI, is our proposed strategy of the use of SMA in the supply chain. In this strategy, due to the DDI feature of SMA, the manufacturer would be able to infer the demand process at the retailer and hence the demand and forecast information. In this case, the manufacturer will be able to base its planning on the demand at the retailer.

Finally, we compare the above two strategies with an ideal demand management strategy, where the supply chain links are able to share the information on demand forecasts. In this strategy, the manufacturer has access to the retailer's demand forecast information and thus bases their planning on the demand at the retailer. As the supply chain links are not constrained by using SMA here, we assume that they use the optimal forecasting method. The three strategies discussed above are summarised in Table 1. It is important to clarify a point about optimality here. Using the Auto-Regressive Integrated Moving Average (ARIMA) methodology we can mathematically specify the optimal MMSE forecasting method for any demand process. This optimality holds only on the basis of minimising the Mean Square Error. It is not necessarily optimal from the perspective of other performance metrics, such as inventory cost.

Information cannot be shared formally	**Demand management strategy 1: NIS:** Supply chain links cannot share information formally and the optimal forecasts are based simply on the orders received.	**Demand management strategy 2: DDI:** Supply chain links cannot share information and hence the upstream link is not aware of the demand at the downstream link. By using SMA, they infer the downstream demand and use the deduced consumer demand in their forecasts.
Information can be shared formally	**Demand management strategy 3: FIS:** Supply chain links share information on the consumer demand. They use the optimal method and the less variable consumer demand for planning.	
	Optimal Forecasting Methods	Simple Moving Average Method

Table 1: Demand Management Strategies

In what follows, we compare the performance of the three strategies shown in Table 1. To do so, we assume that the downstream demand follows a first order autoregressive demand process, AR(1). The assumption that demand follows ARMA type processes (e.g. Raghunathan, 2001, Zhang, 2004; Duc et al, 2008, Hosoda and Disney, 2009) and in particular the AR(1) process (e.g. Lee et al, 2000; Ali, Boylan, and Syntetos, 2012; Hosoda and Disney, 2012; Rostami-Tabar et al, 2013) is very common in the literature. Some empirical studies also provide evidence of AR(1) demand (e.g. Lee et al, 2000). In addition, the sales data of more than 30% of the SKUs available for the purposes of our empirical analysis were identified as AR(1) processes. An avenue for further research would be to generalise our results to ARMA (p, q) processes. We return to the specification of the demand process in Section 6 of the paper.

As noted earlier in Section 2, we assume that SMA is being used by the retailer. Due to the popularity of SMA, there could be instances where SMA is already in use in the supply chains. On the other hand, SMA may be instructed by the manufacturer to the retailer (given appropriate power dynamics) or its use may be the outcome of appropriate incentives provided by the former to the latter (discussed in more detail in Section 6). We assume that the use of SMA is known throughout the supply chain along with the moving average length. We further suppose that SMA is not inappropriately used for demand series that exhibit trends and / or seasonality. That is, we assume some intelligent application of the method (on the part of the retailers) on appropriate demand series as well as consistent use of SMA through time, i.e. no switching to or from this method. Finally, our analysis depends on the manufacturer knowing which SKUs are forecasted using SMA by the retailer. For inventory systems that lack intelligent demand classification, the list of SKUs (for which SMA is used) will be communicated off-line. For systems that rely on forecast based classification schemes, there would need to be an automatic transfer of such information to the manufacturer.

For the purpose of the analytical investigation, the evaluation of the three strategies is performed by comparing Mean Square Error (MSE) expressions. The MSE is used as it is the only theoretically tractable forecast error measure. However, when we move to the empirical analysis, inventory costs are also considered to compare performance. At this point we should also note that the MSE expressions under the NIS and FIS strategies have already been derived in the literature (by Zhang, 2004, and Ali et al, 2012, respectively). Therefore, in this paper we derive the MSE expression for the DDI strategy.

For the remainder of the paper, we denote the demand in any period *t* by d_t, whereas e_t denotes an independent random variable for demand in the same period (t), N is the order of the simple moving average and *L* is the lead-time at both supply chain stages. Additionally, the auto-covariance of lag *k* of demand is represented by γ_k while ρ denotes the autoregressive parameter of demand, $|\rho| < 1$ and τ is a constant term.

We assume that the downstream demand d_t follows an autoregressive demand process of order 1, AR(1), that can be mathematically written in period *t+1* by (1).

$$d_{t+1} = \tau + \rho d_t + \varepsilon_{t+1} \tag{1}$$

Under the DDI strategy, the forecast of the demand is based on SMA which can be expressed at period *t+1* by:

$$f_{t+1} = \frac{1}{N}\sum_{k=0}^{N-1}\left(d_{t\text{-}k}\right) \tag{2}$$

Note that, in this paper, Mean Square Errors are expressed over an interval equal to the lead-time *L* plus one time unit review period (i.e. *L+1*). This is necessitated by the periodic stock control system assumed in the empirical part of our research (see, e.g., Graves, 1999; Lee et al, 2000). In particular, we assume that the retailer controls its inventory system with an order-up-to (OUT) policy, i.e. at the end of every period t, after the demand occurrence dt, the inventory position (stock in hand + planned receipts—backorders) is compared to an OUT level to bring that position up to the prescribed level. The operation of the OUT policy is further discussed in Section 5 of the paper.

We show in *Appendix A* that the MSE of the manufacturer's demand over the lead-time plus one review period under the DDI strategy, which we denote by MSE_{DDI} , is given by (3).

$$MSE_{DDI} = \frac{\sigma^2}{(1-\rho^2)}\left[\begin{array}{l}\left(L+1+\frac{2L\rho}{(1-\rho)}-\frac{2\rho^2(1-\rho^L)}{(1-\rho)^2}\right)+\frac{(L+1)}{N}\left(L+1-\frac{2\rho(1-\rho^N)(1-\rho^{L+1})}{(1-\rho)^2}\right)\\+\frac{2(L+1)^2\rho}{N^2(1-\rho)}\left(N-1-\frac{\rho(1-\rho^{N-1})}{1-\rho}\right)\end{array}\right] \quad (3)$$

By looking at MSE_{DDI} in (3), it is clear that the MSE expression under the DDI strategy reduces as the order of the SMA forecast (N) increases, meaning that the performance of the DDI strategy improves for higher SMA orders. Furthermore, by looking at the three components between brackets in (3), it is clear that the first component is independent of N, in contrast to the other components that are inversely proportional to N and N^2. Since, for low values of L and relatively higher values of N, this first component will be dominant in (3), it is expected that the MSE_{DDI} will be less sensitive to N for low values of L. These expected findings will be confirmed in Sections 4 and 5.

We now move on to present the MSE results under NIS and FIS strategies.

Under the AR(1) process, the MMSE forecasting method over a lead time of duration L can be expressed as follows:

$$f_{t+L+1} = E(\sum_{i=1}^{L+1} d_{t+i} | d_t) = \frac{\tau}{1-\rho}\left\{(L+1)-\sum_{j=1}^{L+1}\rho^j\right\}+\frac{\rho(1-\rho^{L+1})}{1-\rho}d_t \quad (4)$$

It is important to note that the expression for an MMSE forecasting method is dependent upon the ARIMA structure under consideration. That is, the expression presented in (4) holds only for the AR (1) process. Should other ARIMA processes had been considered, the expression would also be different. Please see Lee et al (2000) for the derivation of equation 4.

Under the NIS strategy, the MSE of the manufacturer's demand over the lead-time plus one review period, which we denote by MSE_{NIS}, is given by (5) (Zhang, 2004):

$$MSE_{NIS} = \left[\sum_{i=1}^{L} \left(1 + \frac{\left(\rho - \frac{\rho(1-\rho^{L+1})}{(1-\rho^{L+2})} \right)(1-\rho^{L-i+1})}{(1-\rho)} \right)^2 + 1 \right] \left[\frac{1-\rho^{L+2}}{1-\rho} \right]^2 \sigma^2 \tag{5}$$

Under the FIS strategy, the MSE of the manufacturer's demand over *L+1*, which we denote by MSE_{FIS}, is given by (6) (Ali et al, 2012).

$$MSE_{FIS} = \frac{\sigma^2}{(1-\rho)^2} \sum_{j=1}^{L+1} \left(1-\rho^j\right)^2 \tag{6}$$

The comparison of the analytical expressions discussed above (MSE_{DDI}, MSE_{NIS}, MSE_{FIS}), with respect to the various parameters, is not a straightforward exercise. Thus, we continue, in Section 4, with a numerical investigation to derive insights into the comparative performance of the three strategies.

4. Numerical Investigation

In this section, we numerically investigate the performance of the three strategies by comparing their MSEs. Unlike the results presented in the previous section where the case of $\rho < 0$ was considered, here we refer only to parameter values that correspond to the *bullwhip region* [1] ($\rho >$ 0, varying the autoregressive parameter between 0.01 and 0.99). We restrict our investigation to the above parameter values as previous research has shown that information sharing is only valuable in the bullwhip region (Chatfield et al, 2004; Hosoda and Disney, 2006; Babai et al, 2013).

[1] The occurrence of the Bullwhip Effect is dependent on the parametric values of the demand process. For example in the case of an AR (1) process, previous studies (e.g. Babai et al, 2013) have shown that the Bullwhip Effect only occurs when the value of the auto-regressive coefficient is positive and strictly less than 1. When the autoregressive coefficient is negative, bullwhip effect does not exist or equivalently, the variance of order quantity experienced by supplier is smaller than the variance of demand.

We assume that the standard deviation of the retailer demand noise is $\sigma = 50$. The lead-time values considered in the numerical experiment are $L = 1, 3, 5, 7, 9, 11$. Please note that the above experimental values have frequently been used in the literature (Lee et al., 2000; Ali et al., 2012; Babai et al. 2013), enabling the results presented in our paper to be related to pertinent findings of the work conducted by other researchers.

When the Simple Moving Average forecasting method is used, the values considered for the moving average order are $N = 3, 6, 9, 12$. The range of values used in our experiment both for the lead time (L) and for the moving average order (N) collectively covers a wide range of real world situations.

We first analyse the variation of the MSE related to the three strategies with respect to the autoregressive parameter ρ. Figure 1 shows the results for $L=1$ and $N=6$. The results for various other parameter settings are similar and are presented in *Appendix B*.

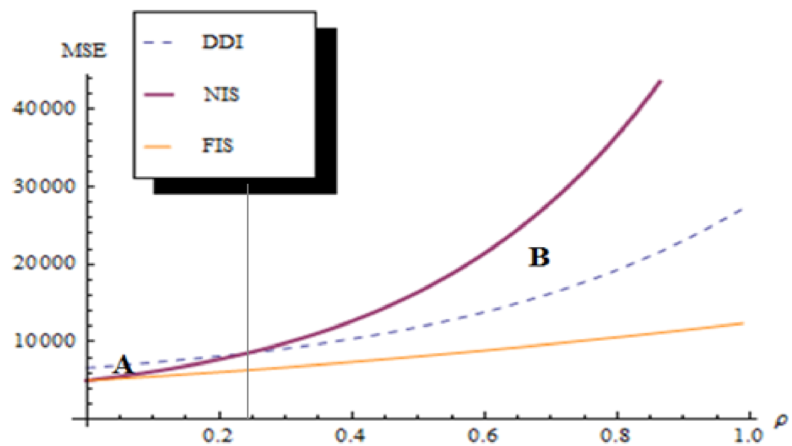

Figure 1: MSE results of the three strategies for L=1 and N=6

The first observation from Figure 1 is an expected result. For all values of ρ, FIS outperforms the other two strategies in terms of MSE reduction. Hence, using the optimal forecasting method and sharing demand forecast information is the best strategy to reduce MSE.

We now focus on the comparison between the NIS and DDI strategies. Figure 1 shows that for low values of ρ, NIS outperforms DDI. However, the performance of the latter improves as the value of ρ increases and the difference between the performances reduces until a breakpoint is reached. For values of ρ higher than the breakpoint, DDI outperforms NIS. For example, for $L = 1$ and $N = 6$ the breakpoint where the comparative performance of the two strategies is reversed occurs at $\rho = 0.24$. The occurrence of the breakpoint and the reversal in the performance of the two strategies can be explained in terms of the forecasting method being used, and the Bullwhip Effect.

The MMSE forecasting method is used in the NIS strategy, which is more accurate than the SMA method used in the case of the DDI strategy. On the other hand, the performance of the NIS strategy is affected by the Bullwhip Effect (as this utilises a more variable demand due to the absence of information sharing) compared to the DDI strategy where the less variable demand is utilised due to inference. In instances where the effect of the better forecasting method outweighs the influence of the Bullwhip Effect, NIS outperforms DDI and vice versa.

Lee et al (2000) showed that the Bullwhip Effect is lesser for lower values of ρ. Hence, for lower values of ρ, the effect of the better forecasting method seems to outweigh the Bullwhip Effect. As the value of ρ increases, the Bullwhip Effect also increases resulting in a breakpoint and subsequently leading to the reversal of performance.

For the purpose of better portraying the difference between the performance of DDI and NIS, we show in Figure 1, the two areas between the DDI and NIS curves for values of ρ lower and higher than the break point, by A and B respectively. The breakpoint varies according to the order of Moving Average (N) and the lead-time (L), as shown in Figure 2.

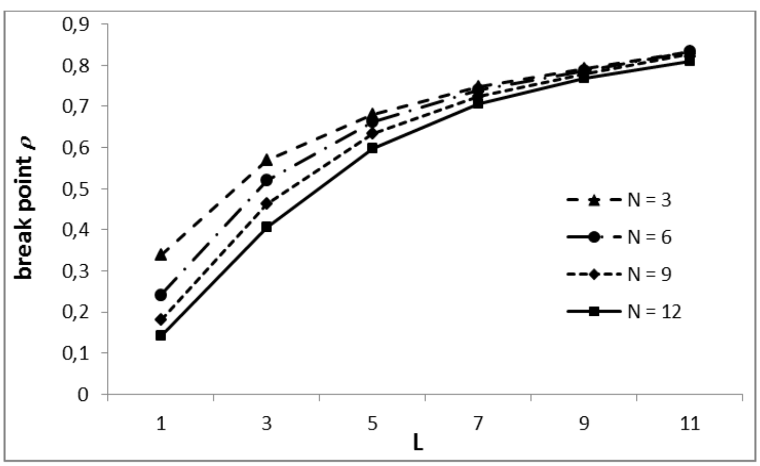

Figure 2: Variation of the breakpoint with respect to *N* and *L*

In terms of L, the numerical results show that the value of the break point increases as the lead time increases. This is expected as, generally, the performance of a MMSE optimal forecasting method compared to a non-optimal forecasting method (e.g., SMA in our case) improves with increasing lead time. On the other hand, Figure 2 shows that the breakpoint decreases with the order of the moving average as the performance of SMA improves with the length of the demand history being used (higher value of N).

5. Empirical Analysis

In this section, we first discuss some details of the dataset available for the purposes of our research and we then present the results of the empirical analysis.

5.1. Demand Dataset, Experiment Setting and Results

The demand dataset available for the purposes of our research consists of weekly sales data over a period of two years for 1,798 products of a major European Supermarket located in Germany. For confidentiality reasons, the company, nature of products and any other related information cannot be disclosed. The lead-time in the grocery industry is usually low and hence we assume a lead-time of one week for the whole range of products. We used the Time Series Expert Modelling function of PASW (version 17) to identify the ARIMA demand process for each series and estimate the relevant parameters. This resulted in 557 series (30.9%) being identified as AR (1) processes and selected for our analysis. In Table 2 we present some descriptive statistics for the sub-sample (557 series) used for the purposes of our research. The distribution of the mean and standard deviation of demand per series is presented across all series through some key quantities: mean, maximum, minimum and quartiles.

557 SKUs	Mean	Std. Dev
Mean	74.7	40.4
Minimum	25.9	9.5
Lower Quartile	34.1	19.9
Median	47.0	27.3
Upper Quartile	78.2	43.9
Maximum	931.8	360.1

Table 2: Descriptive Statistics of the Demand Data

We now present the distribution of the autoregressive parameter ρ in our dataset, which is shown in Figure 3.

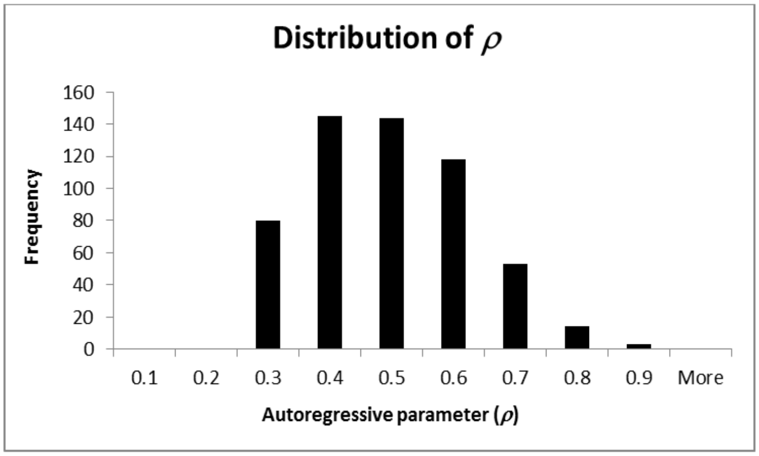

Figure 3: Distribution of the autoregressive parameter (ρ)

The value of ρ in our dataset ranges from 0.22 to 0.86. This finding is clearly in line with some of the datasets used in earlier studies. Lee et al (2000) examined the weekly sales pattern of 165 products in a US supermarket and found the value of ρ ranging from 0.26 to 0.89. Similarly other studies (Erkip et al, 1990; Lee et al, 1997) found that it is common to have positive correlation and value of ρ as high as 0.7 in the high tech and other consumer product industries.

In terms of the design of our experiment, the available sales history (i.e. 104 periods) for each SKU was split into two parts. The first part (within-sample) consisted of 80 time periods and was used for identification and estimation purposes. The second part (out-of-sample) consisted of the remaining 24 time periods and was used for the evaluation of the performance. Hence, the results reported for the two performance metrics (inventory costs and MSE) constitute averages over the last 24 time periods of all of the SKUs. As previously discussed in section 3, in order to analyse the inventory performance of the three strategies, we assume that the downstream member controls its inventory system with an order-up-to (OUT) policy.Note that in order to use realistic assumptions in the empirical evaluation model, demand, orders and inventory holdings are converted to zero, if negative. We assume that in each time period, a unit inventory holding cost h is incurred if the inventory level is positive and a unit backorder cost b is incurred if the inventory level is negative. The total inventory cost is the sum of the holding and backordering costs.

In Table 3, we report the average MSE for the 557 series under the three strategies while in Table 4, we report the average inventory cost results for the same series. The results are obtained for $L = 1, 5, 9; N = 3, 6, 9, 12; h = 1; b = 25$. These control parameters have been chosen to ensure comparability with previously published work in this area (e.g. Lee et al, 2000; Babai et al, 2013). As discussed in the previous section (Section 4), the performance of DDI depends on the values of *L* and *N*.

	MSE Results				% MSE reduction when using DDI rather than NIS
L	FIS	NIS	DDI (for varying *N*)		
L=1	8245	17824	*N=3*	11678	34.5%
			N=6	11593	35.0%
			N=9	11543	35.2%
			N=12	11543	35.2%
L=5	51431	106359	*N=3*	94702	11.0%
			N=6	82662	22.3%
			N=9	77457	27.2%
			N=12	74324	30.1%
L=9	113056	231015	*N=3*	260007	-12.5%
			N=6	218592	5.4%
			N=9	196201	15.1%
			N=12	181307	21.5%

Table 3: Empirical MSE Results

L	Inventory Cost Results				% cost reduction when using DDI rather than NIS
	FIS	NIS	DDI (for varying *N*)		
L=1	367	399	*N=3*	456	-14.3%
			N=6	369	7.5%
			N=9	336	15.8%
			N=12	321	19.5%
L=5	544	714	*N=3*	1044	-46.2%
			N=6	915	-28.2%
			N=9	756	-5.9%
			N=12	679	4.9%
L=9	555	1199	*N=3*	1451	-21.0%
			N=6	1210	-0.9%
			N=9	952	20.6%
			N=12	833	30.5%

Table 4: Empirical Inventory Cost Results

5.2. Discussions on the Empirical Analysis

We first compare the performance of FIS and NIS. Similar to the results of the numerical investigation, FIS outperforms NIS in terms of the two performance metrics. This result means that the strategy to share information would be beneficial for a supply chain compared to not sharing information. Our results thus clearly agree with previous studies in the area (e.g. Lee et al, 2000; Yu et al, 2002; Ali et al, 2012).

We now move our discussion to the comparisons between FIS and DDI. In this case, the demand and the forecast information are available to the manufacturer, either by inference (DDI) or by sharing (FIS), respectively. The superior performance of FIS (in most cases) shows that the optimal forecasting method generally performs better than SMA. This is also consistent with earlier results (e.g., Makridakis et al, 1982) which show that the optimal forecasting methods perform better than SMA. We also find that in two cases (*L=1; N=9, 12*), the SMA forecasts perform better than the MMSE ones in terms of inventory cost. This is not very surprising, as for stationary processes, the performance of SMA generally improves for higher values of N. Nevertheless, a further analysis is currently being conducted by the authors to understand the results in more detail.

It is interesting to note the implications of the two comparisons above. The comparison between FIS and DDI lies in the forecasting methods used, while the effect of the information sharing strategy can be used to explain the comparative performance of FIS and NIS. The savings in inventory cost and reduction in forecast error when we move from the use of the SMA to the optimal forecasting method are relatively modest when compared to moving from no information sharing to an information sharing strategy. In the latter case the savings are considerably higher. This relates to an interesting point about ways to improve demand management; our results show that investing in information sharing mechanisms may return comparatively greater benefits than more accurate forecasting methods.

Now, we discuss the results of the comparison of DDI with NIS. We first compare the MSE results for the two strategies (Table 3). The empirical results show that in most cases (11 out of 12 cases), $MSE_{DDI} < MSE_{NIS}$. Such results agree, overall, with our numerical investigation in Section 4. As discussed in that section, the comparative outperformance of DDI against NIS reduces as *L* increases and *N* decreases, which is why we observe the case where NIS outperforms DDI (*L=9*, *N=3*).

With regards to the inventory costs resulting from the two strategies (Table 4), our analysis shows that DDI outperforms NIS only for the higher values of *N* (*N*=9, 12). (In five out of six cases for the higher values of N, the inventory cost for DDI is lower than that of NIS.) We have assessed the extent to which this result can be attributed to a small number of SKUs. It was found that the overall results are not dominated by a minority of SKUs (e.g. from the effect of outliers). On the contrary, a strong majority of SKUs follow the overall result. We have also assessed the sensitivity of the results to the ratio of b to (b+h) and found that the higher the value of b/(b+h), the lower is the reduction in the inventory cost.

In order to check for the consistency of our findings with other stationary processes, we have also conducted an analysis for MA (1) and ARMA (1,1) demand processes (contained in our empirical dataset). The findings for both processes were consistent with those related to the findings of the AR (1) process i.e. DDI outperformed NIS for large values of *L* and *N*.

The outperformance of DDI for higher values of N is an interesting result. Despite the fact that the MSE values are lower for nearly all values of N, the effect on inventory cost is less pronounced across all relevant control parameter combinations. It is important to note that previous research has shown that forecast accuracy (e.g. MSE) results are not directly translated with the same magnitude to utility measures (e.g. inventory costs in our paper) (see Boylan and Syntetos, 2006).

We have observed the same phenomenon in our empirical analysis. Further research to establish the reasons behind these results would also be very useful towards enhancing our understanding on the relationship between accuracy and accuracy-implication (utility) metrics.

Our numerical analysis in Section 4 showed the existence of a break-point below which the comparative MSE performance of DDI and NIS was reversed. In order to investigate this break-point in our empirical experiment, we analysed the difference in inventory cost between DDI and NIS with respect to the value of ρ. As an example, in Table 5 we report results for $L=1$; $N=6$ in order to contrast the empirical results with the numerical analysis conducted in Section 4. (The results obtained for other parameter settings are similar and thus are not reported here.) Positive values indicate reduced costs by using DDI.

ρ	Inventory cost (NIS)	Inventory cost (DDI)	Percentage Reduction
$0.2<\rho\leq0.3$	222	248	-12%
$0.3<\rho\leq0.4$	262	282	-8%
$0.4<\rho\leq0.5$	354	356	-1%
$0.5<\rho\leq0.6$	433	399	8%
$0.6<\rho\leq0.7$	767	586	24%
0.7- above	1,417	898	37%

Table 5. Inventory Cost Percentage Reduction of Using DDI Rather than NIS as a function of ρ

The results show that NIS performs better than DDI for smaller values of ρ. The comparative performance of NIS decreases up to a break point beyond which there is a reversal in the comparative performance of the two strategies. The actual values for the break point are not the same as found in the numerical analysis in Section 4. However, the existence of the break point and the reversal of the comparative performance are in line with the earlier numerical analysis. It is not surprising to observe the minor differences between the analytical and empirical results. In fact, the empirical results may differ slightly for every dataset. A company wishing to investigate the break-point in their SKUs can implement a similar simulation of its sales forecasts and inventories. Such an exercise will help them with the decisions on the choice of strategies to adopt.

We conclude this section by recalling the overall results on the comparison between DDI and NIS. Tables 3 and 4 exhibit an important result for supply chains where formal information sharing does not take place even though both parties may have the capability and willingness to do so. If the retailer agrees to use SMA to forecast their demand, the upstream link (manufacturer in our case) would be able to infer the actual consumer demand. The manufacturer will then base their planning process on the actual consumer demand rather than the orders from the retailer. By using the less variable consumer demand, the manufacturer would be able to reduce their inventory costs due to improved order forecast accuracy. Our analysis also shows an interesting trade-off in terms of strategies for improving forecast accuracy where information cannot be formally shared. Companies could either consider improving the forecasting method or using a less accurate method if that utilises the consumer demand. Although the accuracy can be enhanced by an improvement in the forecasting method itself, the enhancement is more pronounced by using the actual consumer demand even in conjunction with a less accurate method.

6. Conclusions and Managerial Implications

This paper has several implications, both from academic and practitioner perspectives. Firstly, the results of this study confirm that supply chains should always strive to share information in order to be most effective. Irrespective of the forecasting method adopted, sharing information would always be beneficial as the upstream supply chain links would be using the actual consumer demand in their planning framework.

As discussed in this paper, there are many supply chains where information sharing does not take place. If the retailer does not pass on the information upstream, the manufacturer has two options: base their planning on the orders received from the retailer or try to mathematically infer the consumer demand. Although inference is not possible in general, to date the only method that has been found that may facilitate such inference is the Simple Moving Average (SMA). There could be instances where SMA is already in place e.g. there is evidence to suggest that SMA is used extensively in practice (Ali and Boylan, 2012) and thus the manufacturer may simply ask the retailer for an identification of the SKUs for which this method is used. There is extant literature on manufacturers offering incentives to the retailer to share information e.g. price discounts (Karabati and Kouvelis, 2008; Aditya et al, 2010), investment sharing (Cannella et al, 2015), buyback policy (Chen, 2011), two-way coordination (Gao, 2015), revenue sharing clause (Heese and Kemahlioglu-Ziya, 2016) and VMI (Yu et al, 2002). In capability and trust constrained situations, similar incentives could be offered to retailers for the use of SMA. On the other hand, if the manufacturer is the stronger player between the two, they may instruct the retailer to use SMA.

The implications, as mentioned above, are more relevant for improving the performance of supply chains where information is not shared despite the willingness of both parties to do so. However, it is also important to discuss the implications of the strategy of using SMA in supply chains where at least one partner is not willing to engage in formal information sharing practices due to lack of trust, commitment and confidentiality. An important implication for managers for such supply chains is how the initial collaboration on using a certain forecasting method may result in enhancing trust in the supply chain partners. One of the contributions of the paper is that the scope of the solution presented is not limited to situation where willingness to share information already exists, but also to situations where the parties involved do not trust each other.

Trust building is a continuous process and requires constant commitment from the parties towards the relationship (Revilla and Knoppen, 2015; Xu et al, 2015). Amaral and Tsay (2009) report that supply chain partners will not participate in any collaborative initiative if they do not trust their partner, irrespective of the anticipated financial gains. This is because the two parties are highly conscious of the risk and vulnerability of trusting each other and this level of perceived risk acts as a threshold barrier for trust building (Mayer et al, 1995). Forecast information sharing requires sharing the demand forecasts with the upstream link. The high risk of giving access to forecasts to the other party may prove to be a deterrent to initialise collaborations. However, if the discussions are restricted to sharing the type of forecasting method used, the probability of an initial collaboration is higher. As the relationship then further develops, the supply chain partners can better estimate the actions of the other parties and this may result in a growth of trust to higher levels. Ba (2001) argues that interacting with each other in different contexts and building upon past experience may cultivate trust from a low to high level e.g. from cognitive trust to bonding trust (Slack and Lewis, 2010). As pointed out by Laeequddin et al (1996) "*supply chain members should strive to reduce the partnership risk levels to build trust rather than striving to build trust to reduce the risk*."

If supply chains adopt our recommendations the cost savings would initially be limited to SKUs where SMA may be used. However, the benefits are expected to extend to other SKUs as well as the trust starts to build up and both parties engage in a more extensive demand information sharing process.

Before we close this paper, we would like to discuss some potential limitations and suggest an agenda for further research in this area. Firstly, the mathematical analysis of the paper is limited to an AR (1) process. Although, we have checked and confirmed the consistency of our findings for MA (1) and ARMA (1, 1) processes, our mathematical analysis could be extended to a more general ARMA (p, q) model. Secondly, the empirical analysis conducted in our study was based on data from a major European superstore. Further empirical analysis should be conducted on empirical data from other industries. Finally, in this paper we recommend the use of SMA as this is the only forecasting method known to date to facilitate demand inference. An interesting avenue for further research would be to explore the possibility of DDI through other forecasting methods.

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Appendix A. Derivation of the MSE expression under the DDI strategy

The MSE of the manufacturer's lead-time demand under the DDI strategy is given by:

$$MSE_{DDI} = Var\left[\sum_{i=1}^{L+1}(d_{t+i} - f_{t+i})\right] = Var\left[\sum_{i=1}^{L+1} d_{t+i} - (L+1) f_{t+1}\right]$$
$$= Var\left(\sum_{i=1}^{L+1} d_{t+i}\right) + (L+1)^2 Var\left(f_{t+1}\right) - 2(L+1) Cov\left(\sum_{i=1}^{L+1} d_{t+i}, f_{t+1}\right) \quad (A.1)$$

We now calculate the three components of (A1).

It is known that, for an AR(1) process:

$$\gamma_k = \mathrm{cov}(d_{t+k}, d_t) = \begin{cases} \dfrac{\sigma^2}{1-\rho^2} & if \quad k = 0 \\ \rho\, \gamma_{k-1} & if \quad |k| \ge 1 \end{cases} \quad (A.2)$$

Hence:

$$Var(\sum_{i=1}^{L+1} d_{t+i}) = \sum_{i=1}^{L+1} Var(d_{t+i}) + 2\sum_{i=1}^{L}\sum_{j=i+1}^{L+1} Cov(d_{t+i}, d_{t+j}) = \sum_{k=1}^{L+1}\gamma_0 + 2\sum_{i=1}^{L}\sum_{j=i+1}^{L+1}\gamma_1 \rho^{j-i-1}$$
$$= (L+1)\gamma_0 + 2\gamma_1 \sum_{i=1}^{L}\rho^{-(i+1)}\sum_{j=i+1}^{L+1}\rho^{j} \quad (A.3)$$
$$= (L+1)\gamma_0 + \frac{2\gamma_1}{(1-\rho)}\left[L - \frac{\rho(1-\rho^L)}{(1-\rho)}\right]$$

The second component is given by:

$$Var(f_{t+1}) = Var(\frac{1}{N}\sum_{k=0}^{N-1} d_{t-k}) = \frac{1}{N^2} Var(\sum_{k=0}^{N-1} d_{t-k}) \quad (A.4)$$

Using the same derivation as for the first component:

$$Var(f_{t+1}) = \frac{\gamma_0}{N} + \frac{2\gamma_1(N-1)}{N^2(1-\rho)} - \frac{2\gamma_1\rho(1-\rho^{N-1})}{N^2(1-\rho)^2} \quad (A.5)$$

To obtain the third component:

$$Cov(\sum_{i=1}^{L+1} d_{t+i}, f_{t+1}) = Cov(\sum_{i=1}^{L+1} d_{t+i}, \frac{1}{N}\sum_{k=0}^{N-1} d_{t-k}) = \frac{1}{N} Cov(\sum_{i=1}^{L+1} d_{t+i}, \sum_{k=0}^{N-1} d_{t-k})$$

$$= \frac{1}{N}\sum_{i=1}^{L+1}\sum_{k=0}^{N-1} Cov(d_{t+i}, d_{t-k})$$

$$= \frac{1}{N}\sum_{i=1}^{L+1}\sum_{k=0}^{N-1} \gamma_1 \rho^{i+k-1} \tag{A.6}$$

$$= \frac{\gamma_1 (1-\rho^N)(1-\rho^{L+1})}{N(1-\rho)^2}$$

Substituting (A3), (A5) and (A6) in (A1) gives:

$$MSE_{DDI} = (L+1)\gamma_0 + \frac{2\gamma_1 L}{(1-\rho)} - \frac{2\gamma_1 \rho (1-\rho^L)}{(1-\rho)^2} - \frac{2\gamma_1 (L+1)(1-\rho^N)(1-\rho^{L+1})}{N(1-\rho)^2} + \frac{\gamma_0 (L+1)^2}{N}$$
$$+ \frac{2\gamma_1 (N-1)(L+1)^2}{N^2(1-\rho)} - \frac{2\gamma_1 (L+1)^2 \rho (1-\rho^{N-1})}{N^2(1-\rho)^2} \tag{A.7}$$

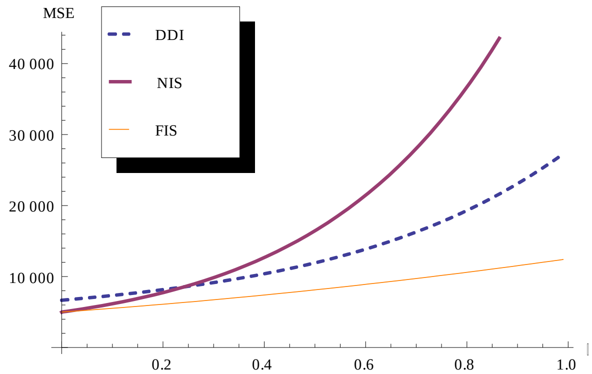
which is equivalent to

$$MSE_{DDI} = \frac{(L+1)}{1-\rho^2}\sigma^2 + \frac{2L\rho}{(1-\rho)(1-\rho^2)}\sigma^2 - \frac{2\rho^2(1-\rho^L)}{(1-\rho)^2(1-\rho^2)}\sigma^2 - \frac{2(L+1)\rho(1-\rho^N)(1-\rho^{L+1})}{N(1-\rho)^2(1-\rho^2)}\sigma^2$$
$$+ \frac{(L+1)^2}{N(1-\rho^2)}\sigma^2 - \frac{2(L+1)^2\rho^2(1-\rho^{N-1})}{N^2(1-\rho)^2(1-\rho^2)}\sigma^2 + \frac{2(N-1)(L+1)^2\rho}{N^2(1-\rho)(1-\rho^2)}\sigma^2 \tag{A.8}$$

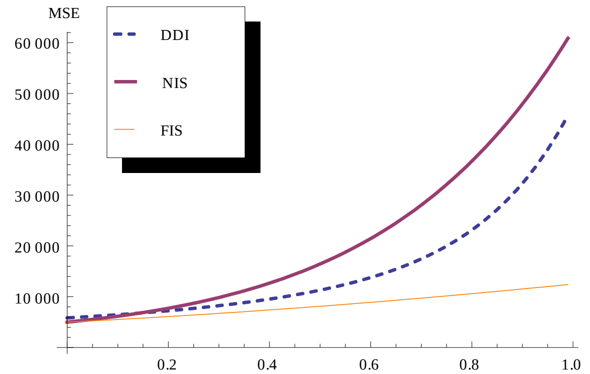
which may be re-written:

$$MSE_{DDI} = \frac{\sigma^2}{(1-\rho^2)}\left[\begin{array}{l}\left(L+1+\frac{2L\rho}{(1-\rho)} - \frac{2\rho^2(1-\rho^L)}{(1-\rho)^2}\right) + \frac{(L+1)}{N}\left(L+1-\frac{2\rho(1-\rho^N)(1-\rho^{L+1})}{(1-\rho)^2}\right) \\ + \frac{2(L+1)^2\rho}{N^2(1-\rho)}\left(N-1-\frac{\rho(1-\rho^{N-1})}{1-\rho}\right)\end{array}\right] \tag{A.9}$$

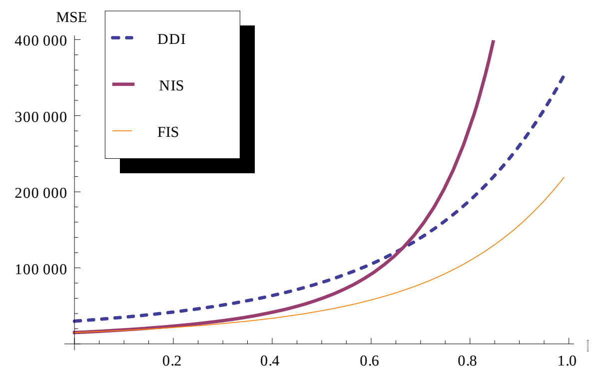
Appendix B. MSE results of the three strategies for different values of *L* and *N*



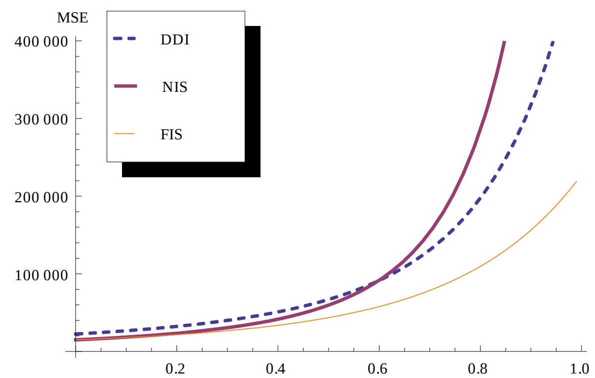
Results for L=1 and N=6



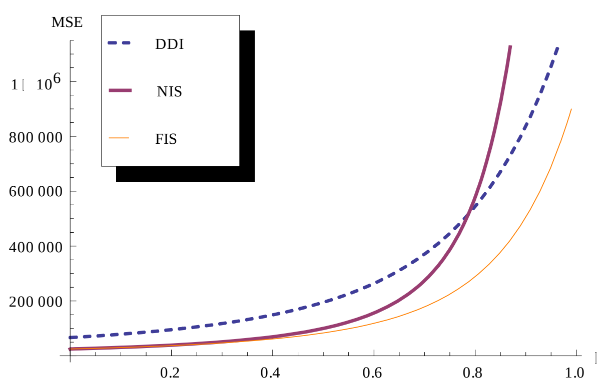
Results for L=1 and N=12



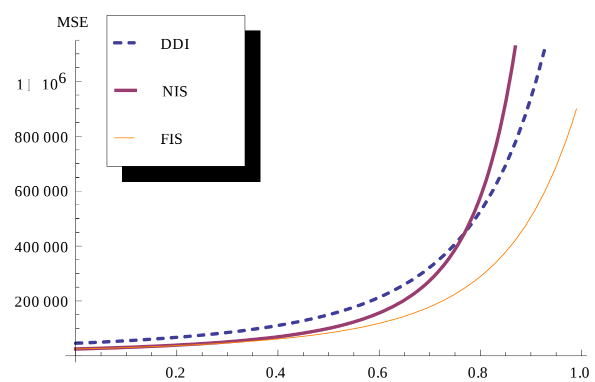
Results for L=5 and N=6



Results for L=5 and N=12



Results for L=9 and N=6



Results for L=9 and N=12