

Data-Driven Inventory Financing: Linking Demand Forecasting, Stock Policies, and Cash Flow Management

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Abstract

Inventory is usually the largest current asset a trading or manufacturing firm must finance, yet the three disciplines that determine its size and cost are often run in isolation. Forecasters optimise accuracy metrics, operations teams set reorder rules, and treasury negotiates credit lines, with little explicit link between them. This paper develops a conceptual model that connects these layers in a single causal chain: forecast error determines safety stock, the stock policy determines average inventory, average inventory determines the financing requirement and borrowing capacity, and the cost of that financing feeds back into the holding cost that governs the stock policy. The approach is deliberately transparent. Every relationship is stated as a closed-form expression and illustrated with numerical examples that can be reproduced by hand or in a spreadsheet. Using a representative distributor, the examples show that halving forecast error releases about \$14,000 of working capital per stock-keeping unit, that higher 2023 interest rates raise total inventory cost by roughly 11 percent relative to a 3 percent borrowing environment, that the financing rate shifts the cost-optimal service level, and that forecast quality materially changes peak borrowing and covenant headroom in a 13-week cash flow forecast. The paper closes with managerial implications and propositions for empirical testing.

Keywords: inventory financing; demand forecasting; safety stock; economic order quantity; asset-based lending; borrowing base; cash conversion cycle; working capital management

DOI: <https://doi.org/10.21590/ijtmh.2023090306>

1. Introduction

For most product businesses, inventory sits at the intersection of operations and finance. Each unit on the shelf represents cash paid to a supplier that will not return until the unit is sold and the customer pays. When interest rates were close to zero for much of the decade before 2022, the financing component of inventory cost was small and frequently ignored in replenishment models. The rapid tightening of monetary policy in 2022 and 2023, which lifted short-term policy rates in the United States to their highest level in more than fifteen years, changed that calculus. Firms that had built buffer stocks during pandemic supply disruptions found themselves carrying expensive, debt-funded inventory just as demand normalised. Reviews of post-pandemic supply chains show how disruption-driven buffering shifted the balance between resilience and capital efficiency (Anene, 2021; Efobi et al., 2023). Simulation and operations research studies of the COVID-19 period quantified the ripple effects of such disruptions (Ivanov, 2020; Ivanov & Dolgui, 2021), building on a broader literature on supply chain risk (Tang, 2006) and on sector studies of resilience, risk dashboards and governance (Eze et al., 2023; Filani et al., 2022; Ogunwole et al., 2021).

At the same time, the data available to plan inventory has improved sharply. Point-of-sale feeds, promotional calendars, weather and macroeconomic indicators, and machine-learning forecasting methods allow many firms to forecast demand with noticeably smaller errors than traditional rules of thumb. The forecasting literature, including large open competitions such as M4 and M5, shows that method choice and the use of external drivers can reduce error substantially, although gains vary by product and horizon. Applied studies report similar gains from predictive analytics in supply chain, procurement and revenue forecasting settings (Aifuwa et al., 2020; Akin-Oluyomi et al., 2023; Tonoyan et al., 2021a).

What is less well articulated is how forecast improvements translate into financing outcomes. A forecast is not valuable in itself; it is valuable because it allows the firm to hold less safety stock for the same service level, to time purchases more closely to sales, and therefore to borrow less and pay less interest. Conversely, the terms of the firm's financing (its interest rate, the advance rate a lender applies to inventory, and the size of its credit facility) constrain which stock policies are feasible at all. Work on data-driven executive decision systems and financial planning analytics makes a similar argument at the enterprise level, calling for operational signals to be wired directly into financial plans (Lawal & Oduleye, 2019b, 2021b; Medon & Oduleye, 2023).

This paper addresses that gap with a conceptual model and transparent numerical examples. It makes three contributions. First, it formalises a three-layer model (forecasting, stock policy, financing) and specifies the variables that pass between the layers. Second, it quantifies each link with simple, reproducible calculations for a representative firm, so that practitioners can adapt the logic to their own data. Third, it identifies two feedback loops, from the cost of capital to the stock policy and from borrowing capacity to the plan, that are often missing from practice, and it states propositions that future empirical work can test.

The remainder of the paper is organised as follows. Section 2 synthesises the related literature. Section 3 describes the methodology. Section 4 presents the conceptual model and Section 5 the numerical illustrations. Section 6 discusses the results, Section 7 sets out their implications, Sections 8 and 9 address limitations and future research, and Section 10 concludes.

2. Literature Synthesis

2.1 Inventory theory and demand forecasting

Classical inventory theory supplies the building blocks of the stock-policy layer. The economic order quantity (EOQ) of Harris (1913) balances fixed ordering costs against holding costs, while Scarf (1960) established the optimality of (s, S) policies under stochastic demand with fixed ordering costs. Textbook treatments such as Silver, Pyke and Thomas (2017) show how safety stock is set as a multiple of the standard deviation of demand, or more precisely of forecast error, over the replenishment lead time. A point that is easy to overlook is that the relevant uncertainty is forecast error rather than raw demand variability: a firm that can predict seasonal or promotional swings does not need to buffer against them. Applied models in asset-intensive settings likewise show that inventory availability targets must be weighed against the cost of the stock that supports them (Okonkwo et al., 2018b), and data-driven lean approaches aim to remove buffers that better information makes unnecessary (Efobi et al., 2022b). Related procurement and supply chain studies stress that order and supplier decisions carry cost consequences well beyond the purchase price (Ike et al., 2022; Okonkwo et al., 2018a, 2021).

In these models the holding cost rate typically bundles together storage, insurance, shrinkage, obsolescence and the cost of capital. Because the cost of capital is often the largest single element, the holding cost rate is in effect a financial parameter disguised as an operational one. That observation is central to the model developed below.

The formal foundations reach back to the optimal inventory policy of Arrow et al. (1951) and are consolidated in standard references (Axsäter, 2015; Cachon & Terwiesch, 2009; Zipkin, 2000). Two refinements matter for this paper. First, when demand is forecast rather than known, safety stock should be based on forecast error, and estimating that error correctly is itself non-trivial (Graves, 1999; Prak et al., 2017; Trapero et al., 2019). Second, the cost of capital in inventory models has long been recognised as a financial parameter: Beranek (1967) examined the financial implications of lot sizing, and a large literature, including Teng (2002) and Gupta and Wang (2009), incorporates supplier payment delays into order quantity decisions.

Forecast quality also propagates along the supply chain. Distorted or poorly shared demand information amplifies order variability and inventory upstream, the bullwhip effect (Lee et al., 1997), and its size depends directly on the forecasting method and lead time (Chen et al., 2000), while sharing demand information can reduce inventory costs (Cachon & Fisher, 2000). Applied procurement studies make the same point about the upstream decisions that set ordering costs and lead times, including data-driven vendor evaluation (Ahiaeke Patrick et al., 2021), contract negotiation and vendor governance (Okonkwo et al., 2019), procurement automation (Akinleye & Adeyoyin, 2021), sustainable procurement practices (Efobi et al., 2022a) and supplier relationship management (Ike et al., 2021).

Hyndman and Athanasopoulos (2021) provide a comprehensive treatment of statistical forecasting methods, from naive and exponential smoothing models to regression with external drivers. Makridakis, Spiliotis and Assimakopoulos (2020) documented in the M4 competition that combinations and hybrid statistical and machine-learning methods tended to outperform single simple methods, and later competitions focused on retail sales extended this evidence to hierarchical, intermittent product data. Syntetos and Boylan (2005) showed that intermittent demand requires specialised estimators, a reminder that accuracy gains are product-specific. Recent applied work extends these ideas to machine-learning forecasts that feed directly into revenue projection and financial planning (Tonoyan et al., 2021a), to predictive budgeting driven by operational and market signals (Adesuyi et al., 2022), and to e-commerce procurement, where better accuracy reduces both stockouts and excess stock (Akin-Oluyomi et al., 2023). Aifuwa et al. (2020) link forecast accuracy explicitly to lower inventory management inefficiencies, which is the first link in the chain modelled here. Supply chain analytics frameworks built to raise forecast accuracy and reduce bottlenecks (Akin-Oluyomi &

Akhigbe, 2023c), integrated data management systems that improve financial forecasting (Agu et al., 2023) and predictive logistics models for volatile environments (Anene & Clement, 2022) point to the same conclusion: forecast quality depends as much on data integration as on the choice of algorithm. For the purposes of this paper, the key output of the forecasting layer is the distribution of forecast error, summarised by its standard deviation and its bias.

The methods compared in Section 5 have a long pedigree. Exponential smoothing originated in the work of Holt, republished as Holt (2004), and Winters (1960), was surveyed by Gardner (1985) and placed on a statistical state space footing by Hyndman et al. (2008), while Croston (1972) remains the reference point for intermittent items. Accuracy should be measured with scale-free metrics that behave well across items (Hyndman & Koehler, 2006). The supply chain forecasting literature documents a persistent gap between theory and practice (Syntetos et al., 2016), the value and risks of judgmental adjustments (Fildes & Goodwin, 2007; Fildes et al., 2009) and the specific challenges of retail (Fildes et al., 2022). Evidence on machine learning is nuanced: an early comparison found that simple statistical methods often matched or beat machine learning (Makridakis et al., 2018), whereas the M5 competition, built on hierarchical retail sales, was dominated by gradient-boosted tree methods (Makridakis et al., 2022), a family that includes the widely used XGBoost (Chen & Guestrin, 2016). Probabilistic deep learning models such as DeepAR (Salinas et al., 2020), applications in online retail (Ferreira et al., 2016) and supply chains (Carbonneau et al., 2008), and the encyclopaedic review by Petropoulos et al. (2022) complete the picture. Kesavan et al. (2010) further show that inventory and margin data themselves improve sales forecasts, which reinforces the two-way link between the forecasting and stock policy layers.

A newer stream integrates forecasting and decision-making, learning order quantities directly from data rather than from a separate forecast (Ban & Rudin, 2019; Bertsimas & Kallus, 2020; Huber et al., 2019). Research on big data analytics in operations, logistics and supply chain management (Choi et al., 2018; Waller & Fawcett, 2013; Wang et al., 2016) stresses that data quality is a precondition for these gains (Hazen et al., 2014). Predictive models developed for marketing, customer lifecycle and location decisions (Basnet et al., 2021; Ogundairo & Ayivi-Donkor, 2023; Oziri et al., 2020; Rukh et al., 2023; Seyi-Lande et al., 2020; Tonoyan et al., 2022a) and for operational reliability in e-commerce (Mayo et al., 2021) use the same toolkit and can supply leading indicators of demand.

2.2 Working capital, inventory and financing

In corporate finance, inventory enters through working capital management. Richards and Laughlin (1980) introduced the cash conversion cycle, which adds days inventory outstanding to days sales outstanding and subtracts days payables outstanding. Deloof (2003) and many subsequent studies link shorter cycles to higher profitability, and Hofmann and Kotzab (2010) extend the perspective to the supply chain as a whole. More recent predictive models apply analytics directly to cash flow and working capital, for example in retail cash flow forecasting (Tonoyan et al., 2021b) and corporate working capital optimisation (Oduleye & Medon, 2023a), while capital allocation models treat inventory as one of several competing uses of scarce funds (Lawal & Oduleye, 2021a). Predictive liquidity models in payment systems (Akomolafe et al., 2023), digital collections platforms that shorten receivable cycles (Osuji et al., 2021) and automated supplier payment systems (Akomolafe et al., 2022) address the receivable and payable sides of the same cycle.

A smaller operations-finance literature models inventory decisions and financing jointly. Buzacott and Zhang (2004) incorporated asset-based financing, in which borrowing capacity depends on the value of inventory and receivables, into production planning, and showed that financing constraints change optimal operating decisions. Dada and Hu (2008) and Kouvelis and Zhao (2012) analysed the newsvendor problem when the retailer must borrow to buy stock, and Chao, Chen and Wang (2008) studied dynamic inventory control under cash-flow constraints. Gaur and Seshadri (2005) considered hedging inventory risk with financial instruments. On the lender side, distributorship and trade finance products (Agboada et al., 2018) and fintech-enabled digital lending (Okafor et al., 2021) are widening access to inventory-linked credit for small and medium-sized firms in emerging markets, which makes the link between operational data and borrowing capacity increasingly practical. Data-driven risk evaluation models used by emerging-market financial institutions (Akomolafe & Agu, 2019b) and studies of small enterprises' access to finance (Michael & Ogunsola, 2019) suggest that the quality of operational information affects both the price and the availability of such credit. Banking and treasury studies in emerging markets add practical perspective on relationship banking, partnership ecosystems, finance policy scenarios, CFO-led strategic finance, product innovation and payment product design (Agboada et al., 2020; Akinola et al., 2020; Ezeako et al., 2019; Isiekwu et al., 2021; Olaogun et al., 2023; Oluwo et al., 2022).

A substantial empirical literature connects inventory to financial outcomes. Inventory turnover varies systematically with gross margin, capital intensity and sales surprise (Gaur et al., 2005), and United States firms reduced inventories substantially over recent decades, with abnormally high inventories associated with poor subsequent stock returns (Chen et al., 2005, 2007). Inventory productivity and abnormal inventory growth help predict future stock returns and earnings (Alan et al., 2014; Kesavan & Mani, 2013), and cross-industry evidence shows that drivers predicted by classical models, such as demand uncertainty and lead times, are visible in firm data (Rumyantsev & Netessine, 2007). Inventory leanness is generally associated with better financial performance (Capkun et al., 2009), but the relationship can turn negative beyond an optimal level (Eroglu & Hofer, 2011), and supply chain disruptions impose large and persistent losses on shareholders (Hendricks & Singhal, 2005).

On the finance side, working capital management affects profitability and value, with evidence for small and medium-sized firms (Baños-Caballero et al., 2012; García-Teruel & Martínez-Solano, 2007), for financially constrained firms (Baños-Caballero et al., 2014), across business cycles (Enqvist et al., 2014) and for shareholder value and investment (Aktas et al., 2015; Hill et al., 2010; Kieschnick et al., 2013). Macroeconomic research shows that inventory investment is highly sensitive to internal finance and credit conditions (Carpenter et al., 1994; Fazzari & Petersen, 1993; Kashyap et al., 1994), which is the aggregate counterpart of feedback loop B in this paper. Bank credit lines are a principal source of corporate liquidity, but their availability depends on borrower cash flow and covenant compliance (Sufi, 2009); credit line usage carries information about default risk (Norden & Weber, 2010); many firms borrow against cash flows rather than specific assets (Lian & Ma, 2021); and lending technologies for small firms range from relationship lending to asset-based lending (Berger & Udell, 2006). Trade credit offers a further channel for funding inventory (Petersen & Rajan, 1997).

2.3 Supply chain finance and the operations-finance interface

Supply chain finance research examines how financial flows can be optimised across firms. Reviews map its definitions and instruments (Gelsomino et al., 2016; Xu et al., 2018) and its adoption in practice (Caniato et al., 2016; Wuttke et al., 2013). The cash-to-cash cycle is the bridging metric between operations and finance (Farris & Hutchison, 2002; Randall & Farris, 2009), and cash flow risk in supply chains has been modelled explicitly (Tsai, 2008). Within operations research, Protopappa-Sieke and Seifert (2010) link inventory control directly to financial performance measures and later show the benefits of sharing working capital among

supply chain partners (Protopappa-Sieke & Seifert, 2017). Trade credit is reviewed by Seifert et al. (2013) and analysed as a tool for risk sharing and inventory financing (Chod, 2017; Yang & Birge, 2018), while buyer-intermediated and contract-based financing are studied by Tunca and Zhu (2018) and Kouvelis and Zhao (2016). Surveys of the operations-finance interface (Babich & Kouvelis, 2018; Birge, 2015; Zhao & Huchzermeier, 2015) and dynamic models linking dividends, capital and physical inventories (Li et al., 2013) confirm that joint optimisation can materially change operating decisions.

2.4 Governance and organisational capabilities

Because the model relies on data flowing between functions, it also depends on control, governance and process capability. Studies on technology-enabled and risk-based internal control and audit (Akomolafe & Agu, 2018, 2019a), financial resilience through integrated governance (Akomolafe & Agu, 2019c), reconciliation and financial workflow design (Dogbatsey et al., 2019), strategic accounting systems and financial reporting (Bola-Sadipe et al., 2019; Medon & Oduleye, 2022), tax and transfer pricing analytics (Lawal & Oduleye, 2018b, 2019a) and fraud and financial risk detection (Adelanwa et al., 2023b; Atakpa & Abetoh, 2022) describe the controls that make inventory and receivables data reliable enough to serve as lending collateral. Financial analytics models linking decisions to value creation, profitability and behaviour (Lawal & Oduleye, 2018a, 2023a, 2023b) and revenue assurance and key performance indicator frameworks (Sakyi et al., 2022b, 2023) provide the measurement layer, while customer service analytics (Sakyi et al., 2022a) and predictive, sustainable business models (Nnabueze et al., 2023) connect it to revenue.

Process improvement research describes the organisational capabilities needed to implement data-driven planning. Relevant contributions include Lean Six Sigma frameworks for small enterprises and manufacturing systems (Ambali et al., 2021; Ezeugwa et al., 2023), lean change management in small business digital transformation (Eyetsemitan et al., 2023), digital transformation and lean methods in pharmaceutical operations and distribution (Obukadata et al., 2021a, 2021b), data-driven lifecycle performance management (Adelanwa et al., 2023a) and supply chain talent and workforce models (Falemi et al., 2020, 2023).

Taken together, these streams establish each link of the chain separately but rarely connect them. Inventory models treat the cost of capital as a fixed input, forecasting studies stop at accuracy metrics, and the operations-finance literature, while analytically rich, is often difficult for practitioners to apply directly. The present study responds by offering a transparent,

spreadsheet-level synthesis that places forecasting explicitly at the start of the chain and follows its effects through to borrowing capacity.

3. Methodology

This study adopts a conceptual modelling design supported by transparent numerical illustration. The design suits problems in which the individual relationships between variables are well established but have not been assembled into an integrated decision framework. The aim is analytical clarity rather than statistical generalisation: the study shows, with reproducible arithmetic, how a change in one layer of the system propagates through the others.

The model was developed in four steps. First, the literature synthesised in Section 2 was used to identify the decision variables and performance measures in each of three layers (demand forecasting, stock policy, and financing and cash flow) and the variables that pass between them. Second, each link was expressed as a closed-form relationship drawn from established theory: the lead-time error and safety stock expressions of inventory theory, the economic order quantity, the weighted cost of capital, the borrowing base formula used in asset-based lending and the cash conversion cycle. Third, the holding cost was decomposed explicitly into physical and financial components so that financing terms enter the stock policy, which creates the feedback loops described in Section 4.4. Fourth, the model was exercised through five numerical examples.

The examples use a single representative item of a hypothetical distributor. Parameter values, listed in Table 1, were chosen to be realistic for 2023 conditions rather than estimated from a specific firm. The borrowing rate reflects a benchmark rate of about 5 percent plus a typical asset-based lending spread, the advance rate and physical holding rate lie within commonly used ranges, and the three forecast error levels represent a naive method, simple exponential smoothing and a driver-based model. Each example varies one element of the system while holding the others at the base case: forecast accuracy (Example 1), the borrowing rate (Example 2), the service level (Example 3) and forecast bias (Example 4). Example 5 moves to a week-by-week setting in which seasonal demand, supplier and customer payment terms and a revolving credit facility interact over a 13-week horizon.

All calculations were scripted and cross-checked by hand, and every figure can be reproduced in a spreadsheet from the equations in Section 4 and the steps in Appendix A. Internal consistency was checked in two ways. The service level identified by incremental comparison

in Example 3 was compared with the analytical optimum, and the reduction in peak borrowing in Example 5 was compared with the value of safety stock removed in Example 1. Both checks agreed, and remaining differences of one unit or one dollar arise only from rounding.

4. Conceptual Model

Figure 1 summarises the model. It has three layers connected by forward links and two feedback loops. The forward chain runs from the statistical properties of the forecast, through the stock policy, to the size, cost and fundability of the inventory investment. The feedback loops run from financing back to operations.

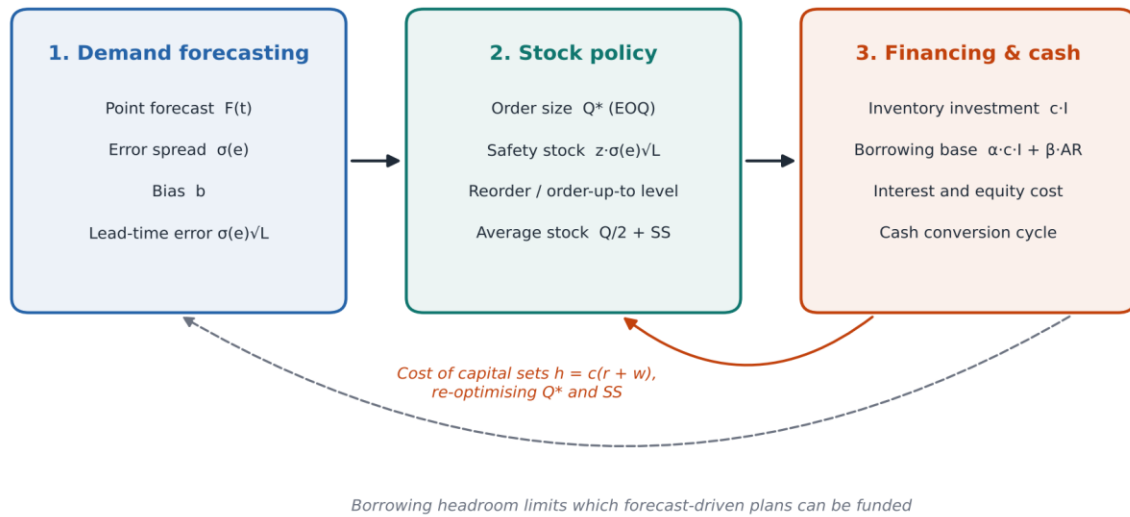


Figure 1. Conceptual model linking demand forecasting, stock policy and inventory financing.

4.1 Demand forecasting layer

Let $D(t)$ denote demand in period t and $F(t)$ the forecast made before that period. The forecast error is $e(t) = D(t) - F(t)$. Two statistics of the error distribution drive everything downstream: its standard deviation σe , which measures dispersion, and its mean b , which measures bias. If errors are approximately independent across periods, the standard deviation of error over a replenishment lead time of L periods is:

$$\sigma L = \sigma e \times \sqrt{L} \quad (1)$$

This is the quantity a firm must buffer against. It falls when the forecasting method improves, when lead times shorten, or both. Bias is equally important but behaves differently: a persistent over-forecast inflates order quantities directly, regardless of the safety stock setting.

4.2 Stock policy layer

For a continuous-review (s, Q) policy with annual demand D , fixed cost per order K , unit purchase cost c and annual holding cost per unit h , the order quantity and safety stock are:

$$Q^* = \sqrt{(2DK / h)} \quad (2)$$

$$SS = z \times \sigma L \quad (3)$$

where z is the standard normal value associated with the target cycle service level. The reorder point is expected lead-time demand plus SS , and average inventory is:

$$\bar{I} = Q^*/2 + SS \quad (4)$$

The crucial modelling step is to decompose the holding cost explicitly into a financial and a physical component. Let w be the physical holding rate (storage, insurance, shrinkage, obsolescence) and r the weighted cost of the capital funding inventory. Then:

$$h = c \times (r + w) \quad (5)$$

If a fraction α of inventory is funded by an asset-based loan at rate rb and the remainder by equity or internal funds with opportunity cost re , then:

$$r = \alpha \times rb + (1 - \alpha) \times re \quad (6)$$

4.3 Financing and cash flow layer

The inventory investment, the portion financed by debt and the resulting interest cost are:

$$\text{Inventory investment} = c \times \bar{I}; \quad \text{Loan} = \alpha \times c \times \bar{I}; \quad \text{Interest} = rb \times \alpha \times c \times \bar{I} \quad (7)$$

Asset-based lenders typically limit borrowing to a borrowing base, calculated by applying advance rates to eligible collateral. With advance rate α on inventory at cost and β on eligible receivables:

$$\text{Borrowing base} = \alpha \times (\text{inventory at cost}) + \beta \times (\text{eligible receivables}) \quad (8)$$

Availability, or headroom, is the lower of the borrowing base and the facility limit, minus the outstanding balance. At the firm level, the link to working capital is captured by the cash conversion cycle (CCC):

$$CCC = DIO + DSO - DPO, \quad \text{where } DIO = \bar{I} / (\text{annual COGS in units} / 365) \quad (9)$$

Finally, the total annual cost of the inventory system combines ordering, physical holding and financing costs:

$$TC = (D/Q) \times K + c \times \bar{I} \times w + c \times \bar{I} \times r \quad (10)$$

4.4 Feedback loops

Feedback loop A (cost of capital to stock policy). Because h contains r , any change in interest rates, advance rates or the firm's equity cost changes the optimal order quantity and, as shown in Section 5.3, the cost-optimal service level. Firms that hold their holding cost rate fixed in the planning system while rates move are running a mis-specified policy. This view is consistent with predictive cost optimisation and data-led cost governance models that treat cost parameters as live inputs rather than fixed assumptions (Adesuyi et al., 2023; Tonoyan et al., 2022c).

Feedback loop B (borrowing capacity to plan). A stock plan is only feasible if it can be funded. When projected borrowing approaches the facility limit or a covenant threshold, the plan must be adjusted, for example by delaying purchases, lowering safety stock on low-margin items or negotiating supplier terms. Better forecasts relax this constraint by lowering the inventory needed for a given service level.

5. Numerical Illustrations

The examples below use a single representative stock-keeping unit (SKU) of a hypothetical distributor. The parameters, listed in Table 1, are chosen to be realistic for 2023 conditions, when variable-rate asset-based loans were priced at a benchmark rate of roughly 5 percent plus a credit spread. All figures are computed directly from equations (1) to (10) and can be reproduced in a spreadsheet. This emphasis on spreadsheet-level transparency follows applied work showing that accessible tools such as Excel and Tableau can support rigorous profitability and procurement analysis (Akin-Oluyomi et al., 2020; Babatope et al., 2023), and it complements simulation-based approaches to financial impact assessment (Tonoyan et al., 2022b).

Table 1. Base-case parameters

Parameter	Symbol	Value
Annual demand (mean weekly demand 1,000 units)	D	52,000 units
Unit purchase cost	c	\$40.00
Unit selling price	p	\$60.00
Fixed cost per order	K	\$500

Parameter	Symbol	Value
Replenishment lead time	L	2 weeks
Target cycle service level (z value)	z	95% (1.645)
Inventory advance rate (debt share)	α	60%
Borrowing rate on asset-based loan	rb	9.0%
Opportunity cost of equity	re	14.0%
Weighted cost of capital, eq. (6)	r	11.0%
Physical holding rate	w	10.0%
Annual holding cost per unit, eq. (5)	h	\$8.40
Economic order quantity, eq. (2)	Q^*	2,488 (rounded to 2,490)

5.1 Example 1: Forecast accuracy and financing cost

Consider three forecasting approaches with progressively smaller weekly error: a naive method that repeats last week's sales ($\sigma_e = 300$ units), simple exponential smoothing ($\sigma_e = 220$) and a driver-based model using promotions, prices and calendar effects ($\sigma_e = 150$). These values are illustrative but within the range commonly reported when moving from naive to driver-based methods for fast-moving items. Holding the order quantity at 2,490 units and the service level at 95 percent, Table 2 traces each method through the full chain.

For the naive method, lead-time error is $300 \times \sqrt{2} = 424.3$ units, so safety stock is $1.645 \times 424.3 = 698$ units. Average inventory is $2,490/2 + 698 = 1,943$ units, an investment of \$77,717. At a 60 percent advance rate, \$46,630 is borrowed at 9 percent, costing \$4,197 a year in interest.

Table 2. Forecast accuracy traced through stock policy to financing (per SKU, annual)

Measure	Naive	Exp. smoothing	Driver-based
Weekly error std. dev. σ_e (units)	300	220	150
Safety stock SS (units)	698	512	349
Average inventory $\bar{I}$ (units)	1,943	1,757	1,594
Inventory investment $c \times \bar{I}$	\$77,717	\$70,272	\$63,758
Asset-based loan (60%)	\$46,630	\$42,163	\$38,255
Equity-funded inventory (40%)	\$31,087	\$28,109	\$25,503

Measure	Naive	Exp. smoothing	Driver-based
Interest on loan (9%)	\$4,197	\$3,795	\$3,443
Opportunity cost of equity (14%)	\$4,352	\$3,935	\$3,571
Physical holding cost (10%)	\$7,772	\$7,027	\$6,376
Ordering cost ($D/Q \times K$)	\$10,442	\$10,442	\$10,442
Total annual cost, eq. (10)	\$26,762	\$25,199	\$23,831
Days inventory outstanding	13.6	12.3	11.2
Cash conversion cycle (DSO 45, DPO 30)	28.6	27.3	26.2

Moving from the naive method to the driver-based model halves safety stock and releases \$13,958 of working capital, of which \$8,375 is a reduction in outstanding debt. Total annual cost falls by \$2,931, or about 11 percent. These figures are for one SKU; for a distributor with 500 comparable items, the same improvement would release roughly \$7 million of working capital and save about \$1.5 million a year. The release is a one-time cash benefit, while the cost saving recurs every year that the better forecast is maintained. Expressing operational improvements in these financial terms is central to cost management and financial analysis models that link operational change to enterprise performance (Oduleye & Medon, 2021, 2023b).

Figure 2 shows the underlying relationship. Cash tied up in safety stock is linear in forecast error, so each unit of reduction in σ_e is worth the same amount of capital: here $1.645 \times \sqrt{2} \times \$40 = \$93$ of working capital per unit of weekly error standard deviation.

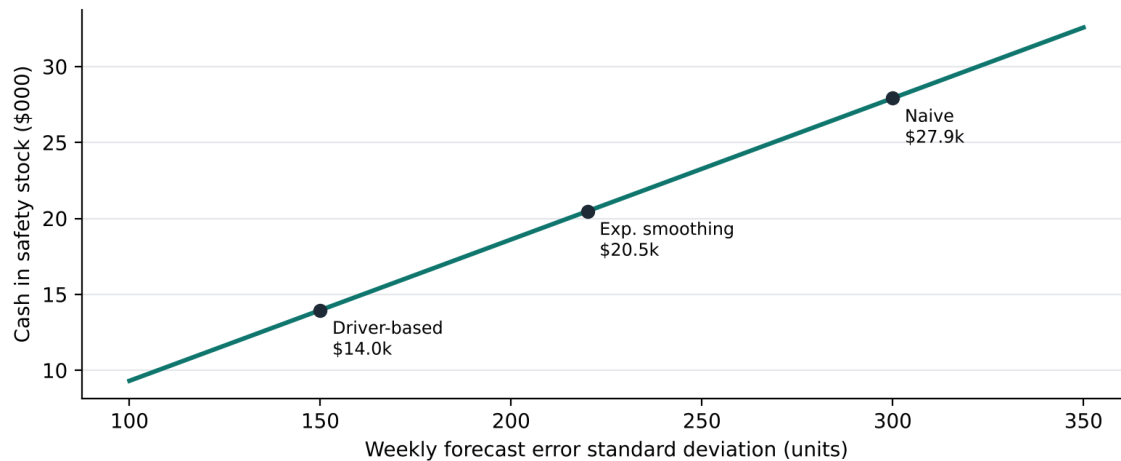


Figure 2. Cash invested in safety stock as a function of weekly forecast error (95% service level, $L = 2$ weeks, $c = \$40$).

5.2 Example 2: Interest rates and the stock policy

Feedback loop A can be quantified by varying the borrowing rate while holding everything else at the base case with the driver-based forecast (Table 3). As the borrowing rate rises from 3 percent, typical of 2021, to 9 percent, typical of 2023, the weighted cost of capital rises from 7.4 to 11.0 percent, the holding cost per unit rises from \$6.96 to \$8.40, and the EOQ falls from 2,730 to 2,490 units.

Table 3. Sensitivity of the stock policy to the borrowing rate (driver-based forecast)

Borrowing rate r_b	Weighted r	h per unit	Q^* (rounded)	Avg. inventory	Investment	Total cost
3%	7.4%	\$6.96	2,730	1,714	\$68,558	\$21,453
6%	9.2%	\$7.68	2,600	1,649	\$65,958	\$22,664
9% (base)	11.0%	\$8.40	2,490	1,594	\$63,758	\$23,831
12%	12.8%	\$9.12	2,390	1,544	\$61,758	\$24,960

Two lessons follow. First, higher rates raise total inventory cost by about \$2,400 per SKU (11 percent) even after re-optimisation, so the effect cannot be fully avoided. Second, re-optimisation still pays: it lowers the investment by about \$4,800 per SKU. A firm that kept the 2021 order quantity of 2,730 units in 2023 would pay slightly more than necessary and, more importantly, would hold capital it could have redeployed. The EOQ cost curve is flat near its minimum, so the cost penalty of a stale order quantity is modest, but the capital effect accumulates across thousands of SKUs.

5.3 Example 3: Financing cost and the service level

Service level targets are often set by policy (for example, "95 percent for all A items") rather than by economics. The model allows the target to be derived instead. Suppose a stockout results in a lost sale with lost gross margin of $\pi = \$20$ per unit. For an (s, Q) policy with lost sales, the cost-minimising probability of a stockout in a replenishment cycle is approximately $hQ / (\pi D)$ (Silver, Pyke and Thomas, 2017). With the base-case values this is $8.40 \times 2,490 / (20 \times 52,000) = 0.020$, implying an optimal cycle service level of about 98 percent.

Table 4 confirms this by comparing the incremental holding cost of each step up in service with the units of shortage avoided. Expected shortage per cycle is $\sigma L \times G(z)$, where $G(z)$ is the standard normal loss function, and there are $D/Q = 20.9$ cycles per year.

Table 4. Service level, safety stock investment and shortage (driver-based forecast, $\sigma L = 212$ units)

Cycle service level	z	Safety stock	Cash in SS	Annual holding cost of SS	Expected units short / yr	Fill rate
90.0%	1.282	272	\$10,874	\$2,284	210	99.60%
95.0%	1.645	349	\$13,957	\$2,931	93	99.82%
98.0%	2.054	436	\$17,427	\$3,660	33	99.94%
99.0%	2.326	493	\$19,740	\$4,145	15	99.97%
99.5%	2.576	546	\$21,857	\$4,590	7	99.99%

Moving from 95 to 98 percent costs \$729 a year in extra holding cost and avoids 60 lost units, a cost of \$12.15 per unit saved, well below the \$20 margin. Moving from 98 to 99 percent costs \$485 to save 18 units, or \$26.94 per unit, which exceeds the margin. The optimum therefore lies close to 98 percent, matching the analytical result. Because h contains the financing rate, the optimum also moves with credit conditions: at a 3 percent borrowing rate the stockout probability formula gives 1.8 percent, and at 12 percent it gives 2.1 percent. The effect is modest for this high-margin item but is considerably larger for low-margin, high-cost items, where financing charges represent a bigger share of the economics.

5.4 Example 4: The cost of forecast bias

Dispersion is not the only forecast property that matters. Suppose the forecast is systematically 8 percent too high, an over-forecast of 80 units per week. Under an order-up-to policy whose

target covers lead time plus one review period (three weeks), the target inventory position is inflated by $3 \times 80 = 240$ units. Until the bias is detected and corrected, the firm carries \$9,600 of unnecessary inventory, borrows an extra \$5,760 against it and incurs about \$2,016 a year in additional holding cost ($240 \times \$8.40$). The bias penalty is of the same order of magnitude as the benefit of moving from exponential smoothing to the driver-based model. This is why the model treats bias as a separate output of the forecasting layer, and why financial controllers have a direct interest in forecast bias metrics, not just accuracy metrics.

5.5 Example 5: A 13-week cash flow forecast with a borrowing base

The final example moves from steady-state averages to the week-by-week dynamics that treasury teams actually manage. A seasonal business unit sells the same product with a peak season in weeks 5 to 10, when weekly forecast demand rises from 1,000 to 1,800 units. Stock is managed with a weekly order-up-to policy: each week the firm orders enough to raise its inventory position to forecast demand over the next three weeks plus safety stock. Suppliers are paid two weeks after receipt; customers pay six weeks after sale. Operating expenses are \$17,000 per week. The firm keeps a minimum cash balance of \$20,000 and uses a \$175,000 revolving credit facility at 9 percent to fund any shortfall, repaying whenever cash exceeds the minimum. The borrowing base is 60 percent of inventory at cost plus 80 percent of receivables. Actual demand is assumed equal to the forecast so that the mechanics remain transparent; the safety stock reflects the forecast error the firm must plan for.

Following the scenario-based approach to financial modelling described by Filani et al. (2023), two scenarios are compared. In the first, the firm uses the naive forecast and carries 698 units of safety stock; in the second, it uses the driver-based forecast with 349 units. In each case the opening revolver balance is \$40,000 plus the value of safety stock, reflecting the assumption that buffer stock has been financed on the revolver. Table 5 shows the weekly detail for the naive scenario.

Table 5. 13-week cash flow and revolver, naive forecast scenario (SS = 698 units)

Week	Forecast (units)	Receipts (units)	Order placed	Ending stock	Collections	Supplier payments	Net cash flow	Revolver	Headroom
1	1,000	1,000	1,300	1,798	\$60,000	\$40,000	\$2,882	\$65,038	\$109,962
2	1,000	1,000	1,500	1,798	\$60,000	\$40,000	\$2,887	\$62,150	\$112,850
3	1,100	1,300	1,700	1,998	\$60,000	\$40,000	\$2,892	\$59,258	\$115,742
4	1,300	1,500	1,800	2,198	\$60,000	\$40,000	\$2,897	\$56,360	\$118,640
5	1,500	1,700	1,700	2,398	\$60,000	\$52,000	−\$9,098	\$65,458	\$109,542
6	1,700	1,800	1,500	2,498	\$60,000	\$60,000	−\$17,113	\$82,571	\$92,429
7	1,800	1,700	1,300	2,398	\$60,000	\$68,000	−\$25,143	\$107,714	\$67,286
8	1,700	1,500	1,100	2,198	\$60,000	\$72,000	−\$29,186	\$136,900	\$38,100
9	1,500	1,300	1,000	1,998	\$66,000	\$68,000	−\$19,237	\$156,137	\$18,863
10	1,300	1,100	1,000	1,798	\$78,000	\$60,000	\$730	\$155,408	\$19,592
11	1,100	1,000	1,000	1,698	\$90,000	\$52,000	\$20,731	\$134,677	\$40,323
12	1,000	1,000	1,000	1,698	\$102,000	\$44,000	\$40,767	\$93,910	\$81,090
13	1,000	1,000	1,000	1,698	\$108,000	\$40,000	\$50,837	\$43,072	\$131,928

Net cash flow equals collections less supplier payments, operating expenses and revolver interest. Headroom equals the lower of the borrowing base and the \$175,000 limit, less the revolver balance.

The pattern is the classic seasonal working capital squeeze. Purchases for the peak are paid in weeks 5 to 9, while the corresponding sales are not collected until weeks 11 to 16. Borrowing therefore peaks in week 9, after the sales peak, and only falls rapidly once collections catch up. In this example the borrowing base is generous because receivables are large, so the binding constraint is the facility limit rather than collateral. Supplier terms are therefore an important lever: negotiation and supplier relationship management can lengthen payment periods and lower ordering costs, easing the seasonal peak (Akinleye & Adeyoyin, 2022a, 2022b; Akokodaripon et al., 2023).

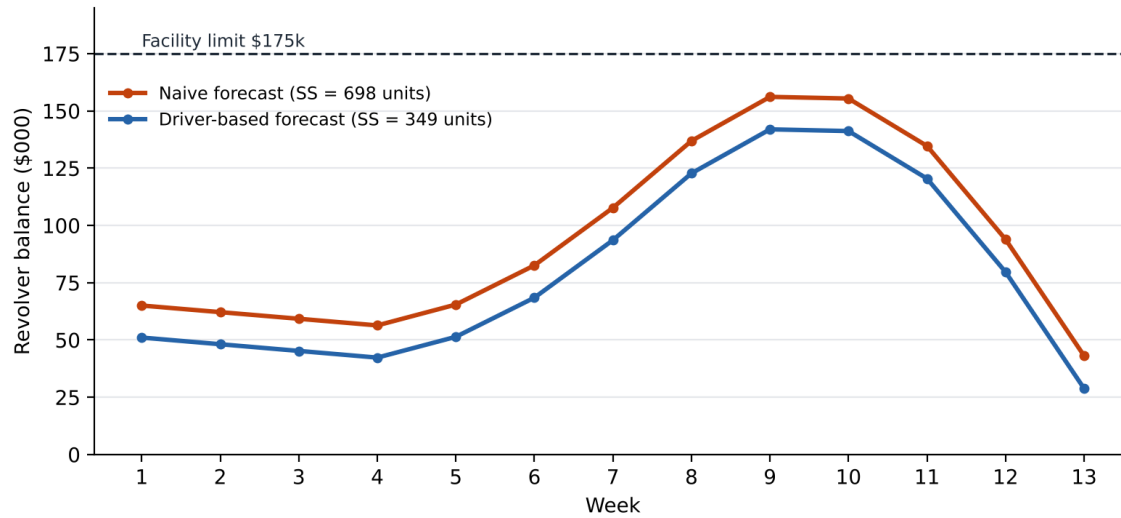


Figure 3. Weekly revolver balance under the two forecasting scenarios.

Table 6. Scenario comparison over the 13-week horizon

Measure	Naive (SS 698)	Driver-based (SS 349)	Difference
Opening revolver balance	\$67,920	\$53,960	−\$13,960
Peak revolver balance (week 9)	\$156,137	\$141,958	−\$14,179
Minimum headroom	\$18,863	\$33,042	+\$14,179
Minimum headroom as % of limit	10.8%	18.9%	+8.1 pts
Interest paid over 13 weeks	\$2,152	\$1,835	−\$317
Closing revolver balance	\$43,072	\$28,795	−\$14,277

The improved forecast reduces peak borrowing by about \$14,000, almost exactly the value of the safety stock removed. The interest saving over 13 weeks is small, but the change in headroom is strategically significant. Many asset-based facilities include a springing covenant that is tested only when availability falls below a threshold, often around 10 to 12.5 percent of the commitment. At a 12.5 percent threshold (\$21,875), the naive scenario would trigger covenant testing in weeks 9 and 10, while the driver-based scenario would not. Forecast quality thus affects not only the cost of financing but also the firm's flexibility and its exposure to lender control at the most demanding point of the year. This is feedback loop B in concrete form: a plan that looks acceptable in annual averages may be infeasible, or at least risky, at its weekly peak.

6. Discussion

Taken together, the examples show that the three layers are tightly coupled. Forecast dispersion maps linearly into capital through safety stock (Example 1). The cost of capital maps into order quantities and service levels through the holding cost (Examples 2 and 3). Forecast bias inflates stock independently of the safety stock setting (Example 4). And the interaction between seasonal buying, payment terms and forecast quality determines peak borrowing and covenant headroom (Example 5). None of these effects is visible if each function works only with its own metrics. Supply chain risk and resilience studies reach a parallel conclusion about the cost of functional silos (Agbabiaka et al., 2019; Awulu et al., 2022; Bello et al., 2023).

The results are consistent with prior evidence. The linear mapping from forecast error to capital mirrors the role of forecast error in safety stock calculation (Prak et al., 2017), and the sensitivity of the optimal order quantity to the financing rate echoes early work on the financial implications of lot sizing (Beranek, 1967). The seasonal borrowing pattern in Example 5 illustrates at firm level why inventory investment responds strongly to the availability of internal finance (Carpenter et al., 1994), and the importance of covenant headroom is consistent with evidence that access to credit lines depends on borrower performance (Sufi, 2009).

7. Implications

7.1 Managerial implications

Several managerial implications follow. First, forecast improvements should be reported alongside the working capital and interest they release, using conversions such as the \$93 of capital per unit of weekly error in Example 1; this gives finance a reason to invest in forecasting and gives forecasters a financial objective. Second, the holding cost rate should be decomposed into physical and financial components, with the financial component linked to the actual facility rate and equity cost and refreshed whenever rates change, at which point order quantities and service targets should be recalculated. Third, service levels should be derived from margin, cost and financing rate rather than set as blanket percentages, and differentiated by item. Fourth, cumulative forecast bias and the excess inventory value it implies should be monitored as a financial risk and included in treasury reporting. Firms should also recognise that environmental, social and governance criteria increasingly shape supplier selection and stock decisions, particularly for small firms in emerging economies (Akinleye, 2023), and may add constraints that the present cost model does not capture.

The results also argue for integrating the treasury cash forecast with the replenishment plan. When the 13-week cash forecast is driven by the same forecast and order-up-to logic that drives purchasing, projected headroom can be checked against covenant thresholds before seasonal buys are committed. Tiered treasury architectures that consolidate cash positions across entities make this integration easier to run at group level (Dada et al., 2021a). Better data can also strengthen the firm in lender negotiations. Asset-based lenders set advance rates partly on the liquidity and predictability of collateral, so demonstrably accurate forecasts and lower obsolescence can support higher advance rates or better pricing. Lenders increasingly use forecasting models in their own credit and sales decisions (Dada et al., 2021b), and quantitative asset valuation models (Tonoyan et al., 2023) can help both sides agree on the collateral value of inventory.

Implementation can proceed in stages. A firm first establishes a shared data foundation: clean sales history, forecast snapshots and actual lead times by item, with forecast error and bias measured consistently. End-to-end supply chain visibility and inventory visibility frameworks offer useful templates (Nnabueze et al., 2021; Okonkwo et al., 2023), and standardised reporting workflows (Alieme et al., 2022), big data and business intelligence capability (Akinleye et al., 2023) and a realistic assessment of analytics readiness, particularly in smaller firms (Alieme et al., 2023), are practical prerequisites. The stock policy parameters are then rebuilt on that foundation, replacing demand variability with forecast error in safety stock formulas and introducing the explicit holding cost decomposition. Next, the replenishment engine is linked to the treasury model so that projected purchases, receipts and payments flow automatically into the cash forecast and borrowing base calculation. Finally, the feedback loops are closed through a regular sales, inventory and finance review in which service targets and seasonal buys are approved jointly against financing headroom. Governance models that align logistics decisions with enterprise strategy across sites and retail networks provide a natural home for this review (Akin-Oluyomi & Akhigbe, 2022, 2023a, 2023b), and automated financial consolidation helps extend it across group entities (Bola-Sadipe et al., 2023). This final step closely mirrors sales and operations planning, whose value lies in cross-functional alignment between demand, supply and finance (Oliva & Watson, 2011; Thomé et al., 2012; Tuomikangas & Kaipia, 2014).

7.2 Theoretical implications

For theory, the study suggests that the holding cost parameter in inventory models should be treated as endogenous to financing conditions rather than as a fixed input, consistent with operations-finance research showing that financing constraints change optimal operating decisions (Birge, 2015; Buzacott & Zhang, 2004). It also positions forecast error, rather than demand variability, as the primary operational driver of the working capital tied up in inventory, linking the forecasting literature to empirical work on inventory and financial performance (Gaur et al., 2005; Kesavan et al., 2010). Finally, the week-level analysis shows that borrowing capacity can act as a binding constraint on stock policy at seasonal peaks, a firm-level mechanism consistent with macroeconomic evidence on credit conditions and inventory investment (Kashyap et al., 1994).

8. Limitations

This study has several limitations. The model assumes normally distributed and serially independent forecast errors, constant lead times, a single item, and linear holding and financing costs. Real systems feature lead-time variability, correlated errors across items, minimum order quantities, volume discounts, intermittent demand and non-linear financing terms such as unused-line fees and tiered pricing. The 13-week example assumes perfect forecasts within the horizon in order to isolate the mechanics. Each simplification can be relaxed with simulation, but at the cost of transparency. Environmental, social and governance considerations in supplier selection and stock decisions are also outside the scope of the model.

9. Future Research

Future research could proceed in two directions. Empirically, five propositions follow from the model. Holding other factors constant, firms with lower forecast error should hold less inventory relative to sales and have shorter cash conversion cycles (P1). Firms that update their holding cost rate in response to changes in borrowing costs should adjust inventory levels more quickly after interest rate shocks such as those of 2022 and 2023 (P2). Among borrowers under asset-based facilities, better forecast accuracy should be associated with higher minimum availability and fewer covenant events during seasonal peaks (P3). Persistent forecast bias should explain a meaningful share of excess and obsolete inventory write-downs beyond what forecast dispersion explains (P4). Finally, lenders should offer higher advance rates or lower spreads to borrowers that can demonstrate more accurate forecasts and lower obsolescence

(P5). These propositions could be examined with firm-level panel data combining financial statements, credit agreement terms and, where available, internal forecast records. Methodologically, the model could be extended to multiple items with correlated demand, stochastic lead times and non-linear financing terms, and embedded in a simulation or optimisation framework that retains the transparent structure developed here.

10. Conclusion

Inventory financing is not only a treasury problem. Its size and cost are set, upstream, by the quality of demand forecasts and the logic of stock policies, and its terms in turn shape which stock policies make economic sense. This paper has offered a conceptual model that makes these connections explicit and a set of transparent numerical examples that quantify them. For the representative firm studied, halving forecast error released about \$14,000 of working capital per item and cut annual inventory cost by 11 percent; higher interest rates raised that cost by a similar proportion and shifted the optimal order quantity and service level; forecast bias carried a cost comparable to a major accuracy improvement; and forecast quality determined whether seasonal borrowing breached a typical covenant threshold. In an environment of higher interest rates and richer data, treating forecasting, stock policy and financing as one integrated system is both feasible and valuable.

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Appendix A. Calculation Details

The following steps reproduce the driver-based column of Table 2 and can be laid out one per row in a spreadsheet.

Step	Calculation	Result
Weighted cost of capital	$0.60 \times 9\% + 0.40 \times 14\%$	11.0%
Holding cost per unit	$\$40 \times (11.0\% + 10.0\%)$	\$8.40
Economic order quantity	$\sqrt{(2 \times 52,000 \times 500 / 8.40)}$	2,488 $\rightarrow$ 2,490
Lead-time error	$150 \times \sqrt{2}$	212.1 units
Safety stock	1.645×212.1	349 units
Average inventory	$2,490 / 2 + 349$	1,594 units
Inventory investment	$1,594 \times \$40$	\$63,758
Loan and interest	$0.60 \times 63,758 = 38,255; \times 9\%$	\$3,443
Equity cost	$0.40 \times 63,758 \times 14\%$	\$3,571
Physical holding	$63,758 \times 10\%$	\$6,376
Ordering cost	$(52,000 / 2,490) \times \500	\$10,442
Total annual cost	Sum of the four cost lines	\$23,831
Days inventory outstanding	$1,594 / (52,000 / 365)$	11.2 days

Note: Small differences of one unit or one dollar between tables arise from rounding of intermediate values.