Analysis of Supply Chain Inventory Management Under Cash Flows Feedback

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Abstract

Past research in supply chain management has predominantly analyzed inventory and cash flows in isolation. While recent studies have sought to integrate these flows, they often rely on the stylized assumption of unconstrained liquidity. In reality, maintaining sufficient liquidity is a persistent challenge, necessitating a reliance on trade credit and highlighting the intrinsic interdependence of physical and financial cycles. This paper employs System Dynamics methodology to model inventory management under explicit cash flow feedback (CFF). Three scenario experiments are conducted to evaluate the impact of localized cash constraints under both stable and growth market conditions. The results demonstrate that downstream liquidity limitations force players to truncate orders based on available cash, significantly degrading demand fulfillment. Furthermore, under market growth conditions, the model reveals diminishing marginal returns on liquidity, identifying a critical threshold beyond which additional capital fails to enhance sales. These findings suggest that stakeholders must strategically balance service-level objectives with cumulative sales and liquidity management to optimize systemic supply chain performance.

Keywords: inventory management, cash flows feedback, CFF, diminishing returns

1 Introduction

In a supply chain, the stakeholders manage three flows: inventory, information, and cash flows to meet customer demand at each supply chain level promptly [14]. Traditionally, most problems in supply chains have been approached through a lens of inventory management, where the main focus of study has been reducing order variability or the bullwhip effect [16, 10, 2]. Another similar interesting phenomenon in supply chain cash flows is cash flow bullwhip, in which working capital variability increases as one moves upstream in the supply chain. Both of these effects are harmful for supply chain growth [19]. In real life, inventory flows are often disrupted due to a lack of capital availability [4]. Likewise, delayed inventory delivery is usually followed by delayed payments [8]. Thus, cash flows are affected by a disruption in inventory flows. Hence, both inventory and cash flows are interdependent, and further research is required to address the problems arising from this interdependence. Towards this, this research focuses on analysing the inventory management of the supply chain under cash flows feedback. The modeling is based on the system dynamics methodology.

Research suggests that cash flows are among the most important metrics for enhancing supply chain performance [12]. In the event of liquidity constraints, businesses begin seeking trade credit, which can boost cash flows. Trade credit has been introduced to alleviate the issues faced by cash-constrained buyers. In trade credit contracts, the buyer is allowed to purchase the product without any immediate cash requirements [5]. Additionally, a certain penalty has been fixed for delayed repayments. However, trade credit policies can also lead to suppliers' bankruptcy in the event of late or default payments. The variability in payments causes financial costs for firms, as it does for operational issues, a phenomenon called 'financial contagion' that propagates upstream in the supply chain [17]. The main cause behind financial contagion is constraints on the financial

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debt of the supply chain firms. These works highlight the importance of integrating cash flow constraints into decision-making about inventory ordering. Along the same lines, this research work is motivated to analyse supply chain performance under three cash constraints scenarios.

Another solution that solves issues arising from financial mismanagement is supply chain finance. Many firms, particularly those most at risk, have sought to extend trade credit from their suppliers to bolster their financing options. Supply chain finance (SCF) aims to enhance financial transactions between organizations by implementing solutions provided by financial institutions or technology firms [6, 7, 11, 15]. Although SCF is an essential method for reducing the burden of payables on buyers and improving suppliers' CF, it introduces additional complexity in transactions between buyers and suppliers. This paper omits consideration of SCF in the model and proceeds to develop a basic framework for a three-stage supply chain. The transactions between upstream and downstream entities occur on a single chain, with a single entity at each stage. The experiments are implemented across different cash-on-hand levels for the retailer, with the focus on meeting higher customer demand by achieving higher service levels or cumulative sales for the downstream player/retailer.

This paper aims to understand how a firm's ability to fulfill demand is strictly bound by its liquidity. Further, the paper addresses a critical gap in multi-tier supply chain modeling: the propagation of systemic inefficiencies caused by localized cash constraints. While most traditional inventory models analyze decision-making under the assumption of infinite liquidity and focus on the movement of products and services [3], this study recognizes that for many firms—particularly Small and Medium Enterprises (SMEs)—ordering decisions are not merely a function of demand forecasts but are strictly governed by available *Funds for Commitment* (FFC).

Motivation behind cash flows feedback

The motivation for this study stems from the fact that cash flow is one of the most important metrics for evaluating supply chain performance. However, it is often ignored in operational planning. As highlighted by [20], market growth can trigger liquidity crises because cash flows often lag sales. Furthermore, while trade credit (TC) is often used as a liquidity buffer [5, 1], the dynamic feedback between a firm's instantaneous cash position and its ordering behavior is rarely modeled. This research work incorporates *Cash Flow Feedback* (CFF) and investigates how localized financial bottlenecks translate into operational obstructions.

Figure 1 illustrates the Causal Loop Diagram (CLD) integrating the inventory and cash flow submodels. For a standalone supply chain system, downstream demand positively influences both sales rates and forecasted demand. Collectively, these drive the desired order rate. This operational requirement is regulated by current inventory levels, forming the balancing loop **B1** that governs order placement, subject to a material delay. Concurrently, the balancing loop **B2** represents the inventory-sales relationship: while a higher sales rate depletes inventory, sufficient inventory levels are necessary to maintain the sales rate. The cash flow submodel is linked via temporal delays in capital flow. Sales are realized as income only after an accounts receivable period (ARP), eventually increasing Cash on Hand (COH). Conversely, procurement creates obligations that are deferred by the accounts payable period (APP) before being realized as expenses, a process captured by the balancing loop **B3**. The net effect of these flows dictates the player's cash on hand (COH). Crucially, this model introduces Cash Flow Feedback (CFF) via reinforcing loop **R1**. This loop endogenizes liquidity's impact on procurement, with available COH serving as a constraint on the order rate, effectively coupling financial health with operational continuity. This CLD serves as the fundamental basis for stock-flow models of all the supply chain players (retailer, distributor, and manufacturer) considered in this study.

This research paper tests different cash levels across stable and growing-demand scenarios under liquidity-aware (CFF) inventory ordering. The levels of cash are constrained (or limited), unconstrained (or infinite), and constrained with trade credit support. Attempts have been made to determine the maximum cash level required to achieve maximum supply chain performance (service levels and cumulative sales), revealing diminishing marginal returns to liquidity. The phenomenon signals exactly when "throwing more money" at the cash constraint stage stops improving supply chain performance. Finally, this research shows that managers must find a careful balance: being too responsive to market changes can actually create chaos and high operational risks if the financial side of the supply chain is not ready to handle the volatility.

This paper is organized into several key sections that systematically analyze inventory management under cash flow feedback. The next section presents section 2 literature survey relevant to this study. This section is followed by section 3, which describes the system dynamics models, and concludes with simulation experiments in section 4. The experiments consist of three major scenarios followed by inferences at the end of each section. The research work finally describes broader conclusions, managerial implications to guide strategic decision-making across supply chain inventory and financial flows, and future directions in section 5, section 6, and section 7 respectively.

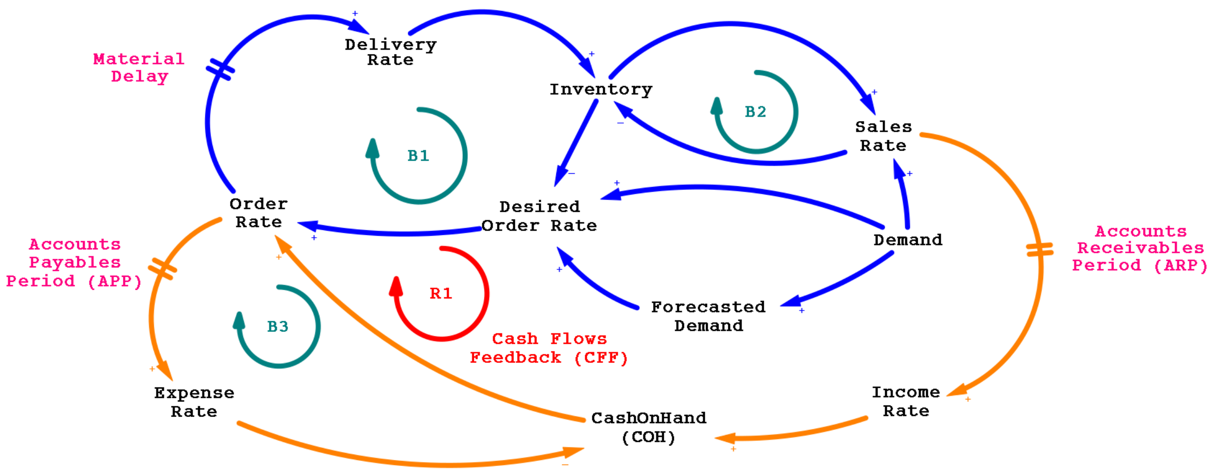


Figure 1: Causal Loop Diagram showing feedback utilization from cash flow submodel to the inventory submodel

2 Literature Survey

The integration of financial and physical flows in supply chain management has evolved from simple cost-minimization models to complex systems recognizing the interdependence of liquidity and operations. This section categorizes the relevant literature into three thematic areas: the interface between inventory and finance, the role of trade credit as a liquidity buffer, and the systemic propagation of financial risk.

2.1 The Inventory Finance Interface

Recent research has increasingly recognized that inventory decisions cannot be made without considering cash flows. For instance, authors in [13] consider two levels of trade credits by focusing on a standalone supply chain. The paper argues that a balanced trade credit term with both upstream and downstream entities can reduce the firm's costs. The paper also emphasizes the importance of collaboration between operations and finance departments through its results.

Another work by Kouvelis (2022) [9] shows that incorporating capital efficiency metrics (such as ROI) can improve supply chain efficiency (leading to increased retailer orders). The results show that buyers tend to be risk-averse and order conservatively, resulting in smaller inventory orders than under traditional profit-maximizing approaches. While these authors show why the interface matters, they often assume the "Buffer" (Trade Credit) is static or unlimited. This significant gap has been highlighted by [20], which shows that due to trade credit terms, cash flows often trail behind sales, meaning market growth can actually trigger liquidity crises for low-margin operations.

Recent empirical evidence by Zou (2025) has shown that market conditions affect trade credit practices [23]. As the market competition rises, SMEs highly rely on trade credit to expand their sales channels, and the scale of trade credit increases as competition in the market rises. On the other hand, when demand slows, the scale of trade credit increases, thereby extending trade credit terms. Empirically, trade credit risks increase whenever macroeconomic events occur. To study the optimal level of trade credit, the literature empirically examined trade credit and found that it follows an inverted U-shaped relationship with risk-adjusted returns (or sustainable profitability).

2.2 Trade Credit as a Liquidity Buffer

To mitigate the risks associated with the timing of cash flows, firms utilize Trade Credit (TC) as a primary financing tool. [5] highlights that TC offers superior flexibility compared to traditional bank loans, particularly in volatile interest rate environments where repayment flexibility saves both time and capital. In multi-level settings, [1] proves that while offering downstream TC can be a "win-win" for both suppliers and retailers by stimulating demand, it introduces stochastic default risks that must be carefully managed.

The choice of financing often depends on the firm's internal state; [21] models an inventory financing portfolio consisting of available cash, trade credit, and bank loans, noting that a firm's reliance on TC is inversely proportional to its internal cash reserves. While [22] shows that TC can significantly optimize costs in warehouse-retailer network designs, these models often assume a static environment, overlooking the dynamic feedback loops between a firm's instantaneous cash position and its ordering behavior.

2.3 Systemic Risk and Propagation

The interdependence created by trade credit leads to "financial contagion" across the supply chain. [17] discovered that payment variability is not only propagated but amplified as it moves upstream—a phenomenon analogous to the physical bullwhip effect. This payment variability amplification is primarily driven by constraints on the financial debt of supply chain firms.

Despite these advancements, a significant limitation persists in the literature: most studies do not explicitly model the feedback between a firm's specific $CashBalance$ and its subsequent $OrderRate$ under conditions of demand uncertainty and varying initial cash on hands.

Furthermore, the concept of "optimum initial cash level" and explicit limits on trade credit are largely absent from existing multi-tier models. This paper addresses these gaps by introducing a three-tier system dynamics model in which ordering decisions are strictly governed by Funds for Commitment (FFC), enabling a detailed analysis of supply chain performance at all stages. By simulating these dynamic constraints, this study provides a more realistic representation of how financial bottlenecks translate into operational obstruction.

3 System Description

This section introduces a multistage supply chain model that integrates inventory management with cash flow dynamics. The model structure comprises two primary submodels: the inventory and order management submodel and the cash flow submodel. Unlike traditional models, this framework captures the feedback loop where cash flow availability directly influences a player's ordering decisions, as illustrated in Figure 2.

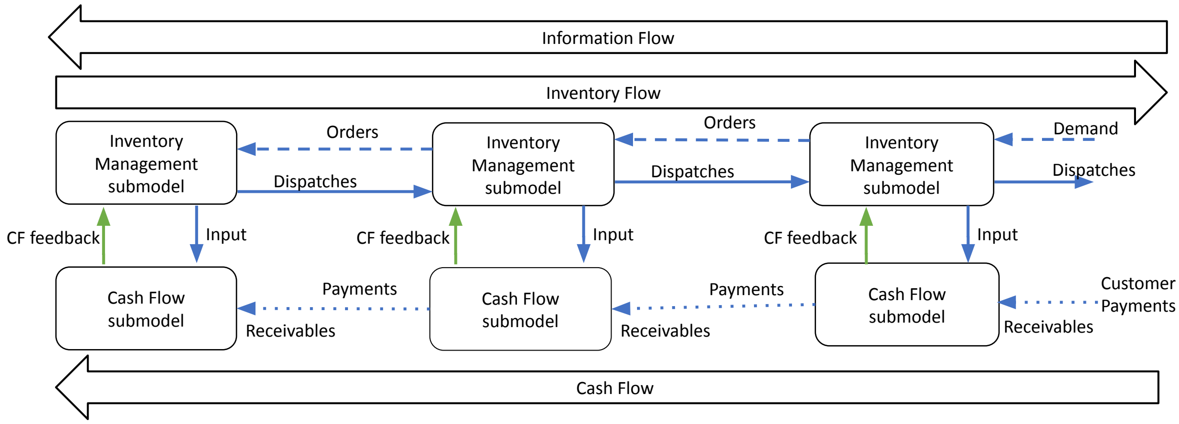


Figure 2: Proposed Supply Chain Model with Cash Flow Feedback

In this system, each player receives demand from their immediate downstream customer, which is fulfilled from available inventory. Unfilled demand results in lost sales. Based on these dispatches, the downstream player makes payments to the upstream player (receivables). These financial interactions, alongside physical stock-and-flow dynamics, are governed by the variables and parameters defined in Table 1.

Table 1 presents a list of notations used in the proposed models.

Table 1: Summary of notations used

Symbol	**Description**
Indices and Sets	
x	Supply chain player index, $x \in \{\mathrm{R}, \mathrm{D}, \mathrm{M}\}$ where R, D, M denote retailer, distributor, manufacturer respectively
t	Time step in the simulation horizon ($t = 1, 2, \ldots, T$)
Parameters	
d	Demand per time step
Decision Variables	
$InitialCOH$	Initial Cash On Hand
Performance Metrics	
SL	Service Level
$CumSales$	Cumulative Sales

3.1 Inventory and Order Management Submodel

The inventory and order management submodel of each SC player is similar to the classical ABVIOBPCS family of models [18]. Figure 3 presents the detailed System Dynamics stock-and-flow model of the inventory submodel for a single player. The underlying equations are presented in Equations (1)-(16). The submodel consists of five stocks: Inventory (Inv), Quantity in Transit (QIT), Cumulative Sales ($CumSales$), Cumulative Desired Shipment ($CumDesShip$), and Forecasted Demand (FD). The inventory stock is influenced by two flows: the Delivery Rate ($DELR$), which increases inventory, and the Sales Rate (SR), which decreases it, as depicted in Equation (1). Similarly, the Quantity in Transit stock is a supply line that's a function of the Dispatch Rate (DR), which increases it, and the Delivery Rate ($DELR$), which decreases it, as mentioned in Equation (2).

Demand (d), is the primary input to the system and it is equivalent to desired shipment ($DSHIP$), mentioned in Equation (3). This desired shipment drives the accumulation of the cumulative desired shipment stock, see Equation (18). Similarly, sales rate accumulates to Cumulative Sales, as shown in (17). Sales rate is limited by the inventory on hand, as mentioned in Equations (4). Maximum sales ($MAXSALES$) depends on the inventory level and the minimum order processing delay ($MINOPD$), denoted in Equation (5).

The Forecasted Demand (FD) stock is updated using an exponential smoothing method with a smoothing constant, ρ. This allows the system to adjust its future expectations based on the current demand (d). The Change in Forecasted Demand (CFD) flow updates this stock based on a comparison between the current demand and the existing FD stock, see Equation (6).

The SC players place orders to manage its stock levels. The Desired Order Rate ($DESOR$) is the sum of three components: the Forecasted Demand (FD), the Inventory Adjustment ($INVADJ$), and the Quantity in Transit Adjustment ($QITADJ$), see Equation (7). The order quantity (OQ) is then determined, ensuring it's a non-negative value, see Equation (8).

The Inventory Adjustment ($INVADJ$) and Quantity in Transit Adjustment ($QITADJ$) flows serve to correct deviations from desired stock levels. $INVADJ$ is calculated based on the difference between the Desired Inventory ($DESINV$) and the current Inventory (Inv), moderated by a fractional adjustment rate, β, see Equation (9). Similarly, the $QITADJ$ is calculated using current QIT, desired QIT, and fractional adjustment rate α, see Equation (10). The Desired Inventory is a function of the Forecasted Demand and an Inventory Coverage (IC) factor, see Equation (11). The Desired Quantity in Transit depends on the Forecasted Demand and the Lead Time (L), see Equation (12).

The Dispatch Rate (DR) represents the rate at which inventories are sold from an upstream player to a downstream player. Thus, the dispatch rate for the retailer (or distributor) is given by the sales rate of the distributor (or manufacturer), as mentioned in (13)-(15). This flow connects the current player to the upstream part of the supply chain. The delivery from upstream is subject to a material delay represented by the Lead Time (L) before it becomes the Delivery Rate ($DELR$) and adds to the inventory, see Equation (16).

Equations (17) and (18), denotes that cumulative sales and cumulative shipments are accumulation of sales rate and desired shipments respectively. The service level is calculated by the ratio of cumulative sales and cumulative desired shipments, as shown in Equation (19).

$$\text{Inventory:} \quad INV_t = INV_{t-1} + (DELR_{t-1} - SR_{t-1}), \tag{1}$$

$$\text{Quantity in Transit:} \quad QIT_t = QIT_{t-1} + (DR_{t-1} - DELR_{t-1}), \tag{2}$$

$$\text{Desired Shipment:} \quad DSHIP_t = d_t, \tag{3}$$

$$\text{Sales Rate:} \quad SR_t = \min(MAXSALES_t, DSHIP_t). \tag{4}$$

$$\text{Maximum Sales:} \quad MAXSALES_t = \frac{INV_t}{MINOPD}, \tag{5}$$

$$\text{Forecasted Demand:} \quad FD_t = FD_{t-1} + \rho \cdot (d_{t-1} - FD_{t-1}), \tag{6}$$

$$\text{Desired Order Rate:} \quad DESOR_t = FD_t + INVADJ_t + QITADJ_t, \tag{7}$$

$$\text{Order Quantity without Cash flow feedback:} \quad OQ_t = \max(DESOR_t, 0), \tag{8}$$

$$\text{Adjustment for Inventory:} \quad INVADJ_t = \beta \cdot (DESINV_t - INV_t), \tag{9}$$

$$\text{Adjustment for QIT:} \quad QITADJ_t = \alpha \cdot (DESQIT_t - QIT_t), \tag{10}$$

$$\text{Desired Inventory:} \quad DESINV_t = FD_t \cdot IC, \tag{11}$$

$$\text{Desired QIT:} \quad DESQIT_t = FD_t \cdot L, \tag{12}$$

$$\text{Dispatch Rate of retailer:} \quad DR_t^R = \max(SR_t^D, 0), \tag{13}$$

$$\text{Dispatch Rate of distributor:} \quad DR_t^D = \max(SR_t^M, 0), \tag{14}$$

$$\text{Dispatch Rate of manufacturer:} \quad DR_t^M = AOR_t^M, \tag{15}$$

$$\text{Delivery Rate:} \quad DELR_t^x = \frac{QIT_t^x}{L}, \tag{16}$$

$$\text{Cumulative Sales:} \quad CumSales = \int SR\, dt, \tag{17}$$

$$\text{Cumulative Desired Shipment:} \quad CumDesShip = \int DSHIP\, dt, \text{ and} \tag{18}$$

$$\text{Service Level:} \quad SL = \frac{CumSales}{CumDesShip}. \tag{19}$$

3.2 Cash Flow Submodel

Figure 4 presents the cash flow submodel for a single player. It comprises of three key stocks: Accounts Receivables (AR), Accounts Payables (AP) and cash on hand (COH). The Accounts Receivables stock represents the money owed to the company by its customers from past sales. This stock increases via the AR Inflow ($ARIN$), which is determined by the Sales Rate (SR) from the inventory submodel. The stock decreases when payments are received, which is modeled by the Cash Received (CR) flow. The flow of cash received is subject to a fixed delay defined as the Account Receivables Period (ARP). The underlying Equations are (20)-(22).

The Accounts Payables stock represents the money the company owes its upstream supplier for purchased inventory. This stock is filled by the AP Inflow ($APIN$), which is directly linked to the Dispatch Rate (DR)—the rate at which the company orders inventory from its supplier. The AP stock is lowered by the Cash Paid (CP) flow, which represents payments made to the supplier. This payment is subject to a fixed delay, known as the Accounts Payables Period (APP), as mentioned in Equations (23)-(25).

Cash on hand (COH) is basically the integration of the difference of income generated by the retailer with the expense rate, as shown in Equation (26). The paper proposes feedback from the cash flow submodel to the inventory flow submodel. Towards this, a new metric called funds for commitment (FFC) has been defined in Equation (27). Basically, FFC considers the amount of cash the company can commit to place inventory orders. FFC is equal to the sum of accounts receivables, and cash on hand, minus accounts payables. Further, the order quantity based on cash on hand ($OQCOH$) is calculated by dividing FFC with total cost per unit (c), as mentioned in Equation (28). Finally, the order quantity is decided based on desired order quantity via inventory flow ($DESOR$) and order quantity based on COH ($OQCOH$), as shown in (29).

$$\text{Accounts Receivables:} \quad AR_t = AR_{t-1} + ARIN_{t-1} - CR_{t-1}, \tag{20}$$

$$\text{Accounts Receivables Inflow:} \quad ARIN_t = SR_t \cdot p, \tag{21}$$

$$\text{Cash Received:} \quad CR_t = ARIN_{t-ARP}, \tag{22}$$

$$\text{Accounts Payables:} \quad AP_t = AP_{t-1} + APIN_{t-1} - CP_{t-1}, \tag{23}$$

$$\text{Accounts Payables Inflow:} \quad APIN_t = DR_t \cdot s, \tag{24}$$

$$\text{Cash Paid:} \quad CP_t = APIN_{t-APP}, \tag{25}$$

$$\text{Cash On Hand:} \quad COH_t = COH_{t-1} + \text{Income Rate}_{t-1} - \text{Expense Rate}_{t-1}, \tag{26}$$

$$\text{Funds For Commitment:} \quad FFC = COH + AR - AP, \tag{27}$$

$$\text{Order Quantity based on COH:} \quad OQCOH = \frac{FFC}{c}, \tag{28}$$

$$\text{Order Quantity with cash flow feedback:} \quad OQ_t = \min\{OQCOH_t, DESOR_t\}, \tag{29}$$

Each downstream player's APP in the SC is identical to its upstream player's ARP; as a result, the AP of every SC player is equivalent to the AR of its upstream player, implying $AP^R = AR^M, AP^D = AR^M$.

4 Simulation Experiments

The experimental framework in this paper is designed to investigate the relationship between financial liquidity and inventory replenishment decisions. Unlike traditional supply chain models that assume unconstrained capital, this paper explicitly models the "Cash Flow Feedback" (CFF) loop, where a player's ability to place orders is governed by their available Cash flow variables. By varying liquidity buffers at different supply chain levels and modeling market growth, this paper isolates the scenarios under which cash flow feedback either limits or improves supply chain performance.

All scenario experiments are based on the following **assumptions**:

- simulation run time is 366 days
- multi-player supply chain model
- the downstream demand is always non-negative
- ordering decisions are based on funds for commitment (FFC) utilizing CFF
- the experiments do not consider any profit margin which justifies no consideration of operational expenses
- if not mentioned about the initial COH, it takes a **standard** initial cash on hand which is sufficient to fulfill mean demand (sales price $*$ mean demand $=$ Rs10000)

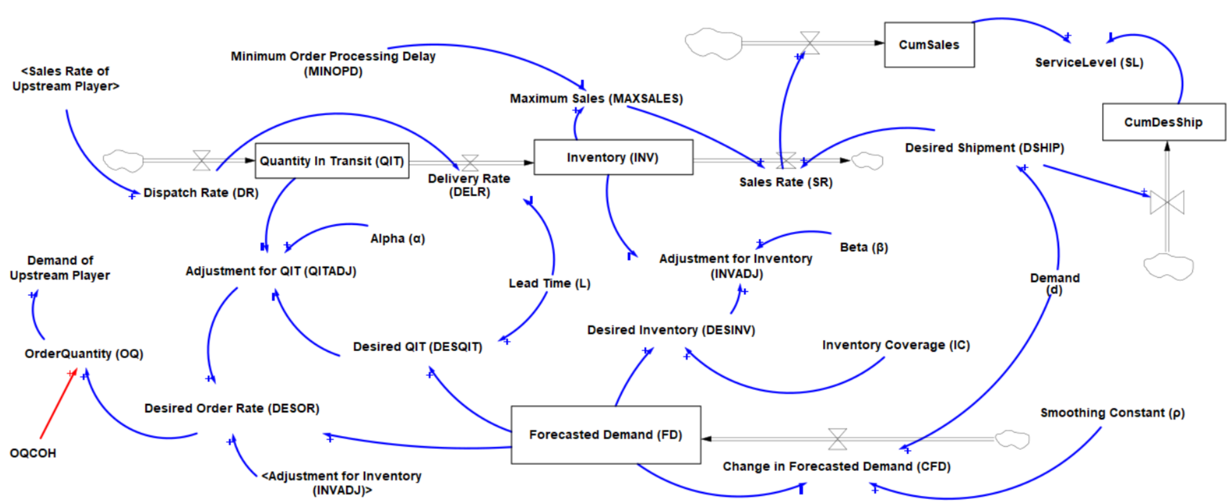


Figure 3: Inventory and Order Management Submodel for a Standalone Supply Chain

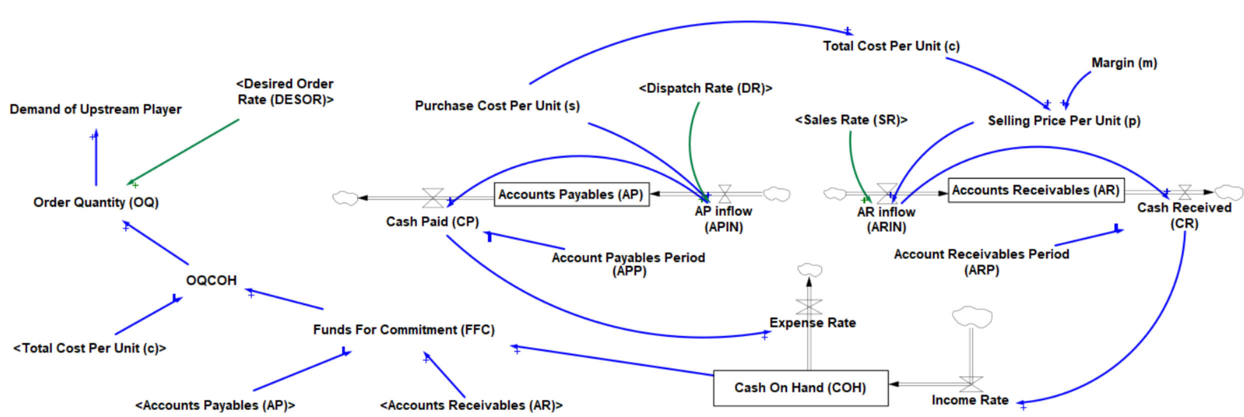


Figure 4: Cash Flow Submodel for a Standalone Supply Chain

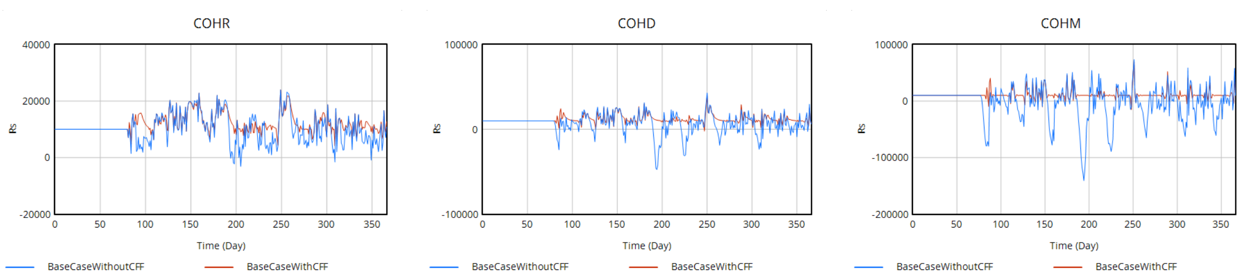
4.1 Scenario 1: BaseCase - A limited cash scenario

This case considers the supply chain experiments under which each supply chain player has limited cash availability. This scenario captures analysis under the standard level of cash; this cash is enough to meet the mean demand but not enough to withstand high-demand shocks. The configuration demonstrates the initial setup of the supply chain model under two scenarios: with and without cash flow feedback. The mean demand is 1000 units per day, and the randomness is introduced at time $t = 60$ days. The demand follows a truncated normal distribution from t onward, allowing only positive demands. The coefficient of variation of demand is 0.25. The scenarios without cash flow feedback (CFF) are shown as BaseCaseWithoutCFF, while BaseCaseWithCFF shows the scenario with CFF. With cash flow feedback, inventory ordering decisions are made based on the funds (or cash) that can be committed to the order. This metric is called funds for commitment (FFC), refer to Equation (27). The behaviour of cash on hand and order quantities is shown in Figure 5, and Figure 6 respectively. The service level at the final simulation time step is shown in Table 2. The scenario results are mentioned as follows:

- Cash on hand goes negative in when the CFF is turned off. Similarly, COH takes only positive values when CFF is enabled.
- The OQ variability is higher without CFF for all the echelons.
- Service level is higher for the retailer without CFF. However, it is lower for the distributor and the manufacturer without CFF than with CFF.

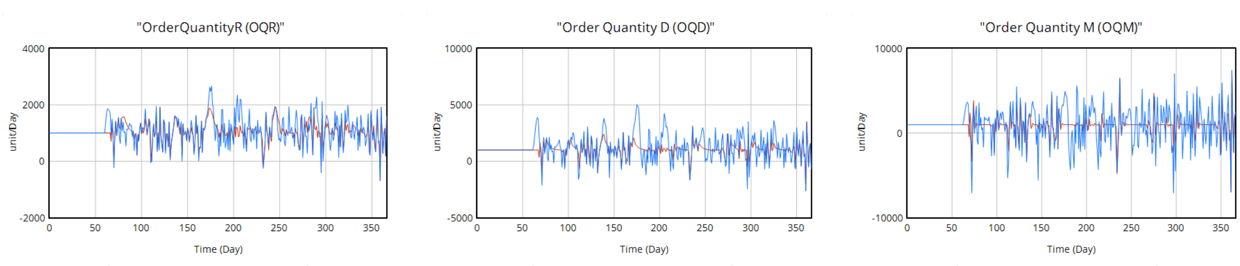
Inference

With cash flow feedback, cash constraints enter ordering decisions; as a result, the retailer is restricting orders, and upstream players can fulfill them. Thus, service level increases as we move upstream, with inventory decisions made under CFF conditions.



(a) Retailer (b) Distributor (c) Manufacturer

Figure 5: cash on hand levels across the supply chain tiers.



(a) Retailer (b) Distributor (c) Manufacturer

Figure 6: Order Quantity across the supply chain tiers.

Table 2: Final Service Level with and without CFF for BaseCase Experiments

Variable	**Time (Day 366)**
service level R: BaseCaseMeanWithoutCFF	0.93
service level R : BaseCaseMeanWithCFF	0.92
service level D: BaseCaseMeanWithoutCFF	0.87
service level D : BaseCaseMeanWithCFF	0.88
service level M: BaseCaseMeanWithoutCFF	0.78
service level M : BaseCaseMeanWithCFF	0.88

One can also view BaseCaseWithoutCFF as a scenario in which there are no cash flow constraints or unconstrained inventory ordering.

4.2 Scenario 2: Unconstrained Cash Flows for Upstream Players

Since the ordering decisions are based solely on the funds committed to that particular player, this case creates a local cash constraint for the retailer. It keeps upstream players, distributors, and manufacturers at unconstrained cash flows. If one focuses on retailers' ordering decisions and service levels, it is clear that cash constraints lead retailers to order less frequently. To determine what happens when the downstream player receives financial support from the upstream player in the form of trade credit (TC), this configuration has been tested. This scenario enables the upstream player-distributor to support liquidity shocks of retailers encountered during inventory ordering.

In addition to the scenarios mentioned in subsection 4.1, this configuration deals with two more scenarios:

- *UnconstUpstreamWithoutTC*: Apart from cash flows feedback, the upstream players have additional cash. The distributor is provided an initial cash of 1 lakh, and the manufacturer is provided an initial cash of 10 lakh.
- *UnconstUpstreamWithTC*. This scenario builds on the scenario mentioned above, where an additional trade credit equal to 10 percent of the distributor's initial COH is provided to support the retailer.

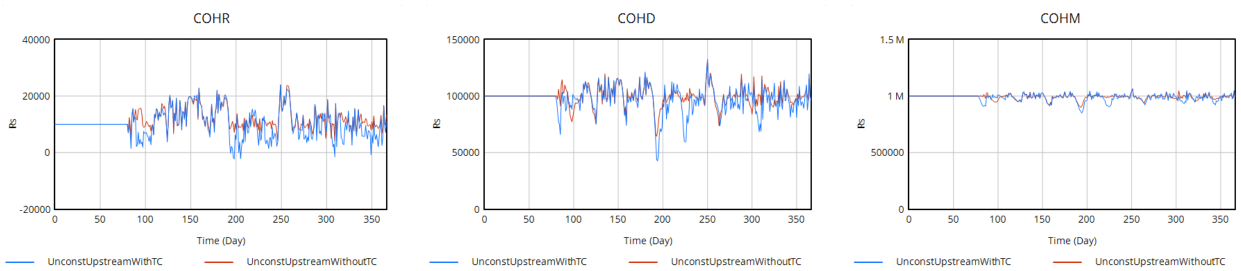
The behaviour of cash on hand, order quantity, and service levels is shown in Figure 7, Figure 8, and Table 3.

So far, there are four experiments: (i) BaseCaseWithoutCFF, (ii) BaseCaseWithCFF, (iii) UnconstUpstreamWithoutTC, and (iv) UnconstUpstreamWithTC. The following observations are drawn from the output of the experiments in this scenario:

- Cases (i) and (iv) are similar and have higher variability in the order quantities.
- For the retailer, cases (i) and (iv) are almost overlapping.
- The retailer's SL is almost the same for all the cases. Cases (iv) and (i) have a higher SL, and cases (ii) and (iii) have a lower SL for the retailer.
- On the contrary, SL for M is lower in cases (i) and (iv), higher in case (iii), and highest in case (ii).

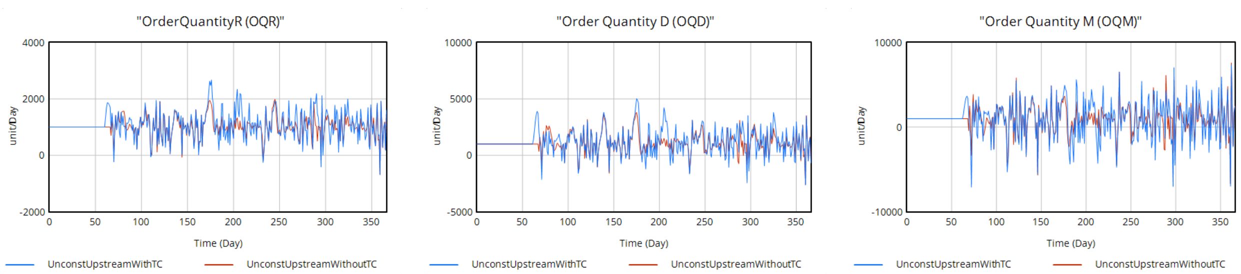
Table 3: Final Service Levels for Unconstrained CF for upstream players

Variable	**Time (Day 366)**
service level R : UnconstUpstreamWithTC	0.93
service level R: UnconstUpstreamWithoutTC	0.92
service level D : UnconstUpstreamWithTC	0.87
service level D: UnconstUpstreamWithoutTC	0.91
service level M : UnconstUpstreamWithTC	0.78
service level M: UnconstUpstreamWithoutTC	0.83



(a) Retailer (b) Distributor (c) Manufacturer

Figure 7: cash on hand levels across the supply chain tiers for unconstrained CF for upstream players



(a) Retailer (b) Distributor (c) Manufacturer

Figure 8: Order Quantity across the supply chain tiers for unconstrained CF for upstream players

Inference

With trade credit, the ordering process mimics that of an unconstrained scenario. Hence, trade credit helps improve inventory ordering, and, as a result, service levels of downstream players improve as well. However, the improvement is not much.

4.2.1 Cumulative Sales for SC performance measurement metric

As observed in previous cases, with CFF, the retailer's service level was low, while the manufacturer's was high. Without CFF (unconstrained CF scenario with TC), the retailer's service level is higher, but the manufacturer's is lower compared to with CFF. So, with CFF, the end customer demand was not fully met, even though the manufacturer's service level was high. This situation leads to confusion as to which player's service level should be high or low to achieve better supply chain performance. This observation also highlights the limitation of service levels as a supply chain metric. Hence, to fully analyze supply chain performance, cumulative sales can serve as the main metric. Cumulative sales are a good indicator of how much fraction of customers are ultimately satisfied with a supply chain player.

The value of cumulative sales is shown in Table 4. The table highlights that TC improves cumulative sales for all supply chain players (R, D, and M), unlike service levels, which showed a reverse trend in both the upstream and downstream supply chains.

Table 4: Final Cumulative Sales of Unconstrained Upstream CF Scenario

Variable	Time (Day 366)
CumSalesR : UnconstUpstreamWithTC	344,164
CumSalesR : UnconstUpstreamWithoutTC	339,215
CumSalesD : UnconstUpstreamWithTC	342,958
CumSalesD : UnconstUpstreamWithoutTC	338,009
CumSalesM : UnconstUpstreamWithTC	343,137
CumSalesM : UnconstUpstreamWithoutTC	338,003

4.3 Scenario 3: Market Growth

So far, the market mean demand has remained at a certain level (1000 units per day) throughout the simulation run. The initial cash-on-hand levels determine whether the retailer will match the unconstrained cash flow service level. The unconstrained cash flow service level also matches the service level with high trade credit when provided as initial cash on hand. So, it can be understood that when a retailer is provided with very large initial cash (InitialCOH >> the standard cash level of 10000, which can only procure the mean inventory level), the service level can be approximated to the service level obtained in the infinite initial COH case. Hence, the case with infinite COH has an initial COH = 1000000. However, this section explores one step further to analyse the scenarios with market growth. To address this challenge, this configuration answers the following questions:

- But, how much TC is required to match the retailer's infinite COH service level?
- Will the order quantity be able to cope with the market growth? How much financial support is required to match the unconstrained CF service level?

For market growth implementation, the mean demand is 1000 units per day until t=100, and it increases suddenly to 1500, and throughout the simulation run, the mean demand remains 1500. In this scenario, the experimental names and their corresponding settings are listed in Table 5. In Table 5, the sigma in the names of the scenarios denotes the standard deviation of demand, and the corresponding equivalent amount is added/subtracted to the initial COH_R before running the model. This standard deviation input is 500 per unit, and the corresponding amount required to fulfill this demand is Rs 5000. Hence, the initial COH of the retailer ($InitialCOHR$) has been varied in all experiments. The experiments were conducted to determine the service level that can be obtained at the infinite cash level, equivalently, at case (b).

Table 5: Experimental Scenarios: Initial COH Configuration for Growing Market Conditions

	Scenarios	**InitialCOHR**	**InitialCOHD**	**InitialCOHM**
a	DemGrowthCOHMeanDemand	10000	10000	10000
b	DemGrowthCOHInfiniteCash	1000000	1000000	1000000
c	DemGrowthCOHMean-1sigma	5000	1000000	1000000
d	DemGrowthCOHMean-2sigma	0	1000000	1000000
e	DemGrowthCOHMean+1sigma	15000	1000000	1000000
f	DemGrowthCOHMean+2sigma	20000	1000000	1000000
g	DemGrowthCOHMean+3sigma	25000	1000000	1000000
h	DemGrowthCOHMean+4sigma	30000	1000000	1000000
i	DemGrowthCOHMean+5sigma	35000	1000000	1000000
j	DemGrowthCOHMean+6sigma	40000	1000000	1000000
k	DemGrowthCOHMean+7sigma	45000	1000000	1000000
l	DemGrowthCOHMean+8sigma	50000	1000000	1000000
m	DemGrowthCOHMean+9sigma	55000	1000000	1000000
n	DemGrowthCOHMean+10sigma	60000	1000000	1000000
o	DemGrowthCOHMean+11sigma	65000	1000000	1000000
p	DemGrowthCOHMean+12sigma	70000	1000000	1000000
q	DemGrowthCOHMean+15sigma	85000	1000000	1000000

Observations

In a broader range, the service level and cumulative sales followed the trend observed in the previous configuration: more retailer cash levels help achieve higher service levels for the retailer, and lower service levels for the manufacturer, and vice versa. When different cash-on-hand levels were tested in this case, one can expect that as one increases the level of cash, cumulative sales will tend to approach the service level offered by an infinite service level (case b). However, this was not the case; cumulative sales increased until the initial cash on hand reached the level of the 12-sigma case (i.e., case *p*), and afterward it decreased slightly and saturated at the level of the infinite COH, i.e., case *b*, as shown in Figure 9.

Hence, analysis shows that, even though it is intuitive that the more cash, the more cumulative sales, which drive the service level, we have evidence that the highest cumulative sales can be achieved even at a lower value of Initial COH. After this COH value, the Cumulative Sales will likely decrease and saturate. These results illustrate the principle of diminishing marginal returns on liquidity. Similar to the relationship between inventory levels and Service Level (SL), there is a threshold beyond which increasing the initial cash buffer no longer yields a proportional increase in sales, as the system reaches its maximum throughput or market demand saturation, as shown in Figure 9. The figure shows that at the COH level of 70000, it has achieved the highest Cumulative sales, and in that case, the service level at the downstream SC level will also be the highest.

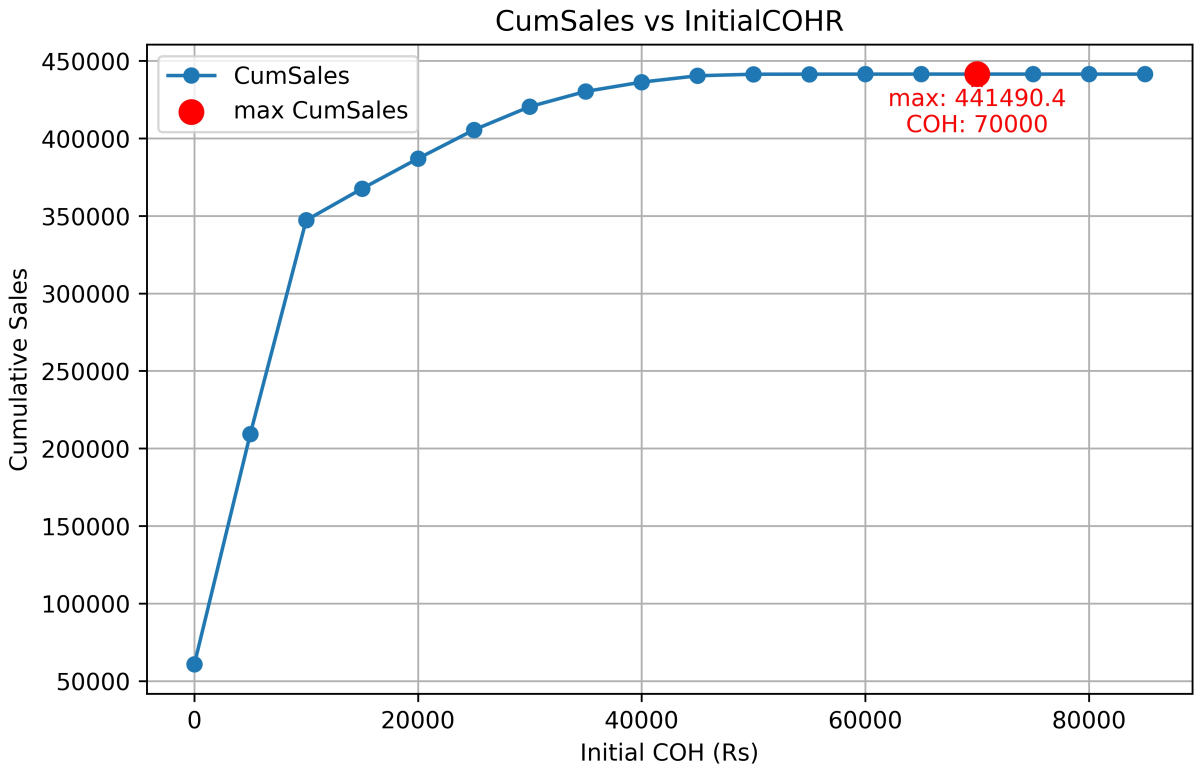


Figure 9: Cumulative Sales vs Initial COH

The results reflect a saturation effect, in which the marginal benefit of additional capital plateaus. It is comparable to increasing safety stock to improve service levels; after a certain point, the cost of holding more resources outweighs the negligible gains in customer fulfillment.

5 Conclusions

Based on the comprehensive experimental results across the various model iterations (scenario 1 through scenario 3), the following conclusions and managerial implications are drawn for this paper:

- **Cash Flow Feedback (CFF) and service levels:** While models without CFF exhibit higher-order quantity (OQ) variability across all tiers, the introduction of cash constraints via CFF restricts retailer ordering, paradoxically leading to higher service levels for upstream players (distributors and manufacturers) as they can more reliably fulfill restricted demand.
- **Impact of Upstream Support:** Financial support in the form of trade credit (TC) or unconstrained upstream liquidity mimics the unconstrained cash flow ordering scenario. While TC helps improve inventory ordering and marginally increases service levels, the benefits are limited.

- **Diminishing Returns on Liquidity:** Experimental evidence suggests a saturation effect regarding initial cash on hand. In growing market scenarios, cumulative sales and service levels increase with higher initial COH up to a specific threshold (approximately at the 12-sigma level/case p in scenario 3), after which gains plateau or slightly decrease. This indicates that excessive liquidity does not yield proportional benefits beyond the system's maximum throughput.

6 Managerial Implications

Based on the inferences and conclusions mentioned above, the following managerial implications are understood from this work:

- Balancing Service and sales: Decision-makers must carefully balance the pursuit of high service levels with the cumulative sales across supply chain stages. A higher service level at a particular stage does not necessarily indicate that the supply chain is doing well; it could result from liquidity constraints at the downstream level.
- Strategic Cash Flows Management: Managers should identify the liquidity threshold beyond which additional cash buffers provide negligible gains in customer fulfillment.

7 Future Research Direction

Future directions can expand on experimenting with more variants of demand patterns, particularly allowing negative demand and order cancellations. It will also be interesting to understand how frequently updating the demand fluctuations in the order rate affects service levels and cumulative sales. Another interesting thing to investigate is to understand the effect of these experiments on inventory order variability and cash flow bullwhip. These experiments also give a chance to analyse the supply chain's performance not just through the lens of inventory flow metrics but also through the lens of cash flow metrics. All these experiments can be implemented under the cash flows feedback-based decision-making condition.

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