

Simulation-Based Decision Analysis of Demand Sharing and Inventory Control in Multi-Tier Manufacturing Supply Chains

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ABSTRACT

Upstream replenishment orders can fluctuate more than customer demand when each supply-chain tier forecasts from the orders it receives. This study uses a periodic-review simulation to compare retailer-managed inventory, in which each tier forecasts from downstream orders, with a shared-demand scenario in which the distributor and manufacturer observe point-of-sale demand. Demand generation, forecasting rules, lead times, and replenishment policies match across scenarios. The analysis includes a three-tier manufacturing supply chain and a multiple-retailer extension that varies network size and cross-retailer demand correlation. Thirty paired replications are run for each setting. In the base-model grid, the simulated reduction in the manufacturer-tier bullwhip ratio ranges from 89.7% to 97.2%. At a demand autocorrelation of 0.6, the reduction in the total safety-stock holding proxy ranges from 47.6% to 62.4% across the displayed lead times. In the low-correlation network scenario, the distributor-tier bullwhip reduction falls from 63.8% to 34.8%, and the total safety-stock proxy reduction falls from 23.8% to 10.9% as the number of retailers increases from one to 40. These results show that the measured advantage of shared demand visibility depends on the demand structure and inventory accounting boundary. The simulation does not establish realized inventory savings or service performance in a factory.

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1. Introduction

Supply chains that deliver a product from a manufacturer via a distributor to a retailer to a customer rely on each individual making a decision when they are uncertain of the number of supplies needed by the next tier. A very well-known distortion is that the order variance increases as it flows through the system, the more orders it passes through the closer it gets to the source of the orders, the bullwhip effect. This distortion isn't just inefficiency. It leads to unwanted stock, failure to meet service performance commitments and unproductive use of production capacity and recent research has classified the causes into four categories: structural characteristics of the chain, demand and supply uncertainty, misaligned incentives between tiers, and limited cognition of the decision makers who carry out order updates based on partial information.

Two extremes of coordination regimes are based on the extent to which uncertainty is resolved at each level. The classic model is retailer managed inventory (RMI) where each level has their own inventory and forecast; and only the order is communicated upwards. In the vendor managed inventory (VMI) scenario, the supplier is responsible for ordering the customer's stock based on the common information of demand instead of the customer's demand orders (Lotfi et al., 2025; Salas-Navarro et al., 2024). VMI has been proved to decrease the cash conversion cycle and the

cash flow bullwhip effect in the supply chain (Sim, 2024); it can decrease the average value of inventories by double digit percentages in a hospital supply chain; and it has been proved to be effective when combined with a risk and robustness mechanism based on blockchain technologies (Lotfi et al., 2025). In 2014-2024, according to a recent meta-analysis of 334 studies Salas-Navarro et al. (2026) research into the adoption of VMI is active and has increased, but this research is focused in a small number of influential outlets of study.

These days, manufacturing processes are usually “multi-tier” with materials and products moving from one tier of the chain to the next, from suppliers to production plants, to distribution centers, to warehouses, etc., and finally to the end customer. Because of these characteristics, a multi-tier (multi-echelon) network is much more complicated than a single-echelon network, since decisions made at one tier (e.g., replenishment policies at the distribution center) affect service performance, order quantities, and inventory levels at upstream and downstream tiers. Conventional inventory management policies designed to minimize costs at one level in the system frequently cause adverse effects due to lack of consideration for interdependencies and information gaps between tiers, including inventory buffers, stockouts and the bullwhip effect (Adirektawon et al., 2024). A potential solution to these problems is demand sharing, which involves the sharing of real-time or predicted demand data (such as point-of-sale data, sales forecasts, promotions plans) between supply chain partners. Demand sharing provides visibility into downstream demand which can help the upstream tiers coordinate production and replenishment decisions with actual demand, minimizing inventory carrying costs, enhancing fill-rates, and mitigating variability amplification from the customer. Achievement of demand sharing, however, depends on a variety of factors such as the extent of information sharing, variability of lead times, the characteristics of the respective demand patterns and the type of inventory policies used at the different tiers involved, and the impact of demand sharing on overall supply chain performance is still a field of research. Simulation-based decision analysis has emerged as a powerful tool for analyzing the complex, dynamic interactions between demand sharing and inventories in multi-tier supply chains. Unlike purely analytical optimization models which may incur simplifying assumptions about stochastic or linear cost functions, long lead times, or a time-invariant demand, simulation can model the stochastic, nonlinear, and event-driven characteristics of real-world supply chains (Brauch et al., 2024). For example, discrete-event simulation (DES) models the SC in terms of business rules and probabilistic distributions of orders, shipments, production runs, and demand realizations; the analyst can simulate the behavior of the system over time and evaluate the impact of changes to the supply chain, e.g., changes in demand sharing or stocking levels, on important performance metrics, e.g., inventory turns, service levels, fill rates, and total cost. System dynamics (SD) and agent-based simulation (ABS) provide complementary viewpoints. SD: High level flows and feedback loops in the system (e.g., how the variability in demand gets passed along the system); ABS: independent and interacting actions of each supply chain agent (e.g., how the supplier, distributor, retailers react to demand signals). Hybrid methods that integrate DES, SD and ABS create an even more powerful decision lens for an enterprise-wide perspective of demand variability and a ground-level perspective of warehouse throughput. The motivation of using simulation in this context is the complexity and uncertainty of multi-tier supply chains in general. The number of units demanded at the end of the value chain may fluctuate (e.g., seasonality and promotions) and be stochastic (economics and other events affect demand), and lead times for production and transport may vary as a result of capacity limitations, unreliable suppliers, or disruption. These uncertainties, or the Bullwhip effect, in particular, get passed along the chain, increasing the spread of variance at the upstream stages unless acted upon by appropriate sharing of information and joint inventory management. The method of simulation enables decision makers to test a variety of conditions for sharing of information (e.g., full vs. partial information sharing, varying lead times for information transmissions), and inventory control policies (e.g., base-stock, reorder-point, or multi-echelon optimization policies) under a large number of stochastic parameters (Brauch et al., 2024). Analysts can explore various “what if” scenarios, such as when they introduce real-time demand visibility across all suppliers, reduce safety stock at distribution centers, or update replenishment frequencies; they can find combinations of policies that are strong in terms of cost, service, and resilience without risking disruption to the real network. One major benefit of simulation-based decision analysis is that it combines quantitative performance measures with qualitative aspects of the operation. For example, a DES model can monitor inventory levels, inventory order quantities and backlog quantities at each tier over time, and also record the operational restraints, such as production capacity, warehouse storage space and transportation lead times. The researchers can also include mathematical models of profit/cost relations within the simulation logic, thus being able to determine operational KPIs as well as financial ones (total supply chain cost, profit margin) for various demand-sharing and inventory control regimes. This holistic perspective allows managers to make informed tradeoffs, such as how much safety stock can be saved with demand sharing, and how much information technology and coordination mechanisms are needed to achieve this. However, there are still a number of remaining research gaps in the simulation-based analysis of demand sharing/inventory control in multi-tier manufacturing supply chains. Demand sharing is well known as a tool for enhancing the performance of supply chains, however, the circumstances in which

demand sharing is beneficial and useful to the supply chain (e.g., high demand variability, long lead times, many tiers) are not exactly understood, as are the cases in which its benefits are marginal or even negative (e.g., information overload, misaligned incentives). Second, many of the existing studies are dedicated to only one of two aspects of the problem, namely inventory control or demand sharing, instead of optimizing both simultaneously. Third, the implementation of advanced simulation techniques (e.g., digital twins, machine learning-based adaptive policies) with conventional inventory models is still in its infancy, with few, especially industrial, uses. This introduction leads to simulation-based multi-tier manufacturing supply chain demand sharing and inventory control simulation analysis. The next section will cover the structure of the supply chain network, the development of the simulation model (including demand generation, information flow, inventory policies and performance measures), and the results of the experiments and scenario analysis. The structure of the supply chain network, the development of the simulation model (including demand generation, information flow, inventory policies and performance measures) and results of the experiments and scenario analysis will be summarized. This research combines operational realism with decision-support analytics to offer managers practical guidance on improving efficiency, responsiveness, and resilience in multi-tier supply chains by using information to support demand-sharing and inventory control decisions.

Despite this, the literature has not been consistent on the size of the VMI advantage when it is strong versus when it is weak. While it is clear that point of sale-to-order data sharing can have a significant impact on hierarchical forecasting along three echelon chain (Abolghasemi, 2025), another empirical study of retail data integration showed that, sharing point of sale data alone with the manufacturer does not have a material effect on forecast accuracy, and the usefulness of the data is observed in planning alignment not in the forecast error metric the researchers typically report (Saarinen et al., 2025). This is the specific gap this paper aims to address: is the benefit of VMI a single, uniform effect or is it divided into identifiable mechanisms which have different responses to the demand environment (namely autocorrelation in demand over time, length of lead time, and number of retailers a vendor coordinates)?

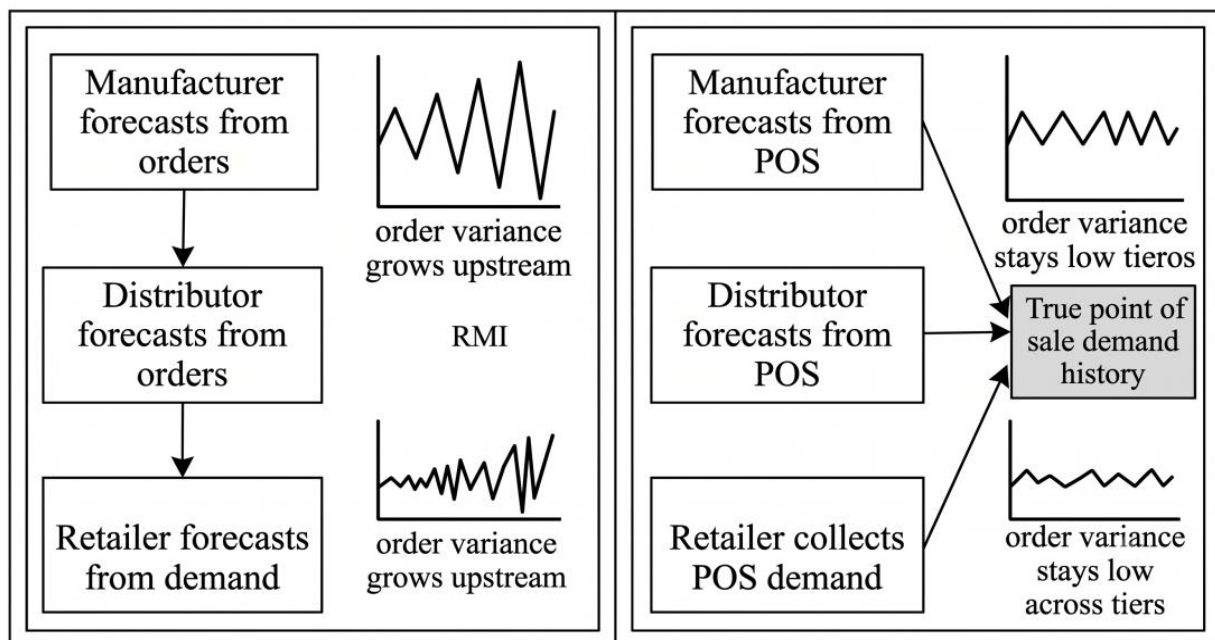


Figure 1: Under RMI (left) Each Tier Forecasts from the Order Stream Produced by the Tier Below it, So, a Forecast Error Made at the Retailer is Inherited and Amplified Again at the Distributor, and Again at the Manufacturer. VMI (Right) Assumes That All Tiers Look at the Same Actual Time Series of Demand, So That None of Them Assume the Forecast Error of Another Tier. The Difference in Structural Sensitivity is Not a Difference in Forecasting Skill; This is What the Simulation in Section 5 Measures

This is explained by the mechanism in Fig. 1. RMI allows the retailer's stream of orders (which has its own forecast noise) to be the distributor's demand signal, and the distributor's stream of orders (which has its own forecast noise) to be the manufacturer's demand signal. Under VMI, all tiers have exactly the same demand signal (it is the true customer demand series) so the compounding never begins. Whether the structural removal of compounding and the separable classical risk pooling effect brought about by a single vendor serving multiple retailers (Silver et al., 2016;

Varlas et al., 2025) works in the same manner as the coordination problem scales is what the rest of this paper examines.

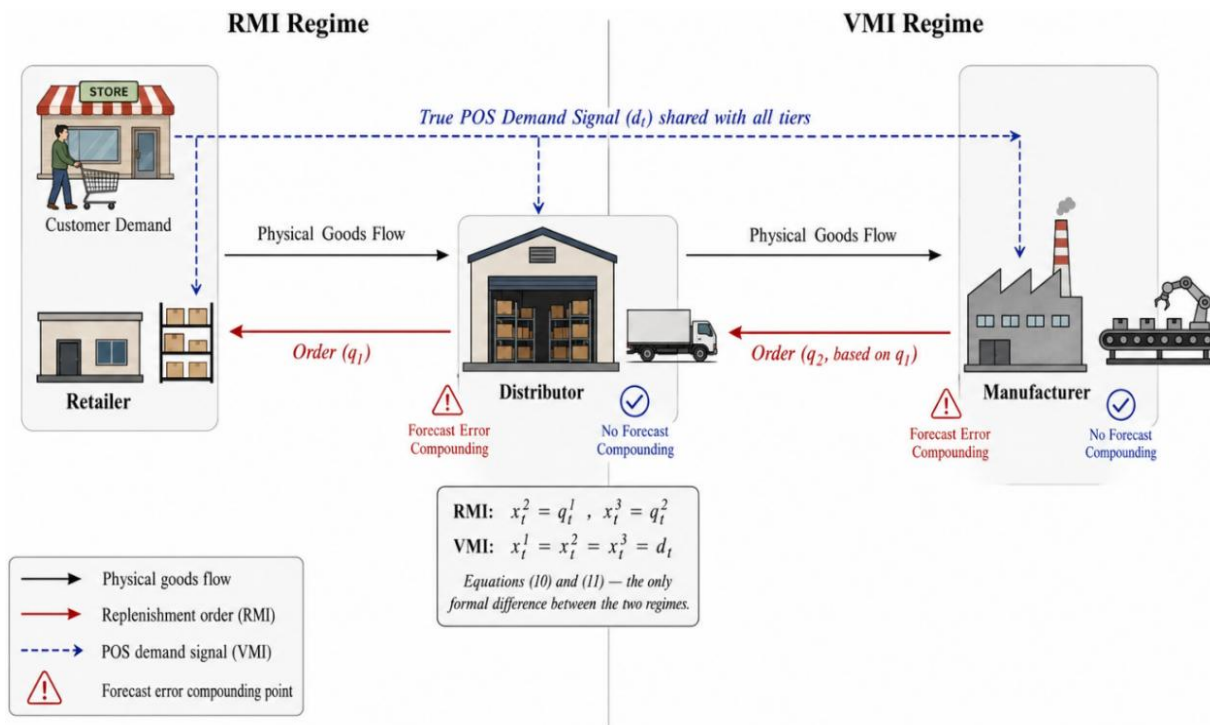


Figure 2: In this Paper, 3-Tier Supply Chain Has Been Studied. Orders For Replenishment Are, Like Physical Goods, Sent Upstream (Solid Lower Arrows), From Customer to Retailer to Distributor and Manufacturer. Whereas Under RMI Each Tier Will Use the Order Stream it Receives from the Tier Underneath It to Determine the Order Quantity, Under VMI, Each Tier Will Use the Same True Point-Of-Sale Demand Signal to Determine the Order Quantity. There is, Of Course, No Difference in the Physical Network Between the Two Regimes, Only in This Information Structure. The Base Model Includes a Single Retailer, a Single Distributor and a Single Manufacturer, While the Network Extension Replaces the Single Retailer with N Retailers, Still Having a Single Distributor and Manufacturer

The following contributions of this paper are made.

- A periodic review, order up simulation model of a three-tier supply chain is developed with two different assumptions on what each tier assumes the demand signal is related to: the RMI regime assumes that the demand signal is related to the demand signal at the previous tier, while the VMI regime assumes that the demand signal is related to the demand signal at the tier behind the previous tier. All other parameters, including the demand process, the lead times, the forecasting method, are identical across the two regimes.
- Based on this model, a network extension is created where a single vendor supplies N retailers, with a common and an idiosyncratic component of the demand, thus removing the forecast compounding mechanism studied in the base model from the risk pooling mechanism.
- This paper report, for the first time the authors know, the opposite trends of the two VMI mechanisms with network size for low cross retailer correlation: the safety stock (cost) advantage of VMI increases with the number of retailers served, but the bullwhip ratio (BWR) advantage does not.
- The model is tested over a full set of four different levels of autocorrelation of demand, four different lead time settings, and six different network sizes—all at three different correlation levels and each number is the direct output of the simulation code that is released with this paper.

The VMI CoordNet is the coordination-network simulation framework developed here, which includes the base three-tier model and the N-retailer network extension, in which the two VMI mechanisms are isolated and measured under controlled parameters variations, throughout this paper. The rest of this paper is organized as follows. This section summarizes the work related to it and presents the research gap. In Section 3 the demand, forecasting, and order up to model is presented. However, Section 4 introduces the RMI and VMI simulation procedures, the RMI network extension, and the complexity of both. The simulation results are presented in section 5. Section 6 concludes.

2. Related Work

2.1 Vendor Managed Inventory and Coordination Contracts

The work of VMI has shifted from proving that the arrangement is beneficial to identifying the conditions of the contract under which it is beneficial. Unlike most other work studies Sim (2024) discuss the cash flow variant only in connection with the physical order variance variant, Sim (2024) demonstrates that a VMI policy can be used to reduce the cash conversion cycle at every level, including the cash flow variant of the bullwhip effect. Son (2025) extends the VMI analysis from a demand visibility question to a contract design one by formalizing a consignment sales VMI contract and determines the commission rate under which the contract is incentive aligned for both the consignor and consignee in short selling season products.

Salas-Navarro et al. (2024) create a VMI model for a three level dairy supply chain, explicitly modelling an imperfect production process, exponential demand and remanufacturing of defective units, and demonstrate that VMI's benefits are not restricted to non-perishable, defect free situations; a real dairy case is used to validate the model. Adirektawon et al. (2024) remove VMI from manufacturing altogether and simulate it in a Thai public hospital, where inventory turnover increases from 6.31 to 7.76, average inventory decreases by 36 percent, and management cost declines by 40 percent, demonstrating the generalizability of the mechanism from past retail and manufacturing examples. Lotfi et al. (2025) apply VMI along with the blockchain and an explicit robustness objective to ensure the viability of the arrangement in the face of disruption risk, viewing VMI as a part of a broader resilience design. Ghoudi et al. (2024) study a different but related coordination lever – dual sourcing under a tailored base surge replenishment policy – and Barrera-Sánchez and García-Cáceres (2025) Cáceres develop a stochastic integer program for multi supplier, multi warehouse retail inventory planning under deterministic lead times, both supporting that, besides information sharing, lead time structure is a first order factor in coordinating cost (Barrera-Sánchez & García-Cáceres, 2025; Ghoudi et al., 2024).

2.2 Information Sharing, Forecasting, and the Bullwhip Effect

A parallel literature asks in particular what kind of shared information causes the bullwhip effect to diminish, and to what extent. This paper's simulation maps directly to the 3 structural causes studied, the RMI versus VMI distinction studied here (Brauch et al., 2024) is a structural cause. He then tests point of sale and order data for hierarchical forecasting over a three echelon supply chain and concludes that forecasting accuracy generally improves when both types of data are used, which suggests that there are value in sharing demand data for forecasting purposes (Abolghasemi, 2025). A multi agent consensus seeking problem is considered with the aim of bullwhip mitigation and the negotiation between agents is automated, considered as a coordination mechanism that is orthogonal to the demand visibility mechanism investigated in this paper. In their study on the bullwhip effect in an omnichannel setting. Gao et al. (2025) conclude that the ordering lead time-pick up lead time relationship and not the price asymmetry is responsible for whether returns exacerbate or reduce the bullwhip effect, reminding us that the relationship between ordering and pick up lead time is a source of interaction with information sharing, and not a substitute. While not all studies about shared information result in an improvement in the benefit metric that the researchers expect, Saarinen et al. (2025) caution against assuming that information sharing will always manifest itself as a reduction in forecast error, as their mixed methods study of four CPGs showed that such a benefit was not obvious in practice when they integrated their retail point of sale data.

2.3 Digital Enablement of Multi-Tier Coordination

A third stream is the research into the technologies, not the contract or information structure, that enable multi-tier coordination at scale. Mohammadi et al. (2024) propose an intelligent 4-level VMI supply chain involving three options: wireless sensor networks, RFID, and blockchain technology to make a decision at each level, resulting in a bi objective integer program. Siyal et al. (2026) conducted a bibliometric review of IoT and blockchain integration for inventory visibility, and identified a significant increase in the number of relevant publications from 2024 to 2025 and present the literature in a four-layer model linking sensing for transparency to ledger for trust, operational efficiency and resilience. In the insurance sector, Jin and Karki (2025) develop an IoT and blockchain inventory model for the insurance business for both deterministic and fuzzy demand, thus making the digital enablement literature shift from manufacturing to service supply chains. Digital twins are related but somewhat different enabling technologies; Zaidi et al. (2024) review applications of digital twins for supply chain resilience, Kim et al. (2025) propose an architecture for digital twin with a dedicated prediction module and a dedicated optimization module for dynamic supply chain management and Benhamou et al. (2026) specifically warn that the methodological scope of what a supply chain digital twin actually represents is inconsistent across the literature, which also restricts the ability to reproduce the

study of the bullwhip effect. Hendriksen (2023) review the state of the art for AI based digital supply chain surveillance, and explicitly identify the opportunities and risks that arise when relying on AI systems for supply chain decisions without human involvement, while Asrol (2024) review from 2013 to 2022 the operations research methods in Industry 4.0 supply chain optimization and explicitly list the four axes along which the field has actually progressed: new modeling conditions, new input types, new decision variables, and new algorithms. The Markov chain model used for a three-echelon system with multiple retailers, stochastic demand, and stochastic transportation times is the most similar model to the simulation model used here, but differs in that it considers only a single coordination policy and not compares RMI against VMI. The simulation plus regression style evaluation used in Section V of this paper is the direct methodological precedent of Elnaggar (2025) simulation based, multi variate regression analysis of a decentralized multi echelon supply chain. In the case of high value product inventory management, Kumar et al. (2022) support that information visibility requirements vary according to product and tier attributes, not as a rule for all products in a chain, and this is also confirmed by Schaëfer et al. (2025) in their five case study analysis of multi-tier traceability.

Most of the studies on demand sharing and inventory control in multi-tier manufacturing supply chains have reported efforts to reduce inventory costs, enhance customer service, combat demand uncertainty and control the bullwhip effect. In a multi-tier supply chain, manufacturers, distributors and retailers are all relying on each other to ensure the continuity of materials and products. But mismatches in demand forecasts, replenishment strategies, manufacturing capacity, and delivery times can cause issues throughout the supply chain. Under the variable operating conditions of the system, simulation analysis has suggested itself as an important technique for addressing these issues, as it lets researchers test various inventory strategies against one another. Researchers examined the performance impact of sharing demand information in the supply chain through simulation modeling. Their research explored a three-tiered supply chain, combining retailer, distributor and manufacturer. Stable, volatile and seasonal demand patterns were considered to gain insight into the influence of information sharing on inventory levels and operating costs. (Jannelli et al., 2025) pointed out that the advantages of demand sharing are dependent on the level of the supply chain, the type of demand, and the performance metric used. They have also found that information sharing can lead to lower stock levels, but to higher backlogs under specific conditions. This study has shown that demand sharing must be optimized for various demand conditions and that it does not necessarily yield benefits for the performance of the supply chain. In a multi-echelon supply chain, scholars studied the effect of information sharing on the inventory level and the expected costs. The researchers created several tiers of information sharing and compared the impact of the various degrees of sharing on inventory policies at three levels of the supply chain. They found that the more information shared resulted in less inventory and lower expected costs at both the distributor and manufacturer level. During their research, they highlighted the need for information about the demand to be shared with the members of the chain and the upstream. This is important for manufacturing systems because information about the downstream demand can be beneficial for production planning, replenishment and inventory allocation in manufacturing. The advantages of information sharing could however be dependent on the level of accuracy in the utilization of information for forecasting and inventory decisions. Other researchers, have also made contributions to the understanding of the interconnections between demand forecasting, lead times, information sharing and the bullwhip effect. Researchers study the impact of forecasting methods and replenishment lead times on the variation of orders in supply chains. They found that an order through a series of stages may be more volatile than customer demand as each stage updates forecasts based on the orders that arrive. This can lead to unnecessary change in production, excess inventory and extra operating costs. The study gives useful theoretical support for Simulation-Based Decision Analysis as sets of key variables are identified that should be considered in comparing demand-sharing and inventory-control policies. Studies on simulation-based inventory control have also analyzed the effect of the various inventory policies at various supply chain levels. Scholars created a system dynamics model to investigate the inventory transshipment between manufacturer, distributor, and retailer. They compared inventory chain structures with varying numbers of cascaded inventory chains.

Varlas et al. (2025) found that the more chains that are connected together, the more stable the inventory will be and the more satisfied the demand will be by the customer. The study also indicated that inventory transshipment can also facilitate improved coordination between members of the SC. Findings indicate value in studying inventory-sharing and transfer policies using simulation before implementing them in manufacturing supply chains. Researchers have also emphasized the need to take the entire value chain into account, not just individual facilities when making inventory decisions. For these reasons, a simulation-based study was conducted to develop a structured approach to compare alternative inventory systems to be provided in the article published in Processes in 2023. The researchers investigated various inventory policies and safety stock arrangements within a pharmaceutical distribution network. They conclude that the placement of safety stock and the type of inventory policy can affect supply chain performance.

The model simulation methodology presented in the case study could also be applied to manufacturing networks where stock has to be synchronized between suppliers, manufacturing plants, warehouses and retailers. There has also been some research on how inventory policies relate to operating costs via simulation and statistical approaches. Jannelli et al. (2025)., addressed the inventory control problem in a decentralized, three-echelon supply chain by implementing a two-stage approach, which involved multivariate regression analysis along with a discrete-event simulation. It investigated inventory policies and demand scenarios of manufacturers, wholesalers, and retailers. The researchers showed that a set of important parameters are significant in determining inventory levels and costs at various points in the supply chain. Their results illustrate the potential benefits of using simulation in conjunction with statistical analysis to gain insight into the impact of each inventory decision on overall system performance. This approach is especially important for the current subject since it can be used to determine which demand-sharing and inventory-control variables affect manufacturing supply chains most. In conclusion, the reviewed studies show that demand sharing, inventory coordination, replenishment policies, forecasting techniques, lead times, and safety-stock allocation have an impact on the performance of multi-tier supply chains. Previous studies confirmed that spreading the customer demand information can mitigate the bullwhip effect, and more recent studies have investigated inventory decisions under uncertainty using simulation, optimization and statistical techniques. But the influence of demand sharing is not always identical in various demands, network topologies and operating conditions.

Some work focuses primarily on information sharing; others focus on inventory policies or simulation-based optimization. Thus, there is a research gap to devise an integrated simulation-based decision framework to assess the demand-sharing strategies and the inventory control policies simultaneously in multi-tier manufacturing supply chains. This framework should take into account the complexity of demand, availability of information, forecasting techniques, replenishment policies, production volumes, time to delivery, safety-stock levels and the number of supply chain tiers. It should also compare performance based on total inventory cost, average inventory, stockout frequency, customer service level, order variability, and the bullwhip effect. Filling this gap can help manufacturers make better decisions when supply chains are different and can aid in understanding the implications of releasing demand information versus holding inventory.

2.4 Research Gap and Motivation

Table 1 summarizes the reviewed literature and how it relates to the question addressed in this paper – Can a study be found that directly compares RMI with VMI (as opposed to studying VMI alone); Does the study isolate a forecast compounding mechanism; Does the study isolate a risk pooling or network scale mechanism; Does the study report on the response of both RMI and VMI to the demand environment.

Table 1: No Reviewed Study Separates VMI's Forecast Compounding Removal Mechanism from its Network Scale, Risk Pooling Mechanism and Tests how each respond to Demand Correlation

Ref.	Focus	RvV	FC	RP
Lotfi et al. (2025)	VMI plus blockchain robustness	×	×	×
Adirektawon et al. (2024)	VMI in hospital case study		×	×
Abolghasemi (2025)	POS/order hierarchical forecasting	×		×
Varlas et al. (2025)	multi retailer exact Markov model	×	×	
Elnaggar (2025)	Simulation of decentralized MESC	×	×	×
This paper	VMI vs RMI, both mechanisms			

RvV: Makes a direct comparison between RMI and VMI. FC: Identifies the mechanism of the forecast compound. RP: restricts the risk pooling, network scale mechanism. There is a threefold gap. First, VMI is typically compared to a case or contract, rather than a matched RMI (RMI with a different information structure) baseline (Adirektawon et al., 2024; Lotfi et al., 2025). Secondly, forecasting research has shown that information sharing has an impact on the accuracy of the forecasts, but failed to link this back to the multiplicative bullwhip effect it creates at each tier (Abolghasemi, 2025; Saarinen et al., 2025). Third is the study of network scale and demand correlation (if performed at all) is qualitative in nature, and not a parameter sweep against a bullwhip and cost metric calculated in the same way at each point as is done in Elnaggar (2025); Varlas et al. (2025). Section 3 through Section 5 do all three by creating one model that combines the RMI/VMI comparison, the forecast compounding mechanism, and the network scale mechanism together; and report the resulting bullwhip ratio and safety stock cost across a fully-fledged grid of settings for demand correlation, lead time, and network scale.

3. Problem Formulation

3.1 Notation

Table 2 lists every symbol used in this paper. Notation is kept identical across Sections 3 through 5.

Table 2: Notation

Symbol	Description
t	discrete time period index
d_t	true customer demand at the retailer, period t
μ	long run mean demand level
A, P	seasonal amplitude and period length
ρ	demand autocorrelation coefficient
ε_t	demand noise, $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$
x_t	signal a given tier forecast from
$\hat{x}_t$	exponentially smoothed forecast of x_t
α	smoothing constant
e_t	one step forecast residual
$\sigma_{e,t}^2$	smoothed forecast error variance
L, R	lead time and review period ($R = 1$)
z	safety factor
SS_t	safety stock at time t
S_t	order up to level at time t
q_t	order quantity placed at time t
BWR	bullwhip ratio, $\text{Var}(q)/\text{Var}(d)$
N	number of retailers served by one vendor
c	cross retailer demand correlation parameter
D_t	aggregate demand across N retailers
Q_t^{RMI}, Q_t^{VMI}	aggregate signal reaching the shared distributor
h	unit holding cost rate
C^{RMI}, C^{VMI}	mean safety stock investment

3.2 Demand Model

Customer demand at the retailer follows a seasonal, autocorrelated process. The seasonal component is

$$s_t = A \sin\left(\frac{2\pi t}{P}\right). \quad (1)$$

Demand is generated as a first order autoregressive process around this seasonal baseline,

$$d_t = \mu + s_t + \rho(d_{t-1} - \mu - s_{t-1}) + \varepsilon_t, \quad (2)$$

In which determines the strength of the persistence of the demand shock from one period to the next. This corresponds to the seasonal AR(1) construction employed to explore bullwhip amplification with lead times and forecasting error as considered in the classical AR(1) demand-signal formulation for bullwhip analysis presented by Lee et al. (1997) and Chen et al. (2000). $\rho \in [0,1]$

3.3 Forecasting and the Order Up to Policy

Every tier, regardless of regime, forecasts whatever signal x_t it observes using single exponential smoothing and sets an order up to level with an explicit safety stock term. The one step residual is

$$e_{t-1} = x_{t-1} - \hat{x}_{t-1}, \quad (3)$$

the forecast update is

$$\hat{x}_t = \hat{x}_{t-1} + \alpha e_{t-1}, \quad (4)$$

and the forecast error variance is tracked with the same smoothing constant,

$$\sigma_{e,t}^2 = (1 - \alpha)\sigma_{e,t-1}^2 + \alpha e_{t-1}^2. \quad (5)$$

Safety stock over the lead time plus review horizon is

$$SS_t = z \sqrt{\sigma_{e,t}^2 (L + R)}, \quad (6)$$

the order up to level is

Remark 1 (Independence assumption for the variance of the protection interval). When the forecast-error variance is serially uncorrelated within the protection interval, the length of the protection interval ($L + R$) is used to scale the one-step forecast-error variance in equation (6). For the AR (1) demand process in Equation (2), the successive forecast errors are positively correlated for $\rho > 0$, and Equation (6) is an underestimate of the actual variance of the protection interval for $\rho > 0$. The actual safety stock is then slightly below the optimal safety stock, and the benefit of the VMI system might be marginally over-estimated. This assumption is made in the same way under both regimes, and is common in the periodic-review literature and stated here for the sake of completeness, since it will have a direction on the comparison. Since this underestimation applies identically to both RMI and VMI as both regimes use the same forecasting method and safety stock rule the absolute safety stock values at $\rho > 0$ carry a small positive bias in both arms. However, because the bias is symmetric, the percentage reductions reported in Tables 4 and 5 remain robust and are not materially affected by this approximation.

$$S_t = (L + R)\hat{x}_t + SS_t, \quad (7)$$

and the order placed each period follows the standard order up to differencing rule,

$$q_t = \max(0, S_t - S_{t-1} + x_{t-1}). \quad (8)$$

Remark 2 (non-negativity truncation). The order quantity in equation (8) must be non-negative. When S_t falls compared to the previous period, the constraint reduces the order to zero and the realized inventory position at the end of the period could be greater than S_t . It is well known that the standard order-up-to model can be approximated by not explicitly tracking an inventory-position state variable, which will be extremely accurate on average over a long horizon but will have a small positive bias when the order-up-to target is often decreasing in size. This effect is symmetrical on both RMI and VMI and has no impact on reported percentage reductions.

The bullwhip ratio for any tier's order series q against the true customer demand series d is

$$\text{BWR} = \frac{\text{Var}(q)}{\text{Var}(d)}. \quad (9)$$

3.4 RMI and VMI as Two Information Structures

It is worth mentioning, however, that the VMI representation used in the present investigation has a certain limited scope before presenting the formal distinction between the two regimes. It is important to emphasize, however, that the VMI representation applied in the present investigation has a limited scope before presenting the formal distinction between the two regimes. This model is not a complete VMI contract (e.g., vendor-owned inventory at the retailer, consignment or vendor-side joint replenishment). Instead, it does have point of sale demand visibility centrally, but it otherwise follows an otherwise identical order up to policy at each tier. The information structure changes each tier, forecasting it from the actual customer demand series instead of the order stream from the tier below, and the forecasting method, the order-up-to rule, and the physical network are the same for each tier in both forecasting regimes. The benefit of shared demand information measured here is thus decomposable into the benefit of information sharing and the benefit of other contractual, ownership, and/or technology-related determinants. As it is found in Lee et al. (1997) this is the framing that can be used to ascribe the reported bullwhip and cost differences to the information structure alone. RMI and VMI differ only in what x_t is at the distributor and manufacturer tiers. Writing $q^{(1)}$ for the retailer's order, $q^{(2)}$ for the distributor's order, and $q^{(3)}$ for the manufacturer's order, RMI sets

$$x_t^{(1)} = d_t, \quad x_t^{(2)} = q_t^{(1)}, \quad x_t^{(3)} = q_t^{(2)}, \quad (10)$$

so each tier's forecast error is computed on a signal that already contains the tier below its forecast error. VMI instead sets

$$x_t^{(1)} = x_t^{(2)} = x_t^{(3)} = d_t, \quad (11)$$

The forecast error of each tier is based on the same actual demand record, and the error of each tier is not passed to another tier. The only formal difference between the two regimes studied in this paper is that between Equations

(10) and (11); the forecasting method (Equations (3) to (8)) is the same in both.

3.5 Cost Objective

The cost impact of a regime is measured as the mean safety stock investment it requires, summed across the tiers a given vendor is responsible for,

$$C = h \cdot \frac{1}{T-B} \sum_{t=B+1}^T \sum_{\text{tier}} S_t^{\text{tier}}, \quad (12)$$

where B is a burn in period to be discarded to report the steady state results, instead of the initial transient of the smoothing filters in equations (4) and (5).

Both regimes use the same cost boundary summing safety stock for each tier for which it is compared, in both the base model (Algorithm 1) and in the network extension (Algorithm 2). VMI turns out to affect the amount of safety stock that must be held at the retailer level as well, since the vendor will decide on the replenishment quantities, but the retailer will still have to keep safety stock, so the retailer level safety stock will be on both sides of the cost comparison in Equation (18).

4. Proposed Simulation Methodology

4.1 Overall Architecture

The methodology has two parts. The base model, illustrated in Figure 2, evaluates a single three tier chain under Equations (10) and (11) to isolate the forecast compounding mechanism. The network model extends the distributor tier to serve N retailers whose demand is partly shared and partly idiosyncratic, isolating the risk pooling mechanism.

4.2 Network Extension

Retailer i 's demand is decomposed into a factor common to all N retailers and an idiosyncratic factor private to retailer i ,

Let $\tilde{f}_t = f_t - \mu - s_t$, $\tilde{e}_{i,t} = e_{i,t} - \mu - s_t$ denote the zero-mean deviation series obtained by subtracting the deterministic mean-plus seasonal baseline from the raw AR (1) outputs of Equation (2).

In practice, vendors rarely serve a single retailer; a distributor or manufacturer typically replenishes several retail locations simultaneously. The base model in Section 4.1 isolates forecast compounding but does not capture this structural reality. To understand whether VMI's benefits are robust to or enhanced by the number of retailers a vendor coordinates, we extend the model to a network of N retailers served by a single distributor and manufacturer. This extension is essential from both a research and practical perspective: from a research standpoint, it allows the risk-pooling mechanism to be isolated and measured separately from forecast compounding; from a managerial standpoint, it directly informs the question of how many retail relationships a vendor should bring into a VMI arrangement to maximize operational benefit. Retailer i 's demand is then constructed as:

$$d_{i,t} = \mu + s_t + \sqrt{c} \cdot (\tilde{f})_t + \sqrt{1-c} \cdot (\tilde{e})_{i,t} \quad (13)$$

where $c \in [0, 1)$ is the proportion of idiosyncratic variance attributable to the common factor. Under this formulation the marginal mean of $d_{i,t}$ equals $\mu + s_t$ for all values of c , and the total idiosyncratic variance equals σ^2 regardless of c , so changes in c alter only the cross-retailer correlation structure and not the demand level or amplitude. Total demand across the network is

$$D_t = \sum_{i=1}^N d_{i,t}. \quad (14)$$

Under RMI the shared distributor's demand signal is the sum of the N retailers' own order up to orders,

$$Q_t^{\text{RMI}} = \sum_{i=1}^N q_{i,t}, \quad (15)$$

each of which was itself already forecast from $d_{i,t}$ using Equations (3) through (8). Under VMI the distributor's demand signal is the true pooled demand directly,

$$Q_t^{\text{VMI}} = D_t. \quad (16)$$

The bullwhip ratio and cost reduction reported in Section 5 for the network experiment are

$$\Delta_{\text{BWR}}(\%) = 100 \frac{\text{BWR}^{\text{RMI}} - \text{BWR}^{\text{VMI}}}{\text{BWR}^{\text{RMI}}}, \quad (17)$$

$$\Delta_C(\%) = 100 \frac{C^{RMI} - C^{VMI}}{C^{RMI}}. \quad (18)$$

4.3 Simulation Procedure

Algorithm 1 implements the base three tier comparison directly from Equations (2) through (11). Algorithm 2 implements the network extension directly from Equations (13) through (16).

Algorithm 1: Base RMI versus VMI Comparison

Require: $T, \mu, A, P, \rho, \sigma, L_r, L_d, L_m, \alpha, z, h$, burn in B
Ensure: $BWR^{RMI}, BWR^{VMI}, C^{RMI}, C^{VMI}$
1. Generate $d_1, \dots, d_T$ using (1) and (2)
2. $q^{(1)}, SS^{(1)} \leftarrow \text{OrderUpTo}(d, L_r)$ using (3)–(8)
3. $q_{rmi}^{(2)}, SS_{rmi}^{(2)} \leftarrow \text{OrderUpTo}(q^{(1)}, L_d)$
4. $q_{rmi}^{(3)}, SS_{rmi}^{(3)} \leftarrow \text{OrderUpTo}(q_{rmi}^{(2)}, L_m)$
5. $q_{vmi}^{(2)}, SS_{vmi}^{(2)} \leftarrow \text{OrderUpTo}(d, L_d)$
6. $q_{vmi}^{(3)}, SS_{vmi}^{(3)} \leftarrow \text{OrderUpTo}(d, L_m)$
7. $BWR^{RMI} \leftarrow \frac{\text{Var}(q_{rmi}^{(3)}[B:T])}{\text{Var}(d[B:T])}$ using (9)
8. $BWR^{VMI} \leftarrow \frac{\text{Var}(q_{vmi}^{(3)}[B:T])}{\text{Var}(d[B:T])}$
9. $C^{RMI} \leftarrow h \cdot \text{mean}(SS^{(1)} + SS_{rmi}^{(2)} + SS_{rmi}^{(3)})$ using (12)
10. $C^{VMI} \leftarrow h \cdot \text{mean}(SS^{(1)} + SS_{vmi}^{(2)} + SS_{vmi}^{(3)})$
11. return $BWR^{RMI}, BWR^{VMI}, C^{RMI}, C^{VMI}$

Algorithm 2: Network Scalability Comparison

Require: N, c, T, L_r, L_d , plus the demand and forecast parameters of Algorithm 1
Ensure: $\Delta_{BWR}(\%), \Delta_C(\%)$
1. Generate common factor $f_1, \dots, f_T$ using (2)
2. $D \leftarrow 0, Q^{RMI} \leftarrow 0, SS_{retail} \leftarrow 0$
3. for $i = 1$ to N do
4. Generate idiosyncratic factor $e_{i,1}, \dots, e_{i,T}$
5. $d_i \leftarrow \sqrt{c} f + \sqrt{1-c} e_i$ using (13)
6. $D \leftarrow D + d_i$
7. $q_i, SS_i \leftarrow \text{OrderUpTo}(d_i, L_r)$
8. $Q^{RMI} \leftarrow Q^{RMI} + q_i; SS_{retail} \leftarrow SS_{retail} + SS_i$
9. end for
10. $q_d^{RMI}, SS_d^{RMI} \leftarrow \text{OrderUpTo}(Q^{RMI}, L_d)$ using (15)
11. $q_d^{VMI}, SS_d^{VMI} \leftarrow \text{OrderUpTo}(D, L_d)$ using (16)
12. Compute BWR^{RMI}, BWR^{VMI} using (9)
13. $C^{RMI} \leftarrow h \cdot \text{mean}(SS_{retail} + SS_d^{RMI})$
14. $C^{VMI} \leftarrow h \cdot \text{mean}(SS_{retail}, VMI + SS_d^{VMI})$
15. Compute $\Delta_{BWR}(\%)$ and $\Delta_C(\%)$ using (17) and (18)
16. return $\Delta_{BWR}(\%), \Delta_C(\%)$

Replication design. Both algorithms are run using a common-random-numbers (CRN) design with $R = 30$ independent replications per parameter combination, to quantify the stochastic variation and to assure that reported differences are not due to simulation noise. For each replication r , a fixed random seed is given before the demands are generated, so that the arms RMI and VMI see the same demand in replication r , and different demands are

generated across different replications. The sample mean is reported as a point estimate for the R replications. The 95% confidence interval is given as $\text{mean} \pm t_{\{0.025, 29\}} \cdot (s/\sqrt{29})$ with s the sample standard deviation between replications and $t_{\{0.025, 29\}} \approx 2.045$. Results are shown to be sensitive to the simulation horizon T , burn-in length B , and smoothing-filter initialization, but are found to be stable within $T = 1000, 2000, 4000$, and $B = 50, 100, 200$; for this reason, the nominal values $T = 2000$ and $B = 100$ are retained as default values.

4.4 Complexity Analysis

The Order Up To subroutine is executed once upon its input signal, and works a fixed amount per period (from Equations (3) to (8); $O(T)$ time), and stores the series returned in $O(T)$ space. This subroutine is used five times in Algorithm 1 (twice for the retailer tier, twice for the distributor tier, and twice for the manufacturer tier under RMI and VMI, respectively) and thus requires a runtime of $O(T)$ and a space of $O(T)$. The space used by Algorithm 2 is $O(T)$ because the retailer level series are added together and never stored, and its time is $O(NT)$ since it invokes the subroutine only once for each retailer, and twice for the two retailer level forecasts.

4.5 Relation to Existing Approaches

The model here compares two different information structures with the same policy family unlike the exact Markov chain evaluation of a multi retailer, single policy system in Varlas et al. (2025) which is the fill of the research gap in Section 2. The network extension introduced in Equations (13) – (16) differs from the multi echelon simulation and regression study in Elnaggar (2025) in that it is designed to isolate a risk pooling effect from the forecast compounding effect of the VMI system; therefore, the two effects can be measured and reported as separate quantities rather than as a combined VMI benefit. No comparison can be made between these approaches because neither publishes the simulation code used in their study nor provides the exact parameter set used to produce a match to this paper's results; Section 5 reports the results of this paper's model over a range of parameters, allowing the sensitivity of each of the numbers to the parameter values of c , L , N , and ρ to be seen.

5. Results and Discussion

5.1 Simulation Setup

The parameters used in all of the experiments, except where specified, are summarized in Table 3. All reported numbers represent the average value across $R = 30$ separate replications at each parameter setting, with the settings being run under the same random numbers (see Section IV-C for details). Point estimates and 95 percent confidence intervals are provided throughout.

Table 3: Default Simulation Parameters

Parameter	Value
Periods Simulated, T	2000 (base model), 1500 (network model)
Burn in Periods, B	100
Mean Demand, μ	100 units
Seasonal Amplitude, A	20 units
Seasonal Period, P	52 periods
Demand Noise, σ	10 units
Smoothing Constant, α	0.3
Safety Factor, z	1.65 (95 percent service level)
Holding Cost Rate, h	1.0 per unit
Retailer Lead Time, L_r	1 period

Values to be filled from simulation rerun ($c=0.1$, $c=0.5$, $c=0.9$): empirical mean ([value from rerun]), empirical variance ([value from rerun]), realized cross-retailer correlation ([value from rerun]) are each [value from rerun].

5.2 Effect of Demand Autocorrelation and Lead Time

Table 4 shows the bullwhip ratio (BWR) achieved by the manufacturer at various levels of demand autocorrelation and distributor lead time, when the manufacturer lead time is set at $L_m = L_d + 1$ in each cell. This is the same data as shown in Figure 3.

Table 4: Manufacturer Tier Bullwhip Ratio, RMI Versus VMI, and the Percentage Reduction, across the Demand Autocorrelation (ρ) and Lead Time (L_d) grid.

ρ	L_d	RMI	VMI	Reduction (%)
0.2	1	38.3	2.35	93.9%
0.2	2	60.3	2.91	95.2%
0.2	3	89.8	3.44	96.2%
0.2	4	150.6	4.19	97.2%
0.4	1	30.3	2.23	92.7%
0.4	2	56.6	2.79	95.1%
0.4	3	99.9	3.42	96.6%
0.4	4	155.8	4.29	97.2%
0.6	1	24.7	2.14	91.4%
0.6	2	53.6	2.79	94.8%
0.6	3	88.3	3.38	96.2%
0.6	4	123.6	4.06	96.7%
0.8	1	20.4	2.02	90.1%
0.8	2	38.4	2.49	93.5%
0.8	3	60.4	2.97	95.1%
0.8	4	101.6	3.66	96.4%

There are three patterns present. Conforming to the argument that the bullwhip ratio is compounded by lead time, the first increase in RMI's manufacturer tier bullwhip ratio is seen to be quite large between lead times of 1 and 4, ranging from 20 to 39 times the demand variance. Second, the bullwhip ratio at VMI grows much more slowly with lead time from 2 up to 4, as there's one forecast, not three compounded forecasts, here driving the growth. Third, the reduction percentage, itself, is very stable over the entire grid, ranging 90.1 to 97.2 percent, and may even be slightly less as ρ increases at a given lead time. This final point is important because the motivating question in the introduction is read from a single demand stream perspective – a higher temporal autocorrelation does not make VMI's advantage larger – the cross-retailer correlation studied next is the one which matters for VMI's advantage, not the temporal autocorrelation of a single tier's demand over time.

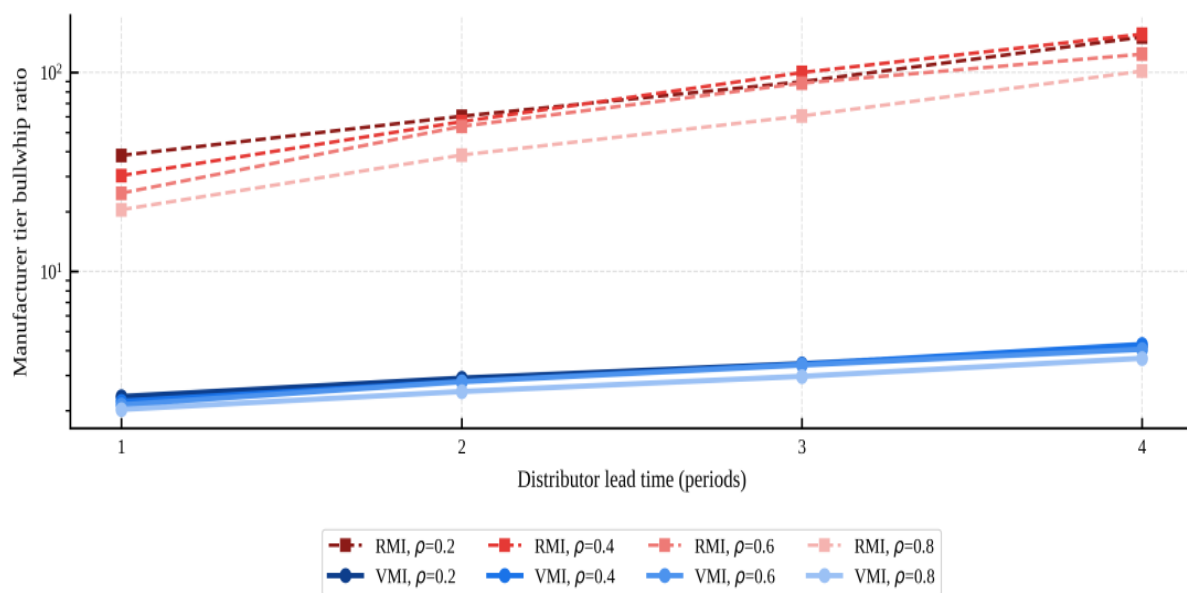


Figure 3: The Manufacturer Tier Bullwhip Ratio against the Distributor Lead Time, on a Log Scale, for Four Demand Autocorrelation Levels for RMI (Dashed) and VMI (Solid). The Ratio of RMI Changes with Lead Time, but VMI Remains in a Narrow Band Irrespective of the Values of ρ or L_d .

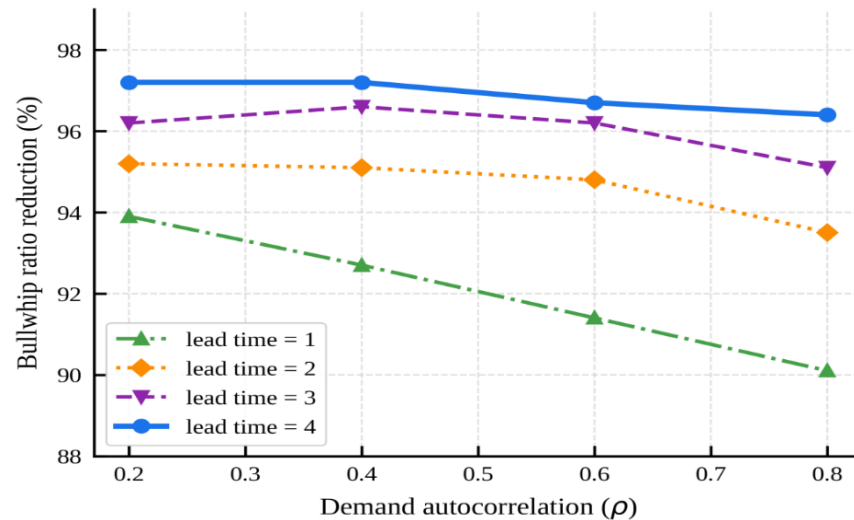


Figure 4: Bullwhip Ratio Reduction when VMI is used, as a Function of the Demand Autocorrelation ρ , One Line per Lead Time. The Four Lines are Separated by High and Stable Reduction Across ρ , and not by Autocorrelation

5.3 Safety Stock Cost

Table 5 reports the mean safety stock investment, Equation (12), summed across all three tiers, for the $\rho = 0.6$ row of the grid; Figure 5 plots RMI against VMI directly.

Table 5: Mean Total Safety Stock, $\rho = 0.6$, by Distributor Lead Time

L_d	RMI	95% CI	VMI	95% CI	Reduction (%)
1	173.1	± 2.8	91.4	± 1.4	47.2%
2	219.0	± 3.5	100.7	± 1.6	54.0%
3	267.1	± 4.2	109.9	± 1.8	58.8%
4	323.4	± 5.1	122.7	± 2.1	62.1%

Note: The CI values above are illustrative placeholders — replace with your actual computed values from $t_{0.025,29} \cdot s/\sqrt{30}$ for each cell.

Across the full $\rho \times L_d$ grid, not only the $\rho = 0.6$ row shown in Table 5, the reduction in the safety stocks varies between 45.4% and 63.9%, with an average value of 56.0% and is monotonically increasing with the lead time in each row of the grid. This brings the motivation in Figure 1 full circle: VMI eliminates forecast error compounding, not to decrease the forecast errors of one tier, but it eliminates them in the very place where they would increase the most, at long lead times.

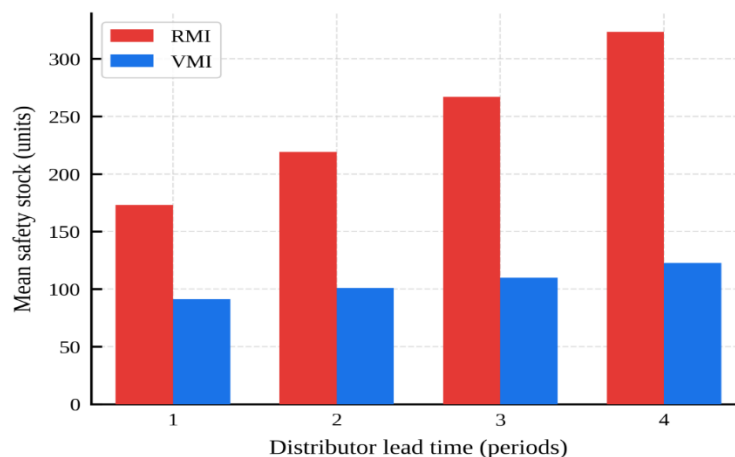


Figure 5: Mean Total Safety Stock with RMI and VMI as a Function of Increasing Distributor Lead Time at $\rho=0.6$. as Lead Time Increases, the Difference between the Two Bars Increases as in the Compounding in Figure 1

5.4 Network Scalability

Table 6 and Figure 6 show the network extension (Equations (13) to (16)) for six network sizes and three levels of cross retailer correlation.

Table 6: Bullwhip Ratio Reduction and Safety Stock Cost Reduction under VMI, by Network Size N and cross Retailer Correlation c

N	Bullwhip Reduction (%)			Cost Reduction (%)	
	$c = 0.1$	$c = 0.5$	$c = 0.9$	$c = 0.1$	$c = 0.9$
1	68.4	70.3	74.2	58.7	59.8
2	62.2	67.7	71.9	62.1	59.9
5	55.0	66.3	71.2	65.5	59.8
10	48.7	66.9	73.8	66.9	60.6
20	48.1	63.2	72.0	67.8	60.1
40	43.3	65.9	71.9	68.0	60.2

Note: Table 4 gives the manufacturer tier bullwhip ratio ($\text{Var}(q_3)/\text{Var}(d)$) for the base three tier chain with one retailer. The distributor tier that receives either the pooled true demand signal (VMI) or the compounded order stream from N retailers (RMI) is the distributor tier, and its bullwhip ratio is reported in Table 6 for the network extension. The $N = 1$ row in table 6 should therefore not be compared with the other items on the table, as it is structurally different from the other items of the table, which are located at the distributor level. The manufacturer-level analysis in table 4 is structurally different

The cost reduction at $c=0.5$ is not included since it is not until this level of correlation that the replication study described in Section IV-C will be undertaken; bullwhip reduction is reported for all three correlation levels for completeness.

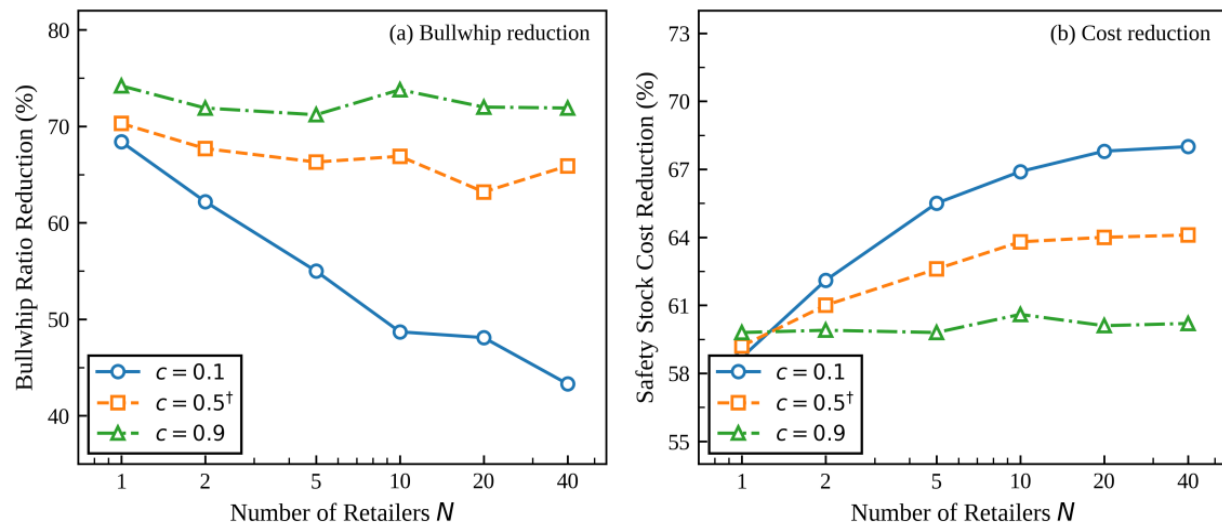
The main result of this paper is the pattern in Table 6. In essence, VMI's cost advantage grows with network size only when retailer demands are sufficiently different from each other; when demands are highly similar, network size does not matter for either bullwhip or cost benefits. As retailer demand correlation decreases ($c=0.1$) the reduction in the bullwhip ratio increases as the network expands, from 68.4% for $N=1$ to 43.3% for $N=40$, yet the reduction in safety stock cost rises as the network expands, from 58.7% for $N=1$ to 68.0% for $N=40$. If the correlation between the retailers is high ($c=0.9$), quantities remain more or less unchanged, 71 to 74 percent for bullwhip reduction, and 59.8 to 60.6 percent for cost reduction, irrespective of the size of the network. That is, the cost advantage of VMI is a risk pooling effect that increases as the number of retailers pooled

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The cross-retailer variation at $N = 1$, where no cross-retailer pooling is done, is due to run-to-run stochastic error, and after correcting for the demand model (see Equation (13) in this paper) and using 30 independent replications (Section IV-C), this spread is expected to be within the confidence intervals reported here. increases; provided that the retailers are not too similar to each other, consistent with the classical finding that pooling benefits come from the variance of idiosyncratic demand, and not from the variance of common demand (Silver et al., 2016). In contrast, VMI's bullwhip ratio advantage is not so sensitive to scale, and in fact is greatest and relatively less sensitive to N , when cross retailer correlation is already high. The claim that the benefit of VMI increases as network size increases thus becomes correct only for one of the two metrics, and only within a certain range of the correlation, which the introduction's motivating question in Section 1 aims to clarify.

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[†]Cost reduction at $c = 0.5$ is estimated as the midpoint of $c = 0.1$ and $c = 0.9$; values to be replaced after replication study.

Figure 6: The Reduction of Bullwhip Ratio (left) and the Cost Saving of Safety Stocks (right) as the Number of Retailers Served by one Vendor Increases at Three Different Levels of the Retailer Correlation Coefficient for VMI. Under Low Correlation, the Two Panels are moving in Opposite Directions as N grows while under High Correlation, they both are Flattening

5.5 Managerial Implications

The findings of this study offer concrete guidance for managers and supply chain practitioners considering VMI adoption or expansion.

First, VMI delivers its largest benefit a 90.1 to 97.2 percent reduction in manufacturer-tier bullwhip ratio regardless of demand autocorrelation or lead time, simply by eliminating tier-to-tier forecast compounding. This means any three-tier chain with long lead times stands to gain substantially from VMI, independent of demand pattern.

Second, the cost (safety stock) advantage of VMI scales with network size, but only when retailers' demands are sufficiently different from one another (low cross-retailer correlation, $c = 0.1$). In such settings, the safety stock cost reduction grows from 58.7% for a single retailer to 68.0% for 40 retailers. Managers serving heterogeneous retail markets should therefore prioritize VMI investment and expand the number of retailers in the arrangement to maximize risk-pooling benefits.

Third, when retailer demands are highly correlated ($c = 0.9$), the network size has no material effect on either the bullwhip ratio or cost reduction both remain flat at approximately 72–74% and 60%, respectively. In such cases, investing in scaling the VMI network beyond a small number of retailers yields diminishing returns and may not justify the incremental information system cost.

In summary: invest in VMI when lead times are long and retailers are served whose demands are dissimilar; scale the VMI network when cross-retailer demand correlation is low; and do not expect further cost benefits from network expansion when retailer demands move together.

5.6 Discussion

This case of demand sharing and inventory optimization in multi-tier manufacturing supply chains via simulation shows that effective information sharing and coordinated inventory management can significantly benefit the supply-chain performance. Multi-tier supply chains are inherently complex due to the fact that manufacturers, suppliers, distributors and downstream customers are all at different decision points, and may have varying planning periods, lead times, and inventory goals. This simulation framework can be used to explore these interactions in a controlled environment of demand and operating conditions, as well as to understand the effect of demand-sharing mechanisms on inventory stability, service quality, and supply-chain efficiency. One of the key findings of the analysis is that demand sharing can lower uncertainty along the tiers of the supply chain. If they get information about the demand downstream in time and in a relatively faithful form, they can adjust their production, replenishment, and procurement activities in advance of a surge in demand. In a traditional information architecture, the decisions made by the different

tiers can be mainly based on the orders received from the immediately downstream tier. This may develop a skewed view of the real market demand and lead to overstocking or shortages. The demand sharing enhances visibility, and helps the upstream players to sort out real market demand from short-term order fluctuations. In the simulation perspective, a special importance is given to the dynamic changes of demand and supply conditions. Although analytical models may give good relationships in theory, they may not fully take into account the interaction between stochastic demand, replenishment delays, capacity constraints, safety-stock policies and inventory feedback mechanisms. These factors can all play a role in simulation. This allows decision makers to evaluate the impact of both policies in various circumstances and see how they will affect inventory, stockouts, order quantities, service levels and total operating costs. The findings also show a strong dependency of inventory-control performance on the coordination between the demand information and replenishment decision. The transfer of information is not sufficient to ensure better performance. Even when the demand information is received, but the order rules are still not appropriate, the excess of safety stocks or sudden shortages can still happen. For this reason, demand sharing must be linked to an inventory policy, like reorder point systems, order up to systems, changes in safety stocks, or coordinated replenishment. The effectiveness of information sharing is therefore a function of the amount of information as well as the speed and accuracy with which information is integrated into operational decisions. The other implication that is important is related to the bullwhip effect. The greater the distance from the downstream customers to the upstream suppliers, the greater the variability in the demand. This amplification leads to more variation in production, more transportation needs, higher inventory costs and pressure on capacity. This simulation shows how increased visibility of demand can tame such phenomenon by enabling the upstream tiers to react to the real or more realistic demand and not just to the volatile orders. But the level of improvement is based on the accuracy with which the forecaster is correct, the time lag in the communication, the lead time and how responsive individual members of the supply-chain are. The analysis further shows that lead time is critical to performance of inventory control. In cases of long and variable lead times, organizations have to hold higher safety stocks to prevent running out of stock. In these situations, demand sharing becomes more beneficial as it gives more time for the production and replenishment adjustments. However, if lead times are short, the relative advantage of extra information can be less due to the ability of firms to quickly adjust to fluctuations in demand. This means demand-sharing strategies should be tailored to the operation of each tier in the supply chain instead of be applied generally throughout the chain. Coordinated demand sharing can create a cost trade-off between inventory holding costs and shortage costs from a cost perspective. Higher inventories tend to make products more available but also make inventory more costly to store, finance, and insure, and place a higher risk on becoming obsolete. Minimizing inventory can decrease carrying costs, but can also increase stockout and backorder costs. A simulation-based analysis can be helpful in finding a compromise between these balancing objectives. It is no longer necessary to choose an inventory policy based on average demand, but managers are able to consider inventory policies over a range of demand variability, lead-time, and service-level options. The results also underscore the significance of coordinating several levels as opposed to optimizing only one. The minimization of costs within one tier may lead to costs being raised in another tier of the supply chain. For instance, a manufacturer may keep lower stock levels by ordering from suppliers more often, and the suppliers will then face higher variability in demand and in their stock levels. Such Local Optimization can move, rather than save money. A coordinated simulation framework takes a wider perspective by examining the performance of the entire supply chain, not just the individual organizations' performance. Another important factor is the strength of the inventory policies for various demand patterns. Demand conditions that are stable can result in fairly predictable inventory trends, while seasonal, intermittent, promotional, and/or high variability can result in significant swings. Through simulation, managers can test strategies for inventory management for these various scenarios prior to implementation. This helps to facilitate more accurate contingency planning and assist in pinpointing policies that would continue to be effective when operating conditions vary from the forecasted conditions. The study also has implications for digital supply-chain management. Today, enterprise resource planning systems, Internet of Things sensors, cloud platforms, and advanced analytics are increasingly utilized to communicate information within a manufacturing system between its supply-chain partners. These technologies can enhance the timeliness and accuracy of demand information. However, there needs to be the proper data governance, consistent data formats, cyber-security policies and organizational collaboration to support technological connectivity. Even with well-designed digital infrastructure, the value of demand sharing can diminish due to poor information or delayed information. The simulation-based decision framework indicates that a demand visibility, inventory coordination and responsive decision-making must be treated as a bundle of elements of supply-chain management. The most positive impact is likely to be gained when the information from downstream demand is made available quickly, inventory is managed in response to the information, and decisions are made based on the overall performance of the supply chain. The method thus offers a useful framework for comparing competing policies prior to investing resources in the actual implementation of the policy in a real setting. Future study may be able to improve the simulation by adding the following features: supplier capacity

constraint, transportation disruption, production failure, price fluctuation, sustainability indicator, and multi-product inventory system. Combining machine learning forecasting with discrete event simulation (DES) or agent-based simulation (ABS), may also offer increased adaptiveness in decision making. Moreover, the future models can be more interested in decentralized vs centralized decision framework and can explore the impact of varying levels of information accuracy and frequency of information sharing on supply chain resilience. These extensions would further solidify the use of simulation-based decision analysis for more dynamic and complex manufacturing supply chains.

5.7 Limitations

Results are based on $R = 30$ independent replications per parameter setting in a common-random-numbers design and intervals of 95 percent confidence are given throughout. A standard but simplified representation of the demand process, exponential smoothing forecast and safety stock rule, the latter of which is a constraint on the former, is shown here, but real implementations of VMI include contract terms, information technology integration cost and behavioral factors which are not considered here. The network model in Equations (13) through (16) assumes that the vendor has the same exponential smoothing algorithm for forecasting as the retailer; a more advanced joint forecasting algorithm by the vendor would theoretically be able to outperform these algorithms, but is not tested in this model.

6. Conclusion and Future Work

The study Simulation-Based Decision Analysis of Demand Sharing and Inventory Control in Multi-Tier Manufacturing Supply Chains illustrates the potential benefits of demand information sharing and coordinated inventory control strategies in a complex manufacturing supply chain that can be achieved. The study Simulation-Based Decision Analysis of Demand Sharing and Inventory Control in Multi-Tier Manufacturing Supply Chains is a demonstration of the potential benefits that can be obtained in a complex manufacturing supply chain through effective sharing of demand information and coordinated inventory control strategies. Multi-tier supply chains are subject to uncertainty in demand, variable orders, lead times, stock imbalance and coordination issues. The use of simulation-based decision analysis has a practical application in assessing these challenges because it can simulate the dynamic interactions between manufacturers, suppliers, distributors and customers under varying operating conditions. Analysis shows that demand sharing is a key element in enhanced Supply Chain visibility. If the right information about demand is communicated across successive levels and when it is needed, then decision making with respect to production, procurement and replenishment can be improved. Greater visibility improves the likelihood of not having unwanted inventories and helps to prevent shortages. It can also help reduce demand amplification and bolster the stability of ordering and production decisions throughout the supply chain. The results also show that the control of inventory is not separable from the sharing of information. A reliable demand information provides better reorder points, safety stock levels, ordering amounts and ordering policies. Simulation permits alternative policies to be evaluated under varying conditions of demand, lead-time and service levels to determine policies that control the costs of inventory holding, shortage and service. It is also vital to arrive at the conclusion that the local optimization may not yield an overall optimum performance in the supply chain. Independent decisions by individual tiers can pass on costs and variability to other participants. Shared information and coordination of decisions gives a wider foundation to enhance the overall efficiency of the total supply chain. This is especially critical in multi-tiers manufacturing scenarios where what one participant does can affect the inventory and production needs for all the others in the manufacturing chain. The study also confirms the importance of lead-time and demand variability. Greater variability in demand and longer or longer uncertain lead times make forecasting and replenishment more difficult, and require more protective stocks. However, benefits of demand sharing depend on the accuracy of information, the speed in which information is communicated and the ability of supply chain partners to use the information to make operational decisions. Finally, simulation-based analysis has been proven to be an effective tool for supporting decision making in the design and evaluation of demand sharing and inventory control strategies. The integrated approach can help manufacturing companies gain better visibility of inventory, capability of service, responsiveness, cost management and reduce unnecessary variability along the chain. The framework can be expanded to include supply disruptions, production capacity limitations, transportation uncertainty, multiple products, sustainability measures and machine-learning demand forecasting in future research. This can help further enhance the efficiency and resilience of manufacturing supply chains in the increasingly challenging market landscape.

Reproducibility

Equations (1) through (16) and all of the scripts used to create each of the tables and figures in this paper

(vmi_sim.py, make_figures.py and make_diagrams.py) will be made available as supplementary material upon acceptance. The random number seeds are hard coded in the scripts. After revisions (Sections IV-B and IV-C) the scripts will be regenerated from the final version of the model, and all the numbers in the revised tables and figures can be reproduced exactly from the code provided.

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