AN EVALUATION OF THE ECONOMIC COST IMPACTS OF CLASSICAL FORECAST ERRORS

by

SHAFI AJIBADE ELEGBEDE

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College of Social Sciences
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Abstract

Evidence from literature suggests that there is no shortage of studies concerned with the supply chain risk management and the associated performance by the individual echelons and functional business areas or through coordinated efforts. Literature has also demonstrated strong association between the performance of supply chain inventory management and control policies and profitability. Thus, integration of operational policies with financial decisions has been seen as an avenue to improve and to better corporate strategic financial objectives in supply chain sector organisations through optimal inventory investment. This is quite important since measures to improve financial performance implicitly influence and restrict operational performance including the management of inventory. However, on the modelling of inventory and finance and in measuring the impact of one on the other, traditional approaches tend to think of one as the input into the other without due consideration for the interconnections between the two over time. In particular, the traditional inventory cost model appears to present a disconnect between operational choices and financial decisions.

This thesis models both and their interconnections explicitly and simultaneously. Supposing a periodic review inventory policy with finite horizon and single perishable product, this study proposes a simple easy to understand solution. Specifically, in evaluating the economic consequences of classical forecast error metrics on inventory control system, study improves the current approach by creating a versatile consolidative costs evaluation function that aligns both operational and financial decisions as well as captures the business contextual considerations. The research study results revealed that we can easily utilise the proposed robust costs structure at the right scale (of demand uncertainty) and in the right scope (of financial capacity) to reveal the real and correct cost effects that facilitates users to produce practically feasible plans for their businesses.

Key Words:

Operations, Forecasting, Forecast Error Metrics, Inventory Management, Inventory Control, Inventory Investment, Inventory Turnover, Working Capital, Free Cash Flow.

Dedication

To God ALLAH (SWT) Be the Glory

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List of Abbreviations

Account Payable (AP)

Account Receivable (AR)

Akaike Information Criteria (AIC)

Augmented Dickey-Fuller (ADF)

Autocorrelation Functions (ACF)

Autoregressive Conditional Heteroscedastic (ARCH)

Autoregressive Integrated Moving Average (ARIMA)

Bayesian Information Criteria (BIC)

Bivariate Pearson Product-Moment Correlation (BPPMC)

Cash Conversion Cycle (CCC)

Cash Credit (CC)

Coefficient of Variation (CV)

Cost of Goods Sold (CoGS)

Cross-Validation (CV)

Cycle Service Level (CSL)

Discounted Cash Flow (DCF)

Double Exponential Smoothing (DES)

Dynamic Harmonic Regression (DHR)

Economic Lot Size (ELS)

Economic Order Quantity (EOQ)

Efficient Market Hypothesis (EMH)

Electronic Point of Sales (EPOS)

Equity Credits (EC)

Exploratory Data Analysis (EDA)

Exponential Smoothing (ES)

Forecast Error Cost Risk (FECR)

Forecast Error Measure (FEM)

Forecast Error Revenue Risk (FERR)

Forecast Error (FE)

Free Cash flow (FCF)

Generalised Autoregressive Conditional Heteroscedastic (GARCH)

Hass Avocado Board (HAB)

Holt-Winters Algorithms (HWA)

Independent and Identically Distributed (IID)

Inventory Carrying Cost Risk (ICCR)

Inventory Conversion Period (ICP)

Inventory Management and Control (IMC)

Inventory Revenue Cost Risk (IRCR)

Information Resources Incorporated (IRI)

Inventory Turnover (iTurns)

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Machine Learning (ML)

Market Value (MV)

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Mean Absolute Error (MAE)

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Mean Error (ME)

Mean Percent Error (MPE)

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Mechanism of Influence Model (MIM)

Minimum Attractive Rate of Return (MARR)

Minimum Mean Squared Error (MMSE)

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Radio-Frequency Identification (RFID)

Receivables Conversion Period (RCP)

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Retail Chain (RC)

Root Mean Square Error (RMSE)

Seasonal and Trend (decomposition using) Loess (STL)
STL Forecasting (STLF)
Simple or Single Exponential Smoothing (SES)
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Standard Deviation (SD)
Standard Deviation of Errors (SDE)
Standard Error (SE)
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Structural Equation Modelling (SEM)
Sum of Square Errors (SSE)
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Working Capital Ceiling (WCC)
Working Capital Level (WCL)
Working Capital Limit (WCL)
Working Capital Position (WCP)

CHAPTER 1

Introduction

1.1. Business Context

Inventory Control[1] can be defined as a framework employed by echelons that constitute a supply chain risk management (SCRM) business function (Tang, 2006; Heckmann et al, 2015), including the retail chains, to organise and to articulate their stock levels (Syntetos et al, 2016; Boulaksil, 2016). This is really important in order to keep adequate stock keeping units (SKUs) at the minimum possible costs and to achieve one, or a mix or match of all of the following business objectives: to fulfil demand to their customers' satisfaction and to maximise and protect profit to their shareholders' delight; to ensure and safeguard business survival (particularly important for a new business and sometimes for a small business) or craft and sustain business growth or create and maintain competitive advantage; and align any or all of the above applicable business objectives with the firm's strategic stability and stance (Bogataj et al, 2016). The importance of effective and efficient inventory control can never be overemphasised. Lambert and Cooper (2000) opine that a significant paradigm shifts of modern business management is that individual businesses could no longer compete as solely autonomous entities, but rather as supply chains. Even with that, added Shin et al (2015), sustaining a suitable level of inventory is a key issue to the operational performance of such a supply chain management (SCM)'s echelons. Indeed, a competently and commendably controlled inventory flow across the value chain is one of the key factors for success of healthy (large or small) firms, found always in fine fettle. In the retail industry, as well as in all other echelons (or components and levels) of a supply chain, the challenge is to find the best-balanced trade-off between stock-out and stock-over (Boylan, 2018; Fildes et al, 2019).

Over two decades ago, Williams and Tokar (2008) reported that inventory accounts for a major cost for many businesses, and that, for example, the cost of holding inventory in the United States in 2006 was estimated at $300 billion. Today, according to Atnafu and Balda (2018), in manufacturing organisations, direct materials represent up to 50% of the total product cost.

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1 Inventory control (or inventory management, in financial or economic term): both terms are used interchangeably in this study.

And for retail chain businesses, inventory constitutes the major asset (Brealey et al, 2006; Boone et al, 2018). Inventory decisions can therefore be high risk and may have huge impact across all or any of the echelons, including the retailers, that constitute a supply chain. Retail firms are required to stock enough inventories to fully satisfy the demands of their customers and preclude any lost sales due to inventory stock-outs. Simultaneously retailers are obligated not to desire to have too much inventory staying on their shelves because of the cost risks of carrying inventory. Having too much stock (which ties down scarce fund) and or having too little stock to meet service level targets could be considered as primary direct causes of business failures (Kourentzes et al, 2019).

A key input to any inventory control systems that can effectively maintain appropriate inventory levels is a forecast or estimate of future consumer demand. Although the literature is rich in the number of empirical studies as well as in the number of available forecasting models and parameterisations, there appears to be little or no consensus on which approach is best for a specific context, and there also appears to be no clear-cut general guidelines on when to pick which model. Traditionally, an important factor with which the performance of inventory can be determined is the accuracy with which forecasts can be made (Wang and Petropoulos, 2016), typically measured based on the use of statistical forecast error metrics such as the Mean Squared Error (MSE), the Mean Absolute Error (MAE) and the Mean Absolute Percent Error (MAPE). However, such error metrics too often provide a poor indication of the costs and benefits associated with the consequent inventory decisions made based on the demand forecasts (Tiacci and Saetta, 2009). In addition, inventory managers find it challenging to make sense of forecast accuracy (Babich et al, 2006; Catt, 2007) and being able to quantify forecast error impacts on their business objectives (Goodwin, 2009). This includes the challenges in assessing the actual costs of forecast errors (Wright et al, 1986; Flores et al, 1993; Tiacci and Saetta, 2009). Another noteworthy business context for retail chains is the issue of perishable inventory (which may include items such as foodstuffs, fruits and vegetables, dairies, drugs, human blood, pharmaceuticals, and photographic films) which is characterised, according to Nahmias (1982) and Díaz et al (2020), by obsolescence. Due to their nature, in time, perishable stocks can become partially or entirely unfit for consumption. Thus, the risk of reduced utility conditions has negative consequences for perishable products. Specifically, their value and demand can drop to zero even shortly before their expiry dates or for slight damages (Herbon and Ceder, 2018). It is, therefore, only plausible to consider perishable products, in terms of their salvaged values, to complete the retail chains business context in this research study.

1.2. Background and Motivation

Motivated by the issues and outcomes of these debates and discussions, this research work will seek to suggest propositions via simulation as well as through empirical study evaluating selected commonly utilised forecasting models and quantifying classical forecast errors with a focus to assessing their practical implications for the retail chain firms. Lambert and Cooper (2000) have demonstrated that successful supply chain management requires cross-echelon integration, but this research study contends that such harmonised coordination must be extended to functional areas (that is, cross-functional integration) within the individual echelons making up a supply chain, and that the finance function must play a critical role within the operations unit and vice versa. The costs of forecast errors while commonly assessed at the operations level but appear to not actually limited to that level. Retail chains need to balance both operational and financial flows in the management of inventory control (Elgazzar et al, 2012; Bendavid et al, 2017). Managing the trade-off between good operations service delivery and the associated costs effectiveness is therefore at the heart of the stock control challenge.

It can be argued that the two business functional areas most involved in these tough tasks are the inventory control entity and its finance management unit. Evidence of this can be deduced from what both functional areas do. While managing the trade-off between customer satisfaction and the cost of service is at the heart of what the inventory control unit does (Bergen et al, 2019), striking the balance between free cash flow and working capital is the main objective of working capital management (Elgazzar et al, 2012). In doing so, forecasting is a core component (Bendavid et al, 2017). Therefore, this thesis speculates that the costs incurred due to forecast errors may result in a decrease in cash available to manage the business, for example by tying up too much inventory in the form of working capital or not having sufficient inventory to fulfil demand. As previously highlighted, good inventory control relies on good estimates of demand obtained through forecasts of the demand utilising forecasting models. Thus, the quality of the resulting forecasts from these models is a key factor in whether either too much or too little stock will be held. How the literature translates forecast performance into inventory requirements varies. This includes simple approaches based on judgemental allocation of inventory using the forecasted demand or using the resulting forecast errors to estimate safety stocks. Most recent approaches combine forecasting and inventory directly through the use of simulation (see, for example, Tiacci and Saetta, 2009; Strijbosch et al, 2011; Barrow and Kourentzes, 2016).

In this research work, the study considers the impact of forecasting through the use of classical forecast error measures and the consequences for inventory control decisions. In another related research work conducted by Bendavid et al (2017), the study hypothesises that inventory control decisions such as the level of inventory kept subsequently have a consequential impact on the working capital in several ways. Working capital can be impacted in terms of the risks of excess inventory (capital is tied down in inventory) and obsolete inventory (loss of scarce fund). Thus, potential indirect impacts on the free cash flow situation (that is, the financial status) of the retail chain firm is also a possible occurrence. As such, forecast performance may be viewed as having a mediating effect on working capital. In the current research work, investigation will be conducted on the relationship between inventory control, working capital and free cash flow through the mediating effect as well as moderating effect of forecast performance as measured through the use of classical forecast error measures.

1.3. Research Questions

The main aim of this research study is to contribute to the conversation about better understanding of forecast model selection and inventory performance evaluation approaches in general. Hence, in reference to the rich evidence from the literature that it is a tough task and a huge challenge for managers being able to quantify forecast error impacts on their business objectives and that the classical error metrics provide a poor indication of the costs and benefits associated with the resulting inventory decisions (Babich et al, 2006; Catt, 2007; Goodwin, 2009), it is only prudent to ask and to investigate the following key research questions as a response to the requirement or obvious heed to what is seemly. Contrary to Modigliani and Miller (1958)'s theory of a perfect capital market, which amounts to the assertion of separate and uncorrelated association between a business's operations decisions and its financial functions, is there actually a close cross-functional link between operations and financial functional units of a business? In other words, there appears to be no such thing as perfect capital market in our practical modern world of today, especially as it relates to retail chains' inventories and investments (see for example, Zakrajšek, 1997; Li et al, 2013; Gong et al, 2014).

- ***Research Question 1***

Specifically, an important question that arises for this thesis is that: Is there association between retail chain business's operational choices and its financial functions and decisions? If so, what are the mechanisms of change?

- ***Research Question 2***

Another critical question for the current study will be: Is the current traditional costs criterion structure adequate, reliable, and robust enough to give managers the right capability they need to evaluate the true costs of classical forecast metrics in the context of inventory control and management risks?

- ***Research Question 3***

If the answer to question 1 is true and or answer to question 2 is no, then can the current traditional costs model, with its lack of consideration for firm's financial status, be recreated and reconstructed to give a good reliability, robustness and quite importantly, strong synergy (for the interaction between operational and financial choices) while the model remains simple?

1.4. Research Aims and Objectives

A major practical goal of this PhD research work is aimed at the retail chains inventory risks management, and it seeks the improvement of the inventory performance evaluation approach through the application of inventory control periodic review policy and by looking at a modification strategy for the current costs structure. In specific terms, the study seeks to provide managers a better and more business context-based evaluation capability to be able to assess the true costs of classical forecast errors. To achieve this, several objectives will be pursued. There will be three components to the research approach adopted for this research study. Each of these research approach elements will form three studied strands, each of which will systematically examine, in sequence and in line with the key research questions and all the other relevant discussions highlighted above. Thus, the following three main research objectives, respectively aimed at each of the three research questions, are pertinent:

1. To investigate relationship between inventory investment and inventory control and demand forecast and the impact of the latter on the former and or vice versa. To understand the mechanisms of change; that is, discerning how the underlying operational as well as economical drivers (such as inventory turnover, forecast error, working capital and free cash flow) influence or are influenced, and what is the effect of the business context.
2. To evaluate and quantify the utility measures, that is, the traditional error metrics such as the mean squared error (MSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE) in terms of inventory variables such as service level, relevant inventory forecast error cost risks (FECR) and forecast error revenue risks (FERR). It should be noted that FECR and FERR are part of this thesis contributions.

3. To explore, develop and propose an alignment and unified model for the cost structure, under the financial constraints or considerations such as working capital, trade credits and cash credits, which minimises operational costs and maximises profitability.

1.5. Research Study Conceptual Framework

In the modern-day retail chain business environment, there are many business intelligence solutions available to implement smart budgeting and demand forecasting. However, in order to be successful, regardless of the solution deployed, it must be both practical and contextual based, and most importantly, it must be driven by pragmatic functional coordination. This is critical because credible studies (see for example, Bendavid et al; 2017; Capkun et al, 2009) have found that there is a direct association between operational performance and financial planning. Thus, for the current research study, the objective framework in Figure 1.1 illustrates conceivable relationship between operational and financial decisions, along with their respective constraints included in this research study.

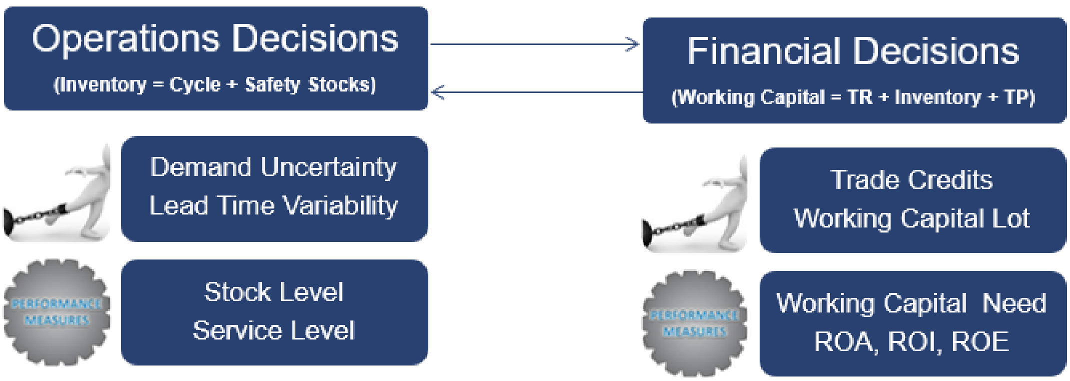

Figure 1.1: The Research Study Objective Framework (Adapted from Protopappa-Sieke, M., and Seifert, R.W., 2010)

It suggests that poor demand forecast performance may have effect on the inventory control decisions such as the level of inventory kept as well as have subsequent consequential impact on the working capital in several ways. In addition, poor financial planning can also impact operational productivity. This is important because, not least is the fact that, a significant part of the cash conversion cycle or the operating cycle (the metrics to measure the length of time it takes to turn investments in inventory and other resource inputs into cash flows) is held and shared by the operational and finance managers. The above framework in Figure 1.1 will form the basis for the overall study strategy.

1.6. Chapter Summary

This thesis introductory chapter provided the business context, background information and motivations for the research work. It sets the scene, in the first section, for the specific supply chain risk management and the business nature by describing the significance of stock keeping and the need for fine balance trade-offs, presented in the context of inventory control and management. The focus is then shifted on to introduction of the importance of demand forecasting (at the retail level within the structure of the supply chain risk management) as it affects inventory control system performance and other business decisions such as in the finance functional area of a retail business. This was followed by the discussion to highlight the nature of the type of items for study consideration. In the next passages following the business context discussion, the chapter moved on to the characterisation of the research questions, aims and objectives as well as the description of the research study conceptual framework in the three sections that follow, respectively. An outline of this research thesis organisation will conclude the chapter as follows.

1.7. Structure of the Thesis

The thesis introduction chapter sets the scene for the study with the characterisation of the research questions, aims and objectives as well as the description of the research study conceptual framework. Chapter 2 provided a review of existing inventory management and control approaches relevant for dealing with supply chain retail inventory products and associated costs structures. In chapter 3, the thesis evaluates literature as it relates to selecting forecasts for inventory management. Chapter 4 outlined the research study methodology envisioned and implemented. The chapter highlighted that the research study would be *context* bound and designed to offer pragmatic solutions to some of the highlighted real-life challenges being experienced in retail chains inventory management and control. Chapter 5 conducted empirical investigations on US markets for perishable products that included milk, salty snacks, yogurt and avocado by looking at and gaining insights into the relationship between forecast accuracy, inventory productivity, and financial performance within the US retail chain firms.

In chapter 6, evaluation of selected forecasting models and the quantification of true economic impacts of emanating statistical forecast errors from these models have been conducted. Simulation and the empirical studies in the chapter looked at and provided the platform where the limitations of the traditional model were addressed, and the proposed models introduced. The thesis proposed a hybrid inventory costs structure that aligns both inventory control and financial decisions as conjectured in the third research study objective. Chapter 8 concludes with thesis contributions, discussion of findings and their managerial implications.

CHAPTER 2

Inventory Management and Control

2.1. Introduction

The purpose of this chapter and the next chapter is to provide a review of existing inventory management and control approaches relevant for dealing with a retail chain inventory of perishable products[2] and associated costs structures. This will include a review of current approaches to inventory control, both theoretical and empirical, the role of forecasting, and consideration of the impact of demand uncertainty on forecasting and inventory cost structures. While there are a wide range of well-established inventory control approaches, the best practice approaches to dealing with demand uncertainty through forecasting are still under debate. In Addition, limitations in the available approaches to assessing inventory costs, and the impact of forecasting on such costs will be identified.

2.2. Inventory Control and Working Capital Management

As will be illustrated in the following sections, the significance of managing *working capital* well cannot be overstated because it is probably the most important, but manifestly most widely employed measure of a firm's liquidity (Bendavid et al, 2017; Lee and Rhee, 2011) – and according to Dunn and Cheatham (1993) and Peel et al (2000), lack of adequate liquidity leads to bankruptcy. But as the working capital can be estimated and it is often described as the difference between the current assets and the current liabilities, it thus has consequences for good inventory management. A direct implication of this is that poor forecasting of a retail firm's working capital requirements can impede investment in current assets, specifically *inventory*. This is important in the focus for this research study. The purpose of managing capital is to ensure that assets such as inventory and liabilities such as debts (including trade credits) are well controlled to guarantee or to ensure that an optimal level of

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2 Perishable products: Refer to retail items which may be slow moving or fast moving but are short life cycle products and or have expiry dates and are thus, opened to high obsolescence.

working capital is upheld and sustained (Ding et al, 2013) for optimal operational (inventory keeping) purposes and to maximise profitability.

Gaur et al (2005) and Bendavid et al (2017) have demonstrated that effective inventory management and control, and coordination with inventory investment policies are essentially significant and play key roles within the supply chain context in general, but particularly in any retail organisation. The reason for inventory as the chief and central concern for the retail chain firms lies in the abundant existence of theoretical as well as empirical evidence (see for example, Hopp and Spearman, 1996; Rajagopalan, 2013) that lack of effective inventory models and mechanisms will result in productivity and performance issues. Lee et al (2015) has argued that these issues will eventually bring about loss in sales, creditworthiness, cost effectiveness, market share, revenue, and by implication may ultimately lead to the failure of the entire business. In other words, unproductive inventory policies will certainly lead to stockouts and customers discontent, which directly distresses performance and imperils the corporate financial objectives of the company.

An important factor in good financial management of inventories, which is capable of leading to success of a supply chain enterprise such as a retail firm, is the effective control of working capital, which is often modelled as a function of current (short term) assets and current (short term) liabilities, or the arithmetic difference between the two (Vernimmen et al, 2017). It plays a pivotal part in making certain that the wheel of inventory operations is kept moving. Judgments and choices relating to working capital are often referred to as working capital management. It concerns the connection between the supply chain short-term assets and short-term liabilities. The classic work of Dewing (1941) and Long et al (1993) elicit that the objective of working capital control is to safeguard firm's ability to continue its operation as well as to ensure that there is sufficient *cash flow* to facilitate impending operational expenses and to fulfil maturing short-term debt. It is observed that typically, no member of a supply chain especially a retail firm is free of capital requirements, because without it many of such firms cannot flourish. Gaur et al (2014) and Bendavid et al (2017) have also shown that effective provisions of working capital do guarantee the realisation of success in business operations whereas its inept control is capable of leading to operation disruptions, revenue restrictions or even insolvency of the business. This implies that the adeptness and good organisation of a retail business enterprise is contingent, largely, on its aptitude and propensity to successfully manage working capital well. Thus, effective capital control is vital and an important factor of a supply chain retail business's inventory operations and overall financial healthiness and robustness.

2.2.1. The Working Capital Effect

Deloof (2003) suggests that a retail business whose projection of working capital is regularly close to optimal requirements will be reckoned as industry benchmark while any that fails to maintain a fitting amount of working capital will most likely become insolvent or even be forced into bankruptcy. The same study and many more (see for example, Dong, 2010; Mansoor and Muhammad, 2012; Arunkmar and Ramanan, 2013) have demonstrated that holding and utilising optimally sufficient working capital will ensure smooth and uninterrupted business operation activities. Nonetheless, Deloof (2003) study also suggests that arriving at this optimal level could be a difficult task for financial managers in the retail firms. Needless to say, therefore, is that though too much or too little working capital is surely detrimental to a retail firm's operations, as this may lead to too much or too little inventory to satisfy demand, but opportunity still exists to assist these managers in carrying out their difficult tasks. To ensure a reasonable margin of safety, a firm's current assets ought to be sufficient enough, essentially, to be able to comfortably offset its current liabilities as necessary. Current assets, in the form of inventory, have to be used in the best way and their financing sources need to be unremittingly managed well in order to guarantee continuous access. Interaction between short term assets including the inventory and short-term liabilities including loans is, therefore, a main theme of this research work because it is the difficult task managers of working capital and or of inventory are charged with.

In the management of a retail business, the overarching goal is to manage operational tasks, such as inventory control and investment of nominal working capital in capital assets at the optimum level (see Van Reenen, 2007; Ding et al, 2013). As a result, some trade-offs will subsequently need to be made between inventory costs and return on capital investment. Evidence (see for example, Bendavid et al, 2017) suggests that working capital forecasting management is quite an important aspect not only in making a retail firm financial management decision but is related also to taking decisions about inventory control operations. Improper management of working capital; that is, over forecasting working capital or under forecasting working capital may mean operational as well as financial agony for firms (Dunn and Cheatham, 1993; Bhattacharya, 2001). For this reason, the logical question facing a firm's financial manager in charge of working capital forecasting as well as for the inventory manager in control of demand forecasting is obviously this: what is the right amount of working capital requirements and particularly, the *optimal* inventory investment needs that satisfy *optimal* demand for the firm's products?

It is worth mentioning that this study recognises the fact that there is no universal rule for an ideal working capital. This is because working capital requirements vary from firm to firm and from industry to industry. Therefore, optimum working capital can only be, and are determined in consideration of, and with the reference to, a firm's particular conditions. In other words, individual company is usually accountable to determine and ensure the requirements of the right working capital in such a way that the working capital amount available is neither too high nor too low for its requirements. However, for the purpose of this research work, the concept of 'optimal' working capital directly relates to the fact Baños-Caballero et al (2012 and 2014) have found that there is an inverted U-shaped association between investment in working capital and firm performance. An implication of their findings, one may argue, is that there is presence of an 'optimal' level of investment in working capital that balances costs and benefits to maximise a firm's value.

Hence, aside from the effective and efficient control and management of inventory, an optimum level of working capital is crucial and at the heart of any supply chain management, and in particular, it is key to the smooth running of a retail chain enterprise. Peel and Wilson (1996) and Gaur et al (2005) extended this effect to the financial health status of a retail firm characterised by poor working capital management practices through the firm's failure to often account for short-term disruptions to cash flow, suggesting that in extreme cases, such a firm may be forced to close its operations. It should be noted that funding needs for working capital can be fulfilled internally or externally. Hubbard (1998) and Bond and Van Reenen (2007) among others have demonstrated that the primary sources of working capital to meet operational expenses in an inventory control functional unit of a firm may be categorised mainly as two; these are, surplus fund achieved through efficient operations (that is, excess of a firm's current assets over its current liabilities) or funding through sources external to the firm. External sources may be either securing trade credit for product procurement from the firm's suppliers or vendors, or loans from a creditor such as a financial institution, for example, a bank.

In summary, previous studies, as demonstrated in this section, show that good and efficient capital management correlates with greater returns of current assets, to sustain a sound, solid and stable liquidity position of a supply chain retail enterprise. So, a suitable system of running working capital is highly essential to ensure a sustained stability of the financial position of a retail chain.

2.2.2. Inventory, Investment and Returns

Studies such as Gaur et al (2005) and Gill et al (2010) have demonstrated that there is strong association between the performance of a supply chain's inventory control policy, its inventory investment and profitability. This research study is focused on incorporation of operational policies with financial decisions motivated by the observation that, it has the potential to drive high productivity in terms of operational performance and consequently, the firm's financial efficiency. And if placed correctly at the heart of a firm's strategic plan, integrated operational-financial framework is the key to facilitating and leveraging profitability progression (Lieberman and Asaba, 1997; Howorth, 2001). And it is also capable of significantly unlocking greater growth in supply chain sector organisations (Ding et al, 2013).

Moreover, aligning operational policies with financial decisions has the potential to be an avenue to improve and to better corporate strategic financial objectives in supply chain retail organisations through optimal inventory investment (that is, the working capital). This is quite important since strategies to better and to boost financial efficiency tacitly impact and confine operational performance including the management of inventory (Zeballos et al, 2013). However, in measuring the impact of one on the other, previous research has tended to focus on modelling inventory separately, and using the resulting output to access financial impact, based on sensitivity analysis or simulation (Bendavid et al, 2017). In this thesis, an integrated model will be proposed for evaluation of classical forecast errors resulting from forecasting of future demands with a consideration for inventory investment constraints. The proposed model, in which a periodic review inventory policy with finite horizon and single product is considered, will explore the essential trade-offs between inventory and financial decisions and takes into account relevant financial constraints such as working capital funding needs and trade credits (countenanced and consented upstream and downstream payment delays) for enhanced supply chain coordination.

Inventory and working capital are also related and both have direct association with both business bottom-line as well as business top-line key performance indicators (Boulaksil and Van-Wijk, 2018). No retail business should, therefore, ever overlook the substantial impact a sustained reduction in working capital and substantial underperformance of the inventory control systems have on top-line performance indicators such as profit margin.

A series of studies have conducted credible statistical and empirical analyses measuring the relationship between working capital performance and profitability and between it and inventory performance. In one of such research works, Deloof (2003) demonstrate this via a sample of 1009 large Belgian non-financial firms for a period of five years. In another usefully relevant study, using a panel data set for the period of 2009 - 2015, Qurashi (2017) found that working capital has a significant and direct impact on the profitability of a firm. Gill et al (2010) also found this to be the case and Bawa and Basu (2019) argue that retail enterprises should take this into consideration. Their study suggests that this is quite important, on one hand, when valuing the return on investment for a working capital enhancement scheme, and on the other hand, to gain support of the finance group for coordinated collaboration work with inventory management and control (IMC) operations team. The latter appears to be as crucial as the former because arguably, a significant share of the cash conversion cycle is owned and influenced by the IMC operational unit. This assertion is from the point of view rooted in what the concept of cash conversion cycle (CCC) is. It is a financial metric that measures the length in time (in days) required for a company to convert cash invested in its operations to cash received (Laghari and Chengang, 2019). An implication of this is that decent demand forecasting and good inventory turnover are as significant as efficiency in forecasting working capital and timely cash receipts from sales (Moussawi-Haidar and Jaber, 2013; Katehakis et al, 2016). Zeidan and Shapir (2017) provide a "*direct evidence that operational efficiency is the main mechanism by which minimizing the CCC drives value creation*". This may explain the reason for the difficult times often faced by the finance managers in achieving incessantly unremitting working capital efficiencies (Brigham and Houston, 2003), because the lack of support of and or better coordination with the IMC group is not good for the business. And when this happens, the effect may also be felt, in retrospect, by the IMC unit of a retail business because of the interconnectedness and association between the two divisions of the business. A recent study conducted by Bendavid et al (2018) shows that arbitrarily imposed constraints on the working capital significantly distort operational decisions.

Therefore, putting all the above research results highlighted here into proper consideration is a strong justification for the current research study to focus on the incorporation and integration of operational policies with financial decisions. Moreover, it also justified the very reason to be motivated by the observation that, this has the potential to drive high productivity in terms of operational performance and consequently, a firm's financial management efficacy.

2.2.3. The Fusion of Inventory and the Finance Functional Areas

As can be deduced from the discussions above and in many more real-world situations, that the current practice of separate strategies to optimise retail business bottom-line and revenue appear not to be working (Gong et al, 2014). It is noted that typically, while the IMC unit will apparently focus its operational inventory optimisation and overriding strategy on cost of service and satisfaction of customers (Kouveils and Zhao, 2012). On the other hand, the finance function of a firm, by tradition, separates their focus from their IMC colleagues and concentrate their WC optimisation policy plans on account receivable (AR) and account payable (AP) approaches (Bendavid et al, 2017). However, a synchronised synergy and subsequent combined effects of both efforts may produce a far better costs benefits and added value such as healthy net cash flows or profit improvement than doing things separately.

Nonetheless, a body of study, for example, Li et al (2013) and Protopappa-Sieke and Seifert (2010) have studied policies relating to operational and financial decisions and compared their model with decentralised system where those decisions are made separately. Protopappa-Sieke and Seifert (2010) found that rises in working capital employed diminish the total operational cost. In addition, a lot of the research work discussed in section 2.2.2 have sought to link for example, inventory turnover and working capital to profitability, and other authors have established associations between cash conversion cycle and profitability. But while all these credible studies have been conducted with the aim to synergise operations decisions with that of financial functions, concentration has been on metrics other than forecast accuracy. To fill this gap, the current study is seeking to synergise, integrate and fuse both financial and operational processes of inventory cost analysis. This should be an important research contribution because according to Fildes and Kingsman (2011), inventory management and control systems reliance on demand forecasting as the main tool to support operational decisions such as the setting of safety stocks (see also Barrow and Kourentzes, 2016) must be taken as a given (inevitable and certain to remain so). Yet it is observed that no study appears to have shown how forecast accuracy is related to all of the other interactive dynamics such as the working capital and the free cash flow both of which appear to be inherent within and integral to the inventory. This may explain why the current separation practices and strategies appear to be neither sustainable, according to Lai et al (2009), nor adequate or robust, according to Ma et al, (2013). More insights into what appears to be inherently forceful relationships, especially one that explores the influence of forecast accuracy, may have the potentials to unlock and are expected to pave ways for more sustainable and robust models to address the integration of operational choices and financial function decisions.

2.3. Inventory Control and Management

As far as the retail industry is concerned, the most important purpose of inventory operations is to decide how much resources are to be arranged and when to order so as to reduce procurement and associated costs, while conforming to the essential requirements. For an inventory management and control to be both effective and efficient, certain requirements must be met. Chief among these requirements, according to Syntetos (2001) work are the following six key areas necessary to be considered:

1. A *classification system* for inventory items relevance and prominence
2. An effective *tracking system* to keep a robust record of the stock levels
3. Inventory *control system* for the inventory parameters estimation which helps to decide whether or not replenishment should be mandated after review, and when and how much to order, in order to optimise business objectives and business benefits
4. *Forecasting process* to predict future demand with minimum forecast error
5. Savvy data analytics and expertise to handle *demand volatility*[3] (that is, demand uncertainty and lead time variability)
6. Correct estimates of total relevant *inventory cost risks* borne out of full understanding of trade-off between stockout and stockover

In general, the consideration of all the right requirements as outlined above and the implementation of the replenishment process described below will help to reduce the *inventory investment* costs, cut *obsolete inventory,* and optimise the rate of *inventory turnover* (Bergen et al, 2019). It is important to note that although the last four listed requirements are the really relevant items to and fall well within the focus of this research study. However, all the six items are entwined and usually, these requirements are often infused into the inventory operations process (Silver et al, 1998). Therefore, discussion of all the six items helps the proper placement and provides good understanding of the bigger picture for the thesis. To this end, requirements 1 to 3 and the inventory cost risks (item 6) discussions follow next while the role of demand forecasting (item 4) and demand volatility (item 5) will be fully discussed in chapter 3.

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3 For the purpose of this research study, demand volatility refers to the combined sum of the uncertain demand and stochastic supply effects.

2.3.1. Inventory Classification System

Above, the first of the outlined requirements is the classification consideration task. The activity necessitates having an *effective* inventory classification system, one of the first major requirements identified by Syntetos (2001). As a first step, classification allows segmentation of the inventory to determine relative importance and frequency of use of each and every product, carried out in a way quite relevant and relative to the second requirement of keeping proper stock status.

One of the most common classifications, and this is quite important in practice within the supply chain retail industry, is the ABC classification analysis policy (Lengu, 2012). This stock classification approach, very often, is used to determine the prominence and the eminence of each stock keeping unit (SKU) of the inventory, most times, in terms of the metric that weighs the significance of an SKU such as on the basis of their relative value of annual consumption or the sales volume (Chopra and Meindl, 2016).

The supply chain retail products of focus for many retailers include fast moving, short life cycle products open to high obsolescence. Hence, in the context of such perishable products such as considered for this research study, the ABC classification becomes critical because obsolescence is highly likely; and as a consequence, Teunter et al (2010) observed in their study that in order to keep costs under control within the retail industry, inventory managers are fundamentally required to consider explicit as well as implicit costs.

Thus, practitioners could consider the carrying costs (also known as holding costs due to excess stock, i.e., stockover) and the backorder costs (due to stockout) of such items as significant within the inventory. These reasons, in part, inform the decision to use and explain why the implicit cost such as the backorder costs and the explicit cost like the holding costs could be, and have been considered as the relevant parameters in the derivation of the total relevant inventory costs structure for the evaluation of forecasting methods.

2.3.2. Inventory Tracking and Recording

The second of these activities is the tracking system task which is concerned with the maintenance of proper stock status records; that is, it handles how best to keep account and regularly update the registers of the inventory levels including on hand inventory and on order inventory of each and every product. According to Syntetos (2001), there are essentially only two ways of “posting” the stock status records. In the first method, receipts are added, and demands are subtracted as they ensue. In this case, each transaction triggers an immediate updating of the status and as a result, this type of control is known as "transactions reporting" (Silver et al, 1998). In the second approach of updating the stock status records, it is done periodically. In this case, an update interval elapses between two consecutive moments at which the stock level is known. It should be noted that a 'continuous' recording of each transaction does not necessarily imply a continuous review policy of the stock control. Since inventory management and control is the means by which products of the correct quality and in correct quantity are made available as and when required with due regards to economic implications in ordering and stocking costs; most of the models, tools and techniques are primarily used to scope and support accordingly, the work and tasks involve in inventory operations process.

It is worth noting that automatic identification and data capture (AIDC) technologies are the more modern approaches that provide direct data capture or entry without much human involvement in the process (Groover, 2016). Once the stock status records have been updated, the inventory control system models, can then be used to check the stock status against one or more control parameters, so that a decision can be made about when and how much to order.

2.3.3. Inventory Control Systems

This is perhaps one of the most important means and aspects of effectively managing inventory. For the purpose of this research study, an inventory control model refers to the day-to-day physical operation of the approach and policy chosen by a supply chain retail firm. In addition, the inventory management and control system also deal with the process of setting the numerical values of the control parameters required in the inventory control system to decide when and how much to order. The classic work by Brown (1967) has established that, in order to effectively achieve the fundamental objectives of inventory control, four series of activities or actions are necessary to be carefully and competently considered. First and foremost, the proper stock record maintenance task (already discussed in the immediate section above) has to be taken; the next step involves the frequency of reordering assessment (that is, how often the assessment for reordering should be done); this step is followed by the determination of the replenishment order placement (that is, when a replenishment order should be placed) and lastly, the replenishment order amount estimation (that is, what the replenishment order size should be) will be carried out. The last three activities (two to four) are encapsulated in what is referred to in this research study as the replenishment process (discussed immediate below).

2.3.4. The Replenishment Process

The replenishment process needs to define review period for reordering, and a volume to be ordered. There is a need as well, for the inventory parameters estimation which helps to decide whether or not replenishment should be mandated after the review. A number of options exist, based on the framework of the review period and order quantities, to drive the reordering. Review of literature reveals that inventory replenishment strategies come in a range of forms. The work of Waldman (2009) has demonstrated that the major approaches include strategies such as the 'order point, order quantity', (*s, Q*) policy, the generalised 'order point, order level, (*s, S*) models, the 'periodic review, order level', (*R, S*) policy, and 'review period, order point, order level' (*R, s, S*) models (see also Hosoda and Disney, 2009; Liao and Chang, 2010).

The two most commonly encountered continuous review systems are of the (*s*, *Q*) or (*s*, *S*) form. After each transaction, the available stock (that is, inventory position given by the stock on hand plus on order minus backorders) is compared with a control number, *s,* variously called an order point, a base stock or a minimum (Brown, 1959). If the inventory position is less than *s* (or in some cases at or below *s*) a replenishment order is released. The replenishment order can be for a standard order quantity *Q* or alternatively enough may be ordered to raise the inventory position to the value *S*, the replenishment level. If all demand transactions are unit-sized, the two systems are identical because the replenishment requisition will always be made when the inventory position is exactly at *s* (so that $S = s + Q$). If the demand sizes vary, then the replenishment quantity in the (*s*, *S*) system also varies. In this latter case, optimisation of *s* and *S* occurs in parallel recognising that cost interactions exist between the two control parameters. Alternatively, the parallel optimisation may be for *s* and *Q* (rather than *s* and *S*) in which case the (*s*, *Q*) and (*s*, *S*) systems are also equivalent in that the replenishment level can be determined as $S = s + Q$ (Wagner, 1975).

In the following sections, since the retail firms are the focus of this research study, the fixed quantity and the fixed period inventory control systems are the relevant policies according to Syntetos (2001) and Wang and Fotios (2016), therefore, both will be the models to be considered for discussion. Even though the discussion of both the perpetual policy and the periodic policy in the thesis report helps to cover the entire picture, the latter will be adopted for the thesis study analysis focus.

2.3.5. The Perpetual Review (*s, Q*) Policy

In this section and the next section, the thesis considers the cost analysis based on two most popular inventory control system models for retailers. This section looks at the 'order point, lot size' (*s, Q*) continuous review policy (often simply referred to as the perpetual or fixed-order inventory control policy). Even though the fixed-order policy has not been directly utilised in the simulations and the empirical analyses that have been undertook in this research work, however its derivation leads to and allows a direct transformation into the fixed-period inventory control system (Silver et al, 2008) which has been considered for this study.

The model of the 'order point, order quantity' (*s, Q*) continuous review policy is one in which the optimal solution depends on cost effects of shortage, that is, backorders or lost sales (the case of when backorders cannot be fulfilled). In order to implement a 'reorder point, lot size' (*s, Q*) inventory policy, stock level is continuously being reviewed and decisions are made based on the values of the decision parameters, s and Q. An order up to the volume of Q is placed as soon as it is observed that inventory has declined to a specified reorder point, s. In this model, lead time, L, is the time lapse or interval between when the order is placed and when the order lands to restock inventory.

A shortage or stockout will occur if demand during the period L is greater than s. The service level is the probability that the inventory will not be depleted during one *order cycle*. If we assume that the reorder point is considerably bigger than the mean demand during the lead time, probability of stockout will be really small. Thus, the expected inventory level at the end of an order cycle, just before replenishment arrives (which is often referred to as the *safety stock*), will be given as inventory level at reorder point minus the mean demand during the lead time. Keeping safety stock is an effective way to protect the inventory system against stockouts during the lead time. This is the inventory effectively maintained to mitigate demand uncertainty and lead time (L) variability while still providing high service levels to customers. Expressed in terms of a target service level, where the safety factor from a table of normal distribution probabilities is used as a proxy, the safety stock will be given as the safety factor multiplied by standard deviation of forecast errors in units over the replenishment lead time. This can be represented mathematically as:

$$S_s = k\sigma\sqrt{L} \qquad (2.1)$$

The safety factor is symbolised as *k* whereas sigma stands for the standard deviation of forecast errors. Again, it should be noted that equation 2.1 is true if it is assumed that demand forecasting error is Gaussian independent and identically distributed (iid) with zero mean and constant variance.

2.3.6. The Periodic Review (*R, S*) Policy

This section will look at the 'review period, order level' (*R, S*) periodic review system (also generally known as the periodic or fixed-time inventory control policy). There is evidence (see Silver et al, 2008) that the analysis of the fixed period (*R, S*) model follows exactly the derivation for the fixed order quantity (*s, Q*) inventory system but in doing so, we have to substitute for s with S and then Q with DR (where D is the average rate of demand in a period) and L with $R + L$. Although, while order can be issued at any time in the (*s, Q*) policy and on-hand inventory volume is known always, order can be placed only at a fixed interval of time in the (*R, S*) inventory control system (Chopra and Meindl, 2016).

Evidence also suggest that the main advantage of the fixed quantity technique is that, to provide the same service level, it requires a smaller amount of safety stock (leading to lower inventory holding costs) than the fixed period policy (Fildes and Kingman, 2011). The reason for this is that in the fixed time system, the safety stock is used as restitution for any uncertainties as regards demand over the lead time plus one inventory review period. For the fixed quantity system, the safety stock is computed by considering lead time demand requirements only. In practice, implementation of the fixed period model is good for inexpensive products as it allows for ease of coordination and less work because the policy does not require continuous review. However, with smaller safety stock and the need for continuous review, the fixed order model may be better to consider for expensive products. Furthermore, the fixed period policy is much more affected by uncertainty and variability than the fixed order model.

For the consideration of the periodic order-up-to (OUT) level (*R, S*) review policy for continuous distribution, the safety stock in terms of service level, review period and the lead time where k the safety factor from a table of normal distribution probabilities represents the proxy for service level, will be given as:

$$S_s = k\sigma\sqrt{R + L} \qquad (2.2)$$

That is, the safety stock will be given as the safety factor multiplied by the standard deviation of forecast errors in units over the replenishment lead time plus the review period.

2.4. Inventory System Cost Structure

As it relates to inventory, many models and work already presented from academic studies appear to be really beneficial and utilisable to the retail chains, and their subjects of focus continue to be relevant and remain topical issues to the inventory and forecasting community. However, far less work has been done in the area of inventory cost criterion and in particular forecasting utility impacts on inventory performance and other management metrics. In this section, approaches to how inventory performance, in terms of system cost structure and as related to supply chain coordination, could be evaluated will be discussed. Limitations (to be fully discussed in thesis chapter 6) of the currently available approaches to evaluating inventory costs will be stated.

2.4.1. Inventory Control Coordination at Different Levels

Evidence from literature suggests that there is no shortage of studies interested in the supply chain risk management and the associated performance by the individual echelons and functional business areas or through coordinated efforts. A very crucial issue in a supply chain risk management is to reduce the cost of capital tied up in inventory, while still providing and keeping a high service level for the end customers (Gumus and Guneri, 2007). Inventory cost impact evaluation and optimisation of inventory systems have been studied in the literature under a wide range of control policies (Waldman, 2009). It is observed from the literature that for the supply chain echelon members to flourish, the inventory decisions at different echelons have to be efficiently coordinated (see for example, Ali et al, 2011). There appears to be two broad body of study streams relating to these subject matters. It is important to note that although the implementation of these two framework approaches seek to improve the forecasting performance impacts on inventory performance, but some studies considered evaluation of the impact of information sharing (not a focus for this thesis) on the replenishment policies being utilised. There is the supply chain wide focused centralised approach (see for example, Federgruen (1993) for a review) for multi-echelon inventory control system. In this approach, the optimal or near optimal solutions of the decision variables at echelons can be estimated, according to Andersson and Marklund (2000), by solving a large and convolutedly complex problem. It appears that a lot of academics may have found this approach to be less robust and improper to capture the contextual situations of individual echelons. Thus, a stream of models (see for example, Axsäter (1993) for a review) with a focus on devolution approach have been considered. To this end, Axsäter (1995) has facilitated echelon-level-based control of an inventory system with a focus on a broad structure for a multilevel inventory system. Lee and Billington (1993) utilised service-level constraints for upstream echelon to model echelon-level-based control of an inventory system evaluation. The classic work by Clark and Scarf (1960) were extended by Lee and Whang (1994) who studied a serial system with stochastic demand in their echelon-level-based evaluation model of an inventory system. Hausman and Erkip (1994) have compared the performance of multi echelon model with single echelon model with service level constraints and considered system with low demand products. Andersson, Axsäter and Marklund (1998) and Andersson and Marklund (2000) introduced a modified cost-structure at the central warehouse and decomposed a multi-level inventory control problem into $N+1$ (N equals the number of retailers) single level problem for each echelon. Specifically, their cost structure includes holding costs at both echelons and shortage costs proportional to the time until delivery at the retail chain.

2.4.2. Inventory Cost Risks Function

2.4.2.1. The Current Expected Inventory Cost Risk Model

Evidence exists in the literature (see for example Silver et al, 2008; Wang and Petropoulos, 2016) that generally, the expected total inventory cost function consists of the costs associated with the inventory held often called the *holding or carrying cost*, the *ordering cost*, the setup or *replenishment cost*, the *backorder cost* and the *shortage cost* (at times also referred to as *lost sales*). Traditionally, in the (s, Q) model, the values of s and Q are the two decision variables required to implement the policy; and in the case of the (R, S) policy, the values of R and S are the two decision variables required to implement the model. In addition, the safety stock (that is, the standard deviation of forecast errors in units over the replenishment lead time multiplied by the safety factor) is an important component of the relevant inventory costs (Catt, 2007; Barrow and Kourentizes, 2016). This thesis, for the purpose of its study focus, will follow Flores et al and Catt works in the aspect of assuming the ordering cost and the setup cost to be constant, that is, fixed (see Flores et al, 1993; Catt, 2007).

For both the (s, Q) and the (R, S) inventory systems, *the total relevant inventory cost of forecast error*, when the ordering cost and the setup cost are assumed to be fixed, will be specified by adding the product of excess holding cost due to the safety stock to the backorder cost also due to the safety stock. This cost structure is useful in terms of a *cost objective* that is *service based* where the need arises to establish, for example, a constraint on customer service and then minimise costs with respect to the service constraint.

The total relevant inventory cost structure described above appears to be ubiquitous in its use by the previous studies that have attempted to capture the economic impacts of classical forecast errors for the supply chain inventory including that of retail chains dealing with obsolescence and seasonal stock. A body of academic authors have carried out research work in attempt to quantify the costs of forecast errors using the concept of the cost structure described above (for example, see Lee et al, 1993; Flores et al, 1993; Catt, 2007). However, these studies have all made oversimplifying assumptions to ensure mathematical tractability of their models and therefore, have failed to deliver the right estimates of key parameters. All of these papers and many more models have assumed the following: (i) a constant lead time, (ii) whole cost of a unit item at the end of period, (iii) full utilisation of specified safety stock, and (iv) full backorder or fully lost sales. But, in practice, for example, lead time is not static and does have uncertainty features in terms of duration due to a number of issues such as availability of materials, handling times by suppliers and logistics problems or challenges including shipping times. All these assumptions are addressed in chapter 6 of the thesis.

CHAPTER 3

Demand Forecasting

3.1. Introduction

Forecasting is one of the most difficult tasks for managers, and this is particularly true when predicting the future trends of sales and markets in today's ever changing technological and economic environment. It is, however, also of critical importance to the future of any organisation or corporate body (Chopra and Meindl, 2013). Risk is a key consideration in operational as well as financial decision making, and business forecasts can help to quantify such risks. This may explain the reason why managers and decision makers in many areas of practice have embraced the use of business forecasts. Even though the need for business forecasting is found in all areas and at all levels of supply chain management organisations, but quite often, it is the demand forecast which plays a crucial role in production and or procurement planning (Flores et al, 2003). A demand forecast will provide information regarding capacity planning, product mix, budgets, advertising and promotion. But besides demand forecasting it is often important to forecast inventory investment or the working capital. And besides and beyond demand and financial forecasting, the prices of raw materials, the prices of supplies and required products, competitor prices, and general market prices are all items to be forecasted. Thus, as a scope for focus, demand forecasting which has been and will always be a big part of most supply chain risk management business, but certainly a significant and integral part of retail firms' inventory planning, operations and strategy.

Since for many retailers, inventory constitutes a major asset (Brealey et al, 2006; Boone et al, 2018), having reliable and accurate demand forecasts becomes important for effective inventory control and management. The challenge often then shifts instantly to one of forecasting challenges; the tasks of selecting among a variety of many different forecasting models, the questions of which forecast model, and which forecast, or combination of forecasts will produce the best results in terms of inventory performance (Ord et al, 2017). Moreover, it is important to recognise the fact that technically, inventory is cash and as such must not be bereft of financial considerations in its analysis. Thus, evaluation of forecasting methods in terms of accuracy, inventory performance, and financial or economic is important (Flores et al, 2003). The forecasting and inventory literature continues to make good progress in achieving greater forecasting accuracy, as well as in optimising inventory performance (Ord et al, 2017; Post et al, 2019), but the latter's financial and economic impact of the selected forecast models appear to still require further insightful information for the retail chain firms' growth and for greater progress within the wider supply chain (More and Basu, 2013; Gelsomino et al, 2016; Bals, 2019). This is a void that the current study seeks to fill.

In this Chapter, the thesis evaluates literature as it relates to selecting forecasts for inventory management. The study considers the three broad approaches to this very important but challenging procedure, that is, the prediction procedure problem of forecasting model selection, on the basis of the following parameters. First of all is the forecast performance as measured using statistical forecast errors (see for example, Makridakis et al, 2018). Secondly, model selection based on the inventory performance as derived from statistical forecast errors as a proxy or through simulation (see for example, Ali et al, 2011) or as obtained by directly optimising forecast models on inventory metrics such as service level or fill rate (see for example, Barrow and Kourentzes, 2016), and finally, forecasting model selection premised on economic performance (see for example, Catt, 2007). As a major focus of this research is on economic impact of forecast models on inventory system, this chapter pays particular attention to how forecast performance evaluation based on the statistical forecast errors are quantified in terms of their economic implications for a retail chain business. This strand of the research work will investigate the different approaches to quantifying forecast performance in economic terms. The obvious questions for academia and for practice is to determine whether forecast models selected contingent on forecast accuracy are consistent with their preferred economic impact in inventory terms. This strand of the research work will also develop alternative approaches to measuring the revenue and cost risk associated with selecting a particular forecast. This should subsequently provide an alternative approach to managers in evaluating forecasts for better decision making.

3.2. Forecasting with Time Series Methods

3.2.1. Overview

Quantitative forecasting methods are commonly classified as either time series methods or causal methods (see for example, Chatfield, 2001; Axsäter, 2006). Smoothing techniques such as exponential smoothing, moving averages, weighted moving averages etc. and trend projection are examples of time series methodology. Time series analysis seeks to identify the trend and the seasonal components of a time series variable (Kourentzes et al, 2014b; Ord et al, 2017). Regression analysis is a common *causal forecasting method* and quantifies the relationship most often linear, but sometimes curvilinear between the variable of forecast and one or more influencing factor variables (Ord et al, 2017). Regression models are also so often referred to as time series regression models since time series data (that is, data collected at regular intervals over time) must be used in their analysis.

In general, the appropriate forecasting method to deploy in practice or adopt for a research study is contingent largely upon what data are available. Quantitative forecasting can be applied when three prerequisites are satisfied. The first of the three preconditions, according to the work of Makridakis et al (1998), is the availability of relevant information about the past (that is, existence of historical data about the variable of forecast). The second qualification directly relates to the first, which is that the available information must be quantifiable. The final requirement is the reasonable assumption that some aspects of the past patterns will continue into the future. Hyndman (2019) opines that in the absence of necessary previous history or if the available data are too little or either not appropriate or applicable to the preferred forecasts, but there is a lot of expertise, proficiency, experience and knowledge, then qualitative (or judgemental) forecasting methods must be utilised.

3.2.2. Times Series Forecasting Methods

In the retail chain, most prediction problems are confronted through the use of time series data (Fildes et al, 2018; Schaer et al, 2019). As this study is concerned with forecasting future demand data for retail chain firms, the focus therefore will be on time series forecasting methods. These approaches are the most widely applied in retail forecasting for generating baseline forecasts and for determining inventory levels (Ma and Fildes, 2017; Kolassa, 2017; Makridakis et al, 2018). An important matter to always address in the utilisation of time series data for forecasting is the issue of 'stationarity'. Thus, a common assumption in many time series systems is that the data sets are stationary (Silver et al, 2008). There is enough evidence (see for example, Makridakis et al, 1998; Axsäter, 2006) to suggest that ideally, stationary processes have the feature of the mean, variance and autocorrelation structure not changing over time. For the purpose of this research study therefore, stationarity is defined as a time series that is characterised with constant variance over time, constant autocorrelation structure over time and with no seasonality (periodic fluctuations) or trend. If any of these variables is present (and are often present in a retail time series datasets), it is important that they are incorporated into the time series model selected for forecasting purposes. Chartfield (1996) proposes decomposition procedures for series in which the trend and seasonal components are prevalent. Thus, it is necessary to note and to emphasis that the time series analysis seeks out, first to model the random mechanism that gives rise to the series of data (that is, fitting a model to some sample datasets), and then using the model to forecast the future values of the data series based on the previous history.

So first, it is observed from the literature that there are a set of formal forecasting systems and approaches, such as Exponential Smoothing (ES) forecasting methods; see Godwin (2010) and Hyndman (2008 and 2019) and Autoregressive Integrated Moving Average (ARIMA) forecasting methods; see Hyndman (2019). While some of these forecasting methods, such as for example the simple (or single) exponential smoothing (SES) method and ARIMA methods, have been designed to deal with only stationary time series data, some can handle time series datasets that are characterized as non-stationary around the mean and systemic non-stationary around the variance. The forecasting techniques capable of conducting prediction for time series datasets that are non-stationary in mean and systemic non-stationary in variance include the double exponential smoothing (DES) or Holt's linear method and the Holt-Winters' method.

Then, there are also a few families of formal forecasting approaches (Chatfield, 2001) which can be used to handle prediction problems involving non-stationary in variance time series datasets that are not systemic.

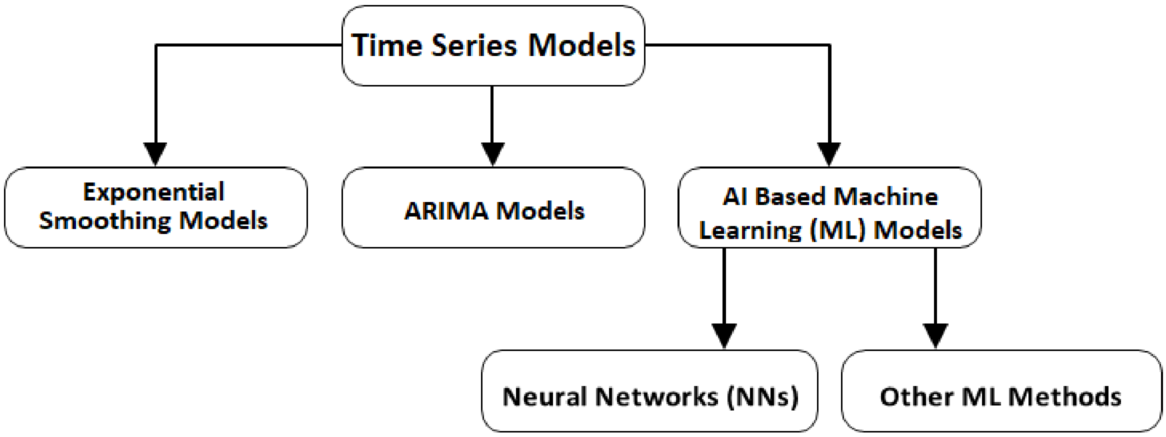


Figure 3.1: A Classification of Time Series Models

These include but not limited to Autoregressive Conditional Heteroscedastic (ARCH), Generalised Autoregressive Conditional Heteroscedasti (GARCH), Brownian Motion, Gaussian Processes, Fourier Analysis, Kalman Filtering (Makidakis et al, 1998). It is noted that both sets of forecasting methods have been around for quite a long time. But while the former set of forecasting models are ubiquitous within the retail industry because most related retail demand forecasting challenges revolve around systemic non-stationary variance and non-stationary mean, the later set of forecasting methods are rarely used, and thus, the later will not be discussed further in this research thesis.

And then, there is large evidence in the academic literature (see for example, Adya and Collopy, 1998; Ahmed et al, 2010; Salaken et al, 2017) to suggest that Artificial Intelligence (AI) has found extensive applications in the field of forecasting. Makridakis (2017) argue that there has been a recent surge in AI based Machine Learning (ML) methods. All these evidence point to the fact, one can argue, that considerable amount of research has been conducted, making use of ML and particularly the Neural Networks (NNs), seeking to promote improvement in time series predictions; especially aiming to minimise loss functions in order to improve forecasting accuracy. A classification of time series forecasting methods has been shown in Figure 3.1 to highlight this recent novel development. Consequently, there have been claims by some authors such as Deng (2014), Zhang and Suganthan (2016) and Salaken et al (2017) of ML methods' practical advantages, or their real value to improve forecasting accuracy, over other alternative techniques. However, for the purpose of this research study, the main family of methods based on Exponential Smoothing (ES) and Autoregressive Integrated Moving Average (ARIMA) models is considered since these being the most popular time series approaches to demand forecasting for the retail industry (Ma and Fildes, 2017; Fildes et al, 2018). But more importantly, because of the fact that the work of Makridakis et al (2018) found that both are better than the ML methods in terms of both '*all forecasting horizons and accuracy measures*'.

To enable the performance of different forecasting methods to be evaluated and in order to examine the effect of these techniques for a specified ARIMA demand process, it is assumed that the retail business utilises four different forecasting models to predict the lead time demand. Of the four forecasting models, two are automatic time series forecasting methods and two are non-automatic models. In this research work, in order to reflect practice in the retail industry, the Simple Exponential Smoothing (SES) and the forecasting method in form of the Minimum Mean Squared Error (MMSE) are the two non-automatic forecasting techniques employed (Ali et al, 2011). Both methods have been implemented in the forecast package for the R system for statistical computing (R Development Core Team, 2008). Automatic forecasting methods have been advocated by many authors to help reduce the effect (issues such as efficiency, capability, and error) of using non-automatic techniques could bring on businesses needing to forecast large numbers of univariate time series. An example of such advocacy is by Hyndman and Khandakar (2008) who elicited that since, "*It is common to have over one thousand product lines that need forecasting at least monthly. Even when a smaller number of forecasts are required, there may be nobody suitably trained in the use of time series models to produce them. In these circumstances, an automatic forecasting algorithm is an essential tool*". Consequently, it is further assumed in this research study that the retail chain business, in addition to the two non-automatic forecasting methods mentioned above, utilises two different forecasting automatic models to predict the periodic or the lead time demand for a specified ARIMA demand process. Exponential Smoothing (ES) and Autoregressive Integrated Mean Average (ARIMA) remains the two most popular and best forecasting methods, whether that is automatic wise or in the form of non-automatic (Makridakis et al, 2018; Hyndman, 2019). As these two methods are also part of the forecast package for the R Environment, ETS () with automatic fitting capabilities and auto.arima () models have been implemented in this study.

3.3. Forecasting evaluation for inventory decision making

In smoothing models' prediction of the future is based on past values of a variable whereas in a regression method, prediction is based on external variables which may affect the system. The "error" term in smoothing techniques, ARIMA models and time series regression method allows for random variation and the effects of respective relevant variables (past values for ES and ARIMA, and predictor variables for regression) that are not included in the model. Further, when computing forecasts using regression models, predictor(s)' information is/are often necessary to determine either of two types of forecasts; that is, '*ex-ante or ex-post*' forecasts, that can be made. The former is produced by means of previous information while the later is produced by means of present information. Hyndman and Athanasopoulos (2016) argue that "*a comparative evaluation of ex-ante forecasts and ex-post forecasts can help to separate out the sources of forecast uncertainty. This will show whether forecast errors have arisen due to poor forecasts of the predictor or due to a poor forecasting model.*" However, using a regression model to forecast time series data poses some challenges in that according to Hyndman (2019), the system may not be completely understood, and it may be extremely difficult to measure the relationships that are assumed to govern the behaviour of an 'understood' system. Furthermore, it may be difficult to know or to forecast relevant predictor variables and that even the main prediction concern may be about what will happen but not why it will happen or sometimes, moving average model may give more accurate forecasts than a regression model.

Training and test sets method (also known as fitting and testing or in-sample and out-of-sample or hold-in and hold-out sets) is an important technique or process of evaluating forecast accuracy using genuine forecasts. It is a procedure usually employed to measure extent of a model performs on new data not used for fitting the model. In this approach, a portion of available data is used for fitting the model while rest of the data is used for testing it and the testing data is then used to determine how well the model will produce good forecasts using new data. According to Hyndman and Athanasopoulos (2016), the size of the test set is typically about 20% of the total sample, although this value depends on how long the sample is and how far ahead you want to forecast. The size of the test set should ideally be at least as large as the maximum forecast horizon required. The same author suggested that practitioners should note that while a model which fits the data well does not necessarily forecast well, a perfect fit can always be obtained by using a model with enough parameters. In addition, over-fitting a model to data is as bad as failing to identify the systematic pattern in the data.

3.3.1. Characteristics of Classical Error Measures

According to Mathews and Diamantopolous (1994), demand forecasting performance is subject to the uncertainty underlying the time series a retail business organisation is dealing with. There are many approaches that may be used to assess forecasting models performance. This thesis will focus on forecast error measure (FEM) based on the work of Davydenko and Fildes (2016). To assess adequacy of a FEM, properties most desirable of an ideal error metric must be taken into consideration. The example of some studies focusing on such appropriate qualities of forecast error necessary to evaluate forecast outputs include that of Zellner (1986) who suggests that the *same loss function* used for forecasts optimisation should be used for its evaluation. Elliott, G. and Timmermann, A. (2004) disagree with Zellner (1986) demonstrating that this is not the case, especially when asymmetries are introduced in the loss function and the forecast error distribution is skewed. Fildes (1992) proposes two properties of 1) *robustness*, that is, how sensitive to outlier is the FEM and 2) *interpretability*, that is, how easy to interpret the FEM is. Other suggested features of FEM, according to the literature (Davydenko and Fildes, 2016), include *generalisability* (that is, usability across the board including allowing negative and zero errors to be used) and *undependability* (that is, not scale or ratio dependent).

The intrinsic properties inherent in error metrics have helped their categorisation. One such typical classification categorises statistical error metrics as percentage errors, percent better, relative errors, scaled errors (Davydenko and Fildes, 2016).

For example, the percent better is an intuitive measure providing precise facts about the percentage of time that a method performs better or worse than another method. Percent better error measure is not influenced by outliers. It is very useful in a context where the size of errors is not vital and can be used to compare two methods. It is disadvantaged in its assumption that small errors are of equal importance to large ones and takes no account of the size of error. But percentage errors are scale-independent, and so are frequently used to compare forecast performance between different data sets. A popular percentage error measure is the MAPE; its limitations according to Davydenko and Fildes (2016) include:

- Zero and negative cannot be used (therefore unsuitable for intermittent data)
- Not robust (for example, extreme or large percentages arise due to relatively low actual values)
- Non-symmetric loss (bias arise due to percentage errors putting heavier penalty on positive errors than on negative errors when forecast is taken as fixed)
- Misleading when errors correlate with actuals

While other dimensions such as symmetry of errors (for example, unbiasedness) may produce the same loss when underpredicting or overpredicting, however, an asymmetric loss function applies a different penalty to the different directions of loss (Hennig and Kutlukaya, 2007). In general, the plasticity in a loss function preference is especially useful in risk-based decision making if the modelling aim is to accurately predict the probability distribution. Asymmetric loss functions prove useful in this regard (Davydenko and Fildes, 2016).

3.3.2. Forecast Accuracy Metrics

Based on the discussion in section 3.3.1 above, a description of some forecast error measures of interest are as follow. The mean error (ME) and the mean percent error (MPE which is ME in percentage terms) indicate whether forecasts are biased high or low. The mean absolute deviation (MAD) is a useful measure of the overall forecast accuracy of a model, and it is computed by averaging the absolute values of the individual forecast errors. The mean squared error (MSE) statistic is the simple average of the squared errors; it is the sum of the population variance of the errors and the square of the mean error. By averaging the squared forecast error, MSE amplifies the effect of large errors in the forecast. The root mean squared error (RMSE) is simply the square root of MSE. RMSE penalizes big errors relatively more than small errors because it squares them first; it is approximately the standard deviation of the errors if the mean error is close to zero. It is a good measurement to use for comparing models in which the mean error is not unescapably zero since it penalizes bias (non-zero mean error) as well as variance. The mean average error (MAE) is the average of the absolute values of the errors, more tolerant of the occasional big error because errors are not squared and the mean average percent error (MAPE which measures errors in percentage terms) is useful for a data that varies over a wide range due to compound growth or inflation or seasonality. It is computed as the average value of the absolute error divided by the actual demand. Both MAE and MAPE appear to be easier for non-specialists to understand and are thus widely seen to provide useful numbers for a presentation than RMSE. Both are also less sensitive to the effects of big outliers and so might give a better estimate of the size of an "average" error especially when the distribution of errors is far from normal. Furthermore, MAPE gives relatively more weight to accuracy in predicting small values because it is computed in percentage terms. MAPE can be influenced a great deal by outliers as its value can become extremely large.

Generally, forecast error metrics need to be both reliable and discriminating. Reliability is the ability of a measure to replicate similar results when applied to different subsamples of the same series while discrimination is the ability of a measure to clearly indicate which method(s) is/are better than others. Although statistical considerations are critical for judging the value of the various accuracy measures, they do not suffice. For these measures to be useful they must also be understood and used most often by people with little or no statistical background. Accuracy measures need, therefore, to be intuitive and simultaneously, provide useful information to decision makers. The various measures reported in the forecasting literature are unique in their own sense but also involve trade-offs as far as the statistical criteria of reliability and discrimination as well as the user-oriented criteria of information-revealing and intuitiveness are concerned. Choosing accuracy measures should also be about the person using them. Forecast practitioners, statisticians and others with a quantitative background may have no problem using for example MSE or MAE or GMRAE. More importantly though is that since analyses based on different measures can lead to different conclusions, it is important to have a clear understanding of the statistical properties of any error measure used. However, measures intended for the general public should be restricted to those having common sense meaning.

3.4. Incorporating Forecasting and Inventory

3.4.1. The Functional Form of Inventory

Inventory is often mainly classified as either financial or functional (Silver et al, 2008). Whereas the first classification, that is, financial form, is adopted for accounting purposes as it recognises the added value to a commodity. The functional form, on the other hand, is founded on operational purposes, that is, how the physical products utility is controlled. Chief amongst the components that make up the functional form of inventory, according to Fildes and Kingsman (2011), are:

- *The cycle stock* – the inventory required to meet demand in the time between order deliveries, that is, during a replenishment cycle
- *The safety stock* (also sometimes referred to as buffer stock) – the required inventory to mitigate demand volatility (that is, variability in demand and fluctuations in lead time)

It is therefore not surprising that much of the focus of operations and forecasting research has been on the functional form of inventory. It must be recognised that inventory control is a complex issue, and its management is often driven by factors beyond the control of production planners, or purchasing and finance departments (Chopra and Meindl, 2016).

In either case, a key decision concerns the decision of how much inventory stock, that is cycle stock plus safety stock should be carried. Two major risks generally govern this planning decision (Silver et al, 2008): 1) the risk of surplus stock and 2) the risk of insufficient stock to fulfil demand. Optimising this decision typically involves identifying *cycle stock* and *safety stock* levels which minimise and mitigate the impact on customer service levels, while having sufficient cash freed up to allow the management of short-term day to day operations and medium to long-term investments (Chopra and Meindl, 2016).

A key input in this decision is determining the future demand for inventory. Consequently, one needs to have an estimate of future demand for inventory, and the associated demand uncertainty and the lead time variability. Forecasts (whether selection or combination or pools) thus play a critical and central role in optimising the decision concerning inventory. Consequently, the evaluation of forecasting methods for optimal decision making is crucial to inventory performance (Kourentzes et al, 2019). The standard approach to forecast evaluation within time series forecasting is commonly facilitated by statistical forecast error metrics such as mean squared error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). Alternatively, forecasts may be evaluated based on an economic case using performance measures such as ordering or holding costs (Flores et al, 1993). Studies which evaluate the performance of forecasting methods can be divided into three streams based on their adopted metrics of performance measurement. The first stream is the classical statistical error metrics-only stream using metrics such as MSE and MAE (see for example, Boylan and Syntetos, 2006; Sanders and Graman, 2009. The second stream combines both the classical statistical error metrics, and the value in inventory units of the amount of surplus inventory holding associated with the forecast errors (see for example, Lee et al, 2000; Boone and Ganeshan 2008; Ali et al, 2011). These typically assume some inventory model which translates the forecast errors and the associated uncertainty into units of *safety stock* required in addition to the *cycle stock* estimates. The third stream combines classical statistical error metrics with either the surplus inventory holding risk in terms of its cost in money value (that is, £ or $) or the total relevant inventory cost risks, also in money (£ or $). This stream again assumes some inventory model, analytical or simulation based, which translates forecast errors and the associated uncertainty into inventory cost in money value (see for example, Flores et al, 1993; Catt, 2007). In summary these approaches are in large based on the use of classical forecast error metrics, and the associated uncertainty captured within the forecast errors, assessed directly, or in terms of inventory unit quantity or dollar value costs. For the purpose of this study, we therefore combine these three approaches above into a single strategy, and rebrand it as Forecast Error Cost Risks (FECR), for ease of readability and to support subsequent analysis.

While some studies (Catt, 2007; Flores et al, 1993; Lee et al, 1993) can be found in the literature which consider the cost risks emanating from the statistical forecast errors associated with the application of forecast models, that is, the FECR strategy, to the best of our knowledge, it appears that no single study can be seen to have evaluated forecasting methods performance by espousing the potential *profit and/or revenue risks*. In particular when deciding optimal *cycle stock, profit and/or revenue risks* posed by *safety stock,* estimation based on forecast errors of the corresponding forecast models has not been considered previously. In this study we discuss the standard approaches that have been adopted in previous research based on the use of forecast error and the associated inventory (cost) risk. We propose an adjusted model for the evaluation of forecast error cost risk. Furthermore, we propose a shift from the current cost-only analysis to a cost-and-benefit paradigm when evaluating the impacts of forecasting. To this end, we develop a new revenue risk model which should be of special interest to various actors within the supply chain including and especially, the retail chains.

3.4.2. Modelling Demand

A first step in an inventory system is estimating future demand. Two general approaches for achieving this are to estimate future demand by employing a forecasting model or estimating directly the demand distribution but fitting one of several candidate distributions. Even when the former approach of employing a forecasting model is used, it is still required to estimate uncertainty reflected in the errors of that forecasting model in order to derive the right safety stock. Several distributions have previously been considered for modelling demand. This includes the Poisson distribution typically applied for slow-moving items, as well as the Gaussian (or Normal) and Gamma distributions all evaluated previously for modelling demand uncertainty and lead time variability within the implementation of inventory policies (Silver and Robb, 2008). For the following reasons that, given its widespread use (Chopra and Meindl, 2016) and its versatility in that many distributions can be transformed into a Normal distribution via the Central Limit Theorem, the Gaussian (or Normal) distribution of demand is assumed in this study.

As it relates to demand, this research study considers and focuses mainly on seasonal and obsolescence product items such as newspapers, tabloids, fresh fruits, winter jackets etc. This has the implications that the entire stockover products from the current period cannot be used to fulfil demand for the next period and hence, must be disposed of by the end of the current period. This is the setup of the classical newsvendor problem with unknown demand distribution and finite selling season. As the company is required to place orders prior to the demand episodes, then the cost of orders which exceed demand must be borne by the company overage, and likewise the cost of underage, when demand exceeds inventory.

In practice the actual demand distribution F is unknown and needs to be estimated given some historical data $\{(D_1, \boldsymbol{x_1}), \dots, (D_n, \boldsymbol{x_n})\}$, where D_i are historical demand observations and $\boldsymbol{x_i}$ are predictor variables which can themselves be historical demand observations.

3.4.3. Lead Time and other System Characteristics

We assume there occurs in the system only a single order within a period, and also no order crossing is allowed (that is, a single supply is assumed). It is also assumed that the set-up cost and ordering cost are fixed and thus, have no effect on the cost structure. Study assumes as well that the replenishment lead time, L periods with a Gaussian distributed demand for each period i, where i = 1, 2, 3, …, L is independent and normally distributed with a mean of D_i and standard deviation of σ_i. Then, for an inventory control system that employs the periodic review policy, the total demand during the lead time periods will be correspondingly Gaussian distributed with a mean of D_T, a standard deviation of σ_T and defined as follows:

$$D_T = \sum_{i=1}^{T} D_i \tag{3.1}$$

and;

$$\sigma_T = \sqrt{\sum_{i=1}^{T} \sigma_i^2 + 2\sum_{i>j} \rho_{ij}\sigma_i} \tag{3.2}$$

Here, $T = R + L$ where R represents the review time interval (for placing orders) to replenish stock. In other words, the expected demand and the standard deviation during the lead time can be evaluated respectively, where demand for each of L periods is independent, and Gaussian distributed with a mean of D per period and a corresponding standard deviation of σ.

3.4.4. Cycle and Safety Stock Level

Where a forecasting model is applied or distribution assumed, cycle stock level is generally driven by the expected value of demand (typically taken as the output of the forecast model or mean of the distribution based on historical data), while safety stock level is based on a mathematical model that incorporates a service level factor, k, randomness in demand, and variations in lead time. Safety stock is especially important in a customer focused supply chain business where level of service is a key success factor. Insufficient safety stock leads to stockout and backorder, both of which impacts, in no small measure, customer satisfaction and loyalty. There are several names by which k is referred to; names such as safety factor, standard score or z-score are among popular names for k. Typical computation of the safety factor, k used in estimating the safety stock are conditioned on either service-based metrics or cost-based metrics. Both approaches and their metrics are interrelated such that if a metric is explicitly set, then the other metrics can implicitly be determined (Silver and Robb, 2008). In this work, we consider service-based metrics.

3.4.5. Service Based Metrics and Safety Stock Under Order-Up-To Policy

The service-based models incorporate the safety factor, k, which is set to meet a planned cycle service level (CSL), Υ_{CSL} given as:

$$\Upsilon_{CSL} = 1 - P(stockout) = P(x \leq k) \tag{3.3}$$

or a projected item fill rate (IFR), Ω_{IFR}, where $G(k)$ is standard normal unit loss function given as follows:

$$\Omega_{IFR} = 1 - \frac{\sigma_T G(k)}{DR} \qquad (3.4)$$

Whereas the cycle service level is the probability that there will not be a stockout within a replenishment cycle, the item fill rate is the fraction of demand that is fulfilled with the inventory on hand out of the cycle stock.

In order to frame our inventory policy, we would need to find the value of k corresponding to a pre-determined or a desired target cycle service level value or item fill rate value. For example, it is analytically important that an extra stock equivalent to 1.28 standard deviations of demand variability must be carried to fulfil demand with a cycle service level Υ_{CSL} of 90% confidence level. Thus, a 90% cycle service level corresponds to a safety factor k of 1.28. The values k corresponding to desired cycle service levels are obtainable from the 'standard normal table' of z-scores. The unit loss function $G(k)$ corresponding to a safety factor value k can also be obtained from the table of normal distribution probabilities that includes it.

For a periodic review (R, S) policy, S is the order-up-to (OUT) level and designates an inventory level predefined as a positive value. This is equivalent to the current inventory added to the replenishment lot size for an order to be placed when inventory levels are reviewed after a fixed period of time, R. Because the OUT level represents the inventory available to meet all demand arising between two consecutive order (or replenishment) periods, stockout will be experienced if demand during this time interval exceeds the OUT level. It is therefore essential that the cycle service level:

$$\Upsilon_{CSL} = Probability\ (D\ during\ R + L\ \leq S) \qquad (3.5)$$

According to the literature (Silver and Robb, 2008; Nahmias, 2009; Chopra and Meindl, 2016), the OUT level and safety stock are related as follows:

$$S^* = D_T + S_s \qquad (3.6)$$

where S_s represents safety stock and S^* the OUT level. It follows that under assumptions of normal distribution:

$$\Upsilon_{CSL} = F(S^*, D_T, \sigma_T) \qquad (3.7)$$

and by definition of the inverse Gaussian, standard normal distribution and its inverse:

$$S^* = F^{-1}(\Upsilon_{CSL}, D_T, \sigma_T) \qquad (3.8)$$

The safety stock can then be evaluated using the following mathematical construct:

$$S_s = F^{-1}(\Upsilon_{CSL}, D_T, \sigma_T) - D_T = F^{-1}(\Upsilon_{CSL}) * \sqrt{T}\sigma_T \qquad (3.9)$$

Assuming that demand is normally distributed during the time interval $R + L$ and the periodic demand means and variances are additive, the safety stock model of equation (3.9) can be expressed as follows:

$$\boldsymbol{S_s = k * \sqrt{R + L}\sigma} \qquad (\mathbf{3.10})$$

where $k = F^{-1}(\Upsilon_{CSL})$ and $T = R + L$. The above equation (3.10) is commonly used to mitigate uncertainty in demand and is well known in the inventory literature (Prak et al, 2017). To shield operation from lead time variability however, mathematical construct for safety stock will be given as the function of mean demand during period and the variance of lead time (Hadley and Whitin, 1963):

$$\boldsymbol{S_s = k * D\sigma_{LT}} \qquad (\mathbf{3.11})$$

In general, literature has shown that ignoring variability in lead time can cause significant degradation of service (Kumar and Arora, 1992; Chopra et al, 2004; Prak et al, 2017). Therefore, given Gaussian distributed demand volatility (where the two events of demand uncertainty and lead time variability are independent), the theoretical formulation for a fully robust safety stock combines protection against demand uncertainty with safeguard from supply fluctuation as thus in the following equation:

$$S_s = k * \sqrt{\left(\sqrt{R + L}\sigma\right)^2 + (D\sigma_{LT})^2} = k * \sqrt{(R + L)\sigma^2 + D^2\sigma_{LT}{}^2} \qquad (3.12)$$

that is, the product of ‘the safety factor’ and ‘the square root of the square of stochastic demand safety stock model, added to the square of the variability in the lead time model.

It is worth noting here that in inventory control and management, service levels and fill rates are used to determine, but also utilised to show significant differences in safety stock requirements for the desired fulfilment ratio. As demand uncertainty interacts with service level, fill rate and safety stock, the retail chain companies are required to understand how well they are fulfilling customers' needs. The thesis will remain focused on the use of cycle service level.

CHAPTER 4

Research Methodology

4.1 Introduction

Saunders et al (2007) research onion demonstrates and exemplifies the stages involved in the design process of a research work. It offers an effective evolution through which a research study methodology can be conceived and implemented. Adapting Saunders et al (2007), this chapter expounds, in line with the research objectives outlined in the thesis introduction chapter, the formation of the complete components making up the focus of this research study. Bryman and Bell (2007) have highlighted the fact that a deductive research seeks to apply theory to observations or findings.

This research work approach will be *deductive* in that the study considers forecasting models that are based on theoretical foundations. In addition, research strategy will be *quantitative* in terms of the data collection and the analyses to be conducted. But more importantly, the research study will be *context* bound and seeks to offer pragmatic solutions to some of the already highlighted real-life challenges being experienced in retail chains inventory management and control. Thus, aside from generated theoretical datasets, real retail historical demand or *empirical datasets* are collected and analysed using proven statistical and mathematical model formulations to find versatile and robust solutions for effective control of stock in retail chain firms.

4.2 Research Design Methods

As this research project is primarily quantitative, it employs analytical evaluation, simulation study, empirical exploration, regression analysis and optimisation technique. There are three components to the research approach adopted for this research work. The three components are: a) illative effects, b) inventory costs structure criterion, and c) inventory-investment functions alignment. Each of these research approach elements forms three studied strands (the details to be discussed in chapters 5, 6 and 7 respectively) in line with the three main research objectives as outlined in the thesis introduction chapter and repeated below for ease of access.

1. To investigate relationship between inventory control and inventory investment, and the impact of the latter on the former and vice versa.
2. To evaluate and quantify the utility measures, that is, the traditional statistical error metrics such as the mean squared error (MSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE) in terms of inventory variables such as relevant inventory forecast error cost risks (FECR) and forecast error revenue risks (FERR), and in relation to service level.
3. To explore and develop an alignment model for optimal inventory costs structure, under financial constraints such as working capital, trade credits and cash credits, which minimises costs and ultimately maximises net cash flow and profitability.

This study will consider whether association is endogenous or exogenous for objective 1 and by impacts, we mean main, moderation and mediation effects. Further, since the study has adopted a predominantly deductive approach in the research work, the methodology of this thesis study is as captured in Figure 4.1. The research study will follow the strategy of developing theoretical structures based upon well specified assumptions. These are then articulated in operational terms at the mathematical modelling level.

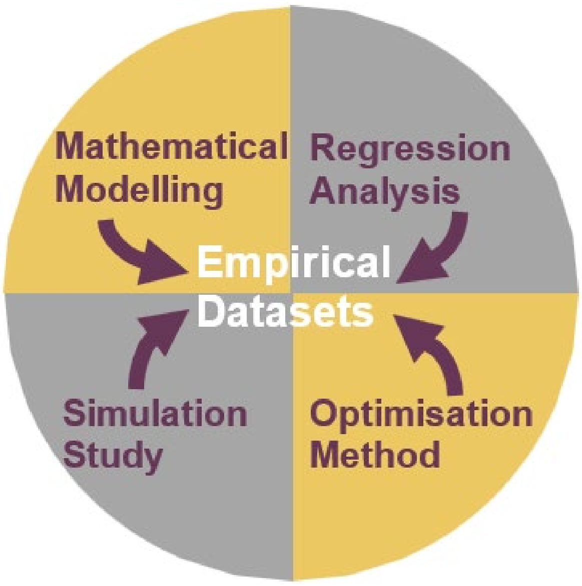


Figure 4.1 Methodology of the Research Study

Then, respectively for each of the above three main research objectives; regression analysis, simulation study and optimisation technique will be conducted using the mathematical models before they are taken home by being tested on empirical data.

4.2.1 Mathematical Modelling for Inventory Control

The number of mathematical inventory models in the literature is enormous and their complexity, as Waldman (2009) situates it, is heavily contingent on the assumptions made on the key subject of demand nature and about the cost structure as well as about the physical characteristics of the inventory system. An important assumption under consideration in this research study is that surplus stocks and stockouts are transferable from a period to the next. Therefore, multiple time period inventory model will be utilised in the current research work. And for the purpose of model validation, the reliability of mathematical models developed or appraised in this research work will be evaluated using simulation study.

It should be noted that the two most basic and simplified inventory control models that can be found in the literature deal with the decision of simultaneously satisfying all demand in a certain time period while ascertaining the optimal order policy that minimises the total relevant inventory cost (Simchi-Levi et al, 2008). These models are the classic work of Harris (1913) known as the economic lot size (ELS) model and its classic extension work by Wilson (1934) often referred to as the economic order quantity (EOQ) model. Both classic ELS and EOQ models, although are respectively overly simplified and simplistic form of reality, have however formed the basis for an immense number of research studies in the literature. This fact will also be the case for this current research work.

In supply chain risk management, the perpetual review policy and the periodic review policy are the two most common types of inventory control models for multiple periods that are subject to uncertainties in inventory systems (Waldman, 2009).

And, as mentioned earlier, the propositions attained from all the methods will also be tested with empirical data in order to ensure the applicability of the theory in real world situations.

4.2.2 Regression Analysis for Inference Study

Regression analysis is a set of statistical approaches that can be utilised to estimate the effect and impact of independent variable(s) on dependent variable(s) and for assessing the strength of their relationships. As a result, regression analysis methodologies can be utilised to ascertain and to classify the regressor variable(s) that are connected to criterion variable(s) and can also be applied to provide a model for predicting an outcome variable from an explanatory variable. But for the purpose of this research work, regression analysis method will be applied for purpose of the former (that is, inferential) rather than the latter reasons. *Multiple regression* analysis will be conducted to model and analyse the correlations, on the one hand between profitability and financial decision variables, and on the other hand between profitability and inventory key performance indicators including three statistical forecast error metrics, that is the mean absolute error, the mean absolute percentage error and the root mean squared error.

4.2.2.1 Multiple Regression Methods

Let i be the i^{th} number of observations for $i = 1, 2, 3, \dots, N$ and j be the j^{th} number of the explanatory variables for $j = 1, 2, 3, \dots, k$, a standard multiple linear regression model can be expressed as:

$$Y_i = \alpha + \sum_{j=1}^{k} \beta_j X_{ij} + \varepsilon_i \qquad (4.1)$$

The model is considered for modelling the response of an outcome variable, Y_i based on explanatory variables, X_{ij}, where the parameters intercept, α and slopes β_j are unknown fixed regression model coefficients. Further, the error term, ε_i can be considered as a random error or noise process consisting of independent and identically distributed normal variables with mean zero and variance, σ^2 $(iid\ N(0, \sigma^2))$.

Typically, and the same apply for this research study, ordinary least squares (OLS) regression is used to fit models of the form described above (Sheather, 2009). OLS is a linear estimation technique, with underlying statistical assumptions, that minimises the sum of the squared residuals (the difference between the observed values and the fitted values). This makes the OLS method a maximum likelihood estimator that is asymptotically efficient in terms of attaining the Cramer-Rao bound for variance, where the response variable, Y_i, is a linear function of the regressors, X_{ij} (Williams et al, 2013)

4.2.3 Simulation Study for Inventory System Performance

According to Wang and Petropoulos (2016), forecasting accuracy is widely reckoned and considered, in theory and in practice, as a positive contributor to the inventory system performance. Thus, for the inventory system, both the first-order and the second-order performance measures will be evaluated. Thus, the inventory variance (that is, the inventory level over time) which is the second-order moments of the inventory system variables and the first-order measure in terms of the average cost linearly associated with system variables are subjects of focus in terms of inventory performance metrics. The rationale behind these measures is that both are significant and relevant in a practical way. For example, the inventory fluctuation measure can be detrimental to retail businesses by inducing both inventory stockout and stockover costs. Both costs can be captured by the average total relevant inventory costs consisting of two components, the holding cost and the backorder cost. Thus, the output from the inventory simulation is the traditional inventory performance function, that is, the cost criterion, calculated in R periods as:

$$TC = hE(i^{+}) + bE(i^{-}) = \frac{h}{R}\sum_{t=1}^{R} i_t^{+} + \frac{b}{R}\sum_{t=1}^{R} i_t^{-} \quad (4.2)$$

where h and b are unit holding cost and backorder cost rates (discussed further in chapters 6 and 7) respectively. Moreover, in a Newsvendor setting the holding cost, h and backorder, b also define the target cycle service level C_{sl} such that $C_{sl} = b/(h+b)$. While $i_t^{+} = \max(i_t, 0)$ and $i_t^{-} = \max(-i_t, 0)$, the term i_t^{+} characterizes the positive on-hand inventory and the term i_t^{-} denotes backorders.

Simulation study will be employed in this research work for two primary reasons. The first reason for its usage arises from the fact that the inherent characteristic of simulation method's capability will undoubtedly enable study to gain a better understanding of the performance of the proposed forecast error cost risk (FECR) and forecast error revenue risk (FERR) models and the factors that affect their values. Secondly, simulation is also required because some model approximations will be employed, and this is not unusual, in the mathematical analysis.

4.2.4 Optimisation Approach

Optimisation approach are a set of mathematical models that make use of differential calculus which is useful in supporting decision making relating to the goal or objective (a quantitative measure of performance) of either minimising effort and risk (e.g., cost or time) or maximising solution and benefit (for example, profit) under some given conditions. There are several classifications of optimisation problems. These include linear programming (LP), quadratic programming (QP) and non-linear programming (NLP). In this study, the LP method designed with the following assumptions will be deployed.

- Objective function and constraints are both linear
- $min c^{T} x \quad s.t. \quad Ax \leq b \quad and \quad x \geq 0$

According to Taha (2017), an LP model consist of three basic components:

1. Decision variables that we seek to determine.
2. Objective (goal) that we need to optimize (maximize or minimize).
3. Constraints that the solution must satisfy.

The LP technique will be utilised in this research work to estimate the optimal integrated relevant inventory costs and optimal replenishment target and order quantity under the working capital constraint that considers cash credits and trade credits.

4.2.5 Forecasting Methods for Theoretical Study

Forecasting methods are basically algorithms for creating forecasts via statistical fitting techniques or models. For the purpose of this research study, the following five forecasting methods will be utilised for two simulated ARIMA (1, 0, 0) and ARIMA (1, 0, 1) monthly data sets.

4.2.5.1 Naïve Model

The naïve model will be used as a benchmark method. The naïve model is technically the random walk method which is basically based on the most recent observation (Hyndman and Koehler, 2006). The mathematical model for the naïve method can be computed as:

$$\widehat{D}_{t+h} | t = D_t \qquad (4.3)$$

4.2.5.2 Exponential Smoothing Models

Exponential smoothing methods are models based on the Holt-Winters Algorithms (HWA). They can be thought of as ad-hoc procedures by their nature because according to Chatfield (2001), they are not explicitly based on stochastic processes. Nonetheless, Ord et al (1997) and Hyndman et al (2002) have demonstrated that all linear and non-linear exponential smoothing techniques are optimal estimators from innovation state space models. The simple exponential smoothing and the ExponenTial Smoothing, also known as 'Error, Trend, Seasonal' have been selected for the simulation study in this thesis.

- ***Simple Exponential Smoothing (SES)***

The simple exponential smoothing is designed to model time series data levels and its forecasts are weighted average of all the past values adjusted by new observation, and with the weights following a geometrically (that is, exponentially) declining pattern. Let D_t be the actual observed value of a time series at current time t and F_t the forecast value. Then a one-step ahead SES forecast from time t would be given as, where α is the smoothing constant or factor and $0 < \alpha < 1$:

$$F_{t+1} = \alpha D_t + (1 - \alpha) F_t \qquad (4.4)$$

- ***ExponenTial Smoothing (ETS)***

For the simulation study, the current research work also employed the statistical framework ExponenTial Smoothing, also known as 'Error, Trend, Seasonal', which is an automatic exponential smoothing state space modelling method to forecast. The R Environment function ets() in the 'forecast package' can be used to implement the ETS estimator and can handle any combination of trend, seasonality and damping (Hyndman et al, 2008). Models can be estimated using ets() function which has been designed to be able to automatically select an appropriate model according to the information criteria of choice (with AIC as default). In returning information about the fitted model, it estimates the model parameters and ensures that they are invertible. In addition, when used with the forecast() function to obtain forecasts on test data subset, it produces prediction intervals for every model. Moreover, it should be noted that the many different ETS models can have additive error as well as multiplicative error elements for their trend and seasonality components but are analogous to other exponential methods including techniques such as SES, Holt's linear method (also known as double exponential smoothing (DES)), Holt-Winter (Hyndman and Khandakar, 2008). Although the authors provided general mathematical models or state space derivatives for all ETS methods, where x_t is a state vector and the error term ε_t is independent and identically distributed (iid) white noise following a normal distribution with mean 0 and variance σ^2, that is, $\varepsilon_t \sim iid(0, \sigma^2)$, as (details in Hyndman and Khandakar, 2008):

$$y_t = w(x_{t-1}) + r(x_{t-1})\varepsilon_t \qquad (4.5)$$

$$x_t = f(x_{t-1}) + g(x_{t-1})\varepsilon_t \qquad (4.6)$$

However, they argue that a more direct approach which generates estimate of the full prediction interval is highly beneficial for an inventory control system where expected costs are contingent and rely upon the entire distribution. Such direct strategy involves simple simulation of many sample paths subject to the last estimate of the state vector, x_t. Then the mean of the simulated values at each future time period produces point forecasts while the percentiles of the simulated sample paths generate the prediction interval.

4.2.5.3 Minimum Mean Squared Error (MMSE) Method

The mean square error (MSE) is a statistical criterion commonly employed in evaluating the accuracy of a forecast method (Devydenko et al, 2010). The minimum mean squared error (MMSE) is simply a formal mathematical criterion to calculate model forecasts. It is an estimator that is designed to focus on electing estimate (or determining model forecasts) by minimising the expected or the mean value of the square of the error, that is, MSE. In other words, MMSE is simply based on MSE.

Let the MSE be defined as $E[(D_t - \widehat{D}_t)^2]$ for a random variable of interest D_t whose estimate is $\widehat{D}_t$. According to Oppenheim and Verghese (2010), then, the MMSE estimate of D_t will be the expected value $E[D_t]$ if all observations are summarised in D_t's marginal distribution (or probability density function (PDF)). And the MMSE estimate of D_t will be the conditional expectation $E[D_t|X = x]$ if D_t is statistically related to another observable specific value x of a random variable X with known joint distribution (or PDF). This implies that the MMSE forecast of D_{t+h} (that is, an h-step ahead forecast from the forecast origin t), is given as:

$$\widehat{D}_t(h) = E[D_{t+h}|x_1, x_2, \dots x_t] \qquad (4.7)$$

Within the R Environment, the use of the predict() function in the 'stats package' and the forecast() function in the 'forecast package' without specified forecasting method will produce MMSE forecast for a given data set.

4.2.5.4 ARIMA Models

The autoregressive integrated moving average (ARIMA) models for forecasting are based on Box and Jenkins (1970) system of approach. The autoregressive moving average, ARMA(*p, q*) structure suggests that it includes the lags of the stationarised data series, that is, the autoregressive (AR(*p*)) terms and the lags of the forecast errors, that is, the moving average (MA(*q*)) terms. If a time series data needs to be differenced in order to secure stationarity, then it becomes an integrated ARMA(*p, q*) form which has been designated as the ARIMA(*p, d, q*) model. The *p*, *d*, and *q* letters stand respectively for the number of autoregressive terms, the number of non-seasonal differencing needed for stationarity, and the number of lagged forecast errors. The general form of ARIMA models formulation can be represented using the backshift operator, often symbolised as B, to express differencing. This is because it is both beneficial and very useful to denote a lagged series by B, not least, due to its great multiplicative power (Makidakis et al, 1998). Thus, in general, and ARIMA(*p, d, q*) process can be formulated, where α is an intercept term and ε_t is a white noise process with mean 0 and variance σ^2, as follows:

$$\phi(B)(1 - B)^d D_t = \alpha + \theta(B)\varepsilon_t \qquad (4.8)$$

In the above model, $\phi(y)$ and $\theta(y)$ are respectively the polynomials of order p and q.
The three common R Environment functions that are available to implement an ARIMA model are the arima() function, the Arima() function and the auto.arima() function. While the Arima() functions is embedded in the forecast package, the arima() function is integrated in the stats package. Hyndman et al (2018) advocates the use of Arima() function rather than the arima() function because the latter neither allows re-fitting a model to new data nor does it returns all forecast class required for forecast() function. According to the same authors, the auto.arima() is preferable over the two in terms of both performance and ease of use. The auto.arima() is simply an automatic ARIMA modelling method incorporated in the forecast package. It has the capability to automatically specify a suitable ARIMA model (Kourentzes and Petropoulos, 2016).

4.2.5.5 Forecasting Models Selection Strategy

To arrive at the five forecasting methods above, variants of these forecasting models have been fitted accordingly to the training data sets for the two generated ARIMA process-based time series data. This step was carried out for same-group model-selection purpose only. Thus, the list below names the same class forecasting methods considered for selection in this research study, with the winner candidates in each group in bold *italics*, as follow:

1. Naïve Models: ***Non-seasonal naive*** (or random walk); Seasonal naïve and Drift naïve.
2. Exponential Smoothing Models: the ***simple exponential smoothing*** *(SES)*, the double exponential smoothing (DES) and Holt Winters (HW) method.
3. ARIMA Models: Arima(), orders considered are: c(0,0,0); c(1,0,0); c(0,0,1); c(1,0,1); c(2,0,0); c(0,0,2); c(1,0,2); *(2,0,1)*; c(2,0,2) and ***auto.arima().***

First and foremost, generally in analysing a study data set, the possible patterns (such as level, trend and seasonality) as from the white noise that may likely occur in them will have to be identified. This will make possible and support the decision of which model or models are the best suited methods for a particular time series data. For example, if no seasonality has been encountered in a data set, the SES and DES algorithms may be considered and the better between the two gets selected. It is also possible to consider the class of linear AR(p), MA(q) their combination (that is, the ARMA(p, q)) and the integrated non-seasonal ARIMA(p, d, q) models. However, if seasonality has been detected in the data set, additive and multiplicative variants of HW and ETS methods and or the seasonal version of the ARIMA model could be considered, and the best algorithm discovered gets selected for producing forecasts. After a model has been fitted, it is crucial to check how well it has done on the data. There are more than a few diagnostic tools accessible to check model performance, in terms of behaviour and accuracy measures, which enable one forecasting method to be evaluated and compared to another model (Hyndman, 2021). The best forecasting model can be found by computing the relevant parameters such that the selection criterion is (or criteria are) minimal. Given a collection of models for the data, the selection criteria such as the Akaike information criteria (AIC), the Bayesian information criteria (BIC), the residual sum of squares (RSS) also known as the sum of square errors (SSE), the root mean square error (RMSE), the mean absolute percentage error (MAPE) and many more are able to evaluate the quality of each model, relative to each of the other models in order to declare the front runner for the candidate forecasting methods. By this means, the tracking of the appropriate AIC and or BIC provide a way for model fit efficiency selection, whilst RSME and MAPE can provide both the fit performance and the performance of predictive capability of a forecasting model.

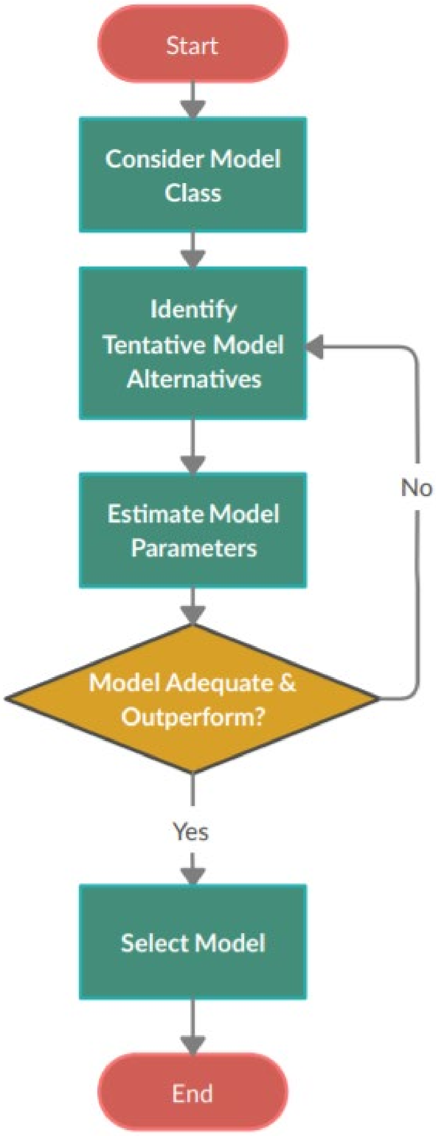


Figure 4.2 Flowchart for Model Selection

A schematic diagram of optimal model selection based on Box et al (2015) methodology and on Hyndman and Khandakar (2008) algorithm is shown in Figure 4.2. The models' output details such as the in-sample fitting indicators, the AIC and BIC values have been used to select winner models among rival candidates of the same model types in this study. Each of the five selected forecasting models will then be used to prepare a multiple month ahead (that is, h = 38 months) rolling window forecasts for the two generated (AR1 and ARMA11) data sets mentioned above for the simulation study. On the other hand, to select winner models among rival candidates of the different model types in this study, the models' output details such as the out-of-sample error indicators, (specifically, the MAE, MAPE and RMSE values) have been used as detailed in respective subsequent chapters 5, 6 and 7.

4.2.6 Forecasting Methods for Empirical Study

In the field of forecasting, an important starting point in considering the choice of forecast strategy to deploy is influenced by the nature and the feature of the data series. The frequency of the data sets is one of those critical features (Trapero, 2010). The frequency of all the data series for this research work is weekly. Unlike quarterly and monthly data sets, weekly, daily and hourly time series by their nature can be high frequency, multiple seasonal data with rather long seasonal periods (Hyndman and Athanasopoulos, 2018). As such, many of the standard forecasting methods are not appropriate to use for their forecasts. Hyndman and Fan (2010), De Livera et al. (2011), Fan and Hyndman (2012) have all argue that because the seasonal versions of ETS and ARIMA models are designed for shorter seasonal periods such as four for quarterly and twelve for monthly data sets, they do not tend to give good forecasting results for data sets with longer seasonal periods such as weekly, daily and hourly time series. There are three models serving as alternative approaches for handling these sets of high frequency, multiple seasonal data with rather long seasonal periods.

In order to examine the effect of the forecasting methods using the weekly demand data, it is assumed that the retailer employs the following three different methods to forecast the lead time demand:

- Seasonal and Trend (decomposition using) Loess Forecasting (STLF) Model
- Dynamic Harmonic Regression (DHR) Model with ARMA error structure
- An exponential smoothing state space (trigonometric) model with Box-Cox transformation, ARMA errors, trend and seasonal components (TBATS) model.

Hyndman and Athanasopoulos (2018) espouse that the above listed three models are more appropriate and optimal forecasting methods designed specifically to deal with high frequency types of data series. According to Hyndman and Athanasopoulos (2020), the decomposition-based method referred to as STLF is a simple but robust approach to modelling and forecasting high frequency time series data. The idea is that, rather than ARIMA or GARCH models approaches of capturing temporal dependencies and auto-correlations in the data, the STLF will explicitly model the data as a combination of trend, seasonal and remainder components. They further opined that the STLF approach is the simplest of the three methods (that is, STLF, DHR and TBATS), but that it is a versatile and robust method both for decomposing time series and for estimating nonlinear relationship. Thus, for the purpose of empirical analysis in our study, these three models (that is, STLF, DHR and TBATS) will be the correct and the applicable forecasting methods for the particular nature of the demand data series, which are weekly, for this research work (Hyndman and Athanasopoulos, 2018 and 2020).

4.2.7 Forecast Accuracy Metrics

In order to evaluate error of prediction, Ord et al, 2017 advocates the use of general-purpose criteria such as the simple mean of the errors, absolute errors and relative errors. The following five statistical forecasting error measures which are traditionally the most often used for the ensuing statistical error measure estimations (Ord et al, 2017; Davydenko and Fildes, 2016) fall into these three types of error metrics. The five statistical forecasting error measures are the mean error (ME), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the mean squared error (MSE) and the mean absolute scaled error (MASE). The mean error is computed as the arithmetic average of the set of forecast errors, effective in identifying systemic bias in a forecast.

$$ME = \frac{1}{n}\sum_{i=1}^{n} e_i$$

Basically, averaging the absolute values of the set of forecast errors gives the statistical error measure called mean absolute error (MAE) which is a useful way to measure variability in absolute terms.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i|$$

Mean absolute percentage error (MAPE) is commonly used as a loss function effective in measuring variability in relative terms and is the absolute magnitude of each forecast error as a percentage of the actual demand and then average the percentages.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|e_i|}{D_i}$$

The mean squared error (MSE) also measures variability in absolute terms and is simply obtained by averaging the squares of the forecast errors.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_i^2$$

The square root of MSE is denoted as the RMSE, where R stands for 'root of'. It is worth noting that because in MSE the unit of the metric will also be automatically squared, by taking the square root of MSE, RMSE has been applied to keep and conserve both the MSE property of penalising higher errors and the original unit of the time series.

The mean absolute scaled error (MASE) is the weighted arithmetic average of the relative mean absolute errors (MAE). The denominator MAE_{Naive} in the MASE formulation as shown below is the mean absolute error for the Naïve model forecast for the time series (Davydenko et al, 2010).

$$MASE = \frac{1}{n}\sum_{i=1}^{n}\frac{e_i}{MAE_{Naive}}$$

MAE (based on the absolute errors) and RMSE (based on the squared errors) are the two most commonly used scale-dependent measures. RMSE and MAE are good measures of accuracy to compare forecast models applied to a particular variable such as a single time series, or to several time series with the same units. While a forecast model that minimises the RMSE will lead to forecasts of the mean, a forecast model that minimises the MAE will lead to forecasts of the median (Hyndman and Athanasopoulos, 2014; Hyndman and Koehler, 2006). Further, while the ME is regularly used for estimating the biasness of forecasts, the three metrics (MAE, MAPE and MSE) that follow ME are quite popular and prevalent and appear to be practitioners' metrics of choice, among many for the estimation of forecast accuracy within the retail chain companies (Hyndman and Athanasopoulos, 2014; Davydenko et al, 2010; Hyndman and Koehler, 2006). In addition, Byrne (2012) and Kim and Kim (2016) highlight that MAPE is the most widely used measure of forecast accuracy and that it is very popular with industry practitioners because it is scale-independent and due to its advantage of interpretability. Consequently, and pursuant to the discussion with respect to the forecast accuracy metrics, the simulation study and the empirical analysis in this research work will focus on these three forecast error measures while mean error will be considered a measure of bias in forecasts. Thus, the results of forecasting methods will be compared using these accuracy measures including the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE). The means of the outputs for these statistical forecast errors across the total simulation runs will be obtained and utilised for study analyses in each of the research study strands.

4.3 Research Datasets

4.3.1 Simulation of Demand Data and Sample Profile

Data for this research study have both been theoretically generated as well as collected empirically. For this research study investigation, to produce forecasts using the five forecasting procedures listed above in section 4.2.5, two demand data sets have been generated. One follows a first order autoregressive, ARIMA (1, 0, 0) process and the other follows a mixed order autoregressive moving average, ARIMA (1, 0, 1) process. In ARIMA (1, 0, 0), a limitation is that only the previous term in the process and the noise term contribute to the output. An implication of this is that the ARIMA (1, 0, 0) model may be ignorant of correlated noise structures (which is unobservable) in the time series. So, ARIMA (1, 0, 1) is also used in this research study. However, to prevent a claim of the data being correlated when in fact they are not, it is important to beware of parameter redundancy in ARIMA (1, 0, 1). Table 4.1 and Table 4.2 below show relevant data characteristics (descriptive statistics) of the generated data sets, respectively, for one following a first order autoregressive, ARIMA (1, 0, 0) process and for the other that follows a mixed order autoregressive moving average, ARIMA (1, 0, 1) process.

Table 4.1 Data Characteristics ARIMA (1, 0, 0)

	ARIMA (1, 0, 0)		
192 Data Series	Mean	Variance	Coefficient of Variance
Minimum	99.49	0.64	0.01
Lower Quartile	99.93	0.94	0.01
Mean	100.00	1.05	0.01
Median	100.03	1.06	0.01
Upper Quartile	100.15	1.13	0.01
Maximum	100.38	1.71	0.01

Table 4.2 Data Characteristics ARIMA (1, 0, 1)

192 Data Series	ARIMA (1, 0, 1) Mean	Variance	Coefficient of Variance
Minimum	119.54	1.24	0.01
Lower Quartile	119.87	1.84	0.01
Mean	120.03	2.54	0.01
Median	120.05	2.19	0.01
Upper Quartile	120.18	3.29	0.01
Maximum	120.42	4.20	0.02

Values shown in both two tables above are averages of relevant measurement properties in terms of measures of central tendency, dispersion, and position for the 192 simulated sets of data from both processes.

4.3.1.1 Data Series Sub-Setting Rules

Hydman (2018) has asserted that for the purpose of data series sub-setting for time series forecasting, eighty percent (80%) of the total dataset is about ideal for the in-sample or training subset. The remaining twenty percent (20%) of total dataset can then be used as the out-of-sample or test subset for evaluation of the forecasting methods predictive performance. This is the sub-setting rule that will be applied to both the simulated data series and the real raw data sets for the empirical study in all the three strands that make up this research work.

4.3.1.2 Simulation Study: Evaluating Accuracy of Forecasting Methods

When building a forecasting model, there is the need to evaluate its performance. *Cross-validation* (CV) is a statistical technique that can help with this requirement. It has been demonstrated by several studies (see for example, Cerqueira, Torgo and Mozeti, 2019; Hyndman and Koo, 2015; Arlot and Celisse, 2010) that this method helps to prevent overfitting, produces more data points for measuring forecast errors and evaluates model performance in a better and more robust way than the simple training-and-test technique. In a simple training-and-test technique implementation depicted in Figure 4.3, the training subset of the available data series is used for fitting a forecasting model. The test subset of the data series is held out to be used for the predictive approach evaluation.

Figure 4.3: Simple training-and-test technique.

The procedure for the CV method is to split the historical dataset into several folds, then train the forecasting model on all folds except one and test the model on remaining fold. There is need to repeat these steps until the forecasting model is tested on each of the folds, and the final forecast error metric for use in further analysis will be the average of the error scores obtained in every fold. Accordingly, for the research study, after sub-setting the training dataset and the test dataset as described in sub-section 4.3.1.1, in fitting and evaluating forecast accuracy for any of the forecasting approaches to be deployed to make weekly demand prediction, a *time series split* (TSS) cross-validation on rolling forecasting window, rolling origin has been implemented. The utilisation of a rolling origin delivers a more dependable appraisal of performance (Fildes, 1992 in Ord et al, 2017). This implementation has been realised by utilising and further partitioning the training set into two folds (the training fold and validation fold) at each of the iterative process on a condition that the validation set is always ahead of the training set.

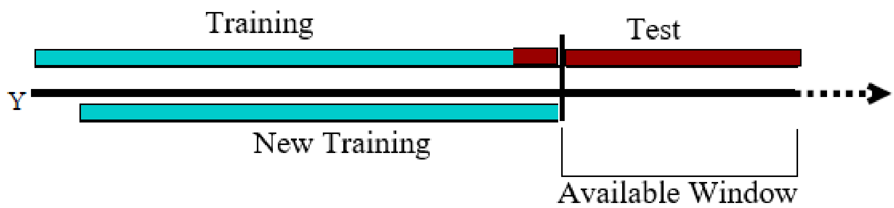


Figure 4.4: An instance of single iteration of the cross-validation statistical system.

Figure 4.4 shows an instance of a single iteration of the cross-validation statistical system where data points are taken from the starting test subset (the dark red colour portion) leading to the indicated 'available window'. The selected observations are added to the starting training subset (torque blue colour section) of the data series Y and used as the new training subset. Then subsequent portion of the remaining data points in the test subset are used for evaluation.

4.3.2 Empirical Data Sets and Sample Profile

The data sets used to conduct empirical analyses in this research study originates from two separate sources but both in the United States:

1) Data have been collected from Hass Avocado Board (HAB), a US based consortium of retailers of a short shelf-life perishable product, known as Hass avocados (HAB, 2018).
2) Data were also collected from the Information Resources Incorporated (IRI) Academic (Bronnenberg et al, 2008). Data sets from IRI include data series for Milk, Yogurt and Salty Snack products.

Table 21 characterises the weekly US Hass avocado (combined for the two types of the avocado product) data series and the IRI Academic retail data sets for three products; both time series are to be employed for the empirical analysis in this research study investigations.

4.3.2.1 The HAB Data Series

The 'Hass' avocado is a *Persea americana cultivar* of dark green fruit, weighing between 200g and 300g with bumpy skin. The HAB claims to exist to help make avocados America's most popular fruit (HAB, 2019). In the HAB's own words, "*HAB is the only avocado organization that equips the entire global industry for success by collecting, focusing and distributing investments to maintain and expand demand for avocados in the United States. HAB provides the industry with consolidated supply and market data, conducts nutrition research, educates health professionals, and brings people together from all corners of the industry to collectively work towards growth that benefits everyone*".

The data sets from HAB consist of real retail Electronic Point of Sales (EPOS or simply retail scan sales history) data for National retail volume (units) and price obtained directly from retailers' cash registers based on actual retail sales of Hass avocados (HAB, 2018) in multiple markets in the United States (US). Packed and loose sales volume of the product have been pooled and reported in total weight by Hass Avocado Board. Although this is a single product, the two variants of the product, conventional and organic types, have further been aggregated and included in the data to be analysed. The average price of avocados reflects a per unit (that is, per avocado) cost, irrespective of multiple units sold in bag packs. The total data points or observed cases for the original dataset collected across 53 US regional locations and what the HAB referred to as 'TotalUS' are 18,249 data points. The final total observed cases for the conventional and organic avocado products, collected across the 53 US regional locations are 16,639 data points, which is made up of 8321 observed cases for the conventional type of avocado and 8318 data points for the organic product type. Each of the two data sets included weekly sales and prices from 4 January 2015 to 31 December 2017.

The three years weekly data sets have been aggregated across the 53 regions and for the 2 product types to produce a total of 157 weeks observations for the investigation analysis work of this research study. According to this historical data on avocado prices and sales volume in multiple US markets, the third year, that is January 2017 to December 2017, consists of 53 weeks while each of the remaining two years consist of 52 weekly observations.

4.3.2.2 The IRI Academic Data Series

The research study also utilised data sets of real retail EPOS data and product information collected directly from the Information Resources Incorporated (IRI) Academic (Bronnenberg et al, 2008) in the US as well. The three IRI data series include historical data sets on prices and sales volume for Milk, Yogurt and Salty Snack products in multiple US markets, and these products have been categorised as having short shelf lives. The observed cases for the products, collected across 1,603 store locations are: (1) 33,871,335 data points for milk, (2) 69,730,746 data points for yogurt and (3) 116,858,658 data points for salty snack. Each of the three data sets included weekly sales and prices from 1 January 2001 to 31 December 2006. Thus, as in the previous study chapter 5, six years weekly data sets have been aggregated for the stores to produce a total of 313 weeks observations for the investigation analysis work in this current chapter. According to the data sets, the sixth year, that is, January 2006 to December 2006, consists of 53 weeks while the rest of the years consist of 52 weekly observations each.

4.3.2.3 Some Notes About Both Data Series

It should be noted that, first, for a number of obvious reasons including perhaps business nature but certainly confidentiality and protection of business strategy, all required data sets are often difficult to obtain from target sources (Cleophas et al, 2009).

Table 4.3: Data Series Weekly Characteristics

	Milk		Snack		Yogurt		Avocado	
Variables	Demand	Price	Demand	Price	Demand	Price	Demand	Price
Observations	313	313	313	313	313	313	157	157
Mean	56.49	2.57	46.73	2.31	47.31	1.98	44.13	1.74
SD	2.50	0.22	3.47	0.13	7.36	0.31	9.71	0.27
Median	56.37	2.47	46.05	2.32	47.49	1.87	44.29	1.70
Trimmed	56.41	2.57	46.34	2.31	47.52	1.97	44.47	1.72
MAD	2.47	0.26	2.96	0.16	7.31	0.29	9.40	0.25
Minimum	50.56	2.26	40.56	2.06	22.67	1.55	7.18	1.24
Maximum	65.57	2.99	61.18	2.65	64.36	2.53	70.10	2.58
Range	15.00	0.73	20.62	0.59	41.69	0.97	62.93	1.34
SE	0.14	0.01	0.19	0.01	0.41	0.02	0.78	0.02
Skew	0.40	0.22	1.24	0.16	-0.35	0.45	-0.57	0.65
Kurtosis	0.37	-1.51	1.95	-0.79	0.31	-1.41	1.48	0.23
CV	0.04	0.09	0.07	0.06	0.10	0.16	0.22	0.15

Standard Deviation (SD); Mean Absolute Deviation (MAD); Standard Error (SE); Coefficient of Variation (CV).

NB: Demand figures for variables (excluding first and last three rows) are in; million units for Avocado and hundred thousand units for Milk, Snack and Yogurt.

As a consequence, the weekly sales volume data sets have been collected as proxies for retail demand. Although it is recognised that sales and actual demand are not the same. However, sales figure as proxy for demand is acceptable to and allowed by the academic world for research analysis purpose. By means of these data sets for sales quantities and price, the relevant target variables for this study can easily be generated with some sound and realistic assumptions, thereby permitting fair tests of the relationships between these variables of interest (Syntetos et al, 2010). Thus, the retail data series described above will be used as demand data sets to create forecasts, to simulate inventory levels including stockouts and to derive financial variables for investigations and analyses in this research study. It is important to highlight at this point that the choice of weekly data sets for the empirical study is deliberate, and it is designed to find out whether or not results similar to the monthly data sets in the simulation work will be obtained.

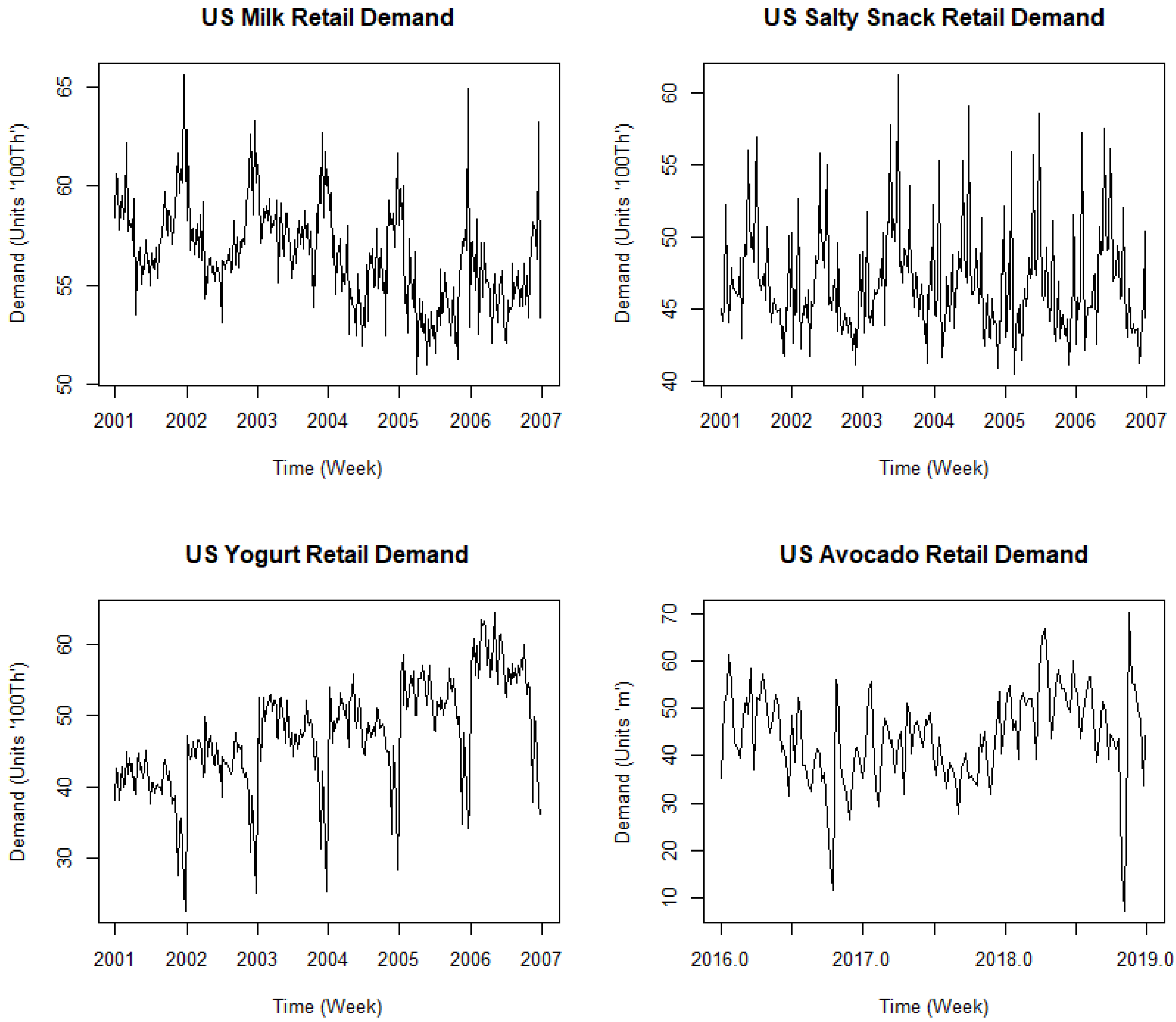


Figure 4.5: Demand over the shown periods appearing to indicate some yearly seasonality for each of the items.

It is also important to point out as well that the US National Retail Federation (NRF) 4-5-4 Calendar establishes 'Sales Release' dates, which are necessary for sales reporting purposes (NRF, 2021). This occurs approximately every five to six years, though this is not always the case. The years 2006, 2012, and 2017 were all 53-week years with 2023 set to be another 53-week year, which may explain why the HAB data series for 2017 and the IRI data series for 2006 would be 53 weeks. The summary statistics and demand time plot for each of the data series are as shown respectively in Table 4.3 and Figure 4.5. It is important to remark that in Table 4.3, the demand figures for variables excluding first and last three rows are in million units for avocado and hundred thousand units for milk, salty snack and yogurt. The table characterises the weekly IRI Academic and Hass avocado US retail market data series.
In these results, the sales data sets for milk and salty snack appear to be skewed to the right, as their mean values are slightly higher than their median amount. Milk indicates the mean to be 5649393 but the median is 5637451, while for the salty snack, the mean is 4673485 and the median is 4604599.

For the yogurt and the avocado data series however, sales appear to be skewed to the left with the mean being 4731019 but the median equals 4748645. Similarly, the mean of 44127892 and median of 44287021. However, the skewness is not substantial since it is $0.4 < 1$ and $-1 < -0.35$ for both milk and yogurt respectively. This is not the case for the salty snack. These results also show that there may be some form of seasonality in every two-year period for the avocado but yearly seasonality for milk, salty snack and yogurt over the 6 years period appear to be slightly stronger with some slight downward trend for the milk data set and upward trend for the yogurt data series can be noticed in the sales data sets plots in Figure 4.5. These real sales data sets will be used as the proxy for actual demand and to generate different forecasts to be used in the simulation and optimisation experiments.

4.3.2.4 Exploratory Data Analysis (EDA)

The original data sets will be explored using the Exploratory Data Analysis (EDA) technique as necessary in the respective chapters. The Fama (1970) efficient market hypothesis (EMH) will be tested through visualisation and component analyses for characteristics of stationarity by looking at the autocorrelation functions (ACF) of each data series signal. For a stationary signal, because dependence is not expected with time, the ACF is thus expected to go to zero for each time lag. Further, three statistical tests are also to be conducted to ascertain the validity of data series. These tests will include Ljung-Box test for independence, Augmented Dickey–

Fuller (ADF) t-statistic test for unit root and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) for level or trend stationarity. In particular, the Ljung-Box test for independence will be used to examine whether there is significant evidence for non-zero correlations at given lags.

4.3.3 Estimating Financial Variables

The method employed to produce the financial performance variables of interest (that is, working capital level and the free cash flow) is an investment-based approach to the pricing of assets that produce income over an investment holding or forecast period (Francis et al, 2000; Myers, 1984). Specifically, the discounted cash flow (DCF) technique has been utilised to generate the financial variables for the research study. A well-known fact is that money in future may be worthless than it is at present because inflation can erode the value of money. However, a pound (£) this period can also be invested to earn returns next period. Thus, the DCF procedure makes use of the concepts of the time value of money (TVM) as it enables venture market value (MV) and or investment intrinsic value (IV, both enterprise and equity). In other words, accounting for uncertainty, the model can be derived from an important underlying assumption; that price is the present value of expected future cash flows or net dividends discounted at the cost of capital (typically the equity capital or the debt capital or a weighted average of both). It is common to determine the discount rate as the opportunity cost, that is, the present value of free cash flow is discounted at the weighted average cost of capital (WACC). It may also assume that all cash flows are discrete; that is, any continuous payments can be approximated by a set of discrete payments (Adams et al, 2003). In addition, Jennergren (2008) and French (2013) opine that in order to reflect actual receipt of cash flows, the DCF model can be utilised to examine the cash flows on a periodic basis. The author Jennergren (2008) encapsulates the periodic approaches to the DCF analysis thus, "*the discounted cash flow model, like other firm valuation models, proceeds in two periods. For each year in the explicit forecast period, there is an individual forecast of free cash flow. On the other hand, all of the years in the post-horizon period are represented through one single continuing value formula, being the steady-state value of the firm's productive assets at the horizon*". This research study adopts the former approach. As mentioned above, the net present value (NPV) is an essential component of the DCF analysis. The NPV modelling gets all the net cash flows and discount them to the start of the period. Let C_t be net cash flow at time t where $t = 1, 2, 3, \dots, n$. The NPV can be computed at a given rate of return (also known as the discount rate), r as follow (Adams et al, 2003):

$$\mathrm{NPV}_t = \sum_{t=1}^{n} \mathrm{C}_t \,(1 + r)^{-t} \qquad (4.9)$$

According to Brigham and Houston (2016) model, the net cash flow or free cash flow (FCF) can be expressed, where per time period, t, C_t (or FCF_t) is the free cash flow, EBIT_t is the earnings before interest and tax (that is, the operating profit), R_t is tax rate, D_t is depreciation, CE_t is capital expenditure and CWC_t is change in net working capital, as follows:

$$\mathrm{C}_t = \mathrm{EBIT}_t\,(1 - \mathrm{R}_t) + \mathrm{D}_t - (\mathrm{CE}_t \pm \mathrm{CWC}_t) \qquad (4.10)$$

And the four important components of working capital level, WCL_t, can be modelled as given by:

$$\mathrm{WCL}_t = \mathrm{I}_t + \mathrm{C}_t + \mathrm{TR}_t - \mathrm{TP}_t \qquad (4.11)$$

In the working capital level model above, I_t represents the inventory for a retail firm in time period, t, C_t is cash for the firm in the same time period, TR_t and TP_t respectively represent the trade receivables and trade payables by this firm also in time period t.

The algorithm and means by which the DCF model procedure has been put to use is described in the Appendix II. It should be noted that as there are a wide range of FCF, the theoretical cash flow known as the unlevered FCF, which refers to a firm's cash flow prior to accounting for financial obligations, is typically the proxy often employed for cash flow when building financial and valuation models (Brigham and Houston, 2016). Thus, the unlevered FCF has been considered for the current research study, especially, since technically, could be used to pursue opportunities that improve stockholders' value and that the debt holders (or creditors) and equity holders (or investors) can access this form of cash flow from a firm's business operations (Jensen; 1986).

4.4 Research Design Process

As highlighted at the beginning of section 4.2, there are three components to the research approach adopted for this research work. Each of the three research approach elements (that is; illative effects, inventory costs, and inventory-investment alignment) are in line with the three main research objectives and will form the three studied strands in chapters 5, 6 and 7 respectively with largely, the same study design process. Figure 4.6 below illustrates the research design process that has been utilised in this research study.

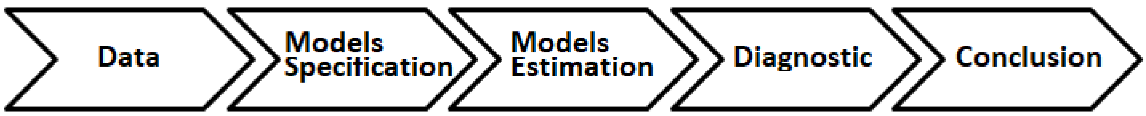


Figure 4.6 Chapter Research Design Process

Models relevant to each study strand have been specified, estimated, and tested to assess the economic impacts of classical forecast errors and how different effects affect business outcomes. While the data phase of the research design process in Figure 4.6 has been discussed in the preceding section 4.3 of this current chapter, each of the remaining phases (except the conclusion phase) of the research process will be discussed in detail and as applicable, in each of the studied strand chapters. And the conclusion phase will be discussed in the discussion and conclusion chapter for the thesis.

CHAPTER 5

Quantifying the Interaction and Intervention in Inventory

5.1. Introduction

5.1.1 Chapter Study Purpose and Motivation

The purpose of this chapter is to study the relationship between forecast accuracy, inventory productivity, and financial performance in the retail industry. In particular, it seeks to:

1. Understand and identify potential relationships among key variables of interest such as working capital, free cash flow, inventory turns and measure of forecast accuracy
2. Examine the mechanism of change (that is, system of causally interacting entities that create effects and or affect effects)
3. Explore the interventions and the interactions between inventory decisions and the choices being made by the finance function within the retail firms.

The motivation for this sub-study is borne out of the fact that the dominant theme of the empirical inventory control literature over the past century has been to improve operational productivity and efficiency through improved forecast accuracy, without sufficient care for the pecuniary implications of forecast performance (Fields, 1989; Amstrong, 2001; Hyndman et al, 2002; and see also chapter 2 and chapter 3 for further details). This current study contends that added operations performance improvement can further be achieved by better understanding the relationship, and in particular, gaining insights into the interactions between forecast accuracy, inventory and financial decision making.

The intended contribution of this chapter of the PhD research study is threefold. It is observed from extensive literature search that, as far as the literature appears to portray, this research study element will be the first attempt that:

a) Systematically investigates the simultaneous degree to which both forecast errors (such as the mean absolute percentage error) and financial performance proxies (such as working capital and free cash flow) impact upon inventory efficiency – see section 5.2 immediate below for description of these variables.

b) Models these antecedents (without latent variables) within a multivariate analysis methodology (MAM) framework of structural equation modelling (SEM) and explores their interactions (Hayes and Preacher, 2010; Kline, 2005)
c) Explicitly explores the forecast error as a mediated influence on financial variables.

In addition, this study chapter is the first step in the right direction towards the overall study aim to offer more empirically based insights into the *relative roles* and importance of different performance criteria across two retail business functional areas (operations and finance).

5.1.2 Organisation of Chapter

The next section is a description of the conceptual framework adopted and of the description of the model. This is followed by the introduction of the study metrics, the discussion of their major premises and conceptual rationale for the hypotheses to operationalise the study model as depicted in the Figure 5.1. Next in the chapter is discussion of the empirical data set used in conducting this component of the research study and then the description of the model specifications for model the proposed hypotheses. The presentation of the findings from estimating the specified hypothesis models is next while the chapter concludes with a discussion of the implications of the outcomes and some suggestions for future research.

5.2 Description of Variables

In this section the criterion variables and explanatory variables of focus for the regression-based study investigation will be indicated. The choice of these variables is primarily guided by previous empirical studies (for example, Gaur et al, 2004; Farris et al, 2010) as observed from academic literature. The chapter study aims to use some of the operational and financial metrics that are not being picked up for assessment of interaction and intervention by the previous research studies (Deloitte, 2019). But in particular, careful considerations have been given to practical usage popularity factor and the importance of variables as key metrics to measure the relevant performances under the study scrutiny (Peel et al, 2000; Prasad et al, 2019). Typically, a retail business firm’s outlook performance is characterised by operations productivity and financial formidability (Deloitte, 2019). The following financial and operational performance measures (as indicated in equations 5.1 to 5.4 below) have been employed to operationalise the conceptual framework proposed in section 5.2 above. These metrics, used as the regression variables for this aspect of the PhD research study have been chosen as the proxies for operational decisions as well as for financial decisions. All the four variables (that is, working capital, free cash flow, inventory turnover and mean absolute percentage error) that have been explored for the chapter study can be computed from the following formulas. Their definitions and their importance for consideration in this study are also discussed in the following sub-sections. The roles of each variable in the chapter study model will be discussed in the hypotheses section.

5.2.1. Working Capital

The authors, Deloof (2003) and Hill et al (2010) have opined that fundamentally, working capital (WC) is one of the most important metrics for evaluating a retail firm's financial fitness, especially in connection to cash conversion cycle (CCC; also known as working capital cycle), and in conjunction with free cash flow. For example, when cash is tied up in working capital than the previous year, the increase in working capital will be treated as a cost against free cash flow (FCF). Working capital is a liquidity and efficiency performance metric that indicates not only a business's ability to effectively meet all of its short-term financial obligations, but it also is closely associated with a retail firm's funding needs necessary to invest on inventory as well as on fixed costs (Afrifa and Tingbani, 2018).

Working capital is often modelled as a function of current (short term) assets and current (short term) liabilities, or the arithmetic difference between the two (Vernimmen et al, 2017). Evidence (see for example, Cooper et al, 1998; Al-Shubiri, 2011) suggests that in a situation where current liabilities are in excess of current assets, a negative working capital will result, which may well lead to poor liquidity; that is, working capital deficit or financial distress for firms. Together, both current assets and liabilities account for four critical areas of a retail business. The four important components of working capital include inventory, trade receivable, cash and cash equivalents including bank balances, and trade payable. Thus, under these assumptions, the working capital level, WCL_t, can be modelled as follows:

$$\mathrm{WCL}_t = \mathrm{I}_t + \mathrm{C}_t + \mathrm{TR}_t - \mathrm{TP}_t \qquad (5.1)$$

In the model above, I_t represents the inventory for a retail firm in time period, t, C_t is cash for the firm in the same time period, TR_t and TP_t respectively represent the trade receivables and trade payables by this firm also in time period t. Subsequently, all equations in this chapter of the thesis follow the same subscript and sub-subscript index format; that is, subscripts other than t will stand for the index of further description or the number of the main conceptual variable while sub-subscripts i and t index size of observation and time period respectively.

5.2.2. Free Cash Flow

Free cash flow is another important measure of a retail firm's financial performance. Jensen (1986) proposed the "Free Cash Flow Theory of Takeovers" in the context of agency conflict. He has referred to FCF as "cash flow in excess of what is required to fund all projects that have positive net present values (NPV) when discounted at the relevant cost of capital". He reasoned that it represents how much excess cash a company has left from its operations that are both distributable to shareholders and could be used to pursue opportunities that improve shareholders value. Moreover, the FCF concept remains very popular among academics, financial managers, financial analysts, and financial statement. Bhandari and Adams (2017) suggested that "both the level of, and change in, cash flow provide useful information in assessing a firm's performance and its future direction".

In view of the foregoing discussion and for the purpose of this chapter study, given the importance as well as the popularity attached to working capital and free cash flow, both have been considered as comprehensive reflections for financial decision variables in respect of inventory investment management and or firm financial performance. According to Brigham and Houston (2016) model, FCF can be expressed where per time period, t, FCF_t is the free cash flow, EBIT_t is the earnings before interest and tax (that is, the operating profit), R_t is tax rate, D_t is depreciation, CE_t is capital expenditure and CWC_t is change in net working capital, as follow:

$$\mathrm{FCF}_t = \mathrm{EBIT}_t\,(1 - \mathrm{R}_t) + \mathrm{D}_t - (\mathrm{CE}_t \pm \mathrm{CWC}_t) \qquad (5.2)$$

5.2.3. Inventory Turnover

For inventory turnover (*iTurns*), a performance measure of productivity or growth in inventory, it is an important operational activity ratio, and provides a typical measure of how effectively a business is utilising its inventory system during a specified period (Chao et al, 2008). It is a classical ratio (see equation 5.3 below) showing how many times a company's inventory is replenished, that is, number of times inventory is sold and replaced over a period of time, say weekly, monthly or annually. Following Deloof (2003) and Gaur et al (2004), the inventory turnover (*iTurns*) variable, I_{T_t} for a retail firm in time period, t, where I_{H_t} is the inventory on hand for the firm in the same time period, N is the number of observation, and GC_t is the cost of goods sold by this firm also in time period t, I_{T_t} can be computed as:

$$I_{T_t} = GC_t \Big/ \frac{1}{N}\sum_{t=1}^{N} I_{H_t} \qquad (5.3)$$

5.2.4. Forecast Accuracy

Forecast accuracy, a demand forecast performance measure, has also been utilised as a regression variable for this chapter study. Forecast accuracy determines the demand planning performance in using a firm's forecasting system to generate and to sustain optimal product availability. It is the single most employed comprehensive dimension by most academics, practitioners and managers of retail inventories (Fildes and Kingsman, 2011). For the purpose of this thesis chapter, forecast accuracy has been characterised by the mean absolute percent forecast error (*MAPE*). Suppose that, E_{F_t} represents the *MAPE* variable for a retail firm in time period, t, where A_t is the actual forecast for the firm in the same time period and F_t is the demand forecast projected by this firm also for time period t, E_{F_t} can be computed according to Hyndman and Koehler, 2006 as:

$$E_{F_t} = \frac{1}{N}\sum_{t=1}^{N} \left|\frac{A_t - F_t}{A_t}\right| \qquad (5.4)$$

In summary of the motives for the selection of these variables, there are indications supporting the fact that working capital, free cash flow and stock turn (or inventory turnover) are key liquidity data points of note for the retail chains (Deloitte, 2019; Farris et al, 2010). Comprehending cash flow is crucial to retail managers, working capital gives a retail business key information regarding the firm's ability to service short-term debts and inventory turnover ratio helps managers of retail firms get a good image of how quickly inventory is sold at current sales levels, and are even availed the opportunity of looking for trends when comparing this ratio over different time periods (Brealey et al, 2012). Deloitte (2019) has described capital deployment and cash flow management as crucial aspects of business performance for the current day retail industry. The study argues that these measures can help "*focus on what is controllable by the business, operationally relevant, and drives performance. Retail business leaders at all levels can see how their decisions have an impact on these important metrics, and industry analysts can pay more attention to the areas that have an impact on performance, value, and organizational health*".

5.3 Theoretical Framework

5.3.1 Mechanism of Influence Model (MIM)

Hayes (2013) advocates that a moderation study and or a mediation modelling can be used to test hypotheses concerning or to establish evidence for the mechanisms of change in order to be able to explain how certain effects occur or in which conditions the change agents coerce or confine such effects. The mechanism of influence model (MIM) illustrated in Figure5.1 and discussed below is a conceptual and statistical model (adapted from Hayes, 2013), and has been put to use for investigating the chapter study objectives stated in section 5.1 (the introduction section) above. The MIM framework is a schematic diagram that connects entities M, X and Y, and can be used to observe the impacts of the first two entities on the exogenous entity Y.

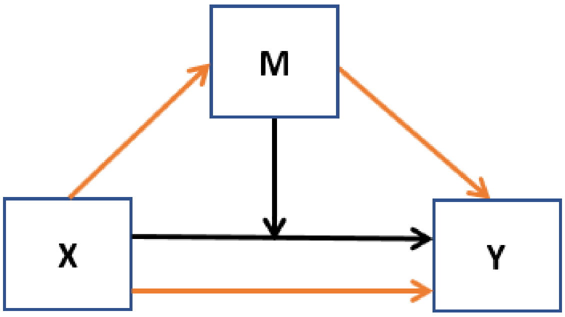


Figure 5.1 Schematic Representation of MIM Model for Quantifying Influences in Inventory. The solid red arrows indicate effects paths for mediation analysis while the solid black arrows show effects paths for moderation analysis (Adapted from Hayes, 2013)

In terms of the focus for this chapter study, the MIM model has been utilised to explore the link between a retail firm's financial performance and its demand forecast accuracy. In addition, it has been used to observe the impacts of both entities on inventory management efficiency, but more importantly, to discern the effects of demand forecast error on financial performance. By analysing inventory control decisions with an analytical model such as MIM, new insights into the effects of further factors affecting the relationship between operational productivity and working capital management can be easily observed (Winklhofer and Diamantopoulos, 2002).

5.3.2 Model Description

Besides the *main* effects among variables, Figure 5.1 combines two separate concepts of causes of change and can thus, be decomposed into a *moderation* (or interaction) effects model and a *mediation* (or intervention) effects model. The three boxes connected together with just only the solid black paths (red arrows removed) represents the concept of interaction effects, while connecting them with only the solid red paths (black arrows removed from the figure) makes the framework a representation of mediation effects concept. It should be noted that this is not a mediated moderated effects model. As such, decomposition of the two separate and different change agent concepts would need to take place in order to operationalise and to conduct analysis. So specifically, the MIM model diagram depicted in Figure 5.1 is a conceptual and graphical representation, on one hand, for the mediation concept where the treatment quantity, X (for example, RMSE or MAPE), affecting the outcome variable of interest, Y (for example, WCL), directly as well as through the mediating metric, M (for example, iTurns). And on the other hand, the framework in terms of moderation concept shows that the impact of the treatment quantity, X (RMSE or MAPE), on the outcome variable of interest, Y (such as iTurns), is dependent on a moderating metric, M (for example, FCF).

It should be noted that moderation just proposes that the size or scale of the relationship between two quantities, for example MAPE and iTurns, changes as the levels or values of the third quantity, such as FCF (called the moderator) change. This will occur in terms of the interaction between the latter and the exogenous variable MAPE (Baron and Kenny, 1986). In the same sense but different way, mediation proposes, essentially, that a mechanism exists through which the influencing quantity, MAPE affects the influenced quantity, WCL. In other words, the mediation analysis helps to decompose effect into its direct and indirect components, while moderation analysis helps to identify control or conditional effects. The choice of roles for these variables are underpinned by theoretical suppositions as discussed in the immediate section that follows, but also in other relevant sections throughout this thesis chapter and in the overall thesis theoretical review chapters (see chapter 2 and chapter 3). For the aspect of the main effect analysis, impacts of X (will be MAPE, FCF and WCL) on the inventory efficiency, Y (that is, iTurns) will be investigated.

5.4 Research Model Hypotheses

5.4.1 The Main Effects

The inherent nature of the sort and style of this study means that it is always good practice, and only plausible, to first examine the *main effects* (that is, the directions and the strength of associations) the study explanatory variables have on the study criterion or outcome variable. This will help to gain a comprehensive and complete understanding as well as to fittingly discern the details of the various relevant effects among the different variables.

A large number of empirical and credible (in terms of contributions, relevance and significance) studies have accentuated and demonstrated how the importance of working capital cannot be overemphasised. For example, Peel et al (2000) in their study stressed how the efficient management of working capital is pivotal to the health and performance of firms in the UK. Deloof (2003) who conducted a study (the most cited article on working capital, see Prasad et al, 2019) of Belgian firms advocated that working capital is a major and an important area of a firm's financial performance and that its mismanagement is highly likely to pose risks on profitability as well as on operations, and ultimately impact firm value. These studies taken together with the description of variables section above show how both WC and FCF are considered relevant and beneficial indicators for the performance of a company, since especially, a corporate financial performance depends on the free cash flow (Bhandari and Adams, 2017) as well as on the working capital (Deloof, 2003; Knauer and Wohrmann, 2013). FCF naturally forms a part of the WC analysis of a firm (see equation 5.2 above). While WC refers to the cash available to invest in the typically standard operations of a firm's business (Afrifa, 2016), FCF accounts for the cash generated and represents how the organisation performs in terms of enhancing the value of its equity (Afrifa and Tingbani, 2018). It is observed though that the balance allocation of funds between components of working capital including inventories and trade creditors (see equation 5.1 above) is critical in working capital management. This is because a large number of previous studies (for example, Lai et al, 2009) have demonstrated that excess working capital may lead to unremunerated use of scarce resources and that inadequate working capital interrupts the smooth flow of business activity including operational productivity or efficiency such as the inventory turnover (iTurns) and profitability. Equally key is the fact that, in the previous thesis chapter (see Chapter 3 of this study) and in the previous section of this chapter, it has also been pointed out that forecast accuracy appears to be popular as well as the most suitable and applicable measure of forecasting effectiveness (Fildes and Kingsman, 2011; Hyndman, 2014). This is important, especially within the context of this study, since it also relates the financial cost impact of an inventory to efforts of the retail firm managers to improve revenue such as gross margin and to optimise return on investment (that is, working capital) and other business ratios for their organisations (Lai et al, 2009; Kerkkänen et al, 2009). The choice of MAPE for this aspect of the current research study has been informed by Byrne (2012) and Kim and Kim (2016) who have highlighted that MAPE is the most widely used measure of forecast accuracy and that it is very popular with industry practitioners because it is scale-independent and due to its advantage of interpretability. Hausman (2004) and Taylor and Oliveria (2004) find that stock requirement or product availability could be affected by forecast accuracy and that both will need to be taken into account in order to accurately estimate performance. Other factors that are capable of influencing inventory and sales include the capital capability of a retail firm (Bendavid et al, 2017) and its cash flow constraints (Boulaksil and Van Wijk, 2018). As a result of the popularity of usage as well as the importance attached to the quantities mentioned above as key performance criteria, the following hypotheses are put forward:

H1 – Forecast errors will be negatively related to inventory efficiency

H2 – Free cash flow (FCF) will be positively related to inventory efficiency

H3 – Working capital level (WCL) could be positively or negatively related to inventory efficiency

5.4.2 Moderation Effects

The hypotheses for forecast accuracy (H1), FCF (H2) and WCL (H3) advanced above are concerned with the individual main effects. But nonetheless, possible interactions between these variables are of real interest to this study, especially since the dimensions for finance and inventory management are measured differently when it comes to performance. This every so often means that they have conflicting goals that, in the end, may undermine each other's efforts. Womack et al (1990) have developed a manufacturing focused framework that centres concentration on driving inventory levels down, exposing inefficiencies, reducing costs and cutting lead times. The Womack framework does not appear to be perfectly adaptable for retail firms, perhaps because in the retail chains, the allocation of inventory risk varies in different situations and for different functional areas of these business organisations (Modigliani and Miller, 1958; Levi et al, 2008; Kouveils and Zhao, 2012).

Typical case in point, retail firm's inventory position or levels resulting from forecast accuracy can create conflict between operations and finance decisions (Levi et al, 2008; Boulaksil and Van Wijk, 2018). For example, Kahneman and Tversky's (1979) prospect theory explains how people assess decisions under uncertainty. This theory is often used to describe loss aversion as the case when a decision maker's utility is concave over gains and convex over losses. According to this loss-averse theory, it is important to recognise that loss aversion can influence, for instance, companies' managers charged with working capital or inventory decisions to run those investments less optimally, or more specifically, to perform poorly because they are more averse to losses than they are attracted to the same-sized gains (Ma et al, 2013).

Consider for instance, a scenario where more cash is currently tied up in inventory than in the previous year. The increase in working capital will be treated as a cost against free cash flow or the inert working capital will inhibit and impede the ability of finance in meeting critical cash flow marks (Bendavid et al, 2017; Boulaksil and Van Wijk, 2018). This situation may be problematic for the finance manager whose primary goal means s/he must maintain a good balance between current assets and current liabilities. However, the increase in inventory may be pleasing to the operations or inventory manager as it might have actually been purposefully designed through demand forecasting to mitigate, for example, certain stockouts due to supply chain volatility or shortages and or to improve sales or customer relation and satisfaction. Or from a loss-averse perspective, that increase in inventory may be due to the feeling of loss by the operations or inventory manager; a feeling which could have been strong enough to have caused him or her to hold on to a poor-performing inventory that has declined significantly in value for whatever reasons (Genesove and Mayer, 2001).

Many empirical studies (for example, Deloof, 2003; Axsäter, 2006; Fawcett et al, 2006) have argued that with inventory control there is a trade-off between fulfilling demand and costs. If a retail firm keeps more stock it could result in more sales, but then it may also be more costly and inflicts strains on the company's working capital and or cash flow (Erhard et al, 2017; Atnafu and Balda, 2018). Thus, the scenario just illustrated has the potential to lead to a situation where the working capital level could be adjusted and set a little low for the next period by the finance manager. In view of that, in addition to the main effects (H1, H2 and H3) hypothesised in the section above, the presence and the nature of *moderation effects* (often referred to as the *interaction or the facilitation effects*) among these performance criteria have been investigated using the assumed MIM model in Figure 5.1 and by further suggesting the following hypothesis:

H4 – Interactions among working capital, free cash flow and forecast accuracy will have an impact on the inventory efficiency.

5.4.3 Mediation Effects

Financial decisions and operational considerations are typically studied separately. The perfect capital market conclusion of the work conducted by Modigliani and Miller (1958) has often been advanced as the motivation for this practice (Ma et al, 2013). But since there is really no perfect capital market (Harris and Raviv, 1991), this reality has now meant that the importance of the interaction between operational considerations and financial choices and their integration is increasingly becoming key requirement for success for retail chain firms in particular but also for business organisations in general (Shah and Shin, 2007; Hameri and Weiss, 2009; Ma et al, 2013). Therefore, in addition to assessing the main effects and the moderation effects, this study examines the possibility of *mediation effects* (also known as the *intervention effects*) among the study variables. Substantial evidence exists from previous studies that with trade credits, inventory decisions have a direct impact on financial performance (see for example, Dada and Hu, 2008; Lai et al, 2009; Yang and Birge, 2010; Bendavid et al, 2017). For example, Bendavid et al (2017) study shows that subjectively imposing constraints on the working capital allowance not only significantly distort operational decisions, but that the restrictions are regularly being violated by inventory projections and replenishments. Lazaridis and Tryfonidis (2006) also concluded in their study that operational performance dictates, to some extent, how the working capital is managed. Noticeably as well, Kerkkänen et al (2009) stated that forecast errors do have other impacts. Thus, this study hypothesised that demand forecast accuracy has a degree of direct and indirect effects on a retail firm's financial performance. In particular, a retail firm's financial performance is not only likely to be affected directly by the demand forecast accuracy, but highly likely to be influenced indirectly through the mediation of its inventory efficiency. To this end, it only seems prudent to investigate the mechanisms of change, that is, the mediation effects by offering an exploratory hypothesis as follow:

H5 – Forecast accuracy engender a change in working capital performance, as a result of inventory efficiency.

5.5 Model Specifications

As noted in thesis chapter 4, regression analysis can be used to determine and to categorise the regressor variable(s) that are connected to criterion variable(s). In more specific terms, it can be employed to describe the direction, the form and the significance of the associations involved between these two categories of variables. Besides, regression analysis methodologies can also be applied to provide a model for predicting an outcome variable from an explanatory variable. But for the purpose of this study, and in what follows in this section, regression analysis has been applied for former (that is, inferential) rather than the latter reasons.

5.5.1 Baseline Specification for Main Effects (H1, H2, H3)

The regression method and the associated model (equation 4.1), described in the previous chapter (the Methodology chapter) will be applied to the conceptual framework in Figure 5.1. The first and foremost of such application is expressed through the following multiple linear regression model for modelling the relationship between the regressor (or explanatory) variables and the response (or outcome) variable for this chapter study.

Model 1: $iTurns_i = \alpha + \beta_1 FCF_{i1} + \beta_2 WCL_{i2} + \beta_3 MAPE_{i3} + \varepsilon_i$

Baseline simple (involving a single regressor and one response variable) or multiple (involving two or more regressors and one response variable) or multivariate (involving many regressors and many response variable) regression models are judged and advocated to be adequate and robust enough to model the *main effects* of explanatory variable(s) on the outcome variable(s). The OLS regression analysis technique has been applied to the specification in Model 1 to analyse and to test the first three proposed hypotheses, that is, H1, H2 and H3 as discussed in Section 5.4.1. These three hypotheses are concerned with the main effects that the study explanatory variables, namely, the free cash flow (FCF), the working capital level (WCL), and the forecast error (MAPE), have impacted on the outcome variable, that is, the inventory turnover (iTurns) for this chapter study. These main effects are characterised by the parameters $\beta_1, \ \beta_2, \ and \ \beta_3$ respectively for the four explanatory variables indicated above.

5.5.3 Specifications for Moderation Effects (H4)

It is observed that the baseline standard linear regressions described above are a powerful tool for estimating the overall effects of change in financial decisions and varying forecast errors on inventory performance such as the inventory turnover. However, the multiplicatively nonlinear nature of interaction terms bounds the ability to interpret the statistical estimate of an interactive effect as forthright as the coefficient of a regular regression parameters and they (the basic linear regressions) also appear to be lacking in the complete capability to clarify the mechanisms of change.

Therefore, further effects analyses have also been conducted to test both the hypothesis four (H4) and hypothesis five (H5). The study analysis tests hypothesis H4 for the presence and nature of *interaction effect* (also referred to as *moderation effect*) among three of the explanatory variables, namely, FCF, WCL and MAPE. The corresponding test model specifications for the hypothesis H4 are as indicated in the three models as follow; that is, Model 2, Model 3 and Model 4.

Model 2: $iTurns_i = \alpha + \beta_1 MAPE_{i1} + \beta_2 FCF_{i2} + \beta_3 (MAPE_{i1} \times FCF_{i2}) + \varepsilon_i$

Model 3: $iTurns_i = \alpha + \beta_1 FCF_{i1} + \beta_2 WCL_{i2} + \beta_3 (FCF_{i1} \times WCL_{i2}) + \varepsilon_i$

Model 4: $iTurns_i = \alpha + \beta_1 MAPE_{i1} + \beta_2 WCL_{i2} + \beta_3 (MAPE_{i1} \times WCL_{i2}) + \varepsilon_i$

All the three possible interaction terms for the three explanatory variables explored for moderation effects for this study are indicated in parentheses. Each of the above models can be rearranged to obtain a *test coefficient* for the explanatory variable as a function of the moderating variable. This means that, using Model 2 as an example, where $MAPE$ is the explanatory variable and FCF is the moderating variable, it is trivial to show that Model 2 can be rewritten as:

Model 2: $iTurns_i = \alpha + (\beta_1 + \beta_3 FCF_{i2})MAPE_{i1} + \beta_2 FCF_{i2} + \varepsilon_i$

According to Hayes and Rockwood (2017), an investigation of a simple moderation is conducted with a hypothesis test or confidence interval for the regression coefficient for the interaction term, such as, $MAPE_{i1} \times FCF_{i2}$, or $FCF_{i1} \times WCL_{i2}$ or $MAPE_{i1} \times WCL_{i2}$. They opined that this is equivalent to an inference about whether the coefficient for the moderator in the linear function defining the explanatory variable's effect, for example, $(\beta_1 + \beta_3 FCF_{i2})$ is equal to zero. Thus, if β_3 is different from zero, it suggests that $MAPE's$ effect on $iTurns$ varies with FCF, in the above example (Model 2).

5.5.4 Specifications for Mediation Effects (H5)

Imai et al (2013) demonstrated that regular regression analysis as specified in Model 1 may be problematic, particularly because it lacks the robustness to handle tests for a causal mediation effect. This is important, especially when better decision making, such as almost always often desirable in retail firms, is contingent on and influenced by being able to extricate, by making a distinction between, the direct effect of some treatment variables (X_i) on certain outcome variables (Y_i) and its indirect effect by means or use of some mediator metrics (M_i). Accordingly, this research study demonstrates the necessity for the application of mediation analysis method in inventory management and control through the application of the relevant models specified below.

Baron and Kenny (1986) suggested that analysis to test for mediation effects has to, as a necessity, follow the *causal step approach*; that is, confirmation of mediation can be conducted through three regression models. This aspect of the thesis work will follow the work of Baron and Kenny (1986) in constructing the following specifications to test for the hypothesis H5. The constructed specifications are as stated in Models 5, 6 and 7 below. Thus, specifications to test for the hypothesis H5 are as stated in Models 5, 6 and 7.

Model 5: $WCL_i = \gamma_1 + \delta MAPE_i + \epsilon_{i1}$

Model 6 $iTurns_i = \gamma_2 + \theta MAPE_i + \epsilon_{i2}$

Model 7: $WCL_i = \gamma_3 + \delta' MAPE_i + \tau iTurns_i + \epsilon_{i3}$

It should be noted, however, that other authors such as MacKinnon and Dwyer (1993) and Tingley et al (2014) for example, argued that the hypothesis H5 can, in fact, be tested for a *causal mediation effect* using the last two of the three specified models, that is, Model 6 and Model 7 above. More details in relation to the mediation effects analysis procedure and also, in respect of the moderation effects estimation method, are provided in section 5.7.

5.6 Data Sets for Sub-Study

5.6.1 Raw Data and Sample Profile

5.6.1.1 Raw Data

The data series used to conduct analyses in this chapter study strand has been described in detail in Chapter 4 (the Methodology chapter). The raw data consists of real sales history and product information from US based markets for short shelf-life perishable products; namely, Hass avocados and milk. Real volume sales data sets have been used as demand to calculate inventory levels, create forecasts and derive financial variables for analyses.

5.6.1.2 Sample Profile for the Regression Analysis

Hair et al (2008) and Lucko and Rojas (2010) have noted that, in order to robustly produce reliable estimates, the role of sample size is central in any statistical analysis. However, the debate regarding suitable sample size for multivariate analysis methods such as SEM and multiple linear regressions (MLR) is both mixed and contentious, to say the least (Austin and Steyerberg, 2015; Bujang et al, 2017).

While power analysis and Monte Carlo simulation are methods of sample size estimation, opinions of its determination are often based on a number of considerations. The factors to consider include observations to regression parameters ratio, confidence intervals, effect sizes or coefficient of determination of the fitted model. Other factors for consideration are the standard errors of the estimated regression coefficients and even the sophistication of the statistical analysis being conducted or a fit-for-all prescribed fixed or range of minimum sample size required for any sort of regression analysis. Gorsuch (1983) recommended a minimum of 5 observations per construct or 100 observations per data analysis. Some sample size guidelines proposed 30 observations per regressor variable (Pedhazur and Schmelkin, 1991) and Green (1991) set a range of 15 to 25. Recent studies such as Bagozzi and Yi (2012) suggested that the sample size should be above 100 and Kline (2010) opined that a very complicated path model needs a sample size of 200. According to more recent studies such as the Schmidt and Finan, (2018), a ratio of 10 observations to 1 regressor variable is a sufficient sample size. Jenkins and Quintana-Ascencio (2020) recommends $N \geq 25$, where N is the number of observations regardless of the number of independent variables used.

Based on these findings, it is considered that a sample size of 31 data points should be fairly sufficient to detect satisfactory high statistical power and accuracy for the current non-complicated simple study. More importantly, since the research analysis for the study chapter involves creation of forecasts and forecast errors, and since there is inverse relationship between forecast accuracy and time horizon for forecasting (Petropoulos, 2014), consideration has to be given to the forecasting horizon. According to Ord et al (2017), "*the horizon often affects the accuracy and usefulness of a forecast*". An implication of this is that forecasts are more accurate for shorter than longer time horizon; the longer the forecasting horizon, the higher the level of uncertainty and the more erroneous the forecast will be. Consequently, the decision to limit this study sample size to 31 observations was driven by the appetite to mitigate or at least limit inaccuracy of the study output results that may likely arise due to longer forecasting horizon as evident below in Figure 5.2 and in Appendix I for all the data series to be modelled.

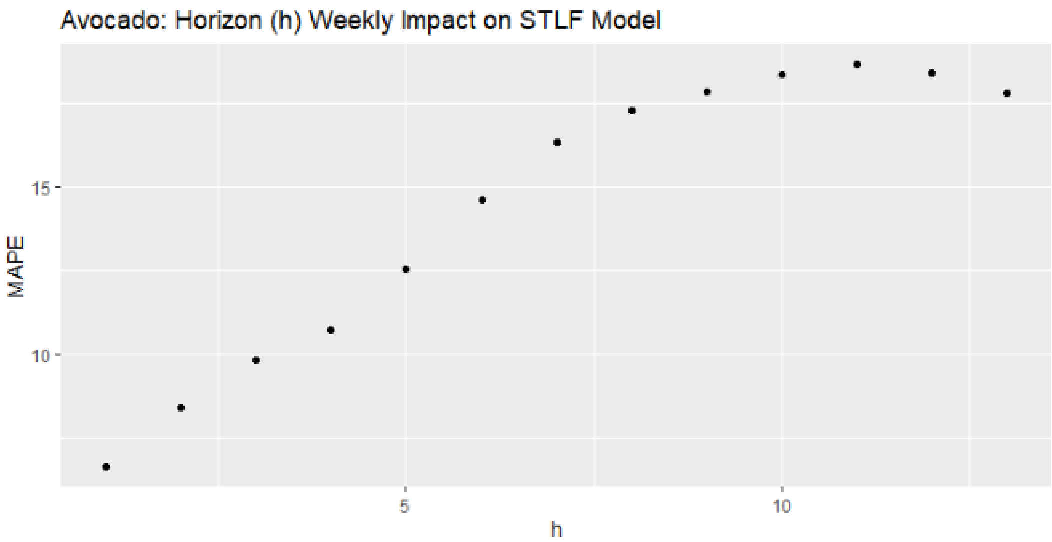


Figure 5.2 Horizon Impact on Forecasting Method

5.6.3 Generating Forecast Variables

5.6.3.1 Exploratory Data Analysis (EDA)

Before creating variables for the chapter study, the raw data sets have been explored as follows. While the thesis reports the EDA output results for the avocado data sets in this study chapter, it should however be noted that the plots for all the data series utilised in this thesis can be accessed in Appendix II. According to Fama (1970) on the efficient market hypothesis (EMH), the asset prices should reflect all available information. A direct implication is that, just as is expected of the demand data, the periodic changes in prices should behave like white noise and or that time series should be Gaussian noise (stationary). This hypothesis is tested utilising the EDA technique by visualising price (in $) and stock volume (in millions) for characteristics of stationarity by looking at the autocorrelation functions (ACF) of each signal. Since dependence is not expected with time for a stationary signal, the ACF is thus expected to go to zero for each time lag. Both plots are produced as indicated in Figure 5.3. Notably, the price series (top left) results in some significant lags exceeding the confidence interval (blue dashed line) of its ACF (bottom left). In comparison, the stock sales volume (top right) results in few significant lags that exceed the confidence interval (blue dashed line) of its ACF (bottom right). Thus visually, it can be concluded from the ACFs that the price time series on the left is unlikely to be stationary (since later lags appear to exceed the confidence interval) while the stock sales volume series on the right may likely be stationary (due to the lags that appear to die out). However, it can be safely said that this avocado dataset and indeed all of the items to be modelled appear to exhibit non-stationarity (see Appendix I for rest of plots). Each of them seems to have varying degrees of seasonality, and some trend only for milk and yogurt.

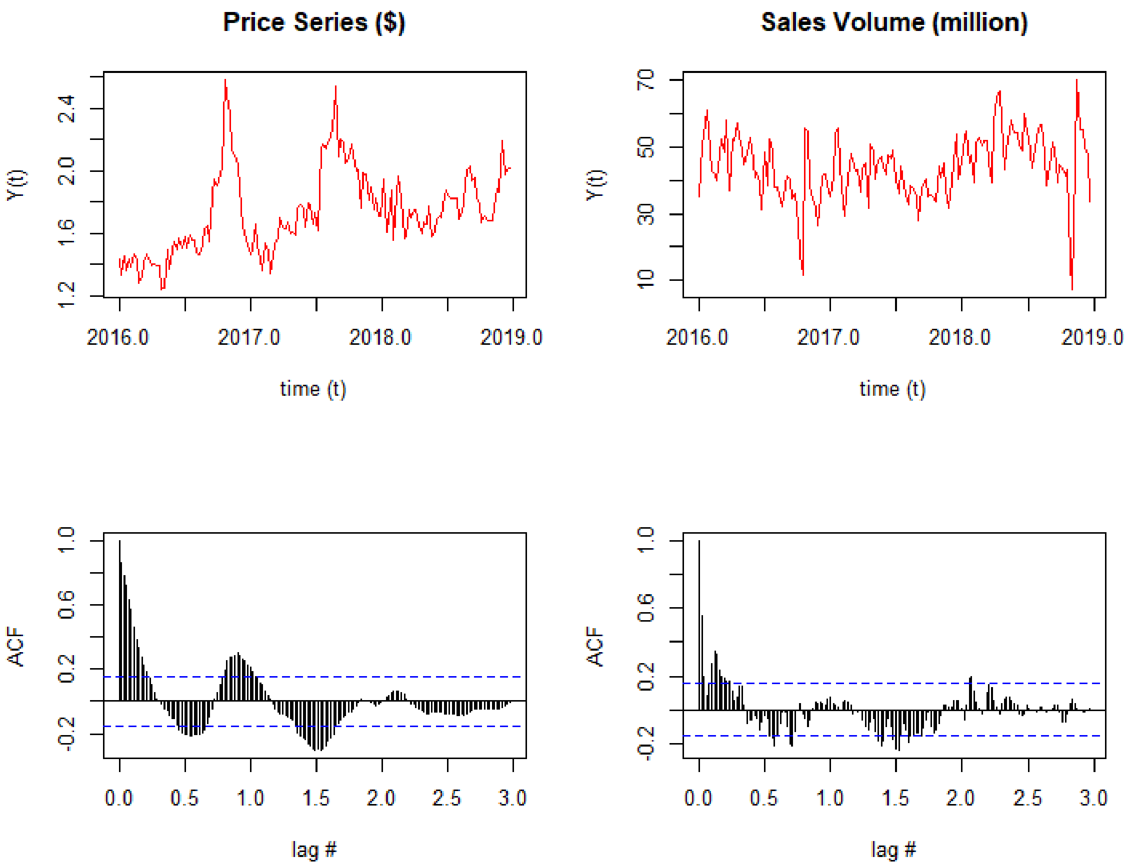


Figure 5.3 Time series and ACF plots for price and stock sales volume.

Further, three statistical tests were subsequently conducted to ascertain the structural reality of both data series. The tests include Ljung-Box test for independence, Augmented Dickey–Fuller (ADF) t-statistic test for unit root and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) for level or trend stationarity.

The Ljung-Box test for independence was used to examine whether there is significant evidence for non-zero correlations at given lags 1 to 25. For the null hypothesis of independence in a given time series, a stationary series will have a larger than 0.05 *p*-value, but the unit root ADF test requires that *p*-value be less than 0.05 while stationarity can be confirmed for *p*-value greater than 0.05 in the KPSS test.

Table 5.1: Statistical Tests for Stationarity: Price and Stock Sales Volume Series

	Before Differencing						After Differencing					
	Box-Ljung		ADF		KPSS		Box-Ljung		ADF		KPSS	
	Price	Sales	Price	Sales	Price	Sales	Price	Sales	Price	Sales	Price	Sales
Test Statistics	553	158	-3	-3	0	0	31	34	-5	-9	0	0
Lag Number	25	25	5	5	4	4	25	25	5	5	4	4
p-Value	0.00	0.00	0.06	0.21	0.02	0.01	0.19	0.10	0.01	0.01	0.10	0.10

NOTE: Augmented Dickey–Fuller (ADF); Kwiatkowski-Phillips-Schmidt-Shin (KPSS)

Table 5.1 shows results for these tests before and after weekly changes (first differencing) was computed for each of the two series and retest conducted. Table 5.1 results reveal that both the price and sales series failed stationarity before first differencing but became stationary after first differencing was applied.

5.6.3.2 Producing the Forecasts

Essential estimates have been obtained for the demand forecasts, from which the forecast errors have been computed, using the following three different methods (described in detail in the methodology chapter) to forecast the lead time demand:

- Seasonal and Trend (decomposition using) Loess Forecasting (STLF) Model
- Dynamic Harmonic Regression (DHR) Model with ARMA error structure
- An exponential smoothing state space (trigonometric) model with Box-Cox transformation, ARMA errors, trend and seasonal components (TBATS) model.

In the field of forecasting, an important starting point in considering the choice of forecast strategy to deploy is influenced by the nature and the feature of the data series. The frequency of the data sets is one of those critical features (Trapero, 2010). The frequency of all the empirical data series for this research work is weekly (see details in the methodology chapter). Unlike quarterly and monthly data sets, weekly, daily and hourly time series by their nature can be high frequency, multiple seasonal data with rather long seasonal periods. As such, many of the standard forecasting methods are not appropriate to use for their forecasts. Hyndman and Fan (2010), De Livera et al. (2011), Fan and Hyndman (2012) have all argue that because the seasonal versions of ETS and ARIMA models are designed for shorter seasonal periods such as four for quarterly and twelve for monthly data sets, they do not tend to give good forecasting results for data sets with longer seasonal periods such as weekly, daily and hourly time series. There are three models serving as alternative approaches for handling these sets of high frequency, multiple seasonal data with rather long seasonal periods. Hyndman and Athanasopoulos (2018) espouse that the three models (STLF, DHR and TBATS) are more appropriate and optimal forecasting methods designed specifically to deal with these high frequency types of data series. They further opined that the STLF approach is the simplest of the three methods but a versatile and robust method both for decomposing time series and for estimating nonlinear relationship. Thus, for the purpose of empirical analysis in our study, these three models (STLF, DHR and TBATS) are the applicable optimal forecasting methods for the particular nature of the demand data series, which are weekly, for this research work.

For the purpose of the empirical study in this chapter, the following three statistical forecasting error measures will be utilised: the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean squared error (RMSE).

For two of the three forecasting methods, parameters estimation has been designed to be computed automatically. Thus, the training data sets were fitted for the STLF and the TBATS methods and rolling window rolling origin forecasts produced for horizons from 1 to 32 weeks using the avocado time series and 1 to 63 weeks using the data series for milk, salty snack and yogurt. However, the best fit K values (of 24, 20, 25 and 2 respectively for milk, salty snacks, yogurt and avocado) for the DHR method have to be estimated and used create the same way as were generated with STLF and TBATS methods. Afterward, the out-of-sample forecast errors (FEs) for each of the above forecast methods were obtained using the cross-validation process already described in chapter 4. While the plots for forecasts can be found in the thesis Appendix III, Table 5.2 below presents the summary of the average values of performance for all the different forecasting methods as discussed. For these US retail markets for the four studied SKUs, as can be observed from Table 5.2, clearly, the best forecasting method deployable for the avocado product is the DHR model in terms of all the three statistical error metrics (that is, RMSE, MAE and MAPE).

Table 5.2: Summary of Accuracy Measures for Forecasting Models

	Milk	Snack	Yogurt	Avocado
Root Mean Squared Error (RMSE)				
STLF	2.11	2.56	3.76	15.98
DHR	3.02	4.12	9.97	12.97
TBATS	2.20	2.10	3.32	15.63
Mean Absolute Error (MAE)				
STLF	1.69	1.89	2.68	12.09
DHR	2.35	3.34	8.08	9.30
TBATS	2.35	3.34	8.08	11.41
Mean Absolute Percentage Error (MAPE)				
STLF	3.09	4.20	5.36	26.44
DHR	4.51	7.51	16.63	19.88
TBATS	3.07	3.58	5.36	24.49

In contrast, while STLF model outperformed the rest of the forecasting methods for the milk, yogurt, and salty snack time series when MAE metric is considered. However, if the consideration is in terms of the RMSE and MAPE performance metrics, outcome indicates that generally, the TBATS model 'just' marginally did better than the STLF strategy.

5.6.4 Generating Finance Variables

The method employed for obtaining the financial performance variables of interest, that is, working capital level and the free cash flow, is the Discounted Cash Flow (DCF) procedure also known as the present value analysis (Myers, 1984 and Francis et al, 2000). The means by which this method can be put to use is described as follow.

Forecasts of the volume of free cash flow created by a retail business operation can be determined after the consideration for its operating expenses, working capital requirements and capital expenditures. By means of a series of reasonable assumptions (such as demonstrated below in this section) about how a firm will perform in the future, DCF analysis is used to predict the cash flows (Myers, 1984). This is followed by the projection of how this business performance translates into the cash flow created and the terminal value and or the enterprise or equity (also known as the market) value of the business at the end of the projection period (Francis et al, 2000). It is important to note that for this research study scope, terminal value or equity and enterprise values of a firm are not subjects of focus, hence, the DCF analysis will terminate at the process stage where working capital and free cash flow have been both generated. Because of its versatility on the account of its theoretical soundness, DCF analysis is widely used by business analysts, academics, and practitioners for any scenario (Brigham and Houston, 2016). Ruback (2002) argues that it is widely accepted as the most theoretically correct valuation technique available because it derives from the bases of the basic economic and financial principles; respectively, that individuals defer consumption and that in the end, the value of a firm will stem from the inherent value of its future cash flows to its financiers. Particularly, it is a very useful method when there is little or no analogous information (Pratt and Grabowski, 2014). It should be noted, however, that the assumptions driving the projections in DCF analysis are critical to the credibility of the output.

Adopting Mills et al (2002) and Jensen (1986) who developed a free cash flow ‘theory of takeovers’ in the context of agency conflict, the following assumptions have been made for the purposes of utilising the DCF analysis to build up working capital and free cash flow figures for this research study. An assumption is that theoretically, investment is basically beneficial only and only if the value of the present investment is equal to or less than the present value of the expected future cash flows. The second key assumption for the DCF model is regarding the growth of the free cash flow – it is considered a non-constant growth for analysis conducted in this study. These assumptions drive the choice of specified quantities for the following variables to operationalise the DCF model.

Consistent with the historical growth rates of the US retail data sets, but as well as conservatively, the revenue has been projected out at varying annual growth rate of 5% for the first year, 3% for the second year and 1% for the third year. It is assumed, on the basis of the concept of economies of scale that as revenue is increasing the cost of goods sold will be going downward (Guy et al., 2005). Therefore, both the operating profit (that is, earnings before interest and tax: EBIT) and the cost of goods sold (CoGS) have each been set at a percentage of the revenue. While the cost of goods sold has been projected diminishingly from 55% of product price for the first year to 45% in the third year, operating costs (which include CoGS, SGA and salaries) for the three-year period steadily decreases at the revenue rate of 65%, 60% and 55% respectively. SGA is the clipping form for selling, general and administrative expenses. This implies that the operating profit grows respectively at 35%, 40% and 45% of revenue for year 1, year 2 and year 3.

Future tax rate is kept constant as a percentage of the operating profit at 30% in this aspect of the research study. This is in line with what has been paid over the past twelve months, and so it is estimated that the same rate will continue to apply and be paid over the next three years. It is assumed that net investment (capital expenditure less depreciation which is a non-cash expense) is expected to increasingly grow from 7% in year 1 to 10% in year 3. Second year is set to see a rate of 8.5% in net investment. To track the level change (the difference) in working capital from year to year, the working capital needs is initialised using current asset set at a percentage (25%) of revenue less current liability (15%) and then projected out to be naturally growing at the same rate levels with the revenue. And finally, to project the expected FCFs in each of the upcoming years, the variables obtained above are summoned into the equation 5.6 (the Brigham and Houston, 2016 model) for FCF which, to simplify analysis for this research study, has been rearranged where NI_t, the net investment is the difference between the capital expenditure and depreciation (Pratt and Grabowski, 2014; Lewellen and Lewellen, 2016), as follows:

$$\mathrm{FCF}_t = \mathrm{EBIT}_t\,(1 - \mathrm{TR}_t) - (\mathrm{NI}_t - \mathrm{CWC}_t) \qquad 5.6$$

As mentioned above, the DCF analysis for this study terminates at this point since the focus is only to generate the working capital and the unlevered free cash flows (and not to determine the terminal value or the equity or enterprise value) of the firm for further regression analysis.

5.7 Model Estimation

5.7.1 Main Effect Method (H1, H2, H3)

Model 1 for this chapter study specified a first order multiple linear regression model. The model thus describes how a single criterion variable is linearly influenced by a number of explanatory variables. This aspect of the chapter study attempts to model the relationship between these three explanatory variables namely, free cash flow (*FCF*), working capital level (*WCL*) and mean absolute percentage error (*MAPE*) and the response variable, namely, inventory turnover (*iTurns*) as shown in Figure 5.4 by fitting a linear regression line to the observed data set. After fitting the regression line, diagnostics investigation is conducted to ensure that the OLS assumptions are not violated; including assessing the residuals to determine whether or not they appear to fit the assumption of a normal distribution.

Figure 5.4 Schematic Path Diagram for Simple Moderation Model

Figure 5.3 illustrates the schematic path diagram for Model 1 for estimating H1, H2 and H3. The multiple regression analysis enables the determination of the overall fit (or variance explained) of the model and the relative contribution of each of the study regressors to the total variance explained.

5.7.2 Moderation Effect Method (H4)

The Model in equation 5.5 described above in Section 5.5.1 can be extended and used for estimating, testing, and probing interactions through the OLS regression technique. It is not uncommon case to find in the literature that it is possible to fit a multiple regression model that includes, for instance, two explanatory variables along with their interaction as shown in the Model 2, Model 3 and Model 4 in Section 5.5.3. The focus, having to assumed linear relationships between variables in the causal system, is on the explanatory variable *MAPE*'s linear effect on outcome variable *iTurns* being dependent on and linearly moderated by a single moderator *FCF* or *WCL*.

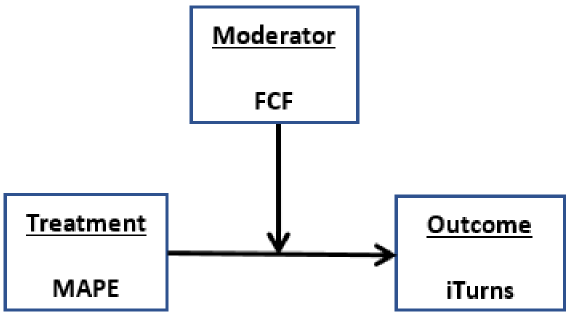


Figure 5.5 Schematic Path Diagram for Simple Moderation Model

This condition is depicted in the schematic path diagram of Figure 5.4 for FCF in Model 2 which is repeated below for ease of model estimation analysis presentation. Note that Figure 5.5 has been extracted from the conceptual framework of Figure 5.1 for the chapter study by leaving out the solid red paths and letting the three boxes be connected together with just only the solid black paths.

Model 2: $iTurns_i = \alpha + \beta_1 MAPE_{i1} + \beta_2 FCF_{i2} + \beta_3 (MAPE_{i1} * FCF_{i2}) + \varepsilon_i$

Theoretically, changes in *MAPE* are expected to cause changes in *iTurns*. The moderating effect, according to Edwards & Lambert (2007), relates to the individual differences or situational conditions which change the initial relationship anticipated between the explanatory variable, *MAPE* and the response variable, *iTurns*. The moderating variable, *FCF* or *WCL*, is the agent of change. It is capable of changing the strength of association between *MAPE* and *iTurns* to either of a weaker or stronger grade as well as having the ability to reverse the direction of the initial relationship through its interaction with the explanatory variable. The term, $MAPE_{i1} * FCF_{i2}$, is interaction term in the Model 2 above.

5.7.3 Mediation Effect Method (H5)

As with the moderation model, the mediation model estimation is typically implemented with ordinary least squares (OLS) regression-based path analysis or a maximum likelihood-based method (Hayes and Preacher, 2010). Thus, mediation analysis is just linear regression reorganised slightly to show the direct effects of an explanatory variable, Xi upon a response variable, Yi, partialling out the effect of a mediator variable, Mi; that is to say in a way of representation that:

$$Xi\ (\text{Forecast Accuracy}) \rightarrow Mi\ (\text{Inventory Efficiency}) \rightarrow Yi\ (\text{Financial Performance})$$

If the direct effect of treatment (Xi) variable on the outcome (Yi) variable completely disappears after mediation estimation is conducted, the mediator (Mi) variable will be said to have fully mediated between Xi and Yi, and this is referred to as a *full mediation*. But if however, some effect of Xi on Yi still exists after mediation estimation, but then in a smaller magnitude, Mi partially mediates between Xi and Yi, and this thus leads to a *partial mediation*.

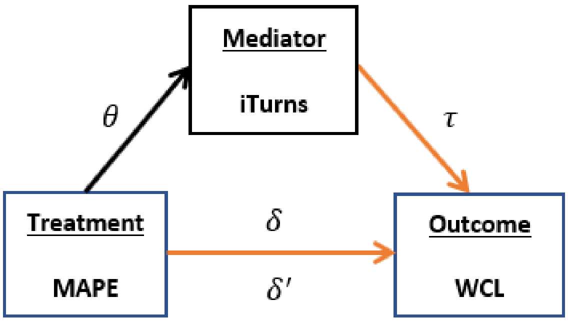


Figure 5.6 Schematic Representations of the Mediation Effect Model Paths

Tingley et al (2014) suggested that the goal of a mediation analysis should be to assess the potential causal mechanisms. To this end, the causal mediation analysis has been conducted to estimate the causal mediation effects of *MAPE* as well as to understand the process in which it causally affects the *WCL*. For the purpose of this chapter study, forecast error is the input or the treatment variable while the inventory turnover is tested as the candidate mediator variable, and the working capital level will be the outcome variable. Using a path diagram and the conceptual framework model behind the study dataset as illustrated in Figure 5.1, the involved mediation effect mechanism is shown above in Figure 5.6. Accordingly, in the Figure 5.6, the treatment variable, that is, forecast error (*MAPE*) is shown to affect the outcome working capital (WCL) variable via the mediator variable, inventory turnover (*iTurns*). In other words, causal association between $MAPE$ and WCL is hypothetically mediated by $iTurns$.

Fairchild and MacKinnon (2009) and (Golob, 2003) posit that in interactions and interventions analysis investigation, a criterion or response variable in a regression model may be a regressor or control variable in other reliance relationships. Thus, in moderation and mediation modelling, estimation often consists of several regression equations describing the interrelationships among several endogenous and exogenous variables (MacKinnon, 2008; Nunkoo and Ramkissoon, 2011). Cheng (2001) points out that multiple regression method lacks the capability to entirely take into account all the interaction and intervention effects among the hypothesised constructs. But SEM is robust enough to estimate a series of interrelated dependence relationships in a model simultaneously while taking into account every connection between each regression equation (Hayes and Preacher, 2010; Nunkoo and Haywantee Ramkissoon, 2011). Hair et al, 1998 allude to the fact that SEM allows for the simultaneous estimation of a set of independent multiple regression equations and possesses the capability to incorporate latent variables into the analysis. Bryne (2001) and Kline (2005) argue that aside from SEM being capable of adequately testing all postulated relationships in a structural model simultaneously, using it often leads to more valid conclusions on the construct (or hypothesis) level. Other methods of analysis may result in less clear conclusions, and or would necessitate several separate analyses (Kline, 2005) argues further.

According to Tingley et al (2014) and Sales (2017), the path coefficients (estimated regression weights) from a series of models specified in Section 5.5.4 (that is, Model 6 and Model 7 repeated below) can be estimated simultaneously using a structural equation modelling (SEM) package such as the *mediation ()* in the R Environment. Before estimating the mediation models, it is important to comprehend the overall effect relative to the other various components which constitute the entire effects to be considered when conducting a mediation analysis. Thus, first and foremost, there is a total (direct) effect which, in the case of this study, is the $MAPE_i$'s direct effect on WCL_i. This effect, which occurs when $iTurns_i$ is not accounted for, can be interpreted as how much a unit change in $MAPE_i$ affects WCL_i. The *total effect* of $MAPE_i$ on WCL_i, can be estimated with δ in the specification of the Model 5.

Model 5: $$WCL_i = \gamma_1 + \delta MAPE_i + \epsilon_{i1}$$

But by means of Model 6 and Model 7, the effect of $MAPE_i$ on WCL_i can be decomposed into a *direct effect* component and an *indirect effect* component.

Model 6: $iTurns_i = \gamma_2 + \theta MAPE_i + \epsilon_{i2}$

Model 7: $WCL_i = \gamma_3 + \delta' MAPE_i + \tau iTurns_i + \epsilon_{i3}$

According to Figure 5.5, when the mediation variable, $iTurns_i$ is brought back into the picture, there will be a direct effect (θ) of $MAPE_i$ on $iTurns_i$ and another but different direct effect (τ) of $iTurns_i$ on WCL_i when controlling for $MAPE_i$. Then there is an indirect effect element of $MAPE_i$ on WCL_i through the facilitation variable, $iTurns_i$ which can be quantified as the product of θ and τ and is interpreted as the expected change in value of WCL_i as the treatment variable, $MAPE_i$ changes by one unit as a result of $MAPE_i$'s effect (θ) on $iTurns_i$ which, in turn, affects WCL_i by its effect (τ). What is then important to note is that the total effect (δ) of $MAPE_i$ on WCL_i in Model 5 is separate and different to the direct effect of $MAPE_i$ on WCL_i after controlling for $iTurns_i$ in Model 7. In this model (that is, Model 7), the direct effect of $MAPE_i$ on WCL_i after controlling for $iTurns_i$ is quantified as δ'. The total effect (δ) of $MAPE_i$ on WCL_i will thus be the sum of the direct effect (δ') and indirect effects ($\theta\tau$):

$$\delta = \delta' + \theta\tau \qquad (5.6)$$

Following Hayes and Preacher (2010) and Sales (2017), although the statistical "significance" tests of the (δ) path and the (δ') path are both available from the standard regression analysis, however, the mediation effect ($\theta\tau$) is best found by bootstrapping the regression model and displaying the empirical confidence intervals. In addition, sensitivity analysis will also be conducted to test how the mediation model's sensitivity departs from the assumptions under which causal mediation effects are identifiable from a data set.

5.8 Empirical Findings

This section discusses findings from the basic statistical methods that have been deployed to describe distributions and bivariate associations numerically. In addition, inferential methods have also been employed to assess whether or not relationships among variables exist. These methods have been used to generate basic descriptive statistics, Pearson point-moment correlations and inferential statistics. Thesis reports results for the avocado data set as it eptomises the rest of the data series for this research study. Result outputs for the milk, salty snacks and yogurt are still accessible in Appendix IV.

5.8.1 Summary Statistics

Having generated the data sets (as just discussed in sections 5.6.3 and 5.6.4 above) for the current investigation, the basic descriptive statistics for the entire 32 data points generated for each of the six variables for this thesis study are examined. These includes inventory turnover (*iTurns*), working capital level (*WCL* in \$), free cash flow (*FCF* in \$), the root mean squared error (*RMSE* in item units), the mean absolute percent error (*MAE* also in units of item) and the mean absolute percentage error (*MAPE* in %). Together with *iTurns*, *WCL* and *FCF*, the MAPE will be the selected forecast error to be used for the inference analyses in this current chapter. The data summary analysis outputs in Table 5.3 for the descriptive statistics indicate that aside from *MAPE* (with a mean = 17.13% and a median = 10.63%), the mean values of the distributions for the rest of the variables, that is, *WCL* (mean = 9.34%, median = 9.30%), *FCF* (mean = 18.65%, median = 19.40%) and iTurns (mean = 1.22%, median = 1.30%) for this study are relatively close to their respective median values. This suggests normality and that statistical mean may be the most appropriate summary statistic for these variables.

Table 5.3 Data Distributional Characteristics

Variables	iTurns	WCL (\$m)	FCF (\$m)	MAPE (%)	RMSE (\$m)	MAE (\$m)
N	31	31	31	31	31	31
Mean	1.22	9.34	18.65	17.13	7.84	5.78
SD	0.67	0.87	4.91	14.46	3.80	2.26
Median	1.30	9.30	19.40	10.63	6.99	5.62
TM	1.22	9.33	19.06	15.75	7.73	5.80
MAD	0.89	1.09	3.20	4.23	2.18	1.98
Minimum	0.07	7.97	2.52	3.13	2.51	1.82
Maximum	2.41	10.85	28.52	43.77	14.17	9.51
Range	2.34	2.88	26.00	40.64	11.66	7.69
Skew	-0.03	0.10	-1.29	0.97	0.51	0.14
Kurtosis	-1.43	-1.30	2.95	-0.89	-1.01	-0.92
SE	0.12	0.15	0.87	2.56	0.67	0.40

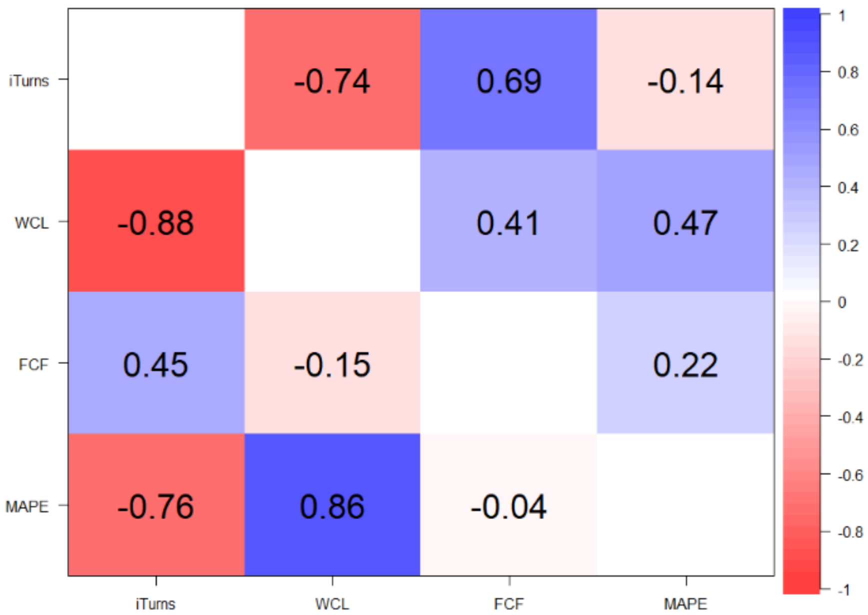
NOTE-: N: Number of observations; SD: Standard deviation; TM: Trimmed mean; MAD: Mean absolute deviation; SE: Standard error of the mean

But it also suggests that there may be outliers affecting the sample mean of *MAPE*. In addition, all the four variables for this study appear to mirror normal skewness, however, *FCF* is slightly long left tailed (negatively skewed) as well as *MAPE* which appears to be marginally long right tailed with positive skewness. All the four variables may be said to have mirrored normality in terms of kurtosis but may be flatted a little (platykurtic, negative Kurtosis values that are less than 3) except for the *FCF* which has a Kurtosis value of 2.95, very close to a mesokurtic value of 3. The distributions of these quantities are examined further below in the bivariate correlation analysis section.

5.8.2 Bivariate Pearson Correlation

In order to explore the concept of relationships among the variables for this study in pairs (two at a time), that is, to examine whether there exists an association and the strength of this association, or whether there are differences between pairs of variables and the significance of these differences, a Bivariate Pearson Point-Moment Correlation (BPPMC) analysis has been conducted.

Table 5.4 The Bivariate Pearson Point-Moment (BPPM) Correlation Coefficients



The BPPMC (a simultaneous analysis of pairs of attributes) output is provided in the Table 5.4, and a scatter plot matrix which contains marginal distributions (kernel density plots and rug plots) for each variable and superimposed with loess (smoothed fit) and linear fit lines on the plots has been generated as shown in Figure 5.7. Analyses for both the common correlation matrix and the partial correlation matrix (to examine just the independent effects of all the variables in a model) have been conducted and compared.

The correlations among the four metrics shown in Table 5.4 indicates that the standard correlation (SC) coefficient values are below the diagonal and the partial correlation coefficient figures are above the diagonal. The partial correlation (PC) assesses the degree of linear relationship between each pair of the quantitative variables, while controlling for other variables. It can be observed from Table 5.4 that a strong negative correlation exists between inventory turnover (*iTurns*) and working capital level (*WCL*) for both types of correlations (r = - 0.88 for SC and r = - 0.74 for PC). This result is as expected (see the hypothesis H3). A number of the results are interesting. In particular, on one hand, is the *weak* negative relationship (r = - 0.15) between *WCL* and free cash flow (*FCF*) for the standard correlation (bottom diagonal), and on the other hand, (r = - 0.14) between forecast error (*MAPE*) and *iTurns* for the top diagonal partial correlation. This is because theoretically, one would have expected a strong association by either pair of the metrics (see for example, Afrifa and Tingbani, 2018). Further, a strong positive correlation (r = 0.86) exists between *MAPE* and *WCL* as indicated by the standard correlation, but that association is portrayed as moderate (r = 0.47), although in the same direction, by the partial correlation.

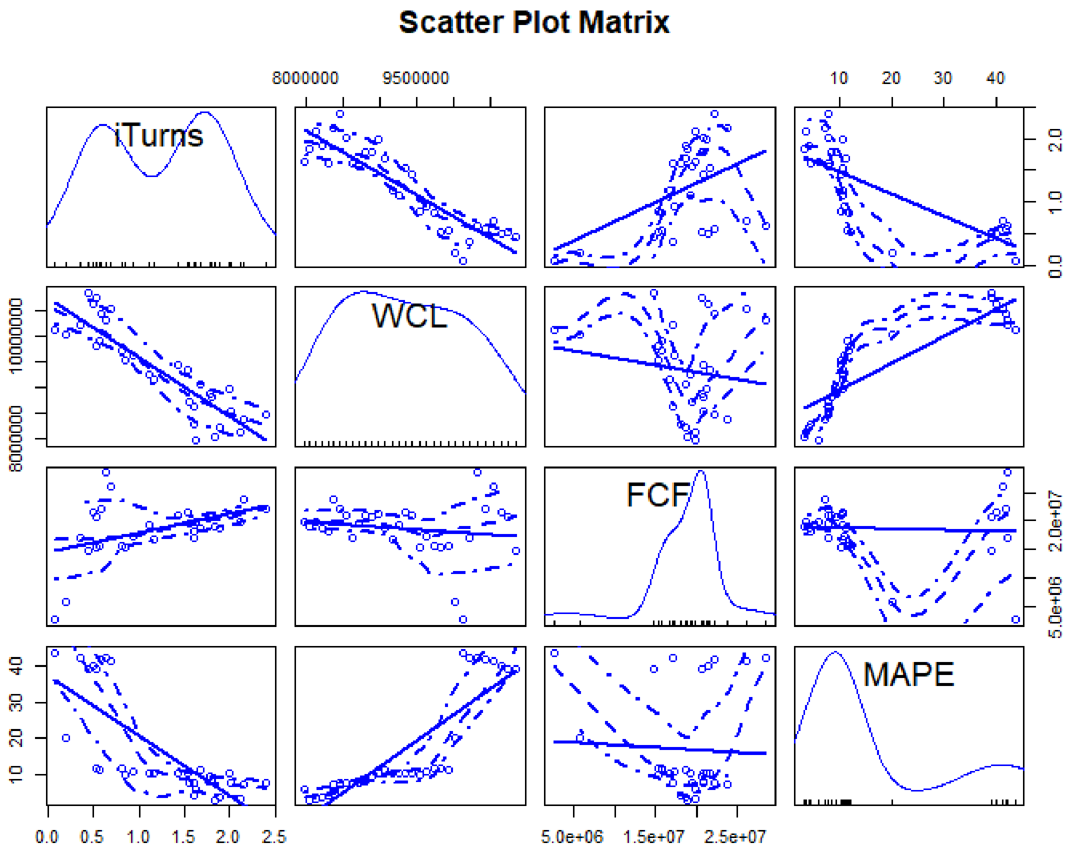


Figure 5.7 Scatter plot matrix of iTurns and other variables for the avocado study dataset, including linear and loess (smoothed fits), and marginal distributions (kernel density and rug plots)

A reversal of this situation is the case observed between *FCF* and *iTurns*. However, as expected (see the hypothesis H2), FCF is negatively correlated with *iTurns* for both SC and PC types of correlations. And similarly, in terms of direction of association, negative correlation does exist between *MAPE* and *iTurns*. Again, this relationship is as expected as stated in the hypothesis H1. Some of the surprise findings may suggest likelihoods of a curvilinear or a confounding issue could be at play. The possibility of the former is examined further below using a scatter plot matrix of Figure 5.7 while both the later and the former will be explored more in the classical regression analysis and SEM techniques sections that follow. In terms of the distributions indicated diagonally, it can be observed that the scatter plot matrix of Figure 5.7 may suggest that inventory efficiency (that is, *iTurns*) appears to be bimodal (with two distinct peaks or local maxima). The *iTurns*, even though may be bimodal, however, it may still be symmetric, as the two halves appear to be mirror images of each other. The forecast error (*MAPE*) may not be unimodal either. The results appear to also point to the possibility that each of the explanatory variables may more or less be skewed to an extent. Besides, considering the scatter plots along with their regression lines, *iTurns* appears to increase with higher free cash flow (*FCF*) and decrease with working capital levels (*WCL*) as well as with forecast error rates. In the same sense, FCF appears to be negatively affected by higher *WCL* and *MAPE*.

5.8.3 Results for Baseline Main Model (H1, H2, H3)

It should be noted that the bivariate Pearson product-moment correlation (PPMC) is only a numerical method and does not provide any inferences about causation but simply reveals relations among continuous variables. For that reason, the regression analysis, an inferential method, has been considered for further exploration of the study dataset.

Table 5.5 BCA Bootstrapped Main Effects Analysis

Criterion Variable	**iTurns**	Model Parameters P.E.	S.E.	BCA (5000) 95% CI Lower	Upper	Model Specification R^2	S.E.	F-Statistic
Main Model						0.938	0.208	142.343 ***
	Main Effects							
	FCF	1.061 ***	0.087	0.891	1.231			
	WCL	- 3.364 ***	1.068	- 5.458	- 1.271			
	MAPE	- 0.267 **	0.126	- 0.514	- 0.020			

Note: Main regression analysis showing effects with confidence intervals (CIs) and standard errors (S.E). Bias corrected accelerated (BCA), Point estimate (P.E.), standard error (S.E.).

** $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$*

The results of the test of relationships, through the use of the ordinary least square (OLS) method, between inventory turnover and the three explanatory variables (forecast error: *MAPE* and financial performance measures: working capital level and free cash flow) are displayed below in Table 5.5. The outputs of the purely modest regression model described in Model 1 yield the above results which suggest that considering the influences of the three independent variables, all have effects on the inventory turnover performance. It is also noted that the impacts of all the three metrics are statistically significant. It can be argued, by this study results, that between the two financial decision variables, working capital in particular have stronger negative impact on inventory turnover and is statistically significant at $p < 0.001$. These results are consistent with a large number of previous studies (see for example, Babich and Sobel, 2004; Gaur et al, 2005).

A major motivation for the current research study is that although inventory turnover performance has been shown to have effect on a business financial performance measure such as a firm's working capital position and availability of essential cash (Bendavid et al, 2017) for the business, but it is strongly suspected that forecast error is likely to be impacting, directly and or indirectly, both performance metrics as well. Accordingly, this hypothesis has led to a further analysis for more insights pertaining to how else might forecast errors from an inventory management and control process affect inventory investment or the financial status of a retail chain business. The result of findings for these analytical investigations are described in the next two sections below. But before proceeding to that, it is important to note that the decision whether or not it is necessary for a researcher to continue to carry out further investigations (such as mediation analysis) into some variables that return statistically insignificant relationship results is controversial (Shrout and Bolger, 2002), to say the least. It is noted that authors such as Bollen (1989) and Hayes (2018) advocate that there is no need for statistically significant relationship between two variables before a mediation analysis can be conducted. They have argued, and this is also the stand of this thesis, that similar to the fact that correlation means no causation, nonexistence of correlation should not and cannot invalidate causation. Nonetheless, for the purpose of this research study and for simplicity, further investigation has been conducted into the indirect effect of a single forecast error (*MAPE*) on a single financial performance measure (*WCL* or *FCF*) as mediated by a single inventory efficiency metric (*iTurns*) using the mediation analysis method and vice versa using the procedure of moderation analysis.

5.8.4 Result for Moderation Models (H4)

Free cash flow (*FCF*) has been examined as a moderator of the relation between forecast error (*MAPE*) and inventory turnover (*iTurns*). Relationship between *MAPE* and *FCF* was estimated in the first step of the regression analysis. And in the second step of the regression analysis, the interaction term between *FCF* and *MAPE* was subsequently estimated, and it explained a significant increase in variance in *iTurns* for Model 2.

Table 5.6 Bootstrapped Moderation Effects Analysis

		Model Parameters				Models Specifications		
				BCA (5000) 95% CI				
Outcome Variable	**iTurns**	PE	SE	Lower	Upper	R^2	SE	F-Statistic
Moderation Model								
	Main Effects					0.917	0.238	159.486 ***
	FCF	1.066 ***	0.099	0.872	1.260			
	MAPE	- 0.634 ***	0.055	- 0.742	- 0.526			
	Interaction Effects					0.939	0.208	142.453 ***
	FCF (Centred)	1.655 ***	0.206	1.251	2.058			
	MAPE (centred)	- 0.580 ***	0.051	- 0.681	- 0.480			
	FCF*MAPE	- 0.593 ***	0.188	- 0.962	- 0.225			

NOTE: Moderation regression analysis showing effects with confidence intervals (CIs) and standard errors (S.E). Bias corrected accelerated (BCA), Point estimate (P.E.), standard error (S.E.). ** $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$*

However, the same procedure conducted for Model 3 on the interaction between FCF and the working capital level (*WCL*) and for Model 4 on the interaction between *MAPE* and *WCL* both returned statistically insignificant results. Accordingly, outcomes for the Model 2 have been reported as shown in Table 5.6 above. Note that Table 5.6 displays the output but while indicating the standardised error values; it also contains unstandardized confidence intervals.

Model 3 for hypothesis H4 can be concluded to have been rejected by the findings from analysis output since interaction between working capital level (*WCL*) and *FCF* was returned as statistically insignificant. While the combination of *MAPE* and *WCL* representing Model 4 also failed the initial main effects analysis for moderation, however, free cash flow (*FCF*) was a significant moderator of the relationship between forecast accuracy (*MAPE*) and inventory turnover (*iTurns*). Note thus, that this aspect of the study result is a confirmation of only the Model 2 for hypothesis H4. Table 5.6 shows the main effects as well as the interaction term values of the statistically significant moderation analysis side by side for *FCF* and *MAPE*. The analysis output suggests that the effect of forecast error (*MAPE*) on the inventory turnover efficiency (*iTurns*) is dependent on the levels of the firm's financial status as characterised by the free cash flow (*FCF*).

In this moderation analysis, both the moderator and the independent variable have been *mean centred* to mitigate multicollinearity (Cohen, 2008). The model (that is, Model 2) result shows a significant interaction between *FCF* and *MAPE* (coefficient = – 0.593, SE = 0.188, $p < .001$; Lower CI = – 0.962 and Upper CI = – 0.225). However, in order to gain a better understanding of what this statistically significant interaction outcome means, *sensitivity analysis* was also conducted, and the simple slopes of the moderating effect have been visually plotted as illustrated in Figure 5.8.

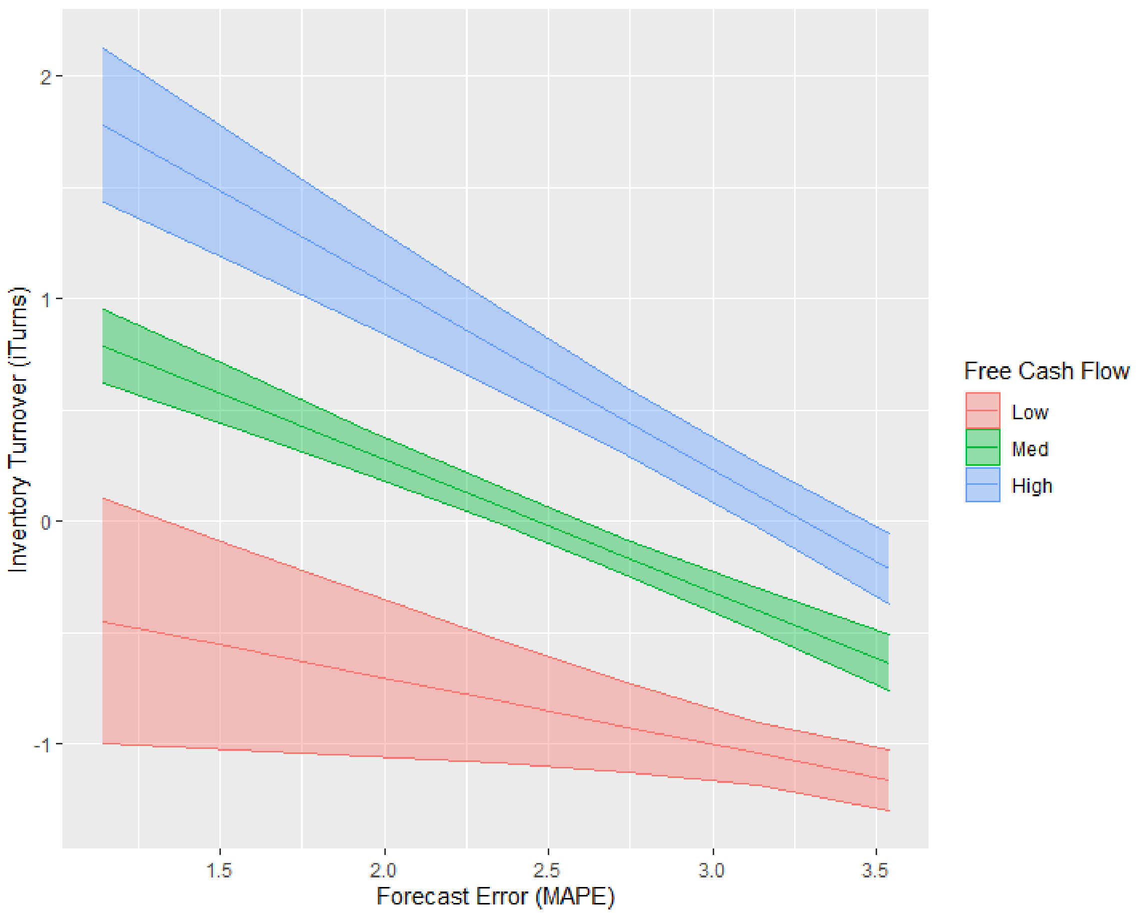


Figure 5.8 Simple slopes of the moderating effect

In conducting a sensitivity analysis to understand moderation effects, it is not unusual to carry out the implementation using the measure of the dispersion of the variables (Tingley et al, 2014). This involves utilising the mean values of the data sets as well as the standard deviation above and below the mean. The unstandardized simple slope for cash amount with one standard deviation (*SD)* below the mean of *FCF* was 16.2, to represent low *FCF* level. The unstandardized simple slope for cash amount with a mean level of *FCF* was 16.7 representing the retail firm's average financial status. And the unstandardized simple slope for cash amount with one *SD* above the mean of *FCF* was 17.1 represents high level of *FCF* position for the firm.

The resulting graph suggests that, just as it was observed from the BPPMC analysis of Table 5.4, the simple slopes of forecast errors at all levels of free cash flow is negative. It can thus, be argued that improved forecast accuracy will only be effective for operational efficiency if the organisation achieves better financial position. This makes sense because, it supports the rationale that working capital could not be set at an allowance level that will impede operations when there is enough fund to meet business needs (Bendavid et al, 2017). Further, at the highest level of free cash flow, the highest operational efficiency can be achieved for a given forecast error reduction.

5.8.5 Results for Mediation Model (H5)

The goal of mediation analysis is to obtain the indirect effect of a specified treatment variable, X on an indicated outcome variable, Y and then estimate its statistical significance. Tingley et al, (2014) demonstrated that the function *mediate ()* method is designed basically, within the mediation package in the open R environment, to run two regressions (X → M and X + M → Y) and test its significance using the two models.

The effect of forecast error *MAPE* on working capital levels was partially mediated via the inventory turnover performance. The summary of results is shown in Table 5.7. As Figure 5.9 illustrates, the regression coefficient between forecast error MAPE and working capital levels and the regression coefficient between inventory turnover and working capital levels are significant. Table 5.7 to shows that the total (direct) effect (δ) of MAPE on WCL is 0.109 with S.E. = 0.008 and t-statistic (direct) value = 13.77 with probability value of 9.41^{-15}. Direct effect (δ') of MAPE on WCL when controlling for iTurns = 0.096 with S.E. = 0.031 and t-statistic (direct) value = 501.843 with probability = 1.13^{-58}. According to Preacher and Hayes (2004), the significance of this indirect effect can be tested using bootstrapping procedures. Unstandardized indirect effects were computed for each of 5,000 bootstrapped samples, and the 95% confidence interval was computed by determining the indirect effects at the 2.5th and 97.5th percentiles. The mean bootstrapped unstandardized indirect effect comes out as 0.017 with standard error of 0.015, and the 95% confidence interval ranged from the lower CI = –0.007 to the upper CI = 0.049. Thus, the indirect effect was statistically significant.

Table 5.7 BCA Bootstrapped Mediation Effects Analysis

		Model Parameters				Model	
				BCA (5000) 95% CI			
Outcome Variable	**WCL**	P.E.	S.E.	Lower	Upper	R^2	F-Statistic
Mediated Model						0.868	95.364 ***
	Total Effect						
	MAPE->WCL (δ)	0.109	0.008				
	Direct Effects						
	MAPE->iTurns (θ)	- 0.768	0.118				
	iTurns->WCL (τ)	- 0.017	0.012				
	MAPE->WCL (δ')	0.096	0.031				
	Indirect Effect						
	MAPE->WCL|iTurns ($\theta\tau$)	0.013					
Mean bootstrapped indirect effect:		0.017 ***	0.015	-0.007	0.049		

NOTE: Mediation regression analysis showing effects with confidence interval (CI) and standard errors (SE). Bias corrected accelerated (BCA), Point estimate (P.E.), standard error (S.E.).

** $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$*

The proportion of the variance for the working capital that is explained by forecast accuracy and inventory turnover in the regression model, R^2 result indicates that 86.8% of WCL's variation is accounted for by both explanatory factors contained in the regression model.

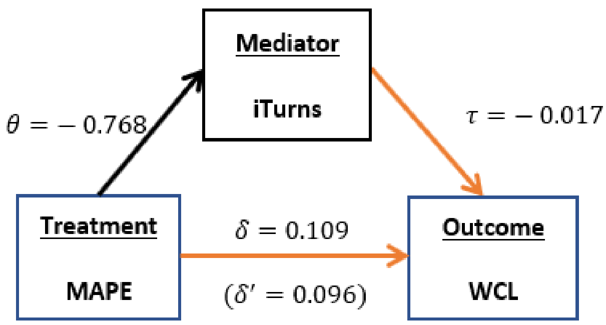


Figure 5.9 Path regression coefficients for the relationship between forecast error (MAPE) and the level of working capital (WCL) as mediated by the inventory turnover (iTurns). The path regression coefficient between MAPE and WCL, controlling for iTurns, is in parentheses. **p < 0.05*

An inference that can be drawn from the baseline impact outputs is that the three independent variables, that is, forecast errors, working capital and free cash flow, all have effects on the inventory turnover performance. It has been observed that the impacts of all the three metrics are statistically significant. Findings suggest that working capital has stronger negative impact on inventory turnover than the free cash flow. The study results also suggest that although inventory turnover performance has been shown to have effect on business financial performance measures such as a firm's working capital position and availability of essential cash for the business (Bendavid et al, 2017), but both in return also impact the inventory performance. In addition, and this is an important study hypothesis, the study analysis output suggests that the effect of forecast error (*MAPE*) on the inventory turnover efficiency (*iTurns*) is dependent on the levels of the firm's financial status as characterised by the free cash flow (*FCF*). Thus, it can be argued that improved forecast accuracy will only be effective for operational efficiency if the organisation achieves better financial position. Moreover, the effect of forecast error (*MAPE*) on working capital levels was partially mediated via the inventory turnover performance.

Evaluation of selected forecasting methods and quantification of economic impacts of emanating classical forecast errors from these models will be conducted in the next study chapter.

CHAPTER 6

Quantifying the Economic Impacts of Classical Forecast Errors

6.1 Introduction

Chapters 2 and 3 of this research thesis report have drawn attention to the fact that accurate demand forecasting with carefully constructed inventory control policies is crucial for the retail chain firms to flourish. Prior to these chapters in the research study introductory chapter, the thesis report highlights that in the recent years, among forecasting practitioners, managers and academics, there has been increasing awareness and growing interest in the economic implications of classical forecast errors on an inventory control system. The introductory chapter further accentuates why this is important as well as being a valid concern considering the contemporary situation of the retail chain globally. On these accounts and on the account of the interaction and intervention effects work in the previous study chapter 5 of this thesis, the current research study chapter considers the accuracy of common and most often used forecasting methods and seeks to capture the true economic consequences associated with managing the inventory control system. In this study chapter therefore, the focus will be mainly on causes of risks inherent in the inventory and their emanative effects. According to the literature (see for example, Syntetos et al, 2009; Ali et al, 2012; Kourentzes et al, 2019), some of the risk factors include, but not limited to, exposure to stockover and stockout since both possess the potential to reduce profits. These problems can happen if the retail business is experiencing poor ***inventory control system*** (relating to *inventory policy* framing, *forecasting accuracy* evaluation and or setting the *safety stock*). These risks may also occur, according to Chopra and Meindl (2016) and Bergen et al (2019), if a retail firm's performance position is perilous in terms of its ***financial control structure*** (in which case a firm's operational function is already suffering from poor *free cash flow* or being treated for poor *inventory investment* due to insufficient or lack of *working capital*). Worse situation, of course, is expected of a business suffering from both cases of a deprived financial functioning and poor inventory control capability. As a result, the thesis addresses the issue of forecasting methods and accuracy evaluation in this research study, but in the knowledge of its interaction, first with the inventory undertakings in this study chapter, and then with the financial functions in the next study chapter. In particular, for the current study chapter, the economic impacts of focus will be in terms of the costs of poor service and relevant inventory costs such as stockout cost, stockover cost and total inventory cost for replenishment decisions characterised by the order up to (OUT) level inventory policy.

The chapter proceeds by presenting and introducing the applicable model framework and notations to be used in the next section. Study starts by describing the key elements involved in the form of notations, inventory settings and setup in section 2. The inventory control setup and theoretical formulation for the experiment is discussed in section 3 followed by the discussion on the traditional inventory cost model and its limitations in section 4. This is followed up in section 5 where the limitations of the traditional model are addressed, and the proposed models introduced. Forecasting setup, demand data simulation discussion and forecasting methods performance results are respectively in sections 6, 7, and 8. Experimental design for the simulation study follows in section 9 and the simulation study results in section 10. The chapter study report ends with empirical study in section 11 and conclusion in section 12.

6.2 Theoretical Formulation and Model Setting and Study Framework

6.2.1 Nomenclatures

The conventional notations to be used throughout the current study chapter are specified in the following Table 6.1 for ease of reference. However, other symbols and notations may be defined as they are introduced along the way in this thesis report.

Table 6.1: Description of notations used in this study chapter

Notations	
t: = 1, 2, 3, … is the discrete time unit for the time series data	R: Review time interval
	C: Desired cycle service level
c: the unit cost	cv: Coefficient of variation
p: the retail unit price	h: the holding cost per unit per period
D_t: Stochastic demand in period t	b: penalty per unit backordered
F_t: is demand forecast (produced in period t - 1) of basic series for period t	μ: stands for the mean of the autoregressive process
ε_t: symbolizes the error in period t	σ: Standard deviation of demand (forecast error) per period
S_t: inventory position at period t	
O_t: order quantity per period	z: Standard normal random variable
S_s: Safety stock	ρ: Stockout probability during the lead time
L: Lead time for replenishment	$\varphi(.)$: Density function

6.2.2. The System Setting and Sequence of Events

In this section, the study chapter considers a simple series supply chain setting that consists of a single supplier that takes orders from a single retailer who receives demand from buyers downstream as shown in Figure 6.1. The dashed arrows in Figure 6.1 indicate the flow of information between entities involved. While the solid arrows above the dashed arrows highlight the flow of product, the solid arrows below the dashed arrows show the flow of cash concerning relevant players.

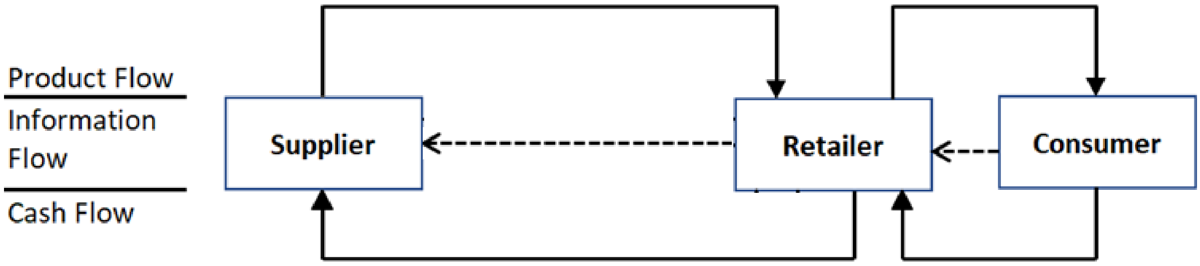


Figure 6.1: Simple series supply chain setting that includes a single supplier and a single retailer taking demand from customers.

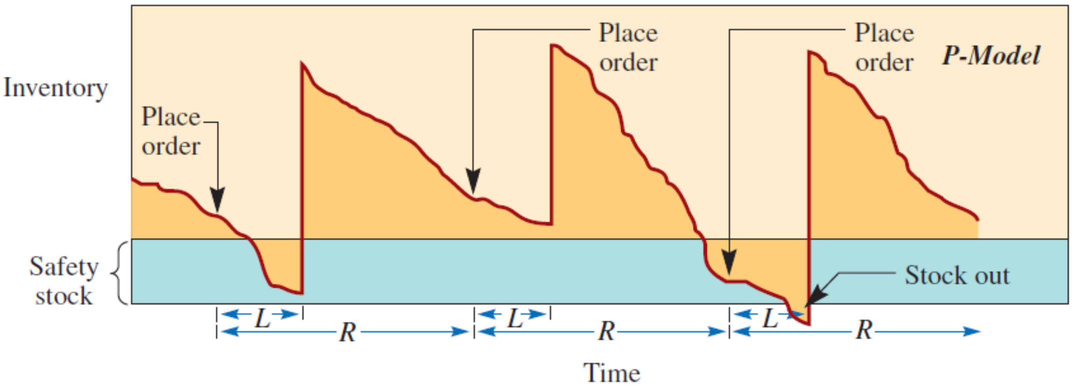


Figure 6.2: Inventory sequence of events under a periodic review policy or P-Model (Adapted from: Jacobs and Chase, 2018).

In supply chain risk management, continuous review stochastic demand models and periodic review stochastic demand models are the two most common types of inventory control models for multiple periods that are subject to uncertainties in inventory systems. This study chapter considers a periodic review policy or (R, S) model (also known as P-Model) inventory management setting involving a single product and finite horizon.

A typical characteristic of this type of policy in an inventory control system is shown in Figure 6.2 for multiple periods. A more detailed behaviour of the policy procedure is as depicted in Figure 6.3 for an instance of a single review period $R > 0$ where null stock level is observed at time zero. Even though, when considering a stock setting situation, it is naturally intuitive to think of the physical inventory on hand. In practice however, the stock situation must be characterised by the inventory position. In view of this, the following sequence of events per period is contemplated.

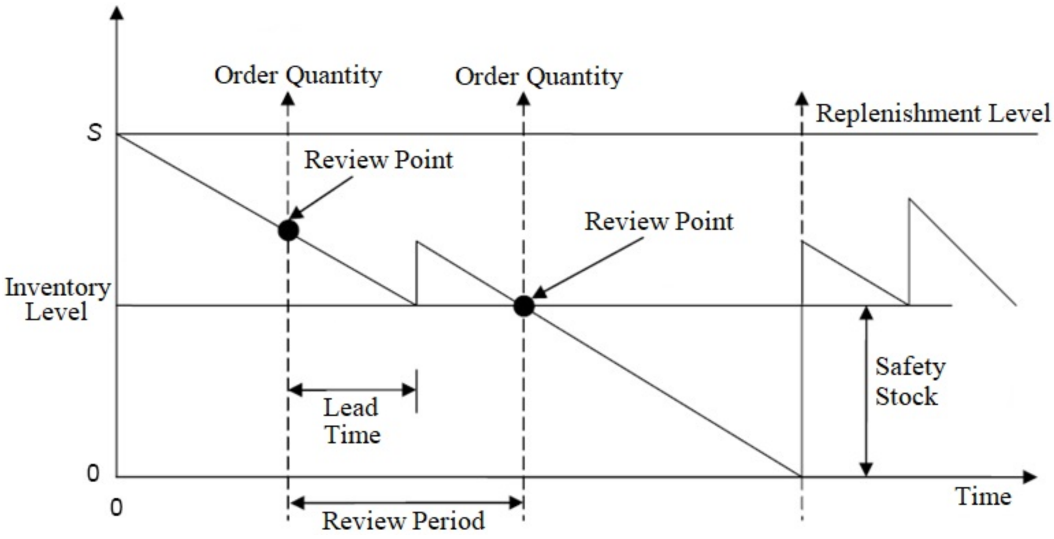


Figure 6.3: Inventory sequence of events under a P-Model for an instance of a single review period $R > 0$ where null stock level is observed at time zero ($t = 0$).

The inventory control system is managed based on an optimal order-up-to (OUT) level, S as shown in Figure 6.3. At the start of period, stock information is updated only once per review period. The inventory position at any time during a review period is defined as the starting inventory position plus all orders placed since the start of the current review period. In addition, positive orders $O_t \geq 0$ can be placed at the beginning of time $t \in (0, R)$ and arrive after lead time $L \geq 0$. In other words, the control procedure is that the inventory position is assessed by the retail firm at the end of every 'R' units of time (see Figure 2; also represented as the 'Review Period' in Figure 3). Variable but adequate replenishment order O_t is then placed with the supplier in a way that enables the inventory position to be raised up to the replenishment level 'S'. The retailer will receive this current order after a lead time, 'L' periods, which have elapsed since placing its order. Backorders are then satisfied. The retail firm receives demands, 'D_t' from consumers for the period. The customers' demands are delivered from the remaining inventory, otherwise those demands are fully backlogged or fully lost, otherwise partial backorder and partial lost sale will simultaneously occur in that period.

It is further considered that the supplier is capable of satisfying the entire orders placed by the retailer. For the start of each period, a single orderable item is considered in this study chapter, where c is the unit purchase cost and fixed or no set up cost is deemed to be incurred. The retail unit price is p, which satisfies the condition that $p > c$. The per period demand for the item is independent and identically distributed (i.i.d.) with density function $\varphi(.)$, with mean μ and standard deviation σ. In addition, a variable lead time of L periods in the procurement cycle will be considered. At the end of each period, every single item designated as stock surplus will certainly incur a unit holding cost $h > 0$ per unit of time (that is, for the period in question). Backlogging unfulfilled demand will be allowed but brings about a unit penalty cost of $b \geq h$ per period plus the cost of delayed revenue and loss of goodwill.

6.2.3 The Simulation Study Experiment and Model Framework

To help manage and make a complex inventory control system work well in dealing with inventory variability phenomenon, forecasting techniques are often being deployed by the retail industry.

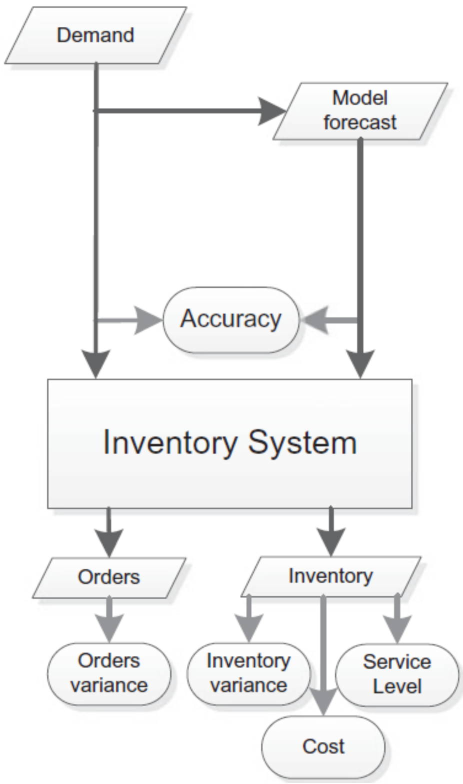


Figure 6.4: Flowchart for Model forecasts fed into the inventory system (source: Wang and Petropoulos, 2016).

The work of Wang and Petropoulos (2016) presented an appropriate flowchart of an inventory system situation where a set of model forecasts as well as the actual demand serve as the input into the inventory system as illustrated in Figure 6.4. By comparing the model forecasts to the actual demands, the forecasting performance can be directly measured in terms of variance of forecast error. Whereas the inventory performance can be measured in terms of inventory variance, inventory costs, service levels and orders variance.

In the case of this research chapter, the investigation interest is in assessing the sensitivity of inventory control results to changes in the control parameter values. These changes can occur as a consequence of utilising different estimation procedures or as a result of experimentation with different possible inventory parameters in order to justify the selection of an optimal inventory control system. As a result, the simulation experiment for the study chapter consists of two main modules: the forecasting module and the inventory control module. The conceptual framework for this inventory control simulation study is graphically demonstrated in Figure 6.5 basically, by further simplifying the Wang and Petropoulos (2016) flowchart of Figure 6.4.

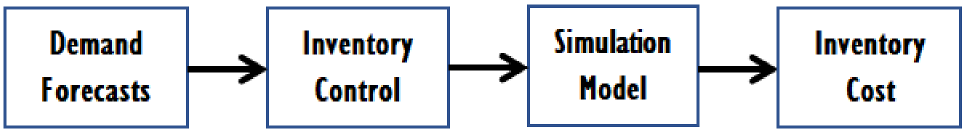


Figure 6.5: Schematic for Inventory Control System Simulation Study

Using the first module, the performance of the estimators (that is, the forecasting methods) will be analysed with respect to their forecasting accuracy. Subsequently, the forecasting performance of the emerged best forecasting strategy will be simulated, in consideration of the inventory (fixed-time review) policy, on generated demands following two ARIMA processes; ARIMA (1, 0, 0) and ARIMA (1, 0, 1). Thereafter, *validation of the study findings are conducted by carrying out empirical study on real retail demand data sets*. Thus, as illustrated in Figure 5 above, to access the simulation method, demand forecasting process will be carried out in order to obtain the variance of the forecast error. Utilising the periodic review (R, S) policy, parameters for the selected inventory procedure will be obtained and fed directly into the simulation system. The tabulated control parameters in Table 6.2 show the control criteria for the optimal condition for this experiment.

Table 6.2: Control Parameters for the Simulation Analysis

Control Variable	Control Parameters
Lead Time	1, 3, 7 (in weeks)
Cycle Service Level	0.90, 0.95, 0.99

The focus of the study chapter is to formulate an inventory cost model for the retailer. The goal of the retail firm, this study chapter assumes, is always to minimise the total relevant inventory cost.

6.3 Inventory Control Setup and Theoretical Formulation

6.3.1 Modelling Demand

As discussed in the previous section, a first step in an inventory control system is the estimation of future demand. Two general approaches for achieving this are to estimate future demand by employing a forecasting model or estimating directly the demand distribution, but fitting one of several candidate distributions. Even when the former approach of employing a forecasting model is used, it is still required to estimate uncertainty reflected in the errors of that forecasting model in order to derive the right and suitable safety stock. Several distributions have previously been considered for modelling demand. This includes the Poisson distribution typically applied for slow-moving items, as well as the Gaussian (or Normal) and Gamma distributions; all evaluated previously for modelling demand uncertainty and lead time variability within the implementation of inventory policies (Silver and Robb, 2008).

Given its widespread use (Chopra and Meindl, 2016) and its versatility in that many distributions can be transformed into a Normal distribution via the Central Limit Theorem, we assume the Gaussian (or Normal) distribution of demand in this study for the following reasons. As it relates to demand, study considers and focuses mainly on seasonal and obsolescence product items such as newspapers, tabloids, foods, fresh fruits, winter jackets etc. This has the implications that, on one hand, the entire stockover products from the current period cannot be used to fulfil demand for the next period and hence, must be disposed of by the end of the current period. This is the setup of the classical newsvendor problem with unknown demand distribution and finite selling season.

And on the other hand, for a periodic review policy (which extends and generalises the newsboy policy), the entire stockover products from the current period can be used to fulfil demand for the next period and even subsequent periods. In either case, as the retailer is required to place orders prior to the demand episodes, then the cost of orders which exceed demand must be borne by the business surplus or stockover, and likewise the cost of shortage or stockout, when demand exceeds inventory. In practice the actual demand distribution F is unknown and needs to be estimated given some historical data $\{(D_1, x_1), \dots, (D_n, x_n)\}$, where D_n are historical demand observations and x_n are predictor variables which can themselves be historical demand observations.

6.3.2 Lead Time and other System Characteristics

The proposed total relevant inventory cost model will be obtained based on the following suppositions that hold for any time, $t \in [0, R)$. Demand rate D_t is a random variable with mean, $E(D_t)$ and standard deviation, σ_t. Lead time is randomly distributed with mean, $E(L)$ and standard deviation, σ_L. Demands are subtracted in the intervals; $(0, t + L)$, $(t, t + L)$. But unknown demands during a review period $(0, t)$ are not subtracted from the inventory position. The inventory level at time $t + L$ is equal to the inventory position at time t minus the demand in interval, $(0, t + L)$. Product unavailability in terms of stockout is allowed in the inventory system. This translates into real and practical situations which are often experienced within the retail industry; this means that this study chapter considers scenarios where demand can either be fully backlogged or allows partial backorders and lost sales.

The study chapter further assumes there occurs in the system only a single order within a period, but that due to stochastic supply (that is, lead time variability) there may or may not be order crossing (that is, replenishment order crossovers) present in the inventory system. It is also believed that the set-up cost and ordering cost are fixed and thus, have no effect on the cost structure. Suppose that the replenishment lead time periods, L with a Gaussian distributed demand for each period t, where t = 1, 2, 3, …, L are independent and normally distributed with a demand mean of D_t and demand standard deviation of σ_t. Then, for an inventory control system that employs the periodic review policy, the total demand during the lead time periods will be correspondingly Gaussian distributed and can be defined as follows.

Besides, while demand during the lead time plus review period is randomly distributed with mean, $E(L + R)$ and standard deviation, σ_{L+R}, stockout in terms of lost sales, partial and full backorder still apply. Based on the condition demand rate and lead time are independent to each other, the expected demand over the lead time plus the review period D_{L+R} is convolution of the two independent variables, the demand rate and the lead time. Thus, the mean and variance of the expected demand during lead time can be computed according to Tersine (1994) as given respectively in equations (6.1) and (6.3):

$$E(D_{L+R}) = E(D_t) \times E(L + R) \tag{6.1}$$

$$Var(D_{L+R}) = \sigma_{L+R}^2 \tag{6.2}$$

Equation (6.2) can be expressed as:

$$\sigma_{L+R}^2 = Var(D_t) \times E(L+R) + \left(E(D_t)\right)^2 \times Var(L+R) \qquad (6.3)$$

6.3.3. The Significance of Safety Stock Level and Cycle Stock Level

To place the importance of cycle stock and of safety stock in context will help to highlight the focus and to comprehend the contribution of this study chapter. It was mentioned in section 3.1 that the two common methods for managing future demand are evaluation by forecasting models or appraising directly the demand distribution but fitting one of several candidate distributions. Whether a forecasting model is applied, or distribution assumed in an inventory control system, cycle stock level is generally driven by the expected value of demand (typically taken as the output of the forecast model or mean of the distribution based on historical data). Whereas safety stock level is based on a mathematical model (usually as shown below in equation 6.4) that incorporates a service level factor, k, which is designed to account for randomness in demand and variations in lead time. For a periodic review rule, the replenishment target stock, S_t is a key decision variable. It is worth noting here that a retail chain prior sales datasets are not the actual demand. Its demand forecast D_t is also a forecast of effective demand and not the actual demand as well. However, using the forecast demand parameters F_t and σ_t to estimate the order-up-to level $S_t = F_t + k\sigma_t$, where k is the safety stock factor, is reckoned as the best the retail chain can do. Nonetheless, since the order-up-to levels depend on the demand forecast, which in turn depends on the actual demand in the previous periods, it thus follows on that the order-up-to levels cannot be determined prior to observing the previous demand datasets. On this account, its computation during the lead time period is reckoned to be the total sum of the expected demand during lead time plus review period, $E(D_{L+R})$ and the safety stock, S_s. The safety stock is given as the product of the standard deviation of the lead time plus review period (that is, σ_{L+R}) and the safety stock factor, that is:

$$S_s = k\sigma_{L+R} \qquad (6.4)$$

Therefore,

$$S_t = E(D_{L+R}) + k\sigma_{L+R} \qquad (6.5)$$

Although both stock levels are quite important in a customer focused retail chain business where level of service is a key success factor, however, the safety stock is especially difficult to model (Kourentzes et al, 2019), and as such, it is discussed further in next section. Nonetheless, poor estimations of both cycle stock level and safety stock level can lead to stockout or stockover. Whereas on one hand, insufficient estimations bring about stockout which engender lost sales or lead to backorder, both of which distress, in no small measure, customer satisfaction and loyalty. On the other hand, however, estimations in excess of a retail business need will negatively impact its operational costs as well as profitability. The use of the safety factor, k in the estimation of the safety stock is designed to moderate and alleviate the difficulty of achieving a desired target service level. For example, suppose z to be the standard normal random variable, the safety factor k satisfies the condition that the allowable stockout probability, ρ during lead time plus review period, is given as:

$$\rho = P(D_{L+R} > S_t) = P(z > k) \qquad (6.6)$$

There are several names by which k is referred to; names such as safety factor, standard score or z-score are among popular names for k. Typical computation of the safety factor, k used in estimating the safety stock are conditioned on either service-based metrics or cost-based metrics. Both approaches and their metrics are interrelated such that if a metric is explicitly set, then the other metrics can implicitly be determined (Silver and Robb, 2008). In this research work, the service-based metrics discussed further in the following sub-section has been considered.

6.3.4. Service-Based Metrics and Safety Stock Under Order-Up-To (OUT) Policy

The service-based models incorporate the safety factor, k (its mathematical model to be examined more in section 6.4.3), which is set to meet a planned Type I service level often referred to as the cycle service level (CSL), C_{sl} given as:

$$C_{sl} = 1 - P(stockout) = P(x \leq k) \qquad (6.7)$$

or a projected Type II service level also known as the item fill rate (IFR), Ω_{IFR}, where $G(k)$ is standard normal unit loss function given as follows:

$$F_r = 1 - \frac{\sigma_T G(k)}{DR} \qquad (6.8)$$

Whereas the cycle service level is the probability that there will not be a stockout within a replenishment cycle, the item fill rate is the fraction of demand that is fulfilled with the inventory on hand out of the cycle stock.

In order to frame our inventory policy, we would need to find the value of k corresponding to a pre-determined or a desired target cycle service level value or item fill rate value. For example, it is statistically significant that an extra stock equivalent to 1.28 standard deviations of demand variability must be carried to fulfil demand with a cycle service level, C_{sl} of 90%

confidence level. Thus, a 90% cycle service level corresponds to a safety factor k of 1.28. The values k corresponding to desired cycle service levels are obtainable from the 'standard normal table' of z-scores. The unit loss function $G(k)$ corresponding to a safety factor value k can also be obtained from the table of normal distribution probabilities that includes it.

Recall that for a periodic review (R, S) policy, S is the order-up-to (OUT) level and designates an inventory level predefined as a positive optimal value. This is equivalent to the current inventory added to the replenishment lot size for an order to be placed when inventory levels are reviewed after a fixed period of time, R. Because the OUT level represents the inventory available to meet all demand arising between two consecutive order (or replenishment) periods, stockout will be experienced if demand during this time interval exceeds the OUT level. It is therefore essential that the cycle service level:

$$C_{sl} = Probability\ (D\ during\ R + L\ \leq S) \qquad (6.9)$$

According to the literature (see for example, Catt, 2007; Silver and Robb, 2008; Flores et al, 1993), the OUT level and safety stock are related as follows, where $T = R + L$, and S_s stands for safety stock and S^* represents the OUT level:

$$S^* = D_T + S_s \qquad (6.10)$$

It follows that under assumptions of normal distribution:

$$C_{sl} = F(S^*, D_T, \sigma_T) \qquad (6.11)$$

and by definition of the inverse Gaussian, standard normal distribution and its inverse:

$$S^* = F^{-1}(C_{sl}, D_T, \sigma_T) \qquad (6.12)$$

The safety stock can then be evaluated using the following mathematical construct:

$$S_s = F^{-1}(C_{sl}, D_T, \sigma_T) - D_T = F^{-1}(C_{sl}) * \sqrt{T}\sigma_T \qquad (6.13)$$

Because demand is normally distributed during the time interval $R + L$ and the periodic demand means and variances are additive, the safety stock model of equation (6.13) can be expressed as follows:

$$S_s = k * \sqrt{R + L}\sigma \qquad (6.14)$$

where $k = F^{-1}(C_{sl})$. The above equation (6.14) is commonly used to mitigate uncertainty in demand and is well known in the inventory literature (Chopra and Meindl, 2016; Nahmias, 2009). To shield operation from lead time variability however, mathematical construct for safety stock will be given as the function of mean demand during period and the variance of lead time:

$$S_s = k * D\sigma_{LT} \qquad (6.15)$$

In general, literature has shown that ignoring variability in lead time can cause significant degradation of service (Kumar and Arora, 1992; Bagchi et al, 1986; Hadley and Whitin, 1963). Therefore, given Gaussian distributed demand volatility (where the two events of demand uncertainty and lead time variability are independent), the theoretical formulation for a fully robust safety stock combines protection against demand uncertainty with safeguard from supply fluctuation as thus in the following equation:

$$S_s = k * \sqrt{\left(\sqrt{R+L}\sigma\right)^2 + (D\sigma_{LT})^2} = k * \sqrt{(R+L)\sigma^2 + D^2\sigma_{LT}{}^2} \qquad (6.16)$$

that is, the product of 'the safety factor' and 'the square root of the square of stochastic demand safety stock model, added to the square of the variability in the lead time model.

6.4 Modelling Expected Inventory Cost Risks

In this section we present the current approach to mathematically modelling the expected inventory cost which minimises the sum of linear inventory holding and backorder cost risks for a given forecasting method.

6.4.1. The Model Assumptions

In this study chapter, it is assumed that c is the cost value of procuring a unit item that carries a selling retail price per unit symbolised as p where $p > c$, and which will yield a gross price margin (often referred to as Markup), to be denoted as m. In general, Markup is the amount that must be added to production or procurement cost of a product to derive the price at which the product should be sold. Further, if H in percentage stands for the cost of holding excess stock as a fraction of item cost per annum, thus, $h = H \div 12$ represents holding cost as a fraction of item cost per unit time (for example, monthly or weekly). The per unit of time backorder cost due to stockout of a unit of item will be represented by b. This implies that the cost of carrying a single unit of item in a month period (that is, one unit of time) will be ch while that of running out of stock by one unit will be mb per cycle period, but $12 * mb$ per year for a cycle period which runs monthly for a full 12 months and $52 * mb$ per year for a cycle period which is weekly and runs for a full 52 weeks. Further note that positive orders $O_t \geq 0$ can be placed at any time $t \in [0, R)$ and arrive after lead time, $L \geq 0$. No fixed costs are incurred, the unit holding cost per unit of time is defined as $h > 0$ and the unit backorder cost per unit of time is given as; $b \geq h$. Note as well that the gross price margin or Markup m stipulated above will be defined as:

$$m = \frac{p-c}{c} \quad (6.17)$$

As a rule, equations can be derived for the expected inventory cost in terms of the replenishment decision variables which in our case are the OUT level S (here index with time t) and the review period R; $S_t(0 \leq t < R)$ and then optimal values are estimated in a way that *minimises the expected cost* per period.

6.4.2. The Current Approach to Modelling the Expected Inventory Cost Risks

For optimal order up to (OUT) level S^*, it is well known that the probability of a stockout during lead time is given by:

$$P(stockout) = P(D_T > S^*) \quad (6.18)$$

that is,

$$P(stockout) = \int_{S^*}^{\infty} f(D_T)dD_T = 1 - F(S^*) \quad (6.19)$$

and the probability of stockover during lead time is given by:

$$P(stockover) = P(D_T < S^*) \quad (6.20)$$

that is,

$$P(stockover) = \int_{0}^{S^*} f(D_T)dD_T = F(S^*) \quad (6.21)$$

Expected inventory cost risks can therefore be evaluated in terms of the expected excess and the expected deficit, at the end of the review period based on whether demand is lower or higher than the optimal OUT level, S^*. Assuming a continuous random variable and taking the expectation over all values of the stochastic demand, inventory cost risks, $E(I_{cr})$ can be evaluated as follows:

$$E(I_{cr}) = \begin{cases} S^* - D_T, & if\ D_T < S^* \\ 0, & if\ D_T = S^* \\ D_T - S^*, & if\ D_T > S^* \end{cases} \quad (6.22)$$

For the continuous random variable and the order-up-to (R, S) policy with optimal OUT level, we therefore compute the expected stockover as follow:

$$E(stockover) = E(S^* - D_T) = \int_{-\infty}^{S^*} (S^* - D_T) f(D_T) dD_T \qquad (6.23)$$

and by the same token, the expected stockout will be:

$$E(stockout) = E(D_T - S^*) = \int_{S^*}^{\infty} (D_T - S^*) f(D_T) dD_T \qquad (6.24)$$

This gives an expected total relevant inventory cost (TRIC) risk, being the sum of overage and underage as follows:

$$E(I_{cr}) = E(stockover) + E(stockout) \qquad (6.25)$$

$$E(I_{cr}) = \int_{-\infty}^{S^*} (S^* - D_T) f(D_T) dD_T + \int_{S^*}^{\infty} (D_T - S^*) f(D_T) dD_T \qquad (6.26)$$

The holding cost and the backorder cost as expressed above in equation (6.26), in essence, is the traditional inventory performance function or the traditional cost criterion, and when calculated in *R* periods, is often approximated (see for example, Wang and Petropoulos, 2016) as:

$$TRIC = hE(i^+) + bE(i^-) = \frac{h}{R}\sum_{t=1}^{R} i_t^+ + \frac{b}{R}\sum_{t=1}^{R} i_t^- \qquad (6.27)$$

where h and b are unit holding cost and backorder cost respectively. Moreover, the term i_t^+ characterizes the positive on-hand inventory and the term i_t^- denotes backorders for all $t > 0$.

6.4.3. The Safety Factor for the Expected Inventory Cost Risk

Let $\phi(.)$ and $\Phi(.)$ be defined, respectively, as being the probability density function (pdf) and the cumulative density function (CDF) for the standard normal. Following the properties of the standard normal distribution as espoused by Hadley and Whitin (1963) and Nahmias (2009), the standard normal unit loss function $G(.)$ is related to the safety factor, k as follow:

$$G(k^*) = \int_{k^*}^{\infty} (x - k)\phi(x) dx = \int_{k^*}^{\infty} x\phi(x) dx - k\{1 - \Phi(k)\} \qquad (6.28)$$

It follows therefore, from the relationship between the standard normal distribution and the normal distribution that:

$$f(S^*) = \frac{\phi(k^*)}{\sigma} \qquad (6.29a)$$

And that,

$$F(S^*) = \Phi(k^*) \qquad (6.29b)$$

Substituting equation (6.29a) and equation (6.29b) back in equation (6.28) leads to the following mathematical model for the standard normal unit loss function as:

$$G(k^*) = \sigma f(S^*) - k - kF(S^*) \qquad (6.30)$$

Given that the optimal safety factor k^* can be obtained, see equation (6.10) and equation (6.14), as follow:

$$k^* = \frac{S^* - D_T}{\sigma\sqrt{R+L}} \qquad (6.31)$$

Then, it follows on from all the foregoing that, again for a continuous random variable with the expectation over all values of the stochastic demand, it is trivial to substitute equations (6.29a), (6.29b), (6.30) and (6.31) back into equation (6.26) and take first derivatives to arrive, when calculated in R periods, at the following total inventory costs risk:

$$E(I_{cr}) = \left(\frac{1}{R}\right)\sum_{t=1}^{R} ch * k\sigma\sqrt{R+L} + \left(\frac{1}{R}\right)\sum_{t=1}^{R} mb * \sigma\sqrt{R+L}G(k) \qquad (6.32)$$

Notice that the above mathematical model for traditional total relevant inventory costs risk consists of two components. First constituent is the cost of holding excess item in the inventory or overstock cost which we referred to in this study as the inventory carrying cost risk (ICCR) and is defined in the above model as:

$$\sum_{t=1}^{R} ch * k\sigma\sqrt{R+L} * \left(\frac{1}{R}\right)$$

The surplus cost described above is every so often referred to as stockover cost or holding cost or overage cost. The cost of poor service or backorder cost, referred to in this study as the inventory stockout cost risk (ISCR), forms the second element of the total relevant cost:

$$\sum_{t=1}^{R} mb * \sigma\sqrt{R+L}G(k) * \left(\frac{1}{R}\right)$$

Again, this cost is sometimes termed as stockout cost or shortage cost or underage cost. The total relevant inventory cost structure above appears to be ubiquitous in its use by the previous studies that have attempted to capture the economic impacts of classical forecast errors for the supply chain inventory including that of retail chains dealing with obsolescence and seasonal stocks.

6.4.4. Limitations of the Current Expected Inventory Cost Risks Model

In what follows in this section of the study chapter, the current study calibrates a clear and robust proposal that corrects and takes care of what could be seen are the failings that make the current traditional inventory cost risks model in equation (6.32) *restrictive and inadequate* for proper and pragmatic evaluation procedure. The traditional model appears to be widespread, sweeping and have been used indiscriminately irrespective of the reality obtainable in practice; that is, whether or not the lead time is fixed and constant or fluctuates in practical reality, and whether or not the whole or none or only a proportion of the safety stock has been practically used up to fulfil demand. Its blanket application and adoption are rife and prevalent in practice, and among the few studies (see for example, Wang et al, 2013; Tiacci and Saetta, 2009; Catt, 2007) that have attempted to evaluate forecasting methods performance in terms of their volume and or economic impacts on the inventory.

6.4.4.1 Limitation 1: Salvage Strategy (or Value)

To start with, it is quite important to note that for seasonal and obsolescence retail items, the traditional model in equation (6.32) will distort the true inventory cost risks. This is because surplus items nearing their expiration dates from stockover are often being offered to customers at a salvage value, and this fact has not been reflected in equation (6.32) in which the product of a unit cost of an item and the holding cost rate, that is, ch has been used in the cost function (see for example, Catt, 2007; Flores et al, 1993).

6.4.4.2 Limitation 2: Stochastic Supply (or Variability)

The second key issue with the traditional inventory carrying cost risk structure which currently, is widely and often being besought is the fact that, oversimplification of model appears to be pervasive due to the prevalent assumption of constant lead time; in other words, it is supposing supply certainty. This restrictive assumption leads to the utilisation of the expression $\sqrt{R+L}\sigma$ in the adoption of loss function and safety stock for quantification of economic metrics. Thus, the following formulation is often used for the safety stock:

$$S_s = k * \sqrt{R+L}\sigma$$

This practice, it can be argued, is unswervingly in contradiction to the evidence espoused in the literature where it has been demonstrated that ignoring variability in lead time can cause significant degradation of service (see for example, Kumar and Arora, 1992; Bagchi et al, 1986; Hadley and Whitin, 1963).

6.4.4.3 Limitation 3: Safety Stock Size

Yet, another critical issue with the traditional inventory carrying cost risks model is that, as can be clearly seen from the above total inventory cost function in equation (6.32), it is assumed that the inventory cost risk to the retailer is based on the whole estimated periodic safety stock units (Catt, 2007; Flores et al, 1993). However, it is neither impossible nor uncommon and in fact, it is more realistic that it is only a fraction of the projected safety stock per period, rather than the whole bulk of it, should be the right amount for the estimation of the inventory cost risks purpose at the end of the evaluation period.

6.4.4.4 Limitation 4: Backorders Size and Lost Sales

In terms of inventory optimisation, backordering process signifies some specific challenges. It is a process of utilising inventory that a retail chain firm falls short of or has not on-hand; that is, a system of future fulfilment of a product demand. In many retail settings facing an out-of-stock situation, it is really difficult to capture the full picture backorders. This, in part, is mainly due to the fact that backorders, like demand, must be correctly captured in an approach that is formal. However, a large number of shoppers would simply move on when they are faced with a stockout situation, without informing the onsite or online store about the unavailable item. And when backorders do occur and are reported, they may sometimes come from the customers, who although were willing to wait, but with some degree of urgency. Customers response to stockouts, in terms of satisfaction and subsequent store choice behaviour, are explored elsewhere (see for example, Fitzsimons, 2000).

In this study chapter, the focus is on the right volume of backorders captured in the context of a retail chain firm and requiring fulfilment of the demand. The current model appears to be inadequate and not robust enough to account for whether or not backordering is full or partial, as well as whether there has been a *real* complete or partial loss of sales, simultaneously, due to *true* stockout. The words 'real' and 'true' are used to capture and illustrate an important phenomenon, interaction effects of restocking process from the backroom to the shelf, within the environment of the retail chain stores. Backroom stock and shelf stock interaction effects have been studied elsewhere (see, for example, Gaukler et al, 2007; Karkkainen, 2003). Gaukler (2010) asserts how item-level Radio-frequency identification (RFID) identification method (which uses electromagnetic waves to transmit information from a tag to a reader device) is useful in controlling stockouts due to this phenomenon. And he has demonstrated the relative contribution of each of the two stocks (that is, shelf and backroom stocks) to the potential overall cost savings. Following Gaukler (2010), backorders and lost sales due to stockouts will be modelled to reflect these effects in this study chapter.

6.5 Proposed Models of Expected Inventory Cost Risks

In this section we make a number of proposals to address each of the limitations identified with the current (traditional) approach to modelling expected inventory cost risk. We compare the current model with the proposed model to highlight where improvements are made.

6.5.1. Addressing the Traditional Model Limitations

The proposed model is built on the principle of addressing each of the previous limitations and documented towards improving and developing a more widely applicable model that takes into account the realities attainable in practice. In other words, the proposed TRIC model has been carefully calibrated to capture the context and to reflect the reality for a retail chain firms. Thus, the real reason to reflate the traditional cost function model is bound by the defined motivation for this research study, which has been discussed in the introductory chapter of the thesis.

6.5.1.1 Addressing limitation 1: Salvage Value

Recall that the current approach does not reflect the salvage value paid by customers in relation to the sales of surplus and deteriorating items from stockover. To address the first limitations, the research study incorporates the product of the holding cost rate and the difference between the procurement cost per unit item and its salvage value. Thus, if stockover occurs, a salvage item value of v where $v < c$ will apply because the item as considered by this study, if you recall, cannot be used to fulfil demand for the next cycle period after the expiry date and hence, must be disposed of by the end of the current cycle period corresponding to the end valid expiry date at a value less than the going price p and the item cost c. Arithmetically, it is better and good practice to express v as a percentage of the product cost in the expression for the inventory holding cost risk. Hence, if it is assumed that α is the fraction of the product cost salvaged by the retail chain, then, $(1-\alpha)$ should be used in the construction of the cost risk function. This implies that the cost of carrying a single unit of item in a month period (that is, one unit of time) will be $(c-v)h$, which will simply translate to $(1-\alpha)ch$ term for the current study model rather than ch term utilised in the traditional model.

6.5.1.2 Addressing limitation 2: Supply Variability

The proposed model adopts the system and the mathematical structure for safety stock as demonstrated in Silver et al (2008) and given in equation (6.16) in section (3.4):

$$S_s = k * \sqrt{(R+L)\sigma^2 + D^2{\sigma_{LT}}^2}$$

which accounts for both demand and lead time volatility. In addition, it also accounts for both uncertainties in the unit loss function for backordering during stockout as:

$$\sqrt{(R+L)\sigma^2 + D^2{\sigma_{LT}}^2}G(k)$$

It is important to remark that the proposed model is a generalised function as it has also been designed to take care of fixed lead time in a system. Hence, if the inventory system does not experience randomness in lead time, the second term inside the square root (that is, $D^2{\sigma_{LT}}^2$) will be zero since the lead time variance (${\sigma_{LT}}^2$) should then be zero. In this case, the model becomes exactly the same as (or revert back to) the current traditional model which assumes constant lead time.

6.5.1.3 Addressing limitation 3: Safety Stock Size

It has been observed that the current inventory cost risk to the retailer is typically based on the whole estimated periodic safety stock units. It is however possible and arguably more realistic to assume that only a portion of the projected safety stock per period, rather than the whole bulk is utilised. In order to correct for this and to set suitable safety stock quantity estimates for the risk evaluation, the current study introduces τ which takes a percentage value of between 0 and 100 (or a fraction from 0 to 1) of the safety stock units excess in the system at the end of the evaluation period. That is to say that τ is the fraction of the safety stock that has been used up per evaluation period by the retail chain.

Thus, it should be noted that when the whole of the safety stock has been used to fulfil demand during the period, then $\tau = 1$. This has the implication that there has been no inventory carrying cost risk involved due to safety stock over estimation; unless, of course, any item has been salvaged in sales. But when the percentage of the safety stock used up during the period is zero, $\tau = 0$, then inventory carrying cost risk is as assumed by the traditional cost function. This thesis believes this to be a true representation of the realistic situation for a retail chain rather than the blanket assumption of the current model in respect of the size of safety stock to be used for the purpose of inventory cost evaluation.

6.5.1.4 Addressing limitation 4: Backorder Size

In this subsection of the chapter study, the backorder component of the traditional cost function for calculating the TRIC per unit time has been carefully modified to be consistent with the pragmatics of retail chains contextual-level realities. In other words, the model will be designed to simultaneously account for a full or fractional backorder and for an outright or partial lost sale. In terms of consideration for lost sales and for the fraction of demand during stockout period which will be backordered, β, the backorder amount will be considered as a variable, which is contingent on the extent of the expected stockout when the operating cycle period comes to a conclusion. Thus, suppose that the expected stockout at the end of an operating cycle period is expressed as:

$$Expected\ stockout = E(D_t - S)^+$$

Then, the expected number of backorders at the end of that cycle is given by:

$$Expected\ backorders = \beta E(D_t - S)^+$$

And the expected number of lost sales at the end of cycle will be:

$$Expected\ lost\ sales = (1-\beta)E(D_t - S)^+$$

This suggests that when stockout occurs, the backorder can be modelled as a function of the expected stockout quantity (Gholami-Qadikolaei et al, 2012), which can be expressed as:

$$\beta = \frac{1}{1 + \theta E(D_t - S)^+}$$

For the purpose of the current study, the exogeneous parameter, θ will be a positive constant, that is, $0 \leq \theta \leq 1$ (Gaukler, 2010). It is a main modelling feature denoting the notion of effective demand at the retail chain shelf. In particular, it exhibits both the importance of stockout in estimating backorder rate, β and the performance of the in-store backroom-to-shelf replenishment process. The better the process performance, the higher θ will be. In specific terms, θ is the probability of unavoidable stockouts (that is, stockouts only occur when there is no more product on the shelf and in the backroom), and the probability of avoidable stockout will be $1-\theta$. Thus, $\theta = 1$ implies that both backroom stock and shelf stock are *actually* empty and unfilled at the point of its estimation, while $\theta = 0$ implies avoidable stockouts because even though, the shelf stock is void but the backroom stock is actually not depleted. Observe that the backorder rate will be one ($\beta = 1$) when the backorder parameter, $\theta = 0$. This has the implication that a full backorder has occurred and suggests that the whole amount of the expected stockout may be backordered. But since this is simply a case of *false* stockout, the demand may be met by the backroom stock. And on the other hand, if $\theta = 1$, there are two notable scenarios that can be observed. First, if the system stockout is very large enough to approximately make $\beta = 0$, then full lost sales will occur. Otherwise, as the system stockout becomes increasingly large, the backorder rate, β gets smaller. This has the implication that fewer customers are able to tolerate (by exercising patience for) their demand to be fulfilled in future (when the next replenishment order flows in).

6.5.2. Developing the Proposed Forecast Error Cost Risks Model

According to Wang and Petropoulos (2016), inventory fluctuation can be detrimental to the retail chain businesses by inducing both inventory stockout and stockover cost risks. Both risks can be captured by the average total relevant inventory costs (TRIC) consisting of two elements. That is, the holding cost and the backorder cost as expressed in equation (6.26). It should be noted that the TRIC will henceforth be referred to in this study as the forecast error cost risk (FECR). The system manager places an order of amount, O_t, after a review period, R to bring the inventory level up to the S level. If we let the FECR per unit time be determined as follow:

$$\text{FECR} = Holding\ Cost + Stockout\ Cost$$

Recall equation (6.26), that the holding cost per cycle will be provided as:

$$E(S - D_t)^+ = \int_{-\infty}^{S} (S - D_t) f(D_t) dD_t$$

and the expected demand during stockout at the end of cycle is given as:

$$E(D_t - S)^+ = \int_{S}^{\infty} (D_t - S) f(D_t) dD_t$$

The latter is a composite function which will lead its decomposition into the two components (see section 6.5.1.4) of the system stockout cost per cycle to be computed, where b and m are penalty cost per unit item and marginal profit per unit item respectively, as:

$$mb\beta E(D_t - S)^+ + m(1 - \beta)E(D_t - S)^+$$

The first term in the above expression will represent the cost of backordering, while the cost of lost sales is represented by the second term. Thus, let the term i_t^+ still characterises the positive on-hand inventory and the term i_t^- denotes backorders, where $i_t^+ = \max(i_t, 0)$ and $i_t^- = \max(-i_t, 0)$ for all $t > 0$, and approximated as usual:

$$FECR = hE(i^+) + bE(i^-) = \frac{h}{R}\sum_{t=1}^{R} i_t^+ + \frac{b}{R}\sum_{t=1}^{R} i_t^- \qquad (6.27)$$

However, the proposed inventory performance function (that is, the proposed cost criterion) when calculated in R periods, and h being the carrying cost per unit item and b the unit backorder cost, will address the limitations discussed in Section 6.4.4 and 6.5.1. Addressing those limitations leads, in essence, to the proposed FECR model which can be obtained by estimating the following:

$$FECR = \sum_{t=1}^{R}(1-\alpha)(1-\tau)chk\sqrt{(R+L)\sigma^2 + D^2{\sigma_{LT}}^2}\left(\frac{1}{R}\right)$$
$$+\sum_{t=1}^{R}(mb\beta + m(1-\beta))\sqrt{(R+L)\sigma^2 + D^2{\sigma_{LT}}^2}G(k)\left(\frac{1}{R}\right) \qquad (6.33)$$

As can be seen from the proposed model above, it comprises adjustment to one of the two main components of the total expected inventory cost risk. The new inventory carrying cost risk (ICCR) component becomes:

$$ICCR = \sum_{t=1}^{R}(1-\alpha)(1-\tau)chk\sqrt{(R+L)\sigma^2 + D^2{\sigma_{LT}}^2}\left(\frac{1}{R}\right) \qquad (6.34)$$

However, the inventory stockout cost risk (ISCR), which is the lost profit cost remains as given in the traditional model:

$$ISCR = \sum_{t=1}^{R}(mb\beta + m(1-\beta))\sqrt{(R+L)\sigma^2 + D^2{\sigma_{LT}}^2}G(k)\left(\frac{1}{R}\right) \qquad (6.35)$$

The proposed total relevant forecast error cost risk (FECR) model is derived by summing the inventory stockover (carrying) cost component and the stockout cost component but incorporating terms to effectively handle all the issues discussed in the previous sections. As mentioned above in section 6.5.1.2, the term $D^2{\sigma_{LT}}^2$ in equations (6.33), (6.34) and (6.35) will be zero if the variance of lead time (${\sigma_{LT}}^2$) is zero, and this implies that the proposed model will restore back (in terms of safety stock and unit loss function) to their respective traditional models when this happens.

6.5.3. Developing the Proposed Revenue Risk Model

In addition to the proposed forecast error cost risk (FECR) model above, the study chapter considers an entirely new economic measure (an alternative to the total relevant forecast error cost) as further contribution towards the efforts of financially quantifying the traditional statistical forecast errors within the supply chain risk management. A very important performance measure for any business is its revenue generation capability from both operational perspective and strategic standpoint. Accordingly, economic quantification of forecast error in terms of maximising revenue rather than cost minimisation, the author believes, is desirable by some stakeholders, such as distributors and retailers who aim to maximise profit, and are uniquely and exclusively in the business of inventory, maximising revenue relative to capacity. Suffice to say then that industry such as the retail chains may be more interested in knowing how much of impacts on revenue and consequently on profit is posed by potential revenue risks due to the error of cycle stock prediction and the projected safety stock. To this end, this study chapter proposes the inventory revenue cost risk (IRCR) model as follows. This research study adopts the standard assumption as previously highlighted in section 6.3 to section 6.5 of this thesis article including that the demand over the lead time is Gaussian distributed with mean D_T and a standard deviation of σ_T. Also, as in the cost function construction, set up cost and ordering cost are assumed to be fixed and so have no effect on the revenue risk structure. Moreover, similar to the cost risk function, the model for the revenue risks over the lead time will be based on whether demand is below or above the OUT level which is the sum of replenishment on order and inventory on hand. The expected revenue when a continuous random variable is considered and the expectation over all values is therefore based on:

$$E(I_{rr}) = \begin{cases} S^* - D_T, & for\ D_T \leq S^* \\ D_T - S^*, & for\ D_T \geq S^* \end{cases} \tag{6.35}$$

The mathematical model for the expected inventory revenue risk which maximises the sum of linear inventory holding and backorder risks at every time period for a chosen forecasting method can, therefore, be constructed as follow by invoking the *Leibniz's Rule* to obtain the optimal OUT level S^* and then exploring the Gaussian and the standard normal distributional relationships as before. The resulting total expected revenue risk function per cycle can be stated as follows:

$$E(I_{rr}) = (p - \alpha c)(1 - \tau)E(stockover) + (1 - \tau)chE(stockover) + pbE(stockout) \tag{6.36}$$

$$E(I_{rr}) = (1 - \tau)[(p - \alpha c)\int_{-\infty}^{S^*}(S^* - D_T)f(D_T)dD_T + ch\int_{-\infty}^{S^*}(S^* - D_T)f(D_T)dD_T] + pb\int_{S^*}^{\infty}(D_T - S^*)f(D_T)dD_T \tag{6.37}$$

As before, finding the first derivative of equation (6.37) and then approximating to conveniently set the estimation to derive the revenue risks at the end of the period for a single period inventory profile, the following is arrived at:

$$ICRR = (p - \alpha c + ch)(1 - \tau)k\sqrt{(R + L)\sigma^2 + D^2{\sigma_{LT}}^2} \quad (6.38)$$

$$ISRR = pb\sqrt{(R + L)\sigma^2 + D^2{\sigma_{LT}}^2}G(k)\left(\frac{1}{R}\right) \quad (6.39)$$

$$FERR = (p - \alpha c + ch)(1 - \tau)k\sqrt{(R + L)\sigma^2 + D^2{\sigma_{LT}}^2} + pb\sqrt{(R + L)\sigma^2 + D^2{\sigma_{LT}}^2}G(k) \quad (6.40)$$

Likewise, for this new revenue risk model, if the inventory system does not experience variability in lead time, the term $D^2{\sigma_{LT}}^2$ in equation (6.38), (6.39) and (6.40) will be zero since the lead time variance (${\sigma_{LT}}^2$) ought to be zero.

6.6 Forecasting Setup

6.6.1 Simulation Study: Forecasting Methods

The following five forecasting methods have been employed for the simulated ARIMA (1, 0, 0) and ARIMA (1, 0, 1) monthly data sets:

- Naïve Model (as a benchmark method)
- Exponential Smoothing Models
  - Simple Exponential Smoothing (SES)
  - ExponenTial Smoothing (ETS, also known as 'Error, Trend, Seasonal', is an automatic exponential smoothing method)
- Minimum Mean Squared Error (MMSE)
- ARIMA Models
  - auto.arima (is automated ARIMA method)

For the simulation study, each of the forecasting models have been used to prepare a thirty-eight months ahead (that is, h = 38 months) rolling window forecasts for the two generated AR (1, 0, 0) and ARMA (1, 0, 1) data sets described in the thesis methodology chapter. The main benefit of using this long horizon is for analysis purpose, but may also confirm previous studies; assertion that the longer the horizon, the lower the accuracy of forecasts (see for example, Ali et al, 2011). In addition, while acknowledging the fact that the models are making fundamentally different assumptions about the process by which future data is generated. It should, however, be noted that the forecast errors on the training data set are the in-sample model measures and they only indicate which model is a better fit to the training data (that is, indication of the training fit of the employed models). But those on the test data set provide the real measures of models' true abilities to make good and unbiased forecasts about the future

(Barrow and Kourentzes, 2016). Thus, the study reports the forecast accuracy metrics for the five models on their test data sets.

6.6.2. Simulation Study: Forecast Accuracy Metrics

For the purpose of this simulation study, the following three statistical forecasting error measures will be utilised as they have been observed to be traditionally, the most often used for the ensuing statistical error measure estimations (Ord et al, 2017; Davydenko et al, 2010); the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the mean squared error (MSE). These error metrics have been discussed in the methodology chapter of the thesis. It should be noted that the standard deviation of errors (SDE) which is just the square root of the MSE (that is RMSE) is often employed as the approximation for MSE (see for example, Hyndman and Athanasopoulos, 2014). And while only the results of these three error measures will be utilised for analysis and discussed in the current study chapter, however, all the error metrics output by the forecast () function in R will be reported.

6.7 Data Sets for the Simulation Experiment

6.7.1. Simulation of Demand Data

The theoretically generated 192 data points following an ARIMA (1, 0, 0) process and another 192 data points that follow an ARIMA (1, 0, 1) process have been used to characterise demand data for the simulation study in this chapter. This enables ability to carry out analysis on the traditional approaches that have been adopted in previous research studies, as well as their comparison with the models proposed by this current study.

These generated data series have been used to produce forecasts using all the five forecasting procedures as listed above. Obtained from the created forecasts are the values of forecast error metrics including RMSE, MAE, and MAPE as well as the economic metric values for the study analysis results for the study chapter. To accomplish these, a breakup has been carried out for each of the data sets employed for this aspect of the study into training subsets and testing subsets as described in next section below.

6.7.2 Simulated Data Series Sub-Setting Rules

Process identification and parameter estimation require the specification of series sub-setting rules to be employed for the simulation research study. Hence, each of the two data series is partitioned into two parts, namely the training data subset (or estimation period) and the test data subset (that is, performance measurement period). The training subsets from the 16 years monthly data series included all the time series from January 2002 until the end of December 2015 and testing subsets including the data series from January 2016 and up to the end of December 2017 for the two ARIMA data sets. In particular, for optimal evaluation of forecasting methods, the total time series of 192 observations are split into two unequal parts of 154 months in-sample subset for the estimation period and 38 months out-of-sample subset for the performance measurement periods. This data set partition policy for the rolling window origin, where the training subset has 154 data points (80% of total time series) while the test subset has 38 data points (20% of total time series) is in line with what Hyndman (2018) has demonstrated as the right ratio that leads to good estimation. In other words, 38 months out-of-sample data subset will be utilised to produce rolling origin forecast from which forecast errors (MAE, MAPE and RMSE) can be obtained.

6.8 Forecasting Methods Performance Results

6.8.1 Simulation Study: Evaluating Accuracy of Forecasting Methods

Performance of the forecasting models utilised for the chapter study has been conducted. After sub-setting the training dataset and the test dataset (as described in the preceding section), in fitting and evaluating forecast accuracy for each and every of the forecasting approaches deployed to make monthly demand prediction, a *time series split* (TSS) cross-validation on rolling forecasting origin has been implemented. The detailed explanation of the implementation of the cross-validation and how it works generally have been discussed in the thesis methodology chapter. At the first iteration, the candidate forecasting strategy is trained on the simulated demand data sets from the first month to the 154th month, then forecast only a month in advance and validate on the actual month 155 which is the first data point for the test data set. Then, for the next iteration, train the forecasting model on data from month 2 to month 155, then predict another one month ahead and validate on the actual month 156, which is the second data point for the test data set. This iterative procedure continues and has been carried out repeatedly until the end of the last value for each of the 38 data points for the test data sets.

6.8.2 Statistical Comparison of the Different Forecasting Strategies

Next step in the study then will be to obtain from the produced forecasts, RMSE, MAE, and MAPE values as well as the economic measures and quantitative ratio correlation measures (that is, the relative measure of variability of the data sets on a ratio scale) of finer forecast. Thus, to examine the forecast accuracy produced by the forecasting models that are being evaluated, their statistic metrics outputs have been recorded. The research thesis reports the means for each of the forecast error distributions for all the five forecasting methods as provided in Table 6.3 and Table 6.4 below, respectively for the ARIMA (1, 0, 0) process and ARIMA (1, 0, 1) process. On examining the error values of all the indicator metrics for the five forecasting models, we can see reductions in the test set prediction indicators for SES, ETS, MMSE and Auto ARIMA models over the Naïve model for the ARIMA (1, 0, 0) process, but this happens only to the Auto ARIMA model in the ARIMA (1, 0, 1) distributions where all the remaining three models, SES, ETS and MMSE seem to have the same prediction capability as for the Naïve model.

Table 6.3 Accuracy measures of the different forecasting strategies for ARIMA (1, 0, 0)

	Naïve	SES	ETS	MMSE	Auto ARIMA
ME	1.28	0.68	0.68	0.68	-0.23
RMSE	1.66	1.25	1.26	1.26	1.06
MAE	1.40	1.02	1.02	1.02	0.82
MPE	1.27	0.67	0.67	0.67	-0.24
MAPE	1.39	1.02	1.02	1.02	0.82
MASE	1.09	0.79	0.80	0.80	0.63
ACF1	0.17	0.17	0.17	0.17	0.14
Theil's U	1.27	0.96	0.97	0.97	0.82

Table 6.4 Accuracy measures of the different forecasting strategies for ARIMA (1, 0, 1)

	Naïve	SES	ETS	MMSE	Auto ARIMA
ME	1.17	1.17	1.17	1.17	-0.29
RMSE	2.19	2.19	2.19	2.19	1.21
MAE	1.84	1.84	1.84	1.84	1.00
MPE	0.24	0.24	0.24	0.24	-0.04
MAPE	0.25	0.25	0.25	0.25	0.13
MASE	0.89	0.89	0.89	0.89	0.48
ACF1	0.50	0.50	0.50	0.50	0.39
Theil's U	1.90	1.90	1.90	1.90	1.05

In other words, for this simulation study statistical evaluation result outputs, according to all the forecasts error measures, especially for the study focused RMSE, MAE, and MAPE error metrics, all forecasting models' performances except for the Auto ARIMA are at per with the Naïve method for the ARIMA (1, 0, 1) distribution process. However, the three forecasting approaches, SES, ETS and MMSE performed marginally better than the Naïve forecasting technique for the ARIMA (1, 0, 0) distribution process. An implication of these findings is that forecasting methods evaluation are affected by the distribution process for an item demand. The best strategy for both distribution processes though, is the Auto ARIMA model as it appears to be more promising for out-of-sample predictions.

6.9 Experimental Design for the Economic Impact Evaluation

6.9.1 Inventory Simulation Setup

Bootstrapped simulation runs using the statistical software, R Environment programming language has been conducted. Using average demand and standard deviation over the lead time plus review period and forecast values as inputs, the open-source software has been deployed to compute and to analyse the key operational parameters and decision variables including order up to level, safety stock, inventory carrying cost, backorder cost, total relevant inventory cost and various ratios such as inventory variance, relative standard deviation and costs ratios.

6.9.2 Experimental Settings: Estimation of Minimum Runs and Warm-up Periods

We estimated the number of runs appropriate for the Monte Carlo simulation as follow.

Table 6.5 Estimation of Minimum Runs for the Monte Carlo Simulation

Runs	1	1000	5000	10000	20000
			Mean		
ICCR	2.3980	2.3980	2.3980	2.3980	2.3980
SRCR	0.0274	0.0274	0.0274	0.0274	0.0274
FECR	2.4254	2.4254	2.4254	2.4254	2.4254
			Standard Deviation		
ICCR	0.7497	0.7481	0.7481	0.7481	0.7481
SRCR	0.0219	0.0218	0.0218	0.0218	0.0218
FECR	0.7513	0.7497	0.7497	0.7497	0.7497
			Margin of Error		
ICCR	1.4663	0.0464	0.0207	0.0147	0.0104
SRCR	0.0428	0.0014	0.0006	0.0004	0.0003
FECR	1.4694	0.0465	0.0208	0.0147	0.0104
			Minimum Runs		
ICCR	860	860	860	860	860
SRCR	1	1	1	1	1
FECR	864	864	864	864	864

For specified precision at 95% confidence level for the mean, we conducted run once each for 1, 1000, 5000, 10000 and 20000 iterations to determine the sample standard deviations for each run. Estimated standard deviations have been used to compute the corresponding margin of error (or the half width of the confidence interval) and the minimum runs required for this Mont Carlo simulation study. The results are summarised in Table 6.5 below. The table of estimations above shows that the smallest number of iteration necessary is 864 runs. But clearly, as we perform more runs, the higher the runs, the more half interval decreases as the sample mean and variance approach the population statistics. Hence, a run of 20000 simulations using different levels of item price margin, service level, annual holding cost rate, and backorder cost rate was conducted for the purpose of this study. While lead time was varied for the proposed model, lead time and review period values are assumed to be constant for the traditional model. Lead time is reckoned to be fixed as one month and review period is also projected to be fixed as one month; hence, review period plus lead time will be two months for the purpose of cost risks and revenue risks calculations associated with the current model.

6.9.3 Experimental Settings: Comparison based on Inventory Metrics

In comparing performance of the various forecasting methods based on inventory setup, systematic evaluation and sensitivity analysis for varying values of corresponding variable or parameter are performed. Thus, relevant factors for the experimental settings are set out as follow. In this experiment, while a unit product cost value of £5 has been used, a 35% of that cost amount, that is, $\alpha = 35\%$ is assumed as the fraction of the product cost that the retailer is able to salvage.

The inventory stockout (also known as shortage or penalty) cost is the cost of loss of goodwill and the lost profit per sale for a demand for a non-procured product. This penalty cost, otherwise refer to in this study as inventory stockout cost risks (ISCR), is computed by presuming that stockout will lead to an inventory backorder loss cost rate (b) of either 40% following the Corsten and Gruen (2004) study, or 50% following Catt (2007), or 60% for extreme case scenario while the inventory carrying (or holding) cost risk (ICCR) is obtained due to a holding cost rate (h) of either 25%, or 30%, or 35% per year (Timme and Williams-Timme, 2003; Catt, 2007) have been considered for this experiment. The inventory item's selling price is set to yield a product price margin or Markup (m) per unit of 50% (Catt, 2007), this means that the product price, $p = £7.50$ applies.

In addition, while service level is set to either 90%, or 95%, or 99% leading to corresponding values of safety factor (k) of 1.28, or 1.64, or 2.33 respectively, the specified values of service level also lead in that order, to corresponding values of expected unit normal loss function (G(k)) of 0.0475, or 0.0211, or 0.0034. And a value of $\tau = 0.75$ means that 75% of the safety stock is assumed to have been used up per evaluation period by the retail chain in this experiment. In theory, just to note, the varying values of the holding cost rate and backorder cost rate are expected to cause the distribution of costs functions to vary due to the fact that as the backorder cost rate rockets, the cost of a stockout should spiral up and, as the holding cost rate is varied, the cost of overstock is expected to fluctuate accordingly.

6.9.4 Experimental Settings: Comparison based on Inventory Revenue and Cost Risk

As a final point, since statistical measures of forecast accuracy do not make cost trade-offs explicit, then it has to be augmented with financial figures. Consequently, comparison of classical error metric data or the ratio measures to the cost data will not only allow implicit determination to be made as to which is more appropriate to use in selecting the frontrunner forecasting method. Besides this, it is a worthy attempt towards the understanding and appreciation of the costs and benefits of a desired service level.

6.10 Discussion of Results

6.10.1 Economical Comparison of the Different Forecasting Strategies

In quantifying the economic impacts of classical forecasts errors discussed in section 8.2, one has to examine the inventory cost impacts by the forecasting models that are being evaluated. Thus, their economic metrics outputs have been recorded. The research thesis reports the means for each of the inventory cost distributions for all the five forecasting methods and discussed as follow for different scenarios shown in Table 8 for both the ARIMA (1, 0, 0) process and ARIMA (1, 0, 1) process.

Three popular traditional statistical forecast error measures, the mean squared error (MSE), the mean absolute error (MAE), the mean absolute percent error (MAPE) have been selected, for further analysis, on each of the two simulated 192 data sets for ARIMA (1, 0, 0) and ARIMA (1, 0, 1) to evaluate the five forecasting methods selected for the simulation study (Naïve, SES, ETS, MMSE, Auto ARIMA methods). We quantify these three statistical forecast accuracy metrics in terms of their economic risks and record the average monthly inventory carrying cost risk, average monthly stockout cost risk and the total relevant forecast error cost risk per month on each of the demand forecast data series produced. We obtained these three economic performance measures for all the twenty-seven control parameter combinations and for each of the six scenario strategic approaches as highlighted in Table 6.6.

Table 6.6 ***Simulated Scenarios Combinations***

Here are the list of all the six simulated scenarios	Evaluation of Inventory Performance Metrics (Economic Risks)		
	Current Cost Risks Approach	Proposed Cost Risks Approach	Proposed Revenue Risks Approach
AR(1, 0, 0)	SCENARIO I	SCENARIO II	SCENARIO V
ARMA(1, 0, 1)	SCENARIO III	SCENARIO IV	SCENARIO VI

For both the traditional cost risks and the proposed cost risks models, the summary simulation results for all the twenty-seven control parameter combinations have been rounded to two decimal places in Tables 6.7, 6.8 and 6.9. The tables show risks scenarios I for current model and II for proposed model, respectively corresponding to 90%, 95% and 99% CSL for the first order autoregressive ARIMA (1, 0, 0). And same for Table 6.10 to Table 6.12 (showing risks scenarios III for current model and IV for proposed model) for the mixed order autoregressive moving average ARIMA (1, 0, 1).

Table 6.7 Auto ARIMA Forecasting Model: ***Summary results for Service Level = 90%***

Summary results for service level target of 90%	A R I M A (1, 0, 0)					
	Current Costs Model ($ million)			Proposed Costs Model ($ million)		
	ICCR	SRCR	FECR	ICCR	SRCR	FECR
h = 0.25	2.36	0.09	2.45	1.54	0.09	1.62
h = 0.30	2.84	0.04	2.88	1.84	0.04	1.88
h = 0.35	3.31	0.01	3.32	2.15	0.01	2.16
b = 0.40	2.84	0.04	2.87	1.84	0.04	1.88
b = 0.50	2.84	0.04	2.88	1.84	0.04	1.89
b = 0.60	2.84	0.05	2.89	1.84	0.05	1.90
Mean	2.84	0.04	2.88	1.84	0.04	1.89

Table 6.8 Auto ARIMA Forecasting Model: ***Summary results for Service Level = 95%***

Summary results for service level target of 95%	A R I M A (1, 0, 0)					
	Current Costs Model ($ million)			Proposed Costs Model ($ million)		
	ICCR	SRCR	FECR	ICCR	SRCR	FECR
h = 0.25	3.03	0.09	3.12	1.97	0.09	2.06
h = 0.30	3.64	0.04	3.67	2.36	0.04	2.40
h = 0.35	4.24	0.01	4.25	2.76	0.01	2.76
b = 0.40	3.64	0.04	3.67	2.36	0.04	2.40
b = 0.50	3.64	0.04	3.68	2.36	0.04	2.41
b = 0.60	3.64	0.05	3.69	2.36	0.05	2.42
Mean	3.64	0.04	3.68	2.36	0.04	2.41

Table 6.9 Auto ARIMA Forecasting Model: ***Summary results for Service Level = 99%***

Summary results for service level target of 99%	A R I M A (1, 0, 0) Current Costs Model ($ million)			Proposed Costs Model ($ million)		
	ICCR	SRCR	FECR	ICCR	SRCR	FECR
h = 0.25	4.30	0.09	4.39	2.80	0.09	2.89
h = 0.30	5.17	0.04	5.20	3.36	0.04	3.40
h = 0.35	6.03	0.01	6.03	3.92	0.01	3.92
b = 0.40	5.17	0.04	5.20	3.36	0.04	3.39
b = 0.50	5.17	0.04	5.21	3.36	0.04	3.40
b = 0.60	5.17	0.05	5.22	3.36	0.05	3.41
Mean	5.17	0.04	5.21	3.36	0.04	3.40

All these results relate to the emerged winner Auto ARIMA forecasting method (which is the best model as discussed in section 7.2). The results for the proposed revenue risks approach also for the Auto ARIMA forecasting method are displayed in Table 6.13 to Table 6.15 to capture risks scenarios V and VI respectively for the first order autoregressive ARIMA (1, 0, 0) and the mixed order autoregressive moving average ARIMA (1, 0, 1).

The three columns for each scenario (current or proposed) indicate the average monthly cost risks that can be incurred across all series. The first column of the three columns for each scenario indicates the average monthly incurred inventory carrying cost due to overstock while the next (second) column specifies the cost of poor service (or opportunity cost) due to stockout. The last (third column) of the three columns for each scenario result shows the average total relevant inventory cost risk associated with statistical forecast error metric. It should be noted that the results from the Auto ARIMA forecasting method presented below is characteristic of the patterns obtained for all the forecasting method employed for this study. The results indicate that the performance of all the lines of approaches considered in this simulation experiment gets poorer as the holding cost rate value rises. This result is as anticipated because as the constituents (such as the costs of capital tied down, insurance, storage, investment, deterioration, damage, obsolescence) of the inventory holding cost rate component of the inventory carrying cost risk become more expensive, the costs incurred by carrying an excess item in inventory is expected to surge upward. The carrying cost may even become extremely high if the procured item involved is very much perishable within a significantly short life cycle. In addition, Flores et al (1993) suggest that the result may also be, for non-stationary process with a variable variance and a mean not remaining near or returning to a long-run mean over time, an indication of the non-stationary nature of the underlying demand pattern. The differences may be considerable and in certain instances increasing the holding cost rate value from 0.25 to 0.35 may result in a remarkable increase of more than a 40% in inventory carrying costs incurred across the remaining control parameter combinations when service is raised from 90% to 99%.

Table 6.10 Auto ARIMA Model: Summary results for Service Level = 90%

Summary results for service level target of 90%	A R I M A (1, 0, 1) Current Costs Model ($ million)			Proposed Costs Model ($ million)		
	ICCR	SRCR	FECR	ICCR	SRCR	FECR
h = 0.25	5.71	0.21	5.92	3.71	0.21	3.92
h = 0.30	6.85	0.09	6.95	4.45	0.09	4.55
h = 0.35	7.99	0.02	8.01	5.20	0.02	5.21
b = 0.40	6.85	0.09	6.94	4.45	0.09	4.54
b = 0.50	6.85	0.11	6.96	4.45	0.11	4.56
b = 0.60	6.85	0.13	6.98	4.45	0.13	4.58
Mean	6.85	0.11	6.96	4.45	0.11	4.56

Table 6.11 Auto ARIMA Model: Summary results for Service Level = 95%

Summary results for service level target of 95%	A R I M A (1, 0, 1) Current Costs Model ($ million)			Proposed Costs Model ($ million)		
	ICCR	SRCR	FECR	ICCR	SRCR	FECR
h = 0.25	7.32	0.21	7.53	4.75	0.21	4.97
h = 0.30	8.78	0.09	8.87	5.71	0.09	5.80
h = 0.35	10.24	0.02	10.26	6.66	0.02	6.67
b = 0.40	8.78	0.09	8.86	5.71	0.09	5.79
b = 0.50	8.78	0.11	8.89	5.71	0.11	5.81
b = 0.60	8.78	0.13	8.91	5.71	0.13	5.83
Mean	8.78	0.11	8.89	5.71	0.11	5.81

Table 6.12 Auto ARIMA Model: Summary results for Service Level = 99%

Summary results for service level target of 99%	A R I M A (1, 0, 1) Current Costs Model ($ million)			Proposed Costs Model ($ million)		
	ICCR	SRCR	FECR	ICCR	SRCR	FECR
h = 0.25	10.39	0.21	10.60	6.76	0.21	6.97
h = 0.30	12.47	0.09	12.57	8.11	0.09	8.20
h = 0.35	14.55	0.02	14.56	9.46	0.02	9.47
b = 0.40	12.47	0.09	12.56	8.11	0.09	8.19
b = 0.50	12.47	0.11	12.58	8.11	0.11	8.21
b = 0.60	12.47	0.13	12.60	8.11	0.13	8.23
Mean	12.47	0.11	12.58	8.11	0.11	8.21

In other words, the above interpretation put in a more direct description and justification is that the higher the inventory carrying cost in relation to the total relevant inventory costs, the lower the retailer should adjust its service level targets to be. On the contrary though, the higher the stockout revenue cost in relation to the total inventory costs, the higher the service level would need to be. All the same, this result appears to be plausible and in perfect agreement with the work of Winston (1987), Flores et al (1994) and Catt (2007) when the optimal service level has to be determined: a trade-off may be required between the inventory carrying cost risk and the stockout revenue cost risk in order to get the pay-off.

Table 6.13 Auto ARIMA Model: Summary results for Service Level = 90%

Summary results for service level target of 90%	A R I M A (1, 0, 0) Proposed Revenue Model ($ million)			A R I M A (1, 0, 1) Proposed Revenue Model ($ million)		
	IRCR	SRCR	FERR	IRCR	SRCR	FERR
h = 0.25	13.36	0.06	13.42	32.26	0.21	32.47
h = 0.30	13.67	0.04	13.71	33.00	0.09	33.09
h = 0.35	13.98	0.01	13.98	33.74	0.02	33.76
b = 0.40	13.67	0.04	13.70	33.00	0.09	33.09
b = 0.50	13.67	0.04	13.71	33.00	0.11	33.11
b = 0.60	13.67	0.02	13.69	33.00	0.13	33.13
Mean	13.67	0.03	13.70	33.00	0.11	33.11

Table 6.14 Auto ARIMA Model: Summary results for Service Level = 95%

Summary results for service level target of 95%	A R I M A (1, 0, 0) Proposed Revenue Model ($ million)			A R I M A (1, 0, 1) Proposed Revenue Model ($ million)		
	IRCR	SRCR	FERR	IRCR	SRCR	FERR
h = 0.25	17.12	0.06	17.18	41.33	0.21	41.54
h = 0.30	17.51	0.04	17.55	42.28	0.09	42.38
h = 0.35	17.91	0.01	17.91	43.23	0.02	43.25
b = 0.40	17.51	0.04	17.55	42.28	0.09	42.37
b = 0.50	17.51	0.04	17.56	42.28	0.11	42.39
b = 0.60	17.51	0.02	17.54	42.28	0.13	42.41
Mean	17.51	0.03	17.55	42.28	0.11	42.39

Table 6.15 Auto ARIMA Model: Summary results for Service Level = 99%

Summary results for service level target of 99%	A R I M A (1, 0, 0) Proposed Revenue Model ($ million)			A R I M A (1, 0, 1) Proposed Revenue Model ($ million)		
	IRCR	SRCR	FERR	IRCR	SRCR	FERR
h = 0.25	23.07	0.06	23.13	58.72	0.21	58.93
h = 0.30	24.88	0.04	24.92	60.07	0.09	60.16
h = 0.35	25.44	0.01	25.45	61.42	0.02	61.44
b = 0.40	16.80	0.04	16.83	60.07	0.09	60.16
b = 0.50	16.80	0.04	16.84	60.07	0.11	60.18
b = 0.60	16.80	0.02	16.82	60.07	0.13	60.20
Mean	16.80	0.03	16.83	60.07	0.11	60.18

Table 6.7 to Table 6.15 also summarise the simulation output for specific service level target values. For each holding cost rate and backorder cost rate, results are summarised across the remaining control parameter combinations and across all data sets.

Regarding the different target service level values, the results indicate that performance deteriorates overall as the service level value increases. For all service levels in the traditional model, all estimations appear to lead to an overestimation of the true quantile, thus providing some evidence that loss of performance is not necessarily in terms of forecasting errors.

Overall, correcting for the error autocorrelation by employing a direct update of the safety stock, as proposed by this study, shows a clear benefit in indication of true costs and benefits, if one considers the average inventory cost value differences between scenarios I and II and between scenarios III and IV in Tables 6.7 to 6.12, and if the average inventory revenue value differences between scenarios V and VI in Tables 6.13 to 6.15 is considered. For all service level targets, the adjustment or updating approach proposed by this study should be preferable as it offers better (realistic) results and a true representative of what should happen in practice. Adjusting the salvage strategy and the safety stock offers an approximate 65% cost decrease in service level for all variance calculation procedures at no expense of any kind. Thus, incorporation of the adjustment can be justified for any good service level target.

Table 6.16 Cost risks measures for 90% Service Level

Mean of Cost Risks For all forecasting methods @ 90% CSL		**Naïve** ($m)	**SES** ($m)	**Auto ETS** ($m)	**MMSE** ($m)	**Auto ARIMA** ($m)
Holding rate = 0.25						
b = 0.4	Stockover	7.06	6.13	6.14	6.14	4.09
	Stockout	0.12	0.10	0.10	0.10	0.07
	Total	7.18	6.23	6.24	6.24	4.16
b = 0.5	Stockover	4.59	3.98	3.99	3.99	2.66
	Stockout	0.12	0.10	0.10	0.10	0.07
	Total	4.71	4.08	4.09	4.09	2.72
b = 0.6	Stockover	34.00	29.49	29.56	29.56	19.68
	Stockout	0.10	0.09	0.09	0.09	0.06
	Total	34.10	29.57	29.65	29.65	19.74

Besides, what we discovered is that the probability of a stockout appears not only to be related to both risks, that is, the inventory carrying cost risk and stockout revenue cost risk; but also that both are certainly not symmetric in any way. This result does lend credence to Flores et al (1994) suggestion that "*the ratio of the underage to the total costs should be an approximate solution to the problem*". So again, thus, the higher the inventory carrying cost in relation to the total inventory costs, the lower the retailer should adjust its service level targets to be. On the contrary though, the higher the stockout revenue cost in relation to the total inventory costs, the higher the service level would need to be.

As is expected, the pattern of economic metrics outputs is very much synonymous with that of the statistical forecast accuracy measures. Table 6.16 to Table 6.18 list the means for each of the cost risks distributions created when the traditional and proposed economic measures of forecasting accuracy are used as performance metrics to evaluate the five forecasting models applied to the combined generated 384 data series.

Table 6.17 Cost risks measures for 95% Service Level

Mean of Cost Risks for all forecasting methods @ 95% CSL		**Naïve** ($m)	**SES** ($m)	**Auto ETS** ($m)	**MMSE** ($m)	**Auto ARIMA** ($m)
Holding rate = 0.30						
b = 0.4	Stockover	9.05	7.85	7.87	7.87	5.24
	Stockout	0.12	0.10	0.10	0.10	0.07
	Total	9.16	7.95	7.97	7.97	5.30
b = 0.5	Stockover	5.88	5.10	5.12	5.12	3.41
	Stockout	0.12	0.10	0.10	0.10	0.07
	Total	6.00	5.20	5.22	5.22	3.47
b = 0.6	Stockover	43.55	37.77	37.87	37.87	25.22
	Stockout	0.10	0.09	0.09	0.09	0.06
	Total	43.66	37.86	37.96	37.96	25.27

The total relevant cost risk of applying each of the five forecasting strategies across all the 384 data sets is shown in the tabulations as the sum of the associated cost risks for stockout and stockover. Table 6.16 indicates stockover cost, stockout cost and total cost risks results for a service level of 0.9 when the backorder rate is set to varying values of 0.4, 0.5 and 0.6 at an annual carrying cost of 25%. Similarly, Table 6.17 and Table 6.18 show these total cost risks at the same backorder rates when the holding cost per year is respectively set at 30% and 35%. The full results for all five forecasting methods and both processes (AR1 and ARMA11) can be seen more vividly in Figure 6.6 below, while in the boxplots of Figure 6.7 below, costs and revenue distributions are displayed for both ARIMA (1, 0, 0) and ARIMA (1, 0, 1) using utility measure output values of RMSE from the Auto ARIMA forecasting method for current and proposed models.

Table 6.18 Cost risks measures for 99% Service Level

Mean of Cost Risks for all forecasting methods @ 99% CSL		Naïve ($m)	SES ($m)	Auto ETS ($m)	MMSE ($m)	Auto ARIMA ($m)
Holding rate = 0.35						
b = 0.4	Stockover	12.85	11.14	11.17	11.17	7.44
	Stockout	0.12	0.10	0.10	0.10	0.07
	Total	12.96	11.24	11.27	11.27	7.51
b = 0.5	Stockover	8.36	7.25	7.27	7.27	4.84
	Stockout	0.12	0.10	0.10	0.10	0.07
	Total	8.48	7.35	7.37	7.37	4.91
b = 0.6	Stockover	55.99	48.56	48.69	48.69	32.42
	Stockout	0.10	0.09	0.09	0.09	0.06
	Total	56.10	48.65	48.78	48.78	32.48

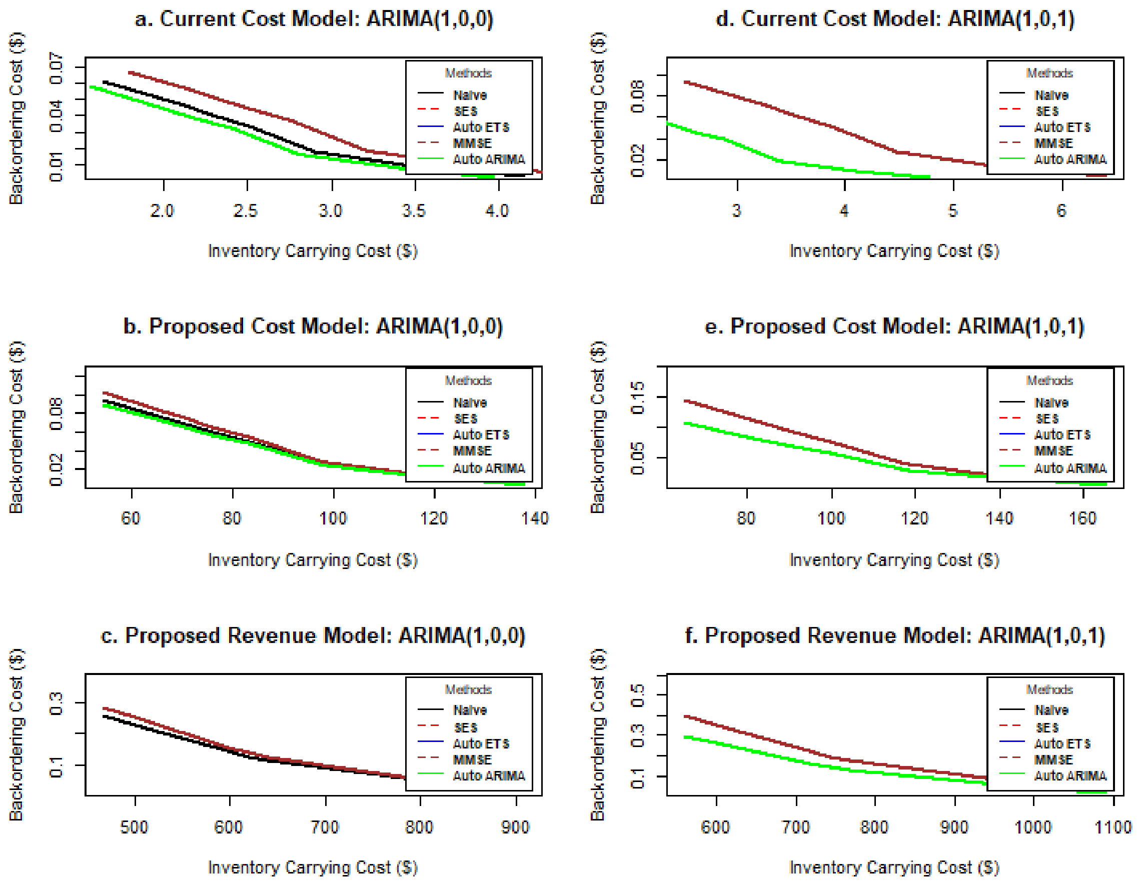


Figure 6.6: Comparison of current and proposed models for all five forecasting methods

It is observed from Figure 6.6 that irrespective of the value of the holding rate (that is, when the annual carrying cost is set to 25% or 30% or 35%), the best forecasting strategy is the Auto ARIMA regardless of the backorder rate. The total cost risk of applying Auto ARIMA forecasting model to the generated time series is best at $2.72, $3.47 and $4.91 respectively for 90%, 95% and 99% cycle service levels and at 50% backorder rate. Based on this result, we take a closer look at the cost risks distributions for this winner forecasting method and show the output in the box and whiskers graphics of Figure 6.7 below.

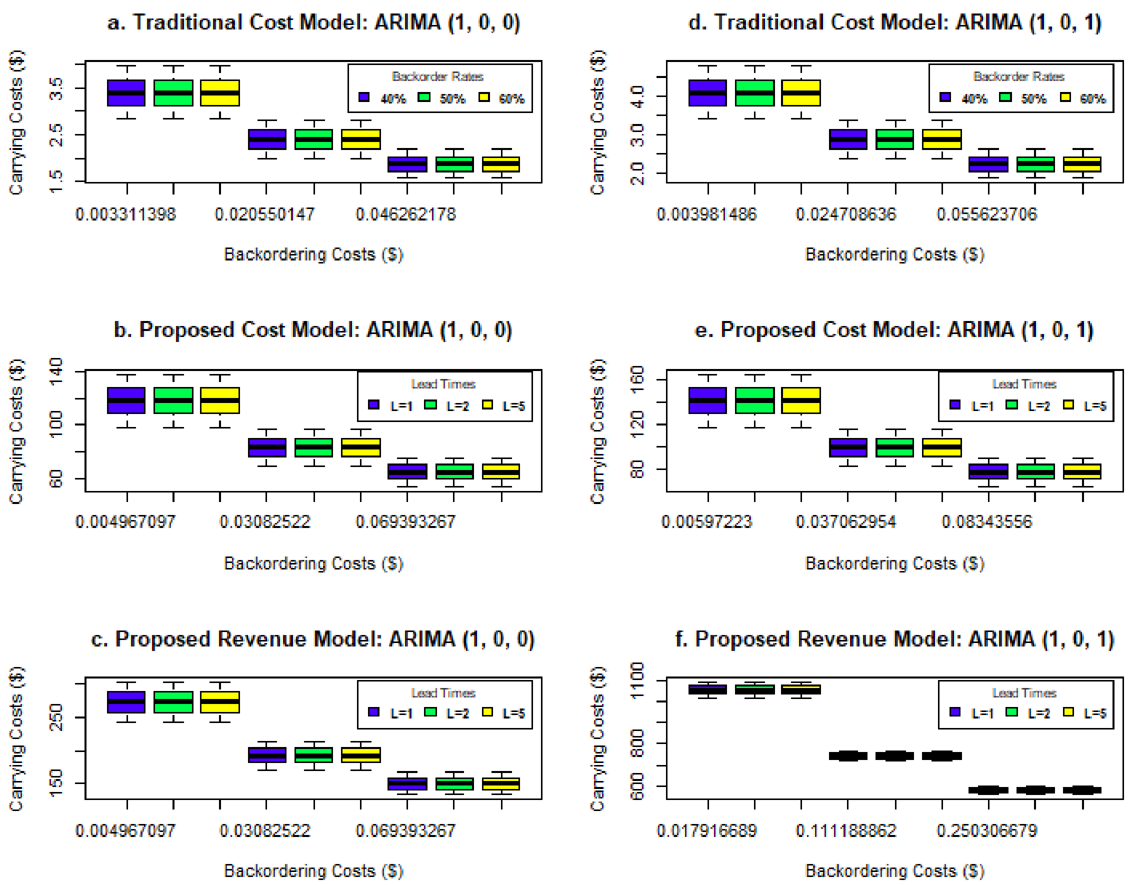


Figure 6.7: Comparison of current and proposed models for the Auto ARIMA forecasting method

The first set of three boxplots at the top left corner for each model represent 99% cycle service level at varying backorder rates of 40%, 50% and 60% respectively from left to right for fixed lead time of one month in the traditional model or varying lead times of 1, 2 and 5 months respectively from left to right for fixed backorder rate at 60% in the proposed models. The middle and bottom right sets of three boxplots provide results respectively for 95% and 90% cycle service levels.

It is observed, as expected, that both processes produced relatively the same spread distribution descriptions in all models. However, clearly discernible is an interesting contrast in the cost risks outputs for the two models (traditional and proposed). Careful contrast of the two models shows some differences. It is noticed from the boxplots and the line graphs that there is a massive surge in cost risks from the current model to the proposed models for both processes. The dramatic increase in risks can only be explained by the modifications that have been made to the traditional model to arrive at the proposed models to account for salvaging strategies and safety stock strength. While this corroborates the fact that the traditional model is not robust enough to capture the real risks of uncertainty in supply, that is, the hazard inherent in lead time variability. On the contrary, the proposed models are versatile and very robust to capture this risk and other realities (as have been discussed in sections 6.4 and 6.5 of this study chapter) in practice within the retail chain sector organisations.

6.11 Empirical Study

6.11.1 Forecasting Methods and Forecast Accuracy Metrics

In order to examine the effect of the forecasting methods, it is assumed that the retailer employs the following three different methods to forecast the lead time demand: the Seasonal and Trend (decomposition using) Loess forecasting (STLF) method, the Dynamic Harmonic Regression (DHR) method and an exponential smoothing state space approach called Trigonometric regressor, Box-Cox transformation, ARMA errors, Trend and Seasonal (TBATS) method (De Livera et al, 2011; Hyndman, 2019). The forecast values obtained from the DHR method, after comparison with the forecast outputs for TBATS method, have been selected and utilised to estimate the forecast errors (MAE, MAPE and RMSE) and inventory turns ratio values for the regression analysis conducted in this thesis chapter. The details of this estimation process are provided as follow. For the purpose of the empirical study in this chapter, just as for the study chapter 5, the following three statistical forecasting error measures will be obtained: the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean squared error (RMSE). But unlike in study chapter 5, all the three statistical error measures will be utilised in the current study chapter.

6.11.2 Data Sets for Empirical Analysis

6.11.2.1 Data Series

Recall that the data sets for the empirical analysis have been obtained from two separate sources in the United States. The dataset from the Hass Avocado Board (HAB, 2018) is a total of 157 aggregated US markets weekly retail demand and average price data series for Hass avocados from January 2016 through to December 2018 expressed in millions of volume sales. The three data sets from the Information Resources Incorporated (IRI) Academic (Bronnenberg et al, 2008) include data series for Milk, Yogurt and Salty Snack products. Each of these three US markets based IRI data sets included 313 aggregated weekly sales and average prices from 1 January 2001 to 31 December 2006. More details regarding all the data series utilised in this research study for the empirical analyses and the two sources of these data sets have been discussed in chapter 4 (the thesis methodology chapter).

6.11.2.2 Data Series Sub-Setting Rules

The HAB avocado dataset and each of the three IRI data series have been partitioned into two parts, namely the training data subset (or estimation period) and the test data subset (that is, performance measurement period). The data sets partition policy for the rolling window origin has been applied in line with Hyndman (2018) rules. Thus, the total time series of 157 observations for the Hass avocado data sets are split into two unequal parts of 126 weeks (that is, 80% of total time series) in-sample subset for the estimation period and 32 (that is, 20% of total time series) weeks out-of-sample subset for the performance measurement periods. The training subsets included all the time series from week 1 of January 2016 until the end of week 22 into 2018 and the testing subsets included data from beginning of week 23, 2018 and up to the end of week 53 in December 2018. In other words, 32 weeks out-of-sample data subset will be utilised to produce rolling forecast from which forecast errors can be obtained.

Since the empirical analysis data sets for the IRI milk, yogurt and salty snacks are also weekly, hence, 250 weeks (that is, 80% of total time series) data sets for the in-sample subset and 63 weeks (that is, 20% of total time series) for the out-of-sample subset have been used for the empirical study. Accordingly, partitioning the 313 US markets retail data sets (for Milk, Yogurt and Salty Snacks) into training subsets included all the time series from January 2001, week 1 until the end of week 42 of 2005 and testing subsets comprised the data from commencement of week 43, 2005 and up to the end of week 53 in December 2006. Specifically, 63 weeks out-of-sample data subset will be utilised to produce rolling forecast from which forecast errors have been obtained

6.11.3 Empirical Study: Evaluating Accuracy of Forecasting Methods

The following is a description, similar to the simulation study, but specifically for this research study, the rolling window, rolling origin forecasting iteration process for the HAB data series as well as for the IRI Academic data sets. At the first iteration, the candidate forecasting strategy is trained on the historical retail performance from week 1 of January 2016 until the end of week 22 into 2018 for the Hass avocados and from week 1 of January 2001 until the end of week 42 into 2005 for the IRI data sets. Then forecast only a week in advance and validate on the actual week 23, in year 2018 of the Hass avocados test data set whereas validation is conducted on the actual week 43, in year 2005 of the IRI test data sets. Afterward, for the next iteration, train the forecasting model on data from week 2 of January 2018 until the end of week 23 into 2018 for the Hass avocados and from week 2 of January 2001 until the end of week 43 into 2005 for the IRI data sets. Then again, predict another one week ahead and validate on the actual week 24, in year 2017 of the Hass avocados test data set and validate on the actual week 44, in year 2005 of the IRI test data set. This iterative procedure continues and has been carried out repeatedly until the end of the 32 and 63 weekly test data sets respectively for the Hass avocados and for each of the three IRI data series.

6.11.4 Statistical Comparison of the Different Forecasting Strategies

It is important to recall that the results of the exploratory data analysis (EDA) conducted on all the time series utilized and report in this thesis for empirical study has shown consistency with theory (Hyndman, 2018); that all the three forecasting approaches deployed have been designed to handle high frequency data series with strong seasonality and trend. In other words, evidence from the visualisation and component analyses supports the fact that the STLF, the DHR and the TBATS models are suitable forecasting strategies to be applied to the tasks at hand since seasonality are not being ignored by these models. Stationarity tests in the form of ADF and KPSS conducted on the dataset showed that stationarity was attainable by first-differencing it at a lag equal to 52 periods; thus, the data appears to be valid. For the reason that the study focus is in using the weekly forecasted demand as a proxy for average demand under the order-up-to level replenishment policy, researcher forecasted out 32 weeks for avocado and 63 weeks for milk, salty snack and yogurt.

Table 6.19 presents the summary of performance for all the different forecasting methods as discussed in Section 4.1. Note that, also presented in this table is the performance of a simple benchmark, the Seasonal Naïve method designated here as sNaïve as well as the combined (global) average results for models. For these US retail markets for the four studied SKUs, as can be observed from Table 6.19, the ME metric indicates that while milk seems to be consistently overstocked, the rest of the products appear to be often under-forecasted. However, the rest of the forecasting error metrics, which are more robust than the ME, tell a different and diverse story; that no forecasting model could solely provide superior out-of-sample performance and predict all the test data better in all cases than the rest of the candidate forecasting methods. From the results of the statistical forecast errors for all forecasting methods as presented in Table 6.19, it can be observed that the outcomes appear to be far from stable with the exception of avocado. Clearly, the best deployable method for the avocado product is the DHR model in terms of all the three statistical error metrics (that is, RMSE, MAE and MAPE) for forecasting methods (in other words, sources of datasets may explain why the result for avocado could be different from milk, snacks and yogurt – all three from same source).

Table 6.19: Summary of Accuracy Measures for Forecasting Models

	Milk	Snack	Yogurt	Avocado
Mean Error (ME)				
sNaïve	0.50	0.28	3.02	4.25
STLF	0.41	-0.60	-0.26	-4.78
DHR	0.86	-0.24	-4.91	-1.73
TBATS	0.39	-0.08	0.79	-4.46
Combined	0.54	-0.16	-0.34	-1.68
Root Mean Squared Error (RMSE)				
sNaïve	3.29	3.39	5.48	15.44
STLF	2.11	2.56	3.76	15.98
DHR	3.02	4.12	9.97	12.97
TBATS	2.20	2.10	3.32	15.63
Combined	2.65	3.04	5.63	15.00
Mean Absolute Error (MAE)				
sNaïve	2.33	2.56	4.29	12.54
STLF	1.69	1.89	2.68	12.09
DHR	2.35	3.34	8.08	9.30
TBATS	2.35	3.34	8.08	11.41
Combined	2.18	2.78	5.78	11.33
Mean Absolute Percentage Error (MAPE)				
sNaïve	4.28	5.59	8.49	27.11
STLF	3.09	4.20	5.36	26.44
DHR	4.51	7.51	16.63	19.88
TBATS	3.07	3.58	5.36	24.49
Combined	3.74	5.22	8.96	24.48

In contrast, while STLF model outperformed the rest of the forecasting methods including the benchmark seasonal naïve and the global average for all the three datasets from the IRI source when MAE metric is considered. However, if the consideration is in terms of the RMSE and MAPE performance metrics, it can be further observed as well that while both STLF and

TBATS forecasting methods did better than the benchmark and the combined strategies, they both appear to be at par in their performance with the TBATS model marginally having done better than the STLF strategy overall. It is also observed that aside from the winning method for a particular metric, all forecasting models excluding the benchmark seasonal Naïve consistently produced forecast error values higher than the average global error values for the combined strategy.

6.11.5 Economical Comparison of the Different Forecasting Strategies

The three popular classical statistical forecast error measures (that is, RMSE, MAE and MAPE) have been selected for further analysis on the empirical data sets to evaluate the three forecasting strategies that have been carefully chosen for the empirical study in this thesis chapter. This chapter study also quantifies the three statistical forecast accuracy metrics in terms of their economic risks and recorded the average weekly inventory carrying cost risks, average weekly stockout cost risks and the total relevant forecast error cost risks per week (see Tables 6.20 to Table 6.26).

Table 6.20 Summary of Economical Comparison of the Different Forecasting Strategies Using Table 6.21 to Table 6.24

	RMSE			**MAE**			**MAPE**			
	DHR	STLF	TBATS	DHR	STLF	TBATS	DHR	STLF	TBATS	**Best Model**
					Milk					
TCM	✓	✗	✗	✓	✗	✗	✓	✗	✗	DHR
PCM	✗	✓	✗	✗	✗	✓	✗	✓	✓	STLF or TBATS
					Salty Snack					
TCM	✓	✗	✗	✓	✗	✗	✓	✗	✗	DHR
PCM	✗	✗	✓	✗	✓	✗	✗	✓	✗	STLF
					Yogurt					
TCM	✗	✓	✗	✗	✓	✗	✗	✗	✗	STLF
PCM	✓	✗	✗	✗	✓	✗	✓	✓	✗	STLF or DHR
					Avocado					
TCM	✗	✓	✗	✗	✓	✗	✗	✓	✗	STLF
PCM	✗	✓	✗	✗	✓	✗	✗	✓	✗	STLF

NB: Traditional Cost Model (TCM); Proposed Cost Model (PCM); Key (tick = best performance; cross = less performance)

Table 6.20 above demonstrates summary of forecasting methods performance results analysis using the total relevant forecast error cost risks from Tables 6.21 to Table 6.24. It compares the traditional cost model (TCM) and the proposed cost model (PCM) outcomes for the empirical data sets (milk, salty snack, yogurt, and avocado) utilised for this research study. The analysis for each error metric (that is, RMSE, MAE, and MAPE) and for each of the three forecasting methods (that is, DHR, STLF, and TBATS). The best performing model is ticked in green and the less performing crossed in red. The last column titled 'Best Model' concludes with the best choice of model TCM or for PCM. In Table 6.20, the first interesting contrast observed between the statistical and economical evaluation strategies is that while DHR model was the best forecasting method clearly elected for the avocado product through statistical comparison (see Table 6.19), however, both the traditional and the proposed inventory cost functions have indicated the STLF model as the preferred candidate for the same product in terms of impacts due to all the three statistical error metrics (that is, RMSE, MAE and MAPE) and for both TCM and PCM. Then between the proposed and traditional cost functions, it is observed that, aside from sharp contrast in selecting forecasting models, the proposed cost model appears to discriminate among forecasting methods better than the traditional cost model by suggesting alternative forecasting strategies as shown in Table 6.20 for milk and yogurt.

Table 6.21: Inventory Costs for 95% Service Level for the Milk

Traditional Cost Model at 95% CSL		STLF	DHR	TBATS	Combined
		MAPE (%)			
L = 1	Stockout	1.05	1.03	1.21	1.10
	Stockover	0.03	0.03	0.04	0.03
	Total	1.08	1.06	1.25	1.13
L = 3	Stockout	1.48	1.45	1.71	1.55
	Stockover	0.05	0.05	0.06	0.05
	Total	1.53	1.50	1.76	1.60
L = 7	Stockout	2.10	2.05	2.42	2.19
	Stockover	0.07	0.07	0.08	0.07
	Total	2.17	2.12	2.49	2.26

Table 6.22: Inventory Costs for 95% Service Level for the Milk

Proposed Cost Model at 95% CSL		STLF	DHR	TBATS	Combined
		MAPE (%)			
L = 1	Stockout	0.61	0.68	0.60	0.63
	Stockover	0.02	0.02	0.02	0.02
	Total	0.63	0.70	0.62	0.65
L = 3	Stockout	0.86	0.96	0.85	0.89
	Stockover	0.03	0.03	0.03	0.03
	Total	0.89	0.99	0.88	0.92
L = 7	Stockout	1.22	1.35	1.21	1.26
	Stockover	0.04	0.04	0.04	0.04
	Total	1.26	1.40	1.25	1.30

In addition, Table 6.21 through to Table 6.26 presents the summary of performance in terms of inventory costs for all the different forecasting methods and evaluation strategies for milk and avocado. Note that also included in the tables is the performance of the combined average for all forecasting methods. Generally, according to the proposed cost approach, the STLF model can be said to have outperformed the other forecasting strategies when confronted with lead time variance. However, all the forecasting strategies can only do well when supply variability (that is, the lead time variance) is low, and fail on a high supply uncertainty in terms of carrying costs (that is, costs due to stockover) or backorder costs (or costs due to stockouts) and thus, total relevant costs for all the three approaches (that is, traditional cost, proposed cost, and proposed revenue).

Table 6.23: Inventory Costs for 95% Service Level for the Avocado

Traditional Cost		STLF	DHR	TBATS	Combined
Model at 95% CSL		MAPE (%)			
L = 1	Stockout	6.53	7.00	6.89	6.81
	Stockover	0.32	0.34	0.33	0.33
	Total	6.85	7.34	7.22	7.14
L = 3	Stockout	9.24	9.91	9.74	9.63
	Stockover	0.45	0.48	0.47	0.47
	Total	9.69	10.38	10.21	10.09
L = 7	Stockout	13.07	14.01	13.78	13.62
	Stockover	0.63	0.68	0.67	0.66
	Total	13.70	14.69	14.44	14.28

Table 6.24: Inventory Costs for 95% Service Level for the Avocado

Proposed Cost		STLF	DHR	TBATS	Combined
Model at 95% CSL		MAPE (%)			
L = 1	Stockout	2.94	3.43	2.82	3.06
	Stockover	0.14	0.17	0.14	0.15
	Total	3.08	3.60	2.96	3.21
L = 3	Stockout	4.16	4.85	3.99	4.33
	Stockover	0.20	0.23	0.19	0.21
	Total	4.36	5.09	4.19	4.55
L = 7	Stockout	5.88	6.86	5.65	6.13
	Stockover	0.28	0.33	0.27	0.29
	Total	6.16	7.20	5.92	6.43

Similar to the simulation study, it is observed from Tables 6.21 to 6.24 that the difference between the proposed model and the current traditional model is significant especially when the cost risks or the revenue risks run into millions of dollars or pounds. For all service level targets, the adjustment or updating approach proposed by this study should be preferable as it offers realistic results and a true representation of what should happen in practice. The inclusion of the item quality status in terms of salvage value strategy and the modification of the safety stock provide an approximate 45% decrease (compared to the traditional cost function) in terms of the indicated inventory costs for the service level for all variance calculation procedures including the combined strategy at no expense of any kind. Thus, incorporation of the adjustments can be justified for any good service level target.

Table 6.25: Inventory Costs for 95% Service Level for the Milk

Proposed Revenue		STLF	DHR	TBATS	Combined
Model at 95% CSL		MAPE (%)			
L = 1	Stockout	2.56	2.35	3.06	2.66
	Stockover	0.08	0.08	0.10	0.09
	Total	2.64	2.42	3.16	2.74
L = 3	Stockout	3.62	3.32	4.32	3.75
	Stockover	0.12	0.11	0.14	0.12
	Total	3.74	3.43	4.46	3.88
L = 7	Stockout	5.12	4.70	6.11	5.31
	Stockover	0.17	0.15	0.20	0.17
	Total	5.29	4.85	6.31	5.48

Table 6.26: Inventory Costs for 95% Service Level for the Avocado

Proposed Revenue		STLF	DHR	TBATS	Combined
Model at 95% CSL		MAPE (%)			
L = 1	Stockout	19.99	20.38	21.70	20.69
	Stockover	0.97	0.98	1.05	1.00
	Total	20.96	21.37	22.74	21.69
L = 3	Stockout	28.27	28.83	30.68	29.26
	Stockover	1.36	1.39	1.48	1.41
	Total	29.64	30.22	32.16	30.67
L = 7	Stockout	39.98	40.77	43.39	41.38
	Stockover	1.93	1.97	2.09	2.00
	Total	41.91	42.73	45.49	43.38

This chapter study has demonstrated that evaluation of forecasting methods must be conducted with a fit for purpose model that not only accounts for reality in practice (De Livera et al, 2011; Catt, 2007), but one that also leads away from the inevitable loss of performance as it is obtainable with the currently proposed models (Hyndman, 2019). A major motivation for this research study is to improve on the contemporary or traditional approach to forecasts accuracy evaluation.; First and foremost, using less restrictive assumptions, it has been shown that the typical safety stock model is neither adequate nor robust and can thus be enhanced. The current study has developed two versatile and robust economic models, one to measure inventory cost risks and the other to measure revenue loss risks, and both have been designed to account for real costs of forecast error variance.

In the next study chapter, focus will subsequently shift to the development of a hybrid inventory costs structure that aligns both inventory control and financial decisions as suggested in the third research study objective in the thesis introductory chapter.

CHAPTER 7

Alignment of Inventory Control and Financial Decisions

7.1. Introduction

In this study chapter, the inventory control model investigated in the immediately preceding chapter of this research study will be extended to include elements of financial undertakings. Traditional literature has demonstrated strong association between the performance of supply chain inventory management and profit margin as well as other business objectives (see for example, Gaur et al, 2004; Rajagopalan, 2013; Lee et al 2015). However, confluence of operational policies with financial decisions has recently started to be seen (see for example, Bendavid et al, 2017) as an avenue to improve and to better corporate strategic financial objectives through optimal inventory and control and investment within the retail industry. This is quite important since strategies to better and to boost financial efficiency tacitly impact and confine operational performance, particularly the management of inventory. However, in measuring the impact of one on the other, previous research studies (such as Gaur et al, 2004; Mohan and Venkateswarlu, 2013; Lee et al 2015) have tended to focus on modelling inventory separately and using the resulting output to access financial impact.

Specifically, in the research work carried out in study chapter 5, the total relevant inventory costs model under a periodic review policy for short shelf life or perishable products has been explored. In this study chapter, just as in the previous chapters, a perishable product will be described as any stock keeping unit (SKU) that keeps its utility during the course of a finite or specified valid lifetime beyond which it is considered to have lost its value and become unsuitable for utilization (Williams and Patuwo, 2004; Kurniawan et al., 2015). Some samples of perishable products include but not limited to (1) agricultural products such as foodstuffs including fruits and vegetables; (2) pharmaceutical products and (3) chemical products. The current study chapter seeks to integrate the components of the same inventory cost model (developed in study chapter 5) with the capital costs of short-term credits accessed by the retail firm for its operational purposes.

The study proposes two modules in one model; one of upstream in the supply chain relative to the retailer and another of the downstream, integrated into one robust exemplar system and exploring the connections as discussed in the previous study strands in chapters 5 and 6. In pursuing this objective, the study chapter explores the notion of bringing together and of fusing the forecast error costs within the inventory system of a retailer in a simple series supply chain (as described in detail in section 2) with the cash costs of its inventory operations. Furthermore, this objective will be pursued taking into account relevant financial constraints such as working capital funding needs and trade credits (countenanced and consented upstream and downstream payment delays) for enhanced supply value chain coordination. The study assumes a periodic review inventory policy with finite horizon and single product.

The chapter proceeds by presenting and introducing the applicable model framework and notations to be used in the next section. Specifically, study starts by describing the key elements involved in the form of notations, inventory settings and setup in section 7.2. The data series for the experiment is introduced in section 7.3 followed by forecasting setup in section 7.4. It then demonstrates the justifications for sharing, for the right reasons, the risks and returns by the retailer with other echelons of the supply chain setting in Section 7.5. In sections 7.6 and 7.7, for both the financier and the retailer, the study chapter respectively frames and articulates cash flows and an optimisation model that takes into account the constraint of working capital restrictions. Empirical results and model estimation are presented in sections 7.8 and 7.9 respectively.

7.2. Theoretical Formulation and Model Setting

7.2.1. Nomenclatures

One important thing to stress from the outset is that the current study chapter builds on the last two study chapters. In particular, it relies heavily on the inventory costs work of the immediate preceding study chapter 6. As a result, reference will regularly be made to both chapters, and sometimes summary of relevant points from these previous chapters will be provided as necessary in the current study chapter for ease of reference and understanding.

All suppositions proposed in the preceding study chapter 6 apply directly to the current study chapter. Therefore, the summary of those assumptions and notations in addition to new assumptions and **c**onventional notations to be used throughout the current study chapter are specified in the following Table 7.1 and or introduced in relevant subsequent sections for ease of reference.

Table 7.1: Description of notations used in this paper

Notations	
t: = 1, 2, 3, … is the discrete time unit for the time series data	b: the penalty cost per unit backordered
D_t: Stochastic demand in period t	h: the holding cost per unit per period
F_t: is demand forecast (produced in period t - 1) of basic series for period t	$\propto$: bankruptcy recovery rate discount factor
ε_t: symbolizes the error in period t	u: upstream payment delay
μ: stands for the mean of the autoregressive process	d: downstream payment delay
σ: Standard deviation of demand (forecast error) per period	O_t: order quantity per period
L: Lead time for replenishment	W_t: working capital level per period
R: Review time interval	$C_{B,t}$: cash balance per period
C_{sl}: Desired cycle service level	S_t: inventory position at period t
cv: Coefficient of variation	r_f: the risk-free interest rate
S_s: Safety stock	M_f: money borrowed (loan) externally for financing requirement
z: Standard normal random variable	$CF_f(.)$: Financier's expected cash flow function
ρ: Stockout probability during the lead time	$CF_r(.)$: Retailer's expected cash flow function
c: the unit cost	$\chi(V_t)$: expected bankruptcy loss (financing cost) function
p: the retail unit price	$\pi(.)$: expected profit function
$\varphi(.)$: Density function	$\Upsilon(.)$: order quantity cost function
	$V_t(.)$: loan repayment demand level

7.2.2. The Study Experiment and Model Framework

In the previous study chapter 6, the simulation experiment utilised for the evaluation of total relevant inventory cost due to forecast errors consists of two main modules: the forecasting module and the inventory control module. The graphical representation of the experiment is repeated below in Figure 7.1.

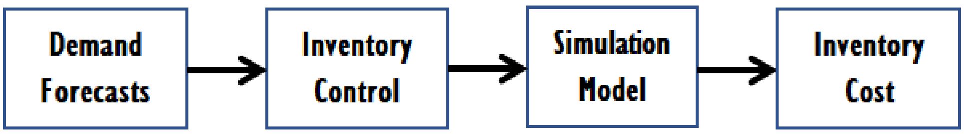


Figure 7.1: Schematic for Inventory Control System Simulation Study

Using the first module, the performance of the estimators (that is, the forecasting methods) was analysed with respect to their forecasting accuracy. Subsequently, the forecasting performance of the emerged best forecasting strategy was simulated, in consideration of the inventory (fixed-time review) policy, on the avocado and the three IRI real demand data. Thus, as illustrated in Figure 1 above, to access the simulation method, demand forecasting process was carried out in order to obtain the variance of the forecast error. Utilising the periodic review policy, parameters for the selected inventory policy were obtained and fed directly into the simulation system. In this study chapter, the work on the inventory cost model investigated in study chapter 6 will be extended to include elements of financial undertakings.

Having previously looked at forecasting and inventory control, this chapter study will consider the assessment of an *integrated inventory cost* to include the element of financial control considerations as shown by the chapter study model in Figure 7.2.

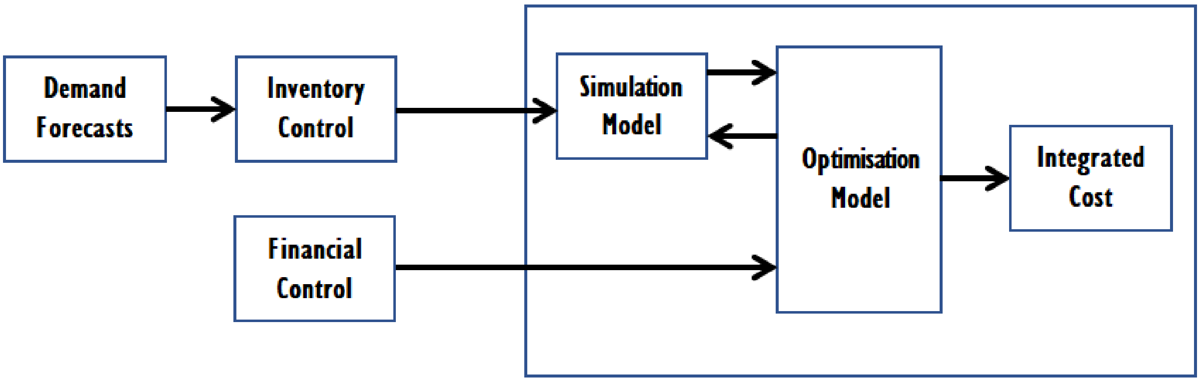


Figure 7.2: Schematic for Simulation-Based Inventory Control Optimisation Study

The simulation-based optimisation experiment illustrated in Figure 7.2 is an optimiser support system that consists of three main modules: the forecasting feature aspect, the financial control element and inventory control component. All the three building blocks will assist research efforts to assess the empirical validity of theoretical findings while the latter two modules will further be used to check the empirical utility of the findings observed in this research work. Relevant outputs from the financial control and the simulation system are fed directly into the optimisation structure where financial considerations are given proper attention alongside the simulated inventory performance functions and parameters.

Specifically, looking at the financial control aspect, study chapter will consider the three main financial decision scenarios facing the retailer in Figure 7.3 which include:

- Equity credit (that is, self-financing of products procurement for operational purpose)

- Trade credit (namely, credit in the form of supplied products with payment delay)
- Cash credit (or loan in the form of cash borrowed from a financier such as a bank)

The focus of the study chapter is to formulate an optimisation model for the retailer under both upstream and downstream transactions, assuming players are either financially constrained or unconstrained but with the motivation mainly for how the retailer is affected. The goal of the retail chain firm, this study assumes, is always to maximise the equity holders' expected cash flow and net worth.

7.2.3. The System Setting and Sequence of Events

This section, relative to the retailer, describes for the supply chain modes, the setting as well as the sequence of events for operational deeds and for financial undertakings. In other words, proposed here is the manners of accomplishing orders to the upstream supplier, the demand from downstream customer and the sequence of events within the timeline. Study considers a simple series supply chain setting that consists of a single supplier that takes orders from a single retailer who receives demand from buyers downstream as shown in Figure 7.3. The dashed arrows in Figure 7.3 indicate the flow of information between entities involved. While the solid arrows above the dashed arrows highlight the flow of product, the solid arrows below the dashed arrows show the flow of cash concerning relevant players.

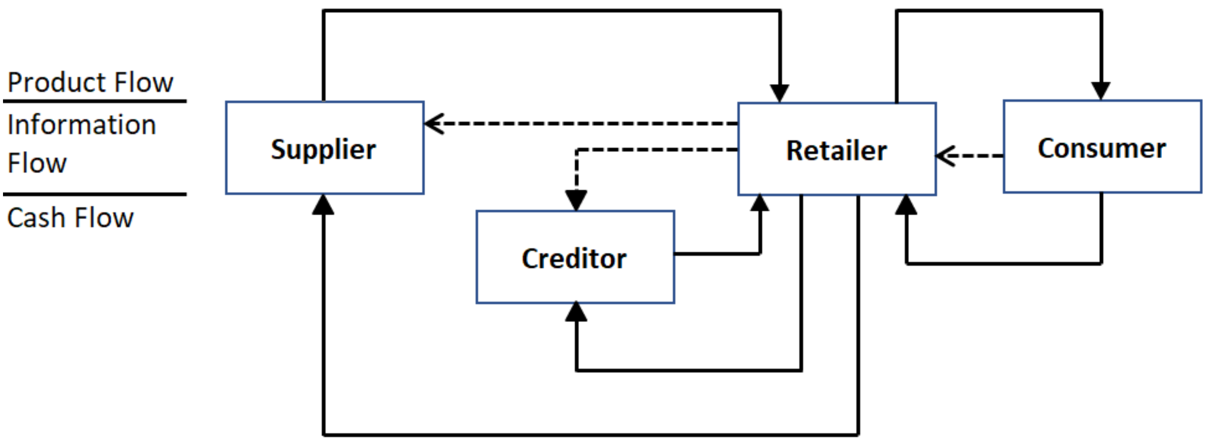


Figure 7.3: Simple series supply chain setting that includes a single supplier and a single retailer taking demand from customers.

In addition to considering a periodic review policy (also known as P-Model) inventory management setting involving a single and perishable product, the following sequence of events per period is contemplated:

- The market actions and reactions are considered as a Stakelberg duopoly game (discussed further in section 7.5) in which there exist merchandise volume capacity, product price and payment terms on offer from the supplier. These supplier's product capacity, price and payment terms are based on supplier's estimated optimal full production and inventory capacity, its internal working capital position and access to external financing.
- The retailer is fully aware of the volume capacity, product price and payment terms on offer from the supplier; the retailer takes a look at its existing inventory, then reviews its own internal working capital situation and access to external financing.
- The retailer then places order, O_t in line with its projected working capital position as at payment due date for the current order.
- The retailer will receive this current order after a lead time, L periods, which have elapsed since placing its order (see Figure 7.4).

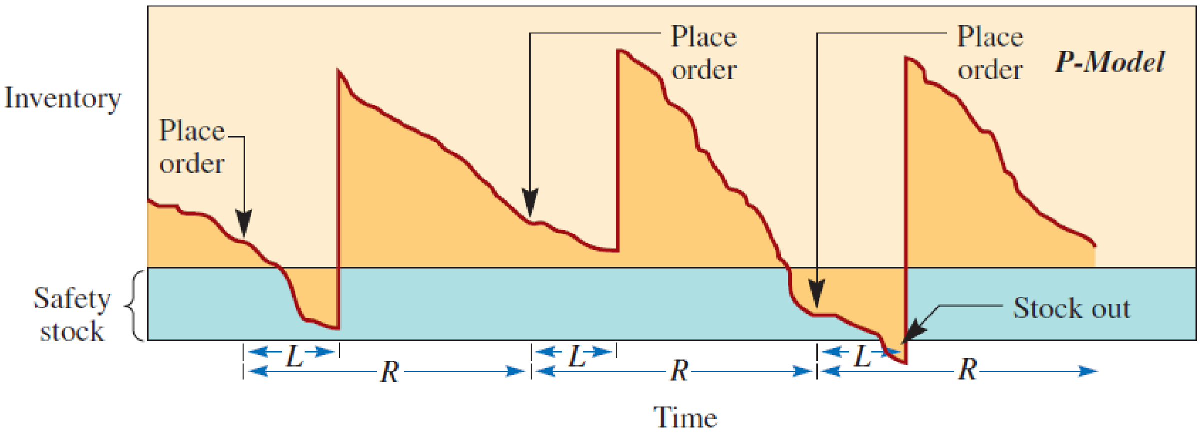


Figure 7.4: Inventory sequence of events under a periodic review policy or P-Model (Adapted from Jacob and Chase, 2018)

- The purchased cost for the order placed by the retailer is paid to the supplier after u periods, shown in Figure 7.5 as purchase conversion period (PCP).
- Backorders are then satisfied.
- The retail firm receives customers' demand, D_t for the period.
- The customers' demands are delivered from the remaining inventory, otherwise those demands are backlogged. This is the inventory conversion period (ICP) in Figure 7.5.
- Revenue arrives from fulfilled backorders and demand after a delay of d time interval since when the orders were honoured and referred to as receivables conversion period

(RCP) in Figure 7.5. Note that the period from payment point to the supplier, right to the time the retailer receive cash for sales refers to the cash conversion cycle (CCC).

- Due shortage cost and stocking cost incurred for the current period can then be accounted for.
- Financing and working capital restrictions will at this point be applied.
- Returns in the form of excess cash, if realised, can now be utilised for salaries, dividends and supplementary investments for further business growth purpose.

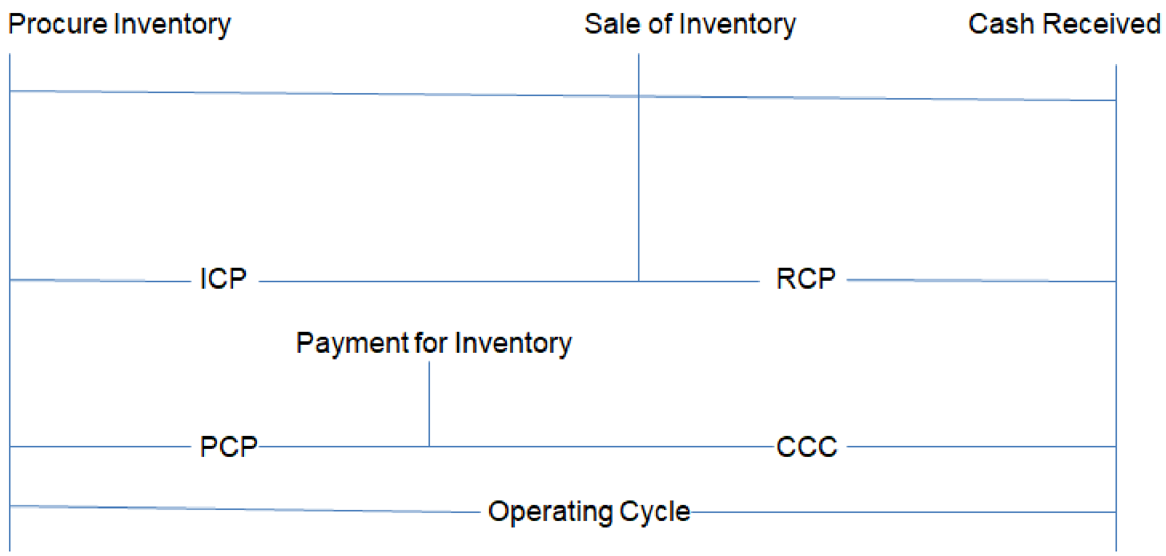


Figure 7.5: Financial sequence of events under an operating cycle policy

It is further considered that the supplier is capable of satisfying the entire orders placed by the retailer. For the start of each period, a single orderable item is considered in this study chapter, where c is the unit purchase cost and fixed or no set up cost is deemed to be incurred. The retail unit price is p, which satisfies the condition that $p > c$. The per period demand for the item is independent and identically distributed (i.i.d.) with density function $\varphi(.)$, with mean μ and standard deviation σ. In addition, a variable lead time of L periods in the procurement cycle is considered. At the end of each period, every single item designated as stock surplus will certainly incur a holding cost h for the period in question. Backlogging unfulfilled demand will be allowed but brings about a unit penalty cost of b per period plus the cost of delayed revenue and loss of goodwill. This study chapter assumes a rebate factor of $\propto \in (0, 1)$. In line with the sequence of events described above, for payment in relation to orders placed with the supplier (upstream) a delay of u time period is considered. While payment due for demand by consumer (downstream) occurs in a delay of d time period.

7.2.4. Inventory Control Setup

As mentioned for Figure 7.4 in the previous sub-section, an essentially two-bin system, often referred to as periodic review policy or order up to level system (R, S) model where replenishment takes place by ordering up to optimal S units every R time periods is considered in this study chapter. The proposed model is based on the following assumptions. The demand rate, D_t at period t, is a stochastic variable with mean, $E(D_t)$ and standard deviation, σ_t. As a result of the above supposition, the optimal order quantity will be the optimal order up to level less the inventory position. As shown later under this section in equation (7.3), the order up to level, S can be said to be the sum of the expected demand (during the lead time plus the review period) and the product of the safety factor k and the variance of forecast error such as the root mean squared error (RMSE) of the forecast error (over the lead time plus the review period). Besides, while the lead time plus review period is randomly distributed with mean, $E(L+R)$ and standard deviation, σ_{L+R}, stockout in terms of lost sales, partial and full backorders are allowed. The expected (but unknown) demand over the lead time plus the review period D_{L+R} is convolution of two independent variables, the demand rate and the lead time plus review period with mean and variance given respectively as equations (7.1) and (7.2):

$$E(D_{L+R}) = E(D_t) \times E(L+R) \qquad (7.1)$$

$$\sigma_{L+R}{}^2 = Var(D_{L+R}) \qquad (7.2a)$$

Equation (2a) can be expressed as:

$$\sigma_{L+R}{}^2 = Var(D_t) \times E(L+R) + \left(E(D_t)\right)^2 \times Var(L+R) \qquad (7.2b)$$

Suppose z to be the standard normal random variable and that the safety factor, k satisfies the condition for the allowable stockout probability during the lead time to be $P(D_{L+R} > S) = P(z > k)$, then the order up to level, S is the sum of *safety stock* and the expected demand over lead time plus review period:

$$S = E(D_{L+R}) + k\sigma_{L+R} \qquad (7.3)$$

Let $F_{L,t}$ be the conditional approximation of the total demand over the lead time, in other words, forecast made at time period t. While $\sigma_{L,t}$ is the conditional approximation of the standard deviation of the forecast error over the lead-time, then equation (7.3) can be rewritten as:

$$S = F_{L+R,t} + k\sigma_{L+R} \qquad (7.4)$$

Prak, Teunter and Syntetos (2017) has shown that when modelling multi-periods for inventory control, the optimisation of safety stock should be given a careful consideration especially if the system experiences cross period lead time (cases where lead times are longer than a period).

In situations where demand and lead time variability are independent and both are normally distributed, as are assumed in the study chapter, the optimised safety stock equation is given under a periodic policy as:

$$S_s = k * \sqrt{(R+L)\sigma^2 + D^2{\sigma_{LT}}^2} \qquad (7.5)$$

7.2.5. Performance Measures

Similar to implementations carried out in the study chapter 6, both the accuracy of the forecasts and the performance of the inventory control system are measured in the current study chapter. However, while the performance procedure for evaluating demand forecast performance in this study chapter will be the same as those employed for the research study in chapter 6, only the root mean squared error (RMSE) metric will be utilised. But the output from the inventory simulation is still the inventory performance function, that is, the cost criterion, calculated in *R* periods as:

$$TC = hE(i^+) + bE(i^-) = \frac{h}{R}\sum_{t=1}^{R} i_t^+ + \frac{b}{R}\sum_{t=1}^{R} i_t^- \qquad (7.6)$$

where h and b are unit holding cost and backorder cost rates respectively. Moreover, in a Newsvendor setting the holding cost, h and backorder, b also define the target cycle service level C_{sl} such that $C_{sl} = b/(h+b)$. While $i_t^+ = \max(i_t, 0)$ and $i_t^- = \max(-i_t, 0)$, the term i_t^+ characterizes the positive on-hand inventory and the term i_t^- denotes backorders.

7.3. Data Sets for Experiment

7.3.1. Data Series

Once more, the time series data sets used to conduct analyses in this chapter study strand is the same as for the previous study strands in chapter 5 and chapter 6, and have been described in detail in Chapter 4 (the Methodology chapter). However, three of the four data sets have been used for this chapter study. And as it has been mentioned before, the raw data sets consist of real retail Electronic Point of Sales (EPOS or sales history) data and product information from US based markets for short shelf-life perishable products; specifically, for this chapter study are Milk, Salty Snacks and Yogurt time series.

7.3.2. Data Series Sub-Setting Rules

As carried out in the previous thesis study chapters, each of the three data sets is partitioned into two parts of estimation period and performance measurement period. The total time series of 313 observations are split into two unequal parts of 250 weeks in-sample subset and 63 weeks out-of-sample subset. The training subsets included all the observations from week 1 of January 2001 until the end of week 42 into 2005 and the testing subsets included data from beginning of week 43, 2005 and up to the end of week 53 in December 2006. The implication of this is that 63 weeks out-of-sample data subset will be utilised to produce a period ahead rolling origin forecasts from which forecast errors can be obtained.

7.3.3. Evaluating Forecast Accuracy

In the same way as before, in the first iteration, the candidate forecasting strategy is trained on the historical retail performance from week 1 of January 2001 until the end of week 42 into 2005, then forecast only a week in advance and validate on the actual week 43, in year 2005 of the test data set. Then, for the next iteration, train the forecasting model on data from week 2 of January 2001 until the end of week 43 into 2005, then predict another a period ahead and validate on the actual week 44, in year 2005 of the test data set. This iterative procedure continues and has been carried out repeatedly until the end of the last week for each of the three 63 weekly test data sets (for milk, salty snack and yogurt).

7.4. Forecasting Setup and Results

7.4.1. Forecasting Methods and Forecast Accuracy Metrics

It is assumed, just as in the previous study chapter 6, that the retailer employs three different methods to forecast the lead time demand (see the study chapter 6 for full details of rationale for these forecasting approaches):

- Seasonal and Trend (decomposition using) Loess Forecasting (STLF) Model
- Dynamic Harmonic Regression (DHR) Model with ARMA error structure
- An exponential smoothing state space (trigonometric) model with Box-Cox transformation, ARMA errors, trend and seasonal components (TBATS) model.

Recall that unlike quarterly and monthly data sets, weekly, daily and hourly time series by their nature can be high frequency, multiple seasonal data with rather long seasonal periods. As such, many of the standard forecasting methods are not appropriate to use for their forecasts. Hyndman and Athanasopoulos (2018) espouse that the three models (STL, DHR and TBATS) are more appropriate and optimal forecasting methods designed specifically to deal with these high frequency types of data series.

The square root of the Mean Squared Error (MSE) is used in this study chapter to measure forecast error and to compare the results for each approach. It is quite natural to use MSE as it incorporates the variance of the forecast error, and it is expressed as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \tag{7.7}$$

Besides, MSE is good to use if the goal is for forecasts that are means of the future distributions which are conditional on the past historical observations (Hyndman and Koehler, 2006). The standard deviation of errors (SDE) which is just the square root of the MSE (that is, RMSE) is often employed as the approximation for MSE (see for example, Hyndman and Athanasopoulos, 2014).

7.4.2. Forecasting Methods Performance Results

7.4.2.1. Statistical Comparison of the Different Forecasting Strategies

This analysis has already been conducted in study chapter 6 and the Table 7.2 presents the summary (in 10^5) of performance for all the three forecasting methods as discussed in Section 4.1. Note that also presented in the table is the performance of a simple benchmark, the Seasonal Naive method designated here as sNaïve and the averaged combined performance across the forecasting strategies.

Table 7.2: Summary of Accuracy Measures

	Milk	Snack	Yogurt
Root Mean Squared Error (RMSE)			
sNaïve	3.29	3.39	5.48
STLF	2.11	2.56	3.76
DHR	3.02	4.12	9.97
TBATS	2.20	2.10	3.32
Combined	2.65	3.04	5.63

From the results of the statistical forecast errors as presented in Table 7.2, it can be observed that using the RMSE forecasting metric for the forecasting strategies, the results appear to be stable with no exception at all. In other words, TBATS model marginally outperformed the STFL forecasting method. It can be further observed as well that while the DHR model did better than the benchmark Naïve method for milk, it appears to have lost in performance for both yogurt and salty snack.

While it is also observed in particular that aside from the TBATS and STLF strategies, both the DHR forecasting model and the benchmark seasonal Naïve generally produced forecast error values higher than the average global RMSE values for the combined strategy.

7.5. Financial Control Setup

7.5.1. The Transaction Strategy Setting

The outcome of findings in the study chapter 5 has demonstrated that effective cash flow management is key to a retail chain business success. And that in order to improve the cash position and maintain firm's financial health status, operating working capital requirements must be kept as optimal as possible. But the competition among members in a supply chain network is one of the significant challenges which are emphasised in supply chain management (Ferrara et al, 2017). There is as well the conundrum whereby the members in a supply chain network want to maximise their individual net profit but each and every member also carries the responsibility to embrace the network coordination under the *strategy of information sharing* to maximise overall supply chain value yield (Ali et al, 2011). To study a dynamic and complex problem of this nature, the Stackelberg leader follower game technique is one of the methods that can be applied (Hennet and Arda, 2008; Yang et al, 2015). In a Stackelberg model, the game or market leader is assumed to be dominant and chooses a strategy first. The game follower then observes this decision and makes their own strategy choice. The former chooses the best possible point based on their anticipation of the latter's best response function. In this study chapter, in order to solve the Stackelberg leader follower game, under the assumption of the feedback structure of information, consideration is given to the Basar and Olsder (1999) advocate of utilisation of the dynamic programming method with appropriate value functions. The objective of the study chapter, therefore, is to formulate an optimisation model for the retailer under both upstream and downstream transactions, assuming players are either financially constrained or unconstrained but with the motivation mainly for how the retailer is affected.

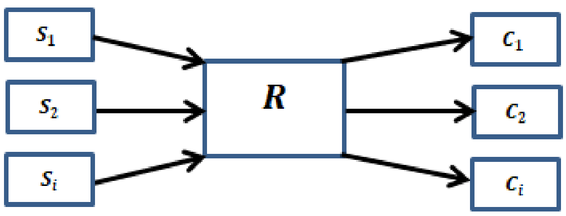


Figure 7.6: Stackelberg leader follower game in a localised two echelon series supply chain network

Thus, in the current study chapter, it is surmised, on one hand, that the supply chain Stackelberg game transaction conditions, in an operation involving the supplier and the retailer, where the supplier is the market leader, is shaped by the supplier. On the other hand, however, in a business contract between the retailer and consumer, the retailer becomes the sole determiner and acts as the Stackelberg game leader. This setup is depicted in the two-echelon series supply chain network of Figure 7.6.

To simplify analysis, relative to the retailer, R, all the suppliers, $S_1, S_2, \dots, S_i$ and the consumers, $C_1, C_2, \dots, C_i$ are assumed to be at the same level as depicted in Figure 7.6 and are thus, assumed to make the same respective decisions due to and in line with all organisational unique business objective of minimising operational costs. As a result, the localised model in Figure 7.6 can be simplified into a global model that has only one supplier, S, and one consumer, C, relative to the retailer as represented in Figure 7.7.

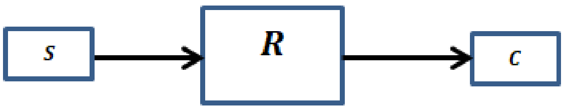


Figure 7.7: Stackelberg leader follower game in a global two echelon series supply chain network

The market leader who is the supplier moves first. The leader can make an optimised price and trade credit offers that are optionally open to the retail chain firm. But in doing this, the supplier's decisions will take into account the potential response from the game follower in respect of these offers. Then, the retailer reviews the supplier's offers in order to make a decision on whether or not to play a part in the game. If the decision is made to take up the offers, the retail chain optimises its reaction to minimise cost risks and maximise returns or benefits. The study chapter supposes that the retailer (in regard to upstream transaction) or the consumer (in respect of downstream transaction) may not have any alternative opportunities but will participate if and only if the expected returns or benefits are respectively non-negative (Fudenberg and Tirole, 1991).

Accordingly in this study chapter, consideration is to three different possible trade transactions involving equity credit, trade credit and cash credit financing arrangements.

These three financing contract scenarios and their meaning and conditions around them are as follow and as will be introduced in relevant subsequent sections:

- Equity credit (self-financing) with immediate payment upstream and downstream
- Trade credit (upstream supplier's trade credit to finance the retailer and downstream customer bankrolled by the retailer's trade credit)
- Cash credit (loan from a financier for financing the retailer with a minimum risk-free interest rate that can rise to a limitless exogenously determined risk-premium interest rate)

Since the focus in this study chapter is the retailer, first to consider is a situation where the retailer has no offer of payment holiday, that is, no offer of trade credits from the supplier. As a result, an immediate payment of cO_t is required for the procured product, where *c* is the purchased price and the replenishment volume of O_t units have been placed. The retailer receives the order after L+R periods later and then obtains revenue p per unit sold. At the other end, and likewise the supplier's condition, the retailer requires from its customer an immediate payment of $pD_{L+R,t}$ for $D_{L+R,t}$ units of demand received before the customer can enjoy the product. Furthermore, it is assumed that for the above contract situations, the retail chain firm holds an ample free cash flow and as a result, a sufficient working capital to fulfil the immediate payment condition imposed by the supply.

In the second scenario, trade credits are on offer whereby the retailer is tolerated to delay payment for up to a period u after restocking has taken place and the customer is permitted a payment holiday up to a period d after the delivery of items purchased. It is necessary to note that the retail chain, under these trade credit contracts (whether that is upstream or downstream), does not necessarily need to seek out a loan with which to finance its working capital. This means that for this scenario, the retailer, even though may be experiencing working capital constraints, but payment to the supplier may be made from realised revenue if no loan in the form of cash has been borrowed. Specifically, working capital funding could be full trade credit or a combination of partial trade credit and partial cash credit.

The third setup involves trade credits upstream and downstream as in the second setting considered above, but that the retail firm, however, requires access to external funding for its working capital.

7.5.2. **The Operating Cycle, Financial Market, and Capital Structures**

In calculating working capital, one of the best approaches is the operating cycle method. This approach bases working capital estimation analysis on a consideration of the real business conditions or industry context. For this method, the longer the operating cycle, the higher the requirement of working capital would be. Suppose the retailer has an internal working capital level, w_t, which may or may not be sufficient for its preferred operation levels. In the case of inadequate working capital, the retail firm can access the external financial organisations such as a bank to borrow some loan. In the operating cycle approach to appraising working capital requirements, the following formula are every so often used to project expected capital needs of a firm. Usually, the formula states that 'Working Capital is the product of Cost of Goods Sold (CoGS, estimated) and number of days of operating cycle divided by 365 days plus bank and cash balance. Let the retailer's working capital in period t be w_t and its cash value in same period be $C_{B,t}$. If demand forecast for the period is F_t and the number of days of operating cycle is d_c, then for a product unit cost of c, it can be given that:

$$w_t = \frac{cF_t d_c}{365} + C_{B,t} \qquad (7.8)$$

The above model in equation (9) implies that the retail firm's working capital, w_t in period t can be defined as the aggregation of its cash value, $C_{B,t}$ and its inventory value, ci_t evaluated at the purchasing value of the product. In other words, this means that:

$$w_t = ci_t + C_{B,t} \qquad (7.9)$$

This research study also embraces a strategy that in a competitive financial market, financiers will grant loan request from retailer if the repayment projection matches the market risk-free interest rate return (Yang and Tseng, 2014). The risk-free interest rate is denoted in this study chapter as r_f. Suppose that for a retail firm to borrow a loan of $\mathcal{M}_f$, a repayment of $\mathcal{M}_f(1 + r_f(\mathcal{M}_f))$ is promised by the firm, where $r_f(\mathcal{M}_f)$ represents the interest rate function contingent upon $\mathcal{M}_f$ for the risky lending. Hence, the retailer repays $\mathcal{M}_f(1 + r_f(\mathcal{M}_f))$ amount to the financier from a successful business accomplishment. In the event of a business undertaking results in failure for the retailer to the point where the firm is unable to repay the loan, the financier is capable of acquiring the residual value of the retail firm by forcing it into bankruptcy. It is further assumed that the financier has the first priority to claim the value of the retail firm but that the firm has limited liability in the case of bankruptcy. If the asset recovery rate of $\propto$ which satisfies the condition that $0 <\propto$

< 1, and if the retail business is worth pD_{L+R} before the bankruptcy procedure is triggered, then the financier can only obtain a residual value of the product of rate and firm worthiness, that is $\propto pD_{L+R}$.

7.6. Model Formulation

Recall that the study focuses solely on the borrowing decisions alongside ordering decisions of the retail chain. The chapter study adopts the logic that with a surplus working capital after the optimal ordering cost has been settled, the retailer can invest as it wishes in other business objectives different from inventory operations, but one which is in-line with firm's overall investments strategy to minimise costs in order to maximise profitability (Gong et al, 2014). Thus, thesis study is concerned with evaluating the effect of inventory control outcomes to changes in the control parameter values in order to justify the selection of an optimal inventory system. But that in addition, study interest now includes considerations for the financial status of the retail chain. As a result, and in accordance with study assumptions as previously discussed that if the retail business is financially unconstrained, then this can be the base case situation. This is the instance occurrence for the first scenario of equity credit funding; in which case the retailer simply utilises (note that it may still be very tricky to do so) its surplus funds, due to a healthy financial status in the form of its free cash flow, to invest in its inventory. Otherwise, the retail chain would need to access external funding in the form of trade credit (that is, a form of borrowing from the supplier) and or cash credit (that is, borrowing from a financial institution such as a bank). Thus, presented first will be the retailer's financiers' balance books or loss-proof-recovery condition. Then, an optimal model will be proposed for the retailer, given the constricting offers from the financier and or the supplier upstream. Thereafter, for the specified deal offers extended to the customer downstream, similar model will be developed to show and account for supplier's and financier's balance book conditions and then the retailer's optimal model.

7.6.1. The Mathematical Model

In formulating a dynamic linear programming problem, the correct definition of the decision variables is a critical first step in the development of the model. When that is accomplished, the task of constructing the objective function and the constraints becomes more straightforward (Taha, 2017). For the problem at hand, the chapter study is required, under a periodic review policy, to determine the periodic or the lead time order volume to be procured by a retail store and of course, its replenishment target stock level. For the purpose of this study, consider a working capital constrained store that retails its product over a planning horizon of T periods, indexed by $t = 1, 2, 3, \ldots, T$. At the commencement of the period t, the retailer has an initial working capital w_t prior to when procurement and financing decisions are made and inventory level i_t, with $w_t > 0$ and $i_t \geq 0$. In each period t, the retail store can replenish its inventory from a supplier with per unit cost c. The product has a fixed retailing price p and a stochastic demand D_t in period t. It is assumed that $D_1, \ldots, D_T$ are independent and identically distributed (iid) positive stochastic variables, with $f(\cdot)$ and $F(\cdot)$ as the density and distribution functions (Li et al, 2013). It is further assumed that any unsold inventory at the end of the planning horizon is salvaged at a value, v per unit with $v < c$ but expressed as percentage, α of the unit cost. At the beginning of the planning horizon, the retailer reviews its inventory stocking level i_t and working capital level $w_t$before deciding on the order volume, denoted as O_t, for the period. The firm then pays the ordering cost cO_t from its own working capital and or short-term credits. The working capital position, w_t at the end of period t is the aggregation of cash and inventory values. While retailer's working capital can build-up over time, an upper limit on the working capital position at the end of any period is assumed. This upper limit, $\mathcal{W}_t$ (hereafter being referred to as the working capital ceiling) cannot be exceeded. For simplicity and ease of exposition, the working capital ceiling is assumed to be known (or predetermined) for all periods. It should be noted that any extra capital, $\mathcal{M}_e = (w_t - \mathcal{W}_t)^+$, may be invested in other prospective business objectives with a fixed return rate denoted as r. It is assumed that the retailer will choose to invest the extra capital rather than deposit it in a bank. The preference to invest over bank deposit is borne out of the fact that bank interest returns are usually less than the expected capital rate of return on investment (ROI) or even the minimum attractive rate of return (MARR) which is the lowest return that one would be willing to accept given the risks associated with an investment project and the other opportunities for investment (Yang and Tseng, 2014). Thus, the yield obtainable from investment by the retailer is assumed to be more than obtainable returns from making deposits in the bank. However, if the additional investment fails, the system's performance is penalised by a book-keeping consequence cost, denoted as ω with the condition that satisfies: $0 \leq \omega \leq 1$.

The order arrives and the inventory level is increased to the order-up-to (OUT) level, S_t, with $S_t = i_t + O_t$. Backorders and customer demand, D_t are fulfilled and the sales revenue, denoted as $R_t = p * \min\{S_t, D_t\}$, is collected. At the end of the planning period, invested capital is returned to the retailer who also receives returns (that is, yields) from the extra investment. The retail business then pays the principal and or interest of the short-term financing contract. In the trade credit contract, the supplier provides the retailer with two different terms of credit payment period. Payment within the preliminary credit period, u_1 entitles the retailer to a certain discount rate, ϑ on the supplier price. At the expiration of this earlier initial credit term and upon arrival of the later and final credit closing date term, u_2 when payment for the product must be made, the retailer will be unable to enjoy the discounted offer. It is assumed in this study that the retailer will pay in original period if there is discount, otherwise payment will take place in the final period, in accordance with the opportunity cost concept.

7.6.1.1. The System State Transitions

Let the state of the system in period t be denoted by $\imath_t$ and w_t. Then, with the preceding discussion and suppositions of the model, the conceivable state transitions from period t to period $t+1$ are expressible as stated below, where $(x)^+ = \max(x, 0)$ and $\mathcal{W}_t = cO_t$:

$$\imath_{t+1} = (\imath_t + O_t - D_t)^+ \qquad (7.10)$$

$$w_{t+1} = \theta c(\imath_{t+1} - \imath_t)^+ + \alpha p * \min(S_t, D_t) + (\omega + r)(w_t - \mathcal{W}_t)^+ - (\theta + r_f)(\mathcal{W}_t - w_t)^+ + (p - \beta\theta c)(1 - \alpha)(1 - \delta) * \min(S_{t-1}, D_{t-1}) \qquad (7.11)$$

The transition of the working capital level consists of five terms. The first term on the right-hand side of the working capital position is the change in the cash value of the inventory. The second term is the sales revenue in period t, when the volume of item available for sale is either the target order up to level, $S_t = \imath_t + O_t$ if $S_t < D_t$ or the periodic demand for the item, D_t if $S_t > D_t$. The third term is the capital and returns (if any) received from the supplementary investments, and the last two terms are related to the cash credit and respectively the upstream and the downstream trade credits. The fourth term combines the payments for the principal and interest of the short-term funding from financier credit and or supplier trade credit payable to the supplier at period u_2 (if operation has been funded, in part or whole, through trade credits; see below for the conditions charted for this). The last term justifies the fact that the on-hand cash position is also updated according to the full or part or default payment for demand from previous period and whether or not product has been sold at a salvage value, α. Suppose that the retail business, in an attempt to drive up demand, shares with its customers the trade discount it enjoys from the supplier. The retail chain firm, therefore, offers a fraction, η of the discount factor, ϑ with its customers who are willing to make prompt payment for purchased products at point d_1 (current period). Otherwise, payment for product demand at point d_2 (next period) is deemed to be made at full price, p.

Aside from the discounted rate factor, a form of risk to the retailer that must be accounted for in this chapter study model analysis is the probability of some customers who are likely to default payment for purchased product. In this chapter study, payment default δ is presumed to be loss profit to the retail company. As well as the consideration for default payment, the risk of obsolescence mitigated with wielded salvaging strategy has also been accounted for in the model proposed by this study.
It is just as important to note as well that the chapter study supposes the retail chain firm will undertake extra investments if and only if $\mathcal{w}_t \geq \mathcal{W}_t$ and the extra invested value may be up to $\mathcal{M}_e = (\mathcal{w}_t - \mathcal{W}_t)^+$; while it seeks financing if and only if $\mathcal{w}_t < \mathcal{W}_t$ and the funding amount required is $\mathcal{M}_f = (\mathcal{W}_t - \mathcal{w}_t)^+$. It is important to reiterate that in order to procure a product in each period, the retail business is able to use its own capital, take a short-term trade credit and or a short-term financing credit with a monotonically increasing in credit size interest rate. Moreover, in the event of bankruptcy and under the following conditions, the supplier can only enforce recoupment up to the value and on the same terms as for the financier (the loan lender):

- Working capital funding needed has been accessed (in part or whole) through short-term trade credits.
- Payment terms have been violated at period $\boldsymbol{u_2}$ to the point where the firm was unable to pay for the product.
- Otherwise, the discounted rate of $\boldsymbol{\vartheta}$ for payments made at $\boldsymbol{u_1}$ also holds for enforcement at that point.
- If working capital requirement has been partly funded from both sources of credit (that is, supplier and financier), the sharing formula is assumed to be the appropriate ratio in which credit has been accessed from these creditors.

On this account, as well as on the account that all decisions are made based on the expected cash flows at the end of the planning horizon, models will be formulated with focus on financier contract terms. The study seeks a twofold principal objective at the end of the planning period. On the one hand is the primary aim to minimise the retail chain firm's total relevant inventory cost (that is, the expected net present value of the total holding and backorder costs) together with its total financial cost (that is, the cost of financing the firm's primary operations and of other investments in the event of failure). And on the other hand, as a consequence of the primary objective seeks to optimise the retailer's expected terminal wealth with respect to the ordering decisions and the working capital control.

7.6.1.2. The System Policy: Dynamic Economic Lot Size Model Based

The inventory control policy to consider for the cost structure model construction, as was previously mentioned, is the periodic review stochastic demand policy for this research study. This model is basically an extension to both the economic order quantity (EOQ) model and the economic lot size (ELS) model. In this thesis subsection, the dynamic ELS model will be reviewed on the basis of the fact that the current study model construction will be based on and an extension of the basic ELS model. The ELS inventory policy is a discrete-time inventory model formulation with deterministic demand varying over time. Apparently, this policy is an inventory system in which no randomness is involved in the construction of future states of the system. Thus, an important system property, it should be noted, is that although inventory may be carried from a period to the next, however, no backorders or lost sales are allowed; as a result, all demand must be met as it occurs. Furthermore, order can be made at each period and replenishment decisions as well as lead time take instant effect.

On the account of the ELS system properties just highlighted above, the objective then, according to Waldmann (2009), will be to schedule the order sizes in a way that allow for the demand to be fulfilled at the minimum total relevant inventory cost (TRIC). Let the known demand for a single item at the time periods $t = 1,2,3, \ldots, T$ be $D_t = D_1, D_2, D_3, \ldots, D_T$. An order size of D_t at time t will incur a cost, if it is assumed that there are fixed set-up and fixed ordering costs, $TRIC = h(i_t^+)$ for carrying inventory i_t^+ in period t, $i_t^+ = \max(i_t, 0)$. To achieve the set objective of minimising the total relevant inventory cost, the nonlinear program below may have to be solved subject to three constraints, in order to be able to meet the demand $D_1, D_2, D_3, \ldots, D_T$ with planned order sizes $O_1, O_2, O_3, \ldots, O_t$:

$$minTRIC(O_t) = \sum_{t=1}^{T} h(i_t^+)$$

Subject to (i) the system state transition of equation (7.10), that is, $i_{t+1} = (i_t + O_t - D_t)^+$; (ii) the given starting condition (that is, the initial state) of $i_1 = 0$; and (iii) the non-negativity restrictions of $i_2 \geq 0, i_3 \geq 0, \ldots i_{T+1} \geq 0$ and $O_1 \geq 0, O_2 \geq 0, O_3 \geq 0, \ldots O_T \geq 0$.

7.6.2. Baseline Models

7.6.2.1. Upstream Transaction

Consider the retail chain's financiers' breakeven condition for the upstream transaction where the retail chain firm, financially constrained, procures O_t units under the contracting condition of a unit cost of c and trade credit offers. The retail chain borrows $\mathcal{M}_f$ from the financier with an undertaken repayment of $\mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right)$. Retail firm fulfilled demand from its replenished inventory and realised revenue after d periods. Since the retail store's financier possesses the first privilege to the retailer's firm value up to the repayment level, its financier cash flow function can be given as follows:

$$CF_f(O_t, \mathcal{M}_f) = \begin{cases} \mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right) & if\ D_t \geq V_t \\ \propto pD_t & if\ D_t < V_t \end{cases} \tag{7.12}$$

Where the repayment demand level, $V_t\ satisfies\ pV_t = \mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right)$. When the demand is greater or equal to the repayment demand level, V_t, the retailer is able to repay the promised amount of $\mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right)$; on the other hand, when the demand is less than the repayment demand level, V_t, the retailer risks being forced into bankruptcy (insolvency, liquidation, impoverishment, economic failure) and the financier can thus acquire a fraction, $\propto$ of the available firm value pD_t. The debt repayment $\mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right)$ is expressible as well, in relation to the repayment level V_t, in which case, the expected financier cash flow function will be:

$$\mathbb{E}_{D_t} CF_f(O_t, \mathcal{M}_f) = \min\left(\propto p\mathbb{E}_{D_t<V_t}[D_t], p\mathbb{E}_{D_t\geq V_t}[V_t]\right) \tag{7.13}$$

Recall that under this risky loan advancing contract, the retailer's financier will be able to provide credit as long as they presume that they can balance their books. Given this condition, the minimum expected return must be equivalent to the risk-free interest return. That is:

$$\mathbb{E}_{D_t} CF_f(O_t, \mathcal{M}_f) = \mathcal{M}_f(1 + r_f) \tag{7.14}$$

7.6.2.2. Downstream Transaction

The financier's condition of unpreparedness to experience loss for the downstream transaction assumes that the retailer offers price, p and holds the inventory, I_t from which demand, D_t is satisfied. The retailer borrows $\mathcal{M}_f$ from a financier, pledging to repay the amount, $\mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right)$. Retailer fulfilled demand from its replenished inventory and realised revenue after d periods. Again, since the retailer's financier possesses the first privilege to the retailer's firm value up to the repayment level, its financier cash flow function can be formulated as follows:

$$CF_f(I_t, \mathcal{M}_f/O_t) = \begin{cases} \mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right) & if\ D_t \geq V_t \\ \propto p(D_t - O_t) & if\ O_t < D_t < V_t \\ 0 & if\ D_t \leq O_t \end{cases} \tag{7.15}$$

Accordingly, the repayment demand level now satisfies; $pV_t = \gamma p O_t + \mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right)$, where γ $(0 \leq \gamma \leq 1)$ represents the proportion of order quantity on supplier's trade credit contract. Again, the same *risk-neutral* rationale as under the upstream arrangement holds; that is, the financier's minimum expected return would still need to be fulfilled as the same value commensurate with the risk-free interest return. That is:

$$\mathbb{E}_{D_t} CF_f(I_t, \mathcal{M}_f/O_t) = \mathcal{M}_f(1 + r_f) \tag{7.16}$$

It is worth to remark that other studies such as Li et al (2014) and Ma et al (2013) have studied retail firms' profitability relating to their terminal wealth goal. Therefore, in line with the focus of this study, which also relates to retail chain's terminal wealth objective, is the retailer's cost effectiveness; optimal cost function models for both upstream and downstream, are thus, developed as follow.

7.6.3. Optimal Models

7.6.3.1. Upstream Transaction

Optimal model for the retail chain firm for upstream transaction implies that the retailer needs to decide the optimal unit O_t to procure due to working capital constraint and given the cost of credit. Besides, due to the fact that retailer can lay claim to firm value only after its financier, thus, the cash flow function for retailer can be formulated as:

$$CF_r(O_t, \mathcal{M}_f) = \begin{cases} pO_t - \mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right) & if\ D_t \geq O_t \\ pD_t - \mathcal{M}_f\left(1 + r_f(\mathcal{M}_f)\right) & if\ V_t < D_t < O_t \\ 0 & if\ D_t \leq V_t \end{cases} \tag{7.17}$$

This cash flow value must then be optimised by the retailer. The optimisation can be achieved through maximisation of profit or minimisation of costs. As earlier mentioned, the former appears to have been extensively studied (see for example, Li et al, 2014), the later will be the focus in this study. Accordingly, given the product unit cost c and the condition that retailer's financier needs to balance books, the retail firm's optimal model relating to its cost objective can be formulate as follow under the following suppositions. Let the demand, in the long run, be greater or equal to the repayment demand level, then the retail chain's total relevant inventory cost (TRIC) will be the sum of the expected net present value of the total holding cost, $hE(i^+)$ and the backorder cost, $bE(i^-)$. And suppose R corresponds to the number of periods taken into account and given that the retail chain is cash constraint, then the retailer's upstream cost objective function can be expressed as specified in the function (7.18) below.

$$\min \mathcal{C}(O_t, S_t) = \left(\frac{\vartheta h}{R}\sum_{t=1}^{R} i_t^+ + \frac{b}{R}\sum_{t=1}^{R} i_t^-\right) + \left(r_f \sum_{t=1}^{R}(\mathcal{W}_t - w_t)^+\right) + \left(\omega \sum_{t=1}^{R}(w_t - \mathcal{W}_t)^+\right) \tag{7.18}$$

The term $\omega(w_t - \mathcal{W}_t)^+$ characterises a loss return performance from the retailer's supplementary investments. The cost of capital payable for the short-term funding of inventory operation is $r_f((\mathcal{W}_t - w_t)^+)$ and represents the credit cost function that the retailer incurs for borrowing from their financier.

7.6.3.2. Downstream Transaction

For the retailer's best primed model for downstream transaction, the retail firm's estimated cash flow function can be expressed as follows:

$$CF_r(I_t, M_f/O_t) = \begin{cases} p(I_t - O_t) - M_f\left(1 + r_f(M_f)\right) & if\ D_t \geq I_t \\ p(D_t - O_t) - M_f\left(1 + r_f(M_f)\right) & if\ V_t < D_t < I_t \\ 0 & if\ D_t \leq V_t \end{cases} \tag{7.19}$$

Thus, by the same token, the retailer's optimal cost objective model is formulated as follow under the conditions of offering the retail unit price p and of extending trade credit to the customer.

$$\min \mathcal{C}(O_t, S_t) = \left(p(1-\alpha)\eta\delta \sum_{t=1}^{R} \min(S_{t-1}, D_{t-1})\right) \tag{7.20}$$

The above model (7.20) accounts for the cash lost due to defaulted payment that is assumed to be unrecoverable from the customer for the demand from the previous period and whether or not product has been sold at a salvage value, α. Either payment default at full value (when $\alpha = 0$) or at the salvaged discount factor of α, both do represent the cost, in the event of default at rate δ, that the retailer incurs for extending trade credit without collateral to the customer. It is important to remark that the discount factor, η that the retailer shared with a defaulting customer only applies if the retail firm has fulfilled its own discount factor obligations to the supplier. Otherwise, the extended discount factor will become void, which then implies that the discount factor $\eta = 1$ in model (7.20) above.

7.6.4. The Combined Costs Model

The retail chain's expected inventory cost will be given by the total relevant inventory cost (TRIC) as well as its total upstream financial cost and downstream financial cost. These have been summed up to formulate the retail chain's overall integrated cost objective function that must be minimised with respect to the order-up-to (replenishment target) level and the order quantity to obtain optimal retailer's expected terminal wealth and ordering decisions at the end of the planning period. Thus, a retail chain firm's inventory system cost optimisation model can be formulated, where $\mathcal{C}$ is the integrated inventory cost, as a dynamic program presented as follows:

$$min\mathcal{C}(O_t, S_t) = \left(\frac{\vartheta h}{R}\sum_{t=1}^{R} i_t^{+} + \frac{b}{R}\sum_{t=1}^{R} i_t^{-}\right) + \left(r_f \sum_{t=1}^{R} (\mathcal{W}_t - \mathcal{w}_t)^{+}\right) + \left(\omega \sum_{t=1}^{R} (\mathcal{w}_t - \mathcal{W}_t)^{+}\right)$$
$$+ \left(p(1-\alpha)\eta\delta \sum_{t=1}^{R} \min(S_{t-1}, D_{t-1})\right) \qquad (7.21)$$

In order to realise the set objective of minimising this model of confluence for the system costs, the realisation task will be driven by the following system dynamics which will adopt Wang and Petropoulos (2016), and which also follow directly from the description of the economic lot size (ELS) model discussed in subsection 7.6.1.2. But this will be carefully accomplished with applicable assumptions to arrive at the right constraint conditions for the proposed dynamic hybrid model presented in equation (7.21) above.

As mentioned previously, formulating a dynamic linear programming problem requires initial step of correctly defining the decision variables in the development of the model. Equally, a key piece of the model LP formulation for the inventory cost problem is the constraints that define the transitions of the inventory as well as the capital and cash. Thus, the construction of the objective function $\mathcal{C}$ has been carefully calibrated, under a periodic review policy, to determine the periodic or the lead time order volume to be procured by a retail store and of course, its replenishment target stock level. The construction of the constraints for the problem at hand, therefore, proceeds as follow. Recall that for all $t > 0$, the current study has assumed the following system dynamics. The research study presumes an ordering policy under a periodic review inventory system with a replenishment target stock level, S_t that can be defined as the sum of demand forecast and the safety stock for the period t, that is:

$$S_t = F_t + S_{s,t}$$

It follows that the order size for period t will then be decided in the following way:

$$O_t = S_t - i_t$$

And the net inventory at the end of the period t, i_t is formulated as:

$$i_t = i_{t-1} + O_{t-1} - D_t$$

The on-hand inventory at the end of the period t is $i_t^+ = \max(i_t, 0)$ and the backorder level at the end of the period t is $i_t^- = \max(-i_t, 0)$.

Thus, for a single SKU and demand during a period, the expected net inventory level just before the order arrives will be:

$$S_t - E(D_t) + (1 - \beta)E(D_t - S_t)^+$$

while the expected net inventory level at the beginning of the cycle will be:

$$O_t + S_t - E(D_t) + (1 - \beta)E(D_t - S_t)^+$$

The dynamic program in equation (7.21) can thus, be optimised by minimising it with respect to the set decision variables, that is, the order size and the target stock level subject to the following three constraints for all $t > 0$ and $O_t, S_t \geq 0$. The first of these constraints is the retail chain firm's financial status:

$$O_t + S_t - E(D_t) + (1 - \beta)E(D_t - S_t)^+ \leq \mathcal{W}$$

This implies that the periodic total inventory investment or asset must not exceed $\mathcal{W}$, which is the upper limit on the retail chain's working capital position. In addition, according to Adriano (2010), collateral constraints imply that financing and risk management are fundamentally linked. This probably explains why financiers do consider debt capacity of a borrower in order to decide the maximum amount they are prepared to finance a business. Thus, this thesis considers the impact of explicitly incorporating a measure of a debt capacity as a constraint. Basically, the constraint on the value of O_t due to debt capacity, d_c ensures that the order volume is less than or equal to the periodic demand plus the minimum between the replenishment stock target or the maximum credit obtainable:

$$O_t \leq D_t + \min\{d_c, (S_t - i_t)\}$$

And finally, model optimisation should help the retailer to mitigate or at least to minimise the risk of stockout which ensures that maximum possible demand is met. A constraint to capture such an important event within the retail chain setting will have to safeguard that the order volume should be larger than or equal to the demand for the period less than the current inventory utilisable. Thus, the final constraint on the value of O_t:

$$O_t \geq D_t - i_t$$

7.7. Simulation-Based Optimisation Setup

7.7.1. Experimental Procedure

In the case of this study chapter, the interest focuses on assessing the sensitivity of inventory control results to changes in the control parameter values. These changes can occur as a consequence of utilising different estimation procedures or as a result of experimentation with different possible inventory parameters in order to justify the selection of an optimal inventory system. As in the previous study chapter 6, the simulation experiment remains the same. To simulate the situation, the lead time and the cycle service level for all the procedures employed in the previous study chapter 6 and in line with the literature such as Corsten and Gruen (2004), Catt (2007) and Syntetos (2009) are utilised.

Table 7.3: Control Parameters for the Simulation Analysis

Control Variable	Control Parameters
Lead Time	1, 3, and 7 (in weeks)
Cycle Service Level	0.90, 0.95 and 0.99

In comparing performance of the various forecasting methods based on inventory setup, systematic evaluation and sensitivity analysis for varying values of corresponding variable or parameter are performed. In this experiment, mean unit product price values of \$2.57 for milk, \$2.31 for salty snack and \$1.98 yogurt (real price values obtained from the IRI demand data sets) have been used. The inventory item's selling price is set to yield a product price margin or Markup (m) per unit of 50% (following Catt, 2007), this means that the unit product cost $c = \$1.29$, $c = \$1.16$, $c = \$0.99$ respectively for milk, salty snack and yogurt apply. Study simulates lead times, L, from the supplier to the retailer of 1, 3 and 5 periods. The rationale for this choice of range of variance of noise is based on the comparison with previous papers (Lee et al, 2000; Raghunathan, 2001; Li et al, 2005). The inventory stockout cost is the cost of loss of goodwill and the lost profit per sale for a demand for a non-procured product. This penalty or backorder cost, otherwise referred to in this study as inventory stockout cost risk (ISCR), is computed by presuming that stockout will lead to an inventory backorder loss cost rate (b) of 60% for extreme case scenario (other scenarios have been subject of discussion in thesis study chapter 6). The inventory carrying (or holding) cost risk (ICCR) is obtained due to a holding cost rate (h) of 25% *per year* (following Timme and Williams-Timme, 2003) have been considered for this experiment. In addition, while service levels are set to 90%, 95%, *and 98%* leading to corresponding values of safety factor (k) of 1.28, 1.64, *and 2.05* respectively. The specified values of service level also lead in that order, to corresponding values of expected unit normal loss function (G(k)) of 0.0475, 0.0211, *and 0.0074*. The simulation solution will result in calculating the values of the following performance metrics for the three approaches:

- Inventory Carrying Cost
- Demand Backorder Cost
- Total Inventory Cost

In summary, three forecasting approaches are presented and RMSE used as the performance metric in this simulation experiment. Simulation is used in this research to establish comparisons between the different forecasting approaches in terms of the statistical forecast error and economic metrics. The results are then matched to find out how the performance metrics of all the models compare.

7.8. Empirical Results

7.8.1. Economical Comparison of the Different Forecasting Strategies

Table 7.4 through to Table 7.6 present the summary of performance in terms of inventory costs for all the different forecasting methods as discussed in Section 4.1.

Table 7.4: Inventory Costs for 90% Service Level for the Milk data set

Mean of Inventory Costs at 90% **CSL**		**sNaïve**	**STL**	**DHR**	**TBATS**	**Combined**
		$	$	$	$	$
L = 1	Stockout	150.20	121.57	146.22	146.22	138.00
	Stockover	6.69	5.41	6.51	6.51	6.15
	Total	156.89	126.99	152.73	152.73	144.15
L = 3	Stockout	212.41	171.93	206.79	206.79	195.17
	Stockover	9.46	7.66	9.21	9.21	8.69
	Total	221.87	179.59	215.99	215.99	203.86
L = 5	Stockout	260.15	210.57	253.26	253.26	239.03
	Stockover	11.58	9.38	11.28	11.28	10.64
	Total	271.74	219.95	264.54	264.54	249.67

Note that also presented in these tables is the performance of a simple benchmark, the Seasonal Naive method designated here as sNaïve. Table 7.4, Table 7.5 and Table 7.6 present the total relevant inventory costs including carrying costs (stockover) and backorder costs (stockout) from the simulation experiment. It can be observed that with the cost metric function, the STLF strategy is the model that clearly minimizes the overall costs. Thus, to summarize for both methods (statistical and economical) of forecasting model selection, while the statistical approach using the forecast errors failed to clearly produce a single winner candidate that offers the best accuracy results across the board, the economic metric has helped to select the STLF model as the best strategy that can be deployed to forecast the SKUs. It has given the best cost performance across the strategies considered in this study.

Table 7.5: Inventory Costs for 90% Service Level for the Salty Snack

Mean of Inventory Costs at 90% CSL		sNaïve	STL	DHR	TBATS	Combined
		$	$	$	$	$
L = 1	Stockout	192.44	155.77	187.34	187.34	176.82
	Stockover	2.97	2.40	2.89	2.89	2.73
	Total	195.41	158.17	190.24	190.24	179.55
L = 3	Stockout	272.16	220.29	264.94	264.94	250.06
	Stockover	4.20	3.40	4.09	4.09	3.86
	Total	276.36	223.69	269.03	269.03	253.92
L = 5	Stockout	333.32	269.79	324.49	324.49	306.26
	Stockover	5.15	4.17	5.01	5.01	4.73
	Total	338.47	273.96	329.50	329.50	310.99

Table 7.6: Inventory Costs for 90% Service Level for the Yogurt

Mean of Inventory Costs at 90% CSL		sNaïve	STL	DHR	TBATS	Combined
		$	$	$	$	$
L = 1	Stockout	240.55	194.71	234.18	234.18	221.02
	Stockover	1.04	0.84	1.01	1.01	0.96
	Total	241.60	195.55	235.19	235.19	221.98
L = 3	Stockout	340.19	275.36	331.18	331.18	312.57
	Stockover	1.47	1.19	1.43	1.43	1.35
	Total	341.67	276.55	332.61	332.61	313.93
L = 5	Stockout	416.65	337.24	405.61	405.61	382.82
	Stockover	1.80	1.46	1.76	1.76	1.66
	Total	418.46	338.70	407.37	407.37	384.48

The results also showed that generally, the STLF model outperforms the other forecasting strategies when confronted with lead time variance. However, all the forecasting strategies can only do well when supply variability (that is, the lead time) is low, and fail on a high supply uncertainty in terms of carrying costs (that is, costs due to stockover) or backorder costs (or costs due to stockouts) and thus, total relevant costs.

7.9. Integrated Cost Model Estimation

In what follows, analysis is conducted to examine the important structural properties of the proposed integrated cost objective model that provide some key features which will help characterise the firm's optimal inventory control policy. The natural next step should then be to investigate how the inventory policy reacts to parameter changes.

7.9.1. Model Illustration

In order to substantiate that the proposed integrated cost model will work the way that it is expected to run or function, it is essential to show that the model on offer agrees with theoretical framework when the basic conditions are fulfilled. Recall that the system conceptual characteristic carries the assumption that demand is normally distributed. For the proposed model to be valid, it should yield a matching or similar outcome as the theoretical model. Accordingly, a plot of the demand distribution is constructed to enable visualisation of both safety stock level and stockout level.

In addition, the plot enables the estimation of how much inventory corresponds to safety stock level; that is, the plot should reveal how much safety stock level is needed to prevent a stockout when the condition of normally distributed demand is met. The following parameters have been considered for analysis of the integrated model. The baseline value for working capital level is initialised at zero. An average unit product price of \$2.57 for milk, \$2.31 for salty snack and \$1.98 yogurt have been used.

Table 7.7: Control Parameters for the Sensitivity Analysis

Control Variable	Control Parameters
C_{sl}	90%, 95%, and 99%
LT	1, 3, 7 (Weeks)
r_f	3% and 12%

While the average unit product cost at 45% of the item price gives $c = \$1.26$, $c = \$1.04$, $c = \$0.89$ respectively for milk, salty snack and yogurt have been applied. A worst-case scenario of 0.75 of customer defaulting with a discount factor of 0.05. Retail chain enjoyed a trade discount factor of 10% with the share of trade credit to cash credit at 1 to 5. Other variable parameter values are displayed in Table 7.7.

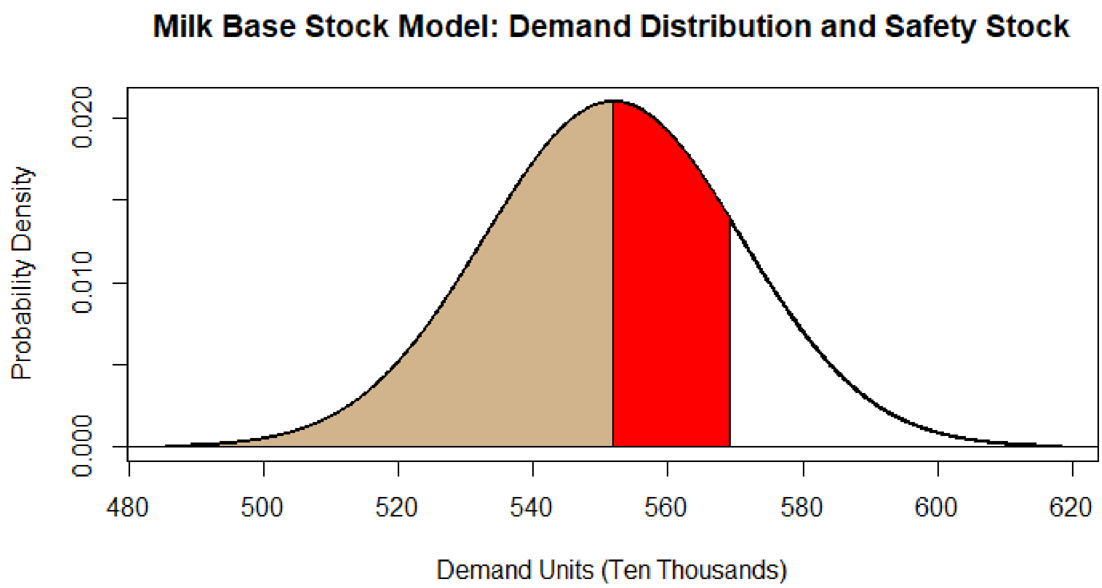


Figure 7.8: Base Stock Model for the IRI Milk Dataset, Demand Distribution and Safety Stock

The base stock analysis corresponding to the IRI milk dataset is presented in Figure 7.8 since it represents a similar pattern to both the salty snacks and the yogurt data series. The demand follows a normal distribution with mean equals 5518734 units (see section shaded brown) and the standard deviation of the demand is 190406. It can be observed from the demand's normal probability distribution graph of Figure 7.8 that about 175000 extra units are needed to be ordered as safety stock (see section shaded red).

7.9.2. Credit Options Evaluation

The credit options below are evaluated by varying some of the decision parameters while keeping others constant for the cost objective function.

- Equity Credit (EC)
- Trade Credit (TC)
- Cash Credit (CC)

Table 7.8: Comparing the Credit Schemes and a Combination Strategy Side-by-Side

Milk						Salty Snack					
CSL (%)	LT	r_f	EC($\$0^5$)	TC+CC($\$0^5$)	TC($\$0^5$)	CSL (%)	LT	r_f	EC($\$0^5$)	TC+CC($\$0^5$)	TC($\$0^5$)
90	1	0.03	195.12	172.25	154.75	90	1	0.03	2.57	79.76	15.99
90	3	0.03	193.52	173.84	156.35	90	3	0.03	1.12	81.21	17.44
90	7	0.03	191.26	176.10	158.61	90	7	0.03	-0.93	83.26	19.49
95	1	0.03	194.31	173.05	155.56	95	1	0.03	1.86	80.47	16.70
95	3	0.03	192.38	174.99	157.49	95	3	0.03	0.12	82.21	18.44
95	7	0.03	189.64	177.72	160.23	95	7	0.03	-2.34	84.67	20.90
99	1	0.03	192.53	174.83	157.34	99	1	0.03	0.28	82.05	18.28
99	3	0.03	189.86	177.50	160.01	99	3	0.03	-2.12	84.45	20.68
99	7	0.03	186.09	181.28	163.78	99	7	0.03	-5.51	87.84	24.07
90	1	0.12	195.12	184.84	154.75	90	1	0.12	2.57	80.43	15.99
90	3	0.12	193.52	186.44	156.35	90	3	0.12	1.12	81.88	17.44
90	7	0.12	191.26	188.70	158.61	90	7	0.12	-0.93	83.93	19.49
95	1	0.12	194.31	185.65	155.56	95	1	0.12	1.86	81.13	16.70
95	3	0.12	192.38	187.58	157.49	95	3	0.12	0.12	82.88	18.44
95	7	0.12	189.64	190.32	160.23	95	7	0.12	-2.34	85.34	20.90
99	1	0.12	192.53	187.43	157.34	99	1	0.12	0.28	82.72	18.28
99	3	0.12	189.86	190.10	160.01	99	3	0.12	-2.12	85.11	20.68
99	7	0.12	186.09	193.87	163.78	99	7	0.12	-5.51	88.50	24.07

NB: Cycle Service Level (CSL); Lead Time (LT); Risk Free Interest (r_f); Equity Credit (EC); Trade Credit (TC); Cash Credit (CC)

Yogurt					
CSL (%)	LT	r_f	EC($\$0^5$)	TC+CC($\$0^5$)	TC($\$0^5$)
90	1	0.03	83.86	731.62	141.64
90	3	0.03	82.60	732.89	142.90
90	7	0.03	80.81	734.67	144.69
95	1	0.03	83.28	732.20	142.22
95	3	0.03	81.78	733.71	143.72
95	7	0.03	79.65	735.83	145.85
99	1	0.03	81.94	733.55	143.56
99	3	0.03	79.88	735.60	145.62
99	7	0.03	76.97	738.52	148.53
90	1	0.12	83.86	739.74	141.64
90	3	0.12	82.60	741.00	142.90
90	7	0.12	80.81	742.79	144.69
95	1	0.12	83.28	740.32	142.22
95	3	0.12	81.78	741.83	143.72
95	7	0.12	79.65	743.95	145.85
99	1	0.12	81.94	741.66	143.56
99	3	0.12	79.88	743.72	145.62
99	7	0.12	76.97	746.63	148.53

NB: Cycle Service Level (CSL); Lead Time (LT); Risk Free Interest (r_f); Equity Credit (EC); Trade Credit (TC); Cash Credit (CC)

In Table 7.8, a comparison evaluation of the three cases under consideration is shown in thousand dollars ($\$0^5$). It can be observed that there are some consistencies in trend for all the three IRI time series under investigation. As expected, increase in supply variability as well as higher service provision attract escalating costs. Similarly, The higher the interest rate premium on borrowing, the higher the cost of capital. The milk dataset indicates, also as expected, that the strategy without firm financial constraint, that is, the equity credits alongside a policy of immediate payment (see column 4), is less effective as it yields the poorest performance in cost. This could be explained by the fact that with immediate payment policy, demand may be low since customers must make instant payment before they can enjoy the product. But the strategy that allows for trade credits both upstream and downstream without borrowing from the financial market (in the last column) performs best; better than additional credit funded by external loan. One valid reason that could be ascribed to this finding is that demand may be high due to the fact that customers are afforded access to a payment holiday in terms of interest-free trade credit. Another reason could be that since taking external loan by the retailer, it is highly likely to attract interest rate premium; this will surely affect the revenue generation especially if cost of borrowing is high as shown in Table 7.8 for all the data sets investigated. And more often than not, the problem is exacerbated by market volatility as shown in Figure 7.9 below.

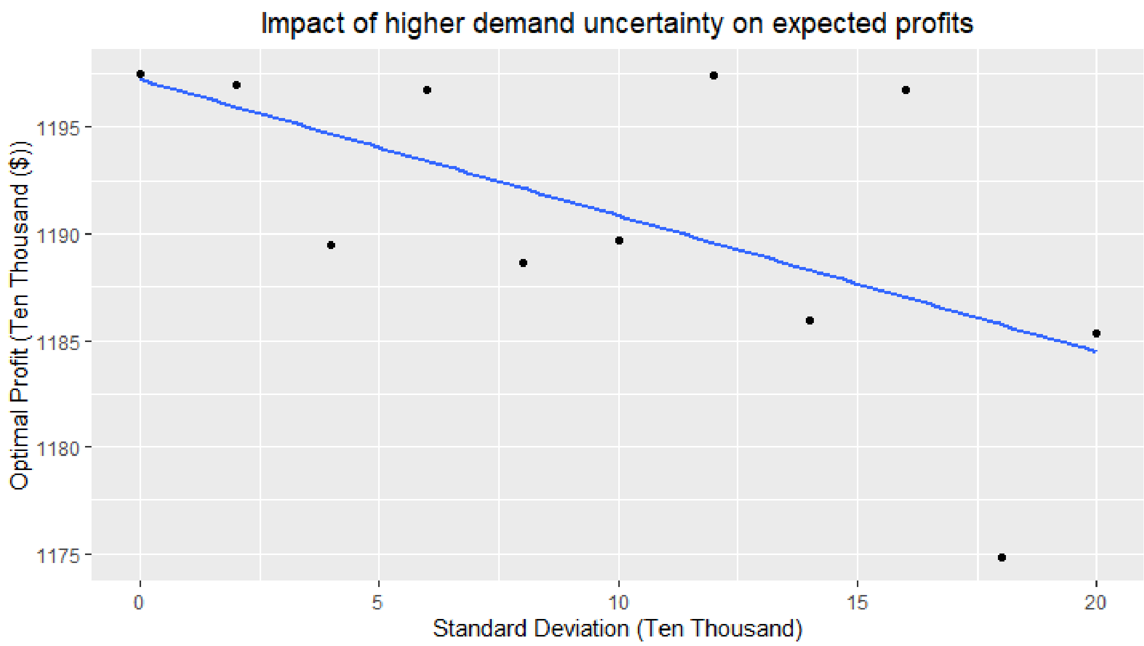


Figure 7.9: Market Volatility Impact on Profitability

All the above findings are consistence with academic evidence and supported by theory such as CAPM (see Watson and Head; 2016). A reason for the demand volatility impacting negatively on expected profit can be explained by the fact that it is capable of causing large forecasting errors, distorting coordination for the retail chain and causse distortion across the entire supply chain imposing excessive forecast error cost risks (Abolghasem et al, 2020).

On the contrary to the insight gained from the milk series, there appear to be few interesting findings from the analysis of the economic impacts on both salty snack and yogurt. The outcomes for these two datasets suggest that the equity credit strategy with the policy of immediate payment is far more effective as it yields the highest performance in terms of cost. But on a deeper analysis, these findings could be due to the stocking status of both items. Consider the average inventory levels for all the three data series in Figure 7.10 to Figure 7.12. There are indications that while the retail chains experienced a lot of stockover for yogurt, stockout for salty snacks appears to be rife. The negative figure for the salty snack item may also be as a result of the huge stocks. Milk data series, on the other hand, seem to be in a balance.

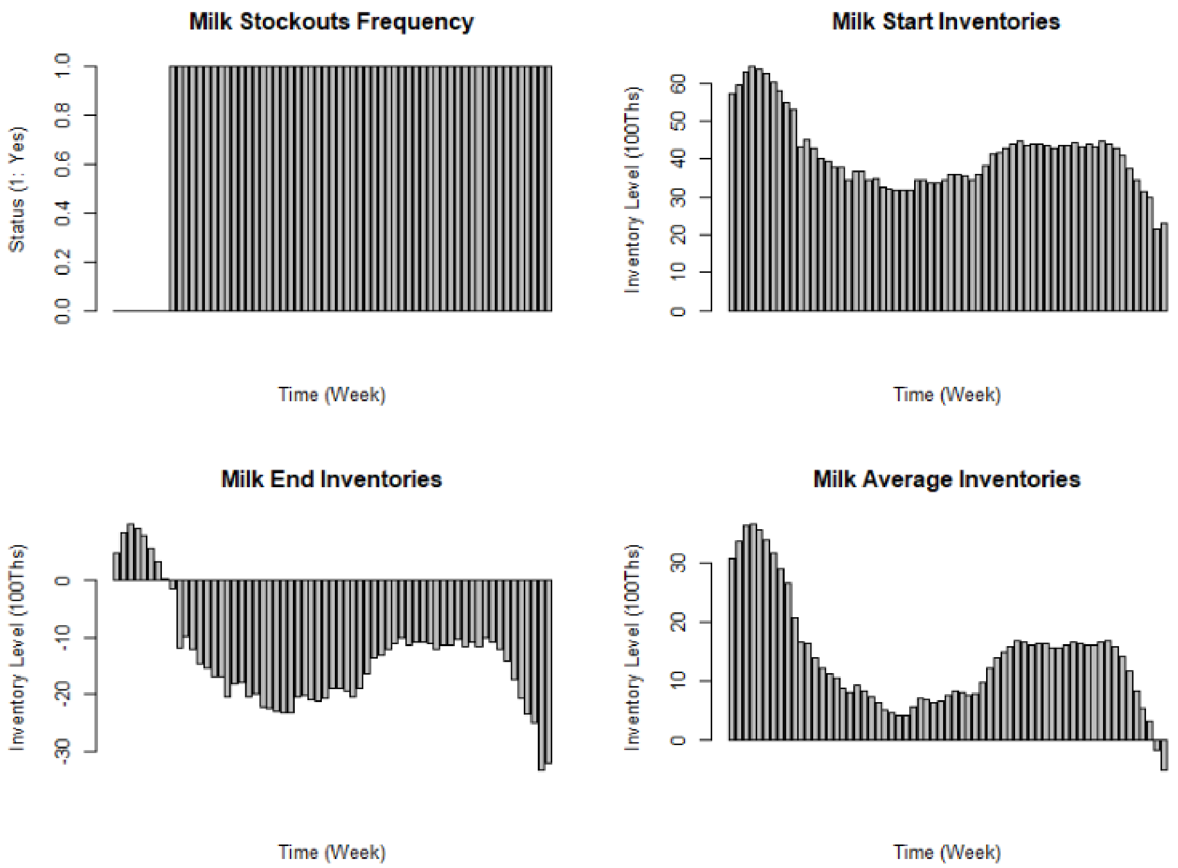


Figure 7.10: Inventory level analysis for milk

Recall, that for this current thesis study, uncertainty is always a factor to account for in forecasting and replenishment decisions as have been shown throughout the various, but particularly this and previous thesis discussion chapters (that is, chapters 6 and 7). And that to address this, service levels and fill rate are useful because they account for the trade-off between cost of stock of on-hand inventory and the cost of stockout.

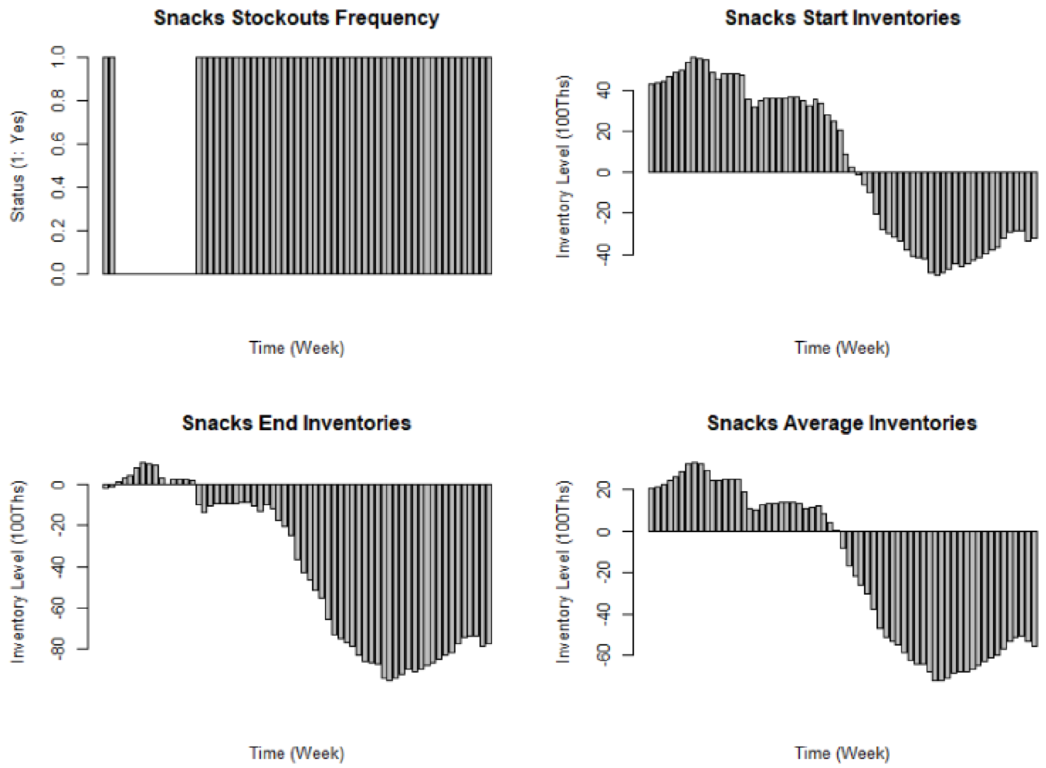


Figure 7.11: Inventory level analysis for salty snack

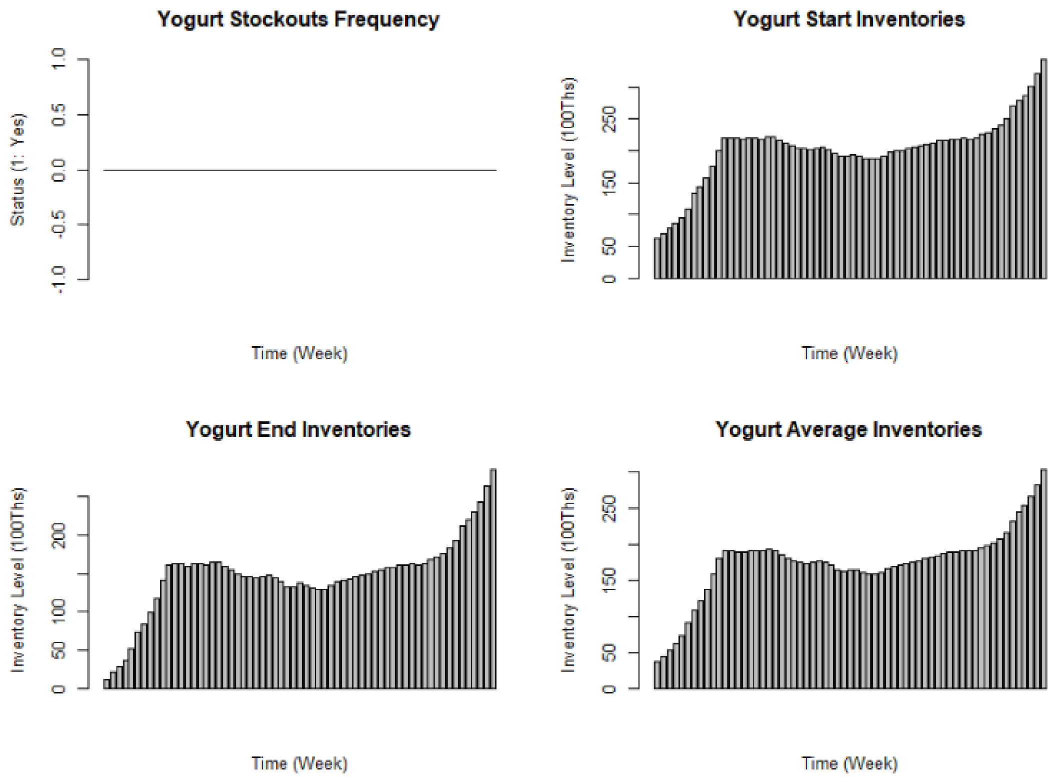


Figure 7.12: Inventory level analysis for yogurt

As demand uncertainty interacts with service level, fill rate and safety stock, the retail chain companies are required to understand how well they are fulfilling customers' needs. In inventory control and management, service levels and fill rates are used to determine, but also to show significant differences in safety stock requirements for the desired fulfilment ratio. Thus, it is very important to be aware of the difference between fill rate and service level. It could be argued that, to claim a retail chain is doing well, based only on service levels analysis, may be misleading and may not be reflective of the reality. Hence, this thesis recognised that being aware of what method is useful to determine safety stock is also of primary importance. This is because significant savings could be achieve using the proper approach.

On the account of this, as Figure 7.10 shows that safety stock with service level appears to be resulting in keeping a much higher safety stock for the milk dataset, the result appears to suggest that the use of fill rates may be more appropriate. This may also help to understand the savings realisable from using fill rate to determine safety stock over service level, and to observe whether or not savings from service level to fill rate increases as uncertainty increases. However, the current thesis study's focus of interest is not the stock volume and the economic differences in using fill rate versus service level to determine safety stock while facing uncertainty. Therefore, while this could be a focus of future study, we will keep the focus of this current research study on service level.

CHAPTER 8

Discussion and Conclusions

8.1 Introduction

In this concluding chapter, the main strands of the research work presented in the thesis are drawn together and the key conclusions are summarised in succinct form. In general, this thesis report has highlighted and hosts a bevy of business benefits: from forecasting methods evaluation and discerning interaction and intervention effects among performance variables between inventory control and the management of its investment to the provision of synergy of an integrated inventory costs model for the operations and financial functional areas. In particular, the thesis examined the interactions between demand forecasting and stock control from a financial point of view. This thesis closing chapter provides a summary of the research work in terms of thesis overview, its key findings, original contributions, and conclusions. In doing so, the strategy of linking it to the research objectives and the research questions given in the introductory chapter has been adopted.

8.2 Thesis Overview

In the thesis introduction chapter, the business context, background information and motivations for the research work was presented. More importantly, it provided the characterisation of the research questions, aims and objectives as well as the description of the research study conceptual framework. The thesis second chapter provided a review of existing inventory management and control approaches relevant for dealing with supply chain retail inventory of perishable products and associated costs structures. Chapter 2 encompassed a review of the current approaches to inventory control, both theoretical and empirical, consideration of the impact of demand uncertainty on inventory control system and cost structures, and the role of demand forecasting. In chapter three, the thesis evaluates literature as it relates to selecting forecasts for inventory management. The study considers the three broad approaches to this very important but challenging procedure, and on the basis of three parameters. First of all is the forecast performance as measured using statistical forecast errors. Secondly, model selection based on the inventory performance but as derived from statistical forecast errors as a proxy or through simulation or as obtained by directly optimising forecast models on inventory metrics such as service level or fill rate. And finally, forecasting model selection premised on economic performance of stock control.

While chapters one, two and three of this research thesis report have drawn attention to the fact that accurate demand forecasting with carefully constructed inventory control policies is crucial for the retail chain firms to flourish, the thesis chapter four outlined the research study methodology envisioned and implemented. The chapter expounded, in line with the research objectives outlined in the thesis introduction chapter, the formation of the complete components making up the focus of this research study. It charted the research work approach to be *deductive* in that the study considered forecasting models that are based on theoretical foundations and alluded to the fact that the research study would follow the strategy of developing theoretical structures based upon well specified assumptions which are then articulated in operational terms at the mathematical modelling level for each of the three main research objectives. In addition, the chapter accentuated and declared that the research strategy is primarily *quantitative* in terms of the data collection and the analyses to be conducted. But more importantly, the chapter together with the introduction chapter underlined that the research study would be *context* bound and designed to offer pragmatic solutions to some of the highlighted real-life challenges being experienced in retail chains inventory management and control.

Chapter five of this thesis studied the relationship between forecast accuracy, inventory productivity, and financial performance within the US retail chain firms. In particular, the chapter conducted and provided results on empirical investigations for the US markets for perishable products that included milk, salty snacks, yogurt and avocado by looking at and gaining insights into the following:

1. Understood and identified relationships among key variables of interest such as working capital, free cash flow, inventory turns and measure of forecast accuracy
2. Examined the mechanism of change (that is, system of causally interacting entities that create effects and or affect effects)
3. Explored the interventions and the interactions between inventory decisions and the choices being made by the finance function within the retail chain firms.

The research study in chapter six was dedicated to an investigation of and considered the accuracy of common and most often used forecasting methods. The chapter undertook to capture the true economic consequences associated with managing the inventory control system. In other words, evaluation of selected forecasting models and the quantification of economic impacts of emanating classical forecast errors from these models have been conducted in this study chapter. The chapter provide a discussion on the inventory control setup, the theoretical formulations and the traditional inventory cost model and its limitations. Both the simulation and the empirical studies in the chapter looked at and provided the platform where the limitations of the traditional model were addressed, and the proposed models introduced. The chapter focused mainly on the causes of risk factors, such as exposure to stockover and stockout, inherent in the inventory and their emanative effects. It addressed the issue of forecasting methods and accuracy evaluation but in the knowledge of its interaction with the inventory undertakings. In particular, the economic impacts of focus were based on the costs of poor service and relevant inventory costs such as stockout cost, stockover cost and total relevant inventory cost (TRIC) for replenishment decisions characterised by the order up to (OUT) level inventory policy.

In the thesis chapter seven, focus subsequently shifted to the development of a hybrid inventory costs structure that aligns both inventory control and financial decisions as conjectured in the third research study objective in the thesis introductory chapter. Thus, similar to the immediately preceding chapter, chapter seven of the thesis addressed the issue of forecasting accuracy evaluation but in the knowledge of its interaction with both the operational and the financial functions. In other words, the inventory control model investigated in chapter six was extended to include elements of financial undertakings. This is quite important since strategies to better and to boost financial efficiency tacitly impact and confine operational performance, particularly the management of inventory. Specifically, the study chapter integrated the components of the TRIC model with the capital costs of short-term credits accessible by the retail chain firms for their operational purposes. To achieve this, the study chapter proposed two modules in one model; one of upstream in the supply chain relative to the retailer and another of the downstream, integrated into one robust exemplar system and explored the connections as discussed in the previous study strands in chapters 5 and 6. In pursuing this objective, the study chapter explored the notion of bringing together and of fusing the forecast error costs within the inventory system of a retailer in a simple series supply chain with the cash costs of its inventory operations. For both the financier and the retailer, the study chapter respectively frames and articulates cash flows and an optimisation model that takes into account the constraint of working capital restrictions.

8.3 Discussion of Findings

In the introductory chapter of this thesis, several key research questions were formulated. Those questions will form the basis for the research investigation work findings discussion in this section of the thesis chapter. Thus, the following provides the summary of results from the various studies conducted as answers to the key research questions.

- *Research Question 1*

Is there association between retail chain business's operational choices and its financial functions, and if so, what are the mechanisms of change?

8.3.1 Findings from the Baseline Main Model

The results of the multiple linear regression tests of relationships between outcome variable (inventory turnover) and the three criterion variables (that is, the forecast error, the working capital level and the free cash flow) suggest that all have effects on the inventory turnover performance. It has been observed that the impacts of all the three metrics are statistically significant. In addition, findings showed that between the two financial decision variables investigated, working capital has stronger negative impact on inventory turnover than the free cash flow. Furthermore, although previous research studies have demonstrated that inventory turnover performance has effect on business financial performance measures such as a firm's working capital position and availability of essential cash for the business, but both in return also impact the inventory performance as shown by the current study results from the baseline impact outputs.

8.3.2 Result for Moderation Models

A further investigation into possible moderation effects among the four variables of interest mentioned above revealed an interesting finding. Free cash flow has been found to be a significant moderator of the relationship between forecast accuracy and inventory turnover. In other words, the study output suggests that the effect of forecast error on the inventory turnover efficiency is dependent on the levels of the firm's financial status as characterised by the free cash flow. The study finding showed that at the highest level of free cash flow, the optimal operational efficiency can be achieved for a given forecast error reduction and that improved forecast accuracy will only be effective for operational efficiency if the organisation achieves better financial position. This interesting and thus makes sense because, it supports the rationale that working capital could not be set at an allowance level that will impede operations when there is enough fund to meet business needs.

8.3.3 Results for Mediation Model

The effect of forecast error on working capital levels was partially mediated via the inventory turnover performance and the indirect effect was statistically shown to be significant.

In summary, all these findings based on research question 1 support the suggestion that there is actually a close cross-functional link between the operations and the financial functional units of a retail chain business.

- *Research Question 2*

Is the current traditional costs criterion structure adequate, reliable, and robust enough to give managers the right capability they need to evaluate the true costs of classical forecast metrics in the context of inventory control and management risks?

8.3.4 Findings from the Simulation Study

In this research study, statistical as well as economical comparisons of the different forecasting strategies revealed that automated forecasting models where parameters are automatically estimated have been found to perform better than other models that require more expert effort for modelling and parametrisation as well as computational power. In the simulation study, the best forecasting strategy is the Auto ARIMA regardless of the evaluation metric (forecast error measure or economic cost measure) utilised.

As was expected, both processes, that is ARIMA (1,0, 0) and ARIMA (1, 0, 1), produced the same spread distribution descriptions in all models. However, study found an interesting contrast in the cost risks outputs of the two models (traditional and proposed). Careful contrast of the two models shows some differences. Outcome showed a massive surge in carrying cost risks from the proposed models compared to the traditional model for both processes. The dramatic increase in risks can only be explained by the modifications that have been made to the traditional model to arrive at the proposed models to account for salvaging strategies and safety stock strength. This finding corroborates the fact that the traditional model is not robust enough to capture the contextual and the real risks of uncertainties inherent in both demand and supply. On the contrary, the proposed models demonstrated versatile and robust capabilities to capture this risk and other realities in practice within the retail chain sector organisations.

8.3.5 Findings from the Empirical Study

In empirically evaluating the accuracy of the studied forecasting methods, findings showed that no forecasting model could solely provide superior out-of-sample performance and predict all the test data better in all cases than the rest of the candidate forecasting methods. Clearly, the best forecasting method deployable for the avocado product is the DHR model in terms of all the three statistical error metrics (that is, RMSE, MAE and MAPE). In contrast, while STLF model outperformed the rest of the forecasting methods including the benchmark seasonal naïve and the global average for all the three datasets from the IRI source when MAE metric is considered. However, if the consideration is in terms of the RMSE and MAPE performance metrics, it can be further observed as well that while both STLF and TBATS forecasting methods did better than the benchmark and the combined strategies, they both appear to be at par in their performance with the TBATS model marginally having done better than the STLF strategy overall. It is also observed that aside from the winning method for a particular metric, all forecasting models excluding the benchmark seasonal Naïve consistently produced forecast error values higher than the average global error values for the combined strategy. Further analysis on the empirical data sets to evaluate these three forecasting strategies selected for the empirical study found an interesting contrast between the statistical and economical evaluation strategies. It was observed that while DHR model was the best forecasting method clearly elected for the avocado product through statistical comparison (see thesis section 6.11), however, both the traditional and the proposed inventory cost functions have indicated the STLF model as the preferred candidate for the same product in terms of economic cost impacts due to all the three statistical error metrics (that is, RMSE, MAE and MAPE). Then between the proposed and traditional cost functions, it is observed that, aside from sharp contrast in selecting forecasting models, the proposed cost model appears to discriminate among forecasting methods better than the traditional cost model by suggesting alternative forecasting strategies (that is, two forecasting methods performing at the same level) for milk and yogurt. Generally, according to the proposed cost approach, the STLF model can be said to have outperformed the other forecasting strategies when confronted with lead time variance. However, all the forecasting strategies can only do well when supply variability (that is, the lead time variance) is low, and fail on a high supply uncertainty in terms of carrying costs (that is, costs due to stockover) or backorder costs (or costs due to stockouts) and thus, total relevant costs for all the three approaches (that is, traditional cost, proposed cost, and proposed revenue).

- *Research Question 3*

Can the current traditional costs model, with its lack of consideration for the firm's financial status, be recreated and reconstructed to give a good reliability, robustness and quite importantly, strong synergy (for the interaction between operational and financial choices)?

8.3.6 Findings from the Empirical Datasets Utilisation with the Integrated Model

This research question has been investigated in the context of the cost function proposed in study chapter six. The proposed cost function in that chapter has thus been extended to account for financial constraints in inventory control cost evaluation relating to operational decisions.

To summarize for both methods (statistical and economical) of forecasting model selection, while the statistical approach using the forecast errors failed to clearly produce a single winner candidate that offers the best accuracy results across the board, the economic metric has helped to select the STLF model as the best strategy that can be deployed to forecast the SKUs (see thesis section 7.8). It has given the best cost performance across the strategies considered in this study. The results also showed that generally, the STLF model outperforms the other forecasting strategies when confronted with lead time variance. However, all the forecasting strategies can only do well when supply variability (that is, the lead time) is low, and fail on a high supply uncertainty in terms of carrying costs (that is, costs due to stockover) or backorder costs (or costs due to stockouts) and thus, total relevant costs.

The following credit options, equity Credits (EC), trade Credit (TC) and cash Credit (CC), have also been evaluated by varying some of the decision parameters while keeping the others constant for the integrated cost objective function. A comparison evaluation of the three cases under consideration reveals, as expected, that increase in supply variability as well as higher service provision attract escalating integrated inventory costs (see thesis section 7.9). Similarly, the higher the interest rate premium on borrowing, the higher the cost of capital. The strategy without firm financial constraint, that is, the equity credits alongside a policy of immediate payment has been found to be less effective as it yields the poorest performance in cost. This could be explained by the fact that with immediate payment policy, demand may be low since customers must make instant payment before they can enjoy the product. But the strategy that allows for trade credits both upstream and downstream without borrowing from the financial market performs best; better than additional credit funded by external loan. One valid reason that could be ascribed to this finding is that demand may be high due to the fact that customers are afforded access to a payment holiday in terms of interest-free trade credit. Another reason could be that since taking external loan by the retailer is highly likely to attract interest rate premium; this will surely affect the revenue generation especially if cost of borrowing is high. The higher the interest rate premium on borrowing, the higher the cost of capital and the lower the gross or net profit will be. Investigation also revealed that market volatility impacted negatively on expected profit. These findings are consistence with Abolghasem et al (2020) which suggests that, for example, a reason for the negative effect can be explained by the fact that demand volatility is capable of causing large forecasting errors, distorting coordination for the retail chain and causse distortion across the entire supply chain imposing excessive forecast error cost risks.

8.4 Contributions of the Thesis

A major motivation for this PhD research study is to improve on the contemporary and traditional approach to forecasts accuracy impacts evaluation in the context of inventory control and management systems. Thus, the research work contributions will be explicitly addressed in terms of the overall research aim of this thesis, which is simply to pursue the research motivation based on more realistic assumptions than in the previous research studies (such as Flores et al, 1993; Catt, 2007). The following three main research objectives, as already highlighted in the introductory chapter but repeated here for the benefit of hindsight, have been conscientiously pursued:

1. To investigate relationship between inventory investment and inventory control and demand forecast and the impact of the latter on the former and or vice versa.
2. To evaluate and quantify the utility measures, that is, the traditional error metrics such as the mean squared error (MSE), the mean absolute error (MAE) and the mean absolute percentage error (MAPE) in terms of inventory variables such as service level, relevant inventory forecast error cost risks (FECR) and forecast error revenue risks (FERR).
3. To explore, develop and propose an alignment and unified model for the cost structure, under the financial constraints or considerations such as working capital, trade credits and cash credits, which minimises operational costs and maximises profitability.

Consequently, the thesis study contributions have theoretical as well as managerial implications.

8.4.1 Theoretical Implications

This research work, in its first contribution (objective 1), has made an attempt to:

a. Systematically investigates the simultaneous degree to which both forecast errors (such as the mean absolute percentage error) and financial performance proxies (such as working capital and free cash flow) impact upon inventory efficiency.
b. Models these antecedents (without latent variables) within a multivariate analysis methodology (MAM) framework of structural equation modelling (SEM) and explores their interactions.
c. Explicitly explores the forecast error as a mediated influence on financial variables.

Furthermore, this thesis fills some voids in the literature in terms of the economic quantification of statistical forecast errors such as MSE, MAE and MAPE (objective 2), by extending results on utilisation of forecast methods to automatic forecasting methods such as the ExponenTial Smoothing (ETS) and Auto ARIMA, and to the methods such the dynamic harmonic regression (DHR) model and the trigonometric with Box-Cox transformation, ARMA errors, trend and seasonal components (TBATS) which are suitable for high frequency time series.

In addition, using less restrictive assumptions, it has been shown that both the traditional inventory cost structure and the typical safety stock model utilised in its calculation by studies such as Flores et al (1993) and Catt (2007) are neither adequate nor robust enough for estimating the total relevant inventory cost (TRIC) risks for retail chain firms and can thus be enhanced. As a result, the traditional model has been modified leading to the proposition of two extended inventory cost metric models. These are versatile and robust economic models, both of which have been designed to account for the real costs of forecast error variance. While the first of these two models have been carefully constructed to estimate the exact context-based stock cost risks, the other model is well devised to measure the revenue risks at stake due to statistical forecast errors (objective 2).

Further, in this research study, an approach for the joint evaluation of financial and stock control policies has been proposed. This proposed model is a global system performance template which aligns total relevant inventory cost with associated costs incurred due to the inventory operational impacts on the financial performance metric such as the working capital level. The approach has been tested on real retail chains dealing with perishable products, uncertain demand and supply variability (objective 3).

8.4.2 Managerial Implications

Evaluation of forecasting methods has been traditionally carried out majorly with the use of statistical forecast error measure models and sometimes with inadequate and less than robust financial metric models (see for example, Catt, 2007). The statistical forecast error measures provide a poor indication of the real costs and consequences resulting from forecasts. And this has continued to create huge challenge for managers in the manufacturing and retail sector organisations because it is preventing them from being able to assess the true costs and financial impacts of forecast errors generated by their forecast techniques (Goodwin, 2009; Tiacci and Saetta, 2009). Besides, the various traditional operational as well as financial models that have been put forward in the literature (see for example, Flores et al, 1993; Catt, 2007) as possible solutions to the problem have been developed under particularly restrictive assumptions. Nevertheless, it is quite essential to help enhance managers' understanding of and let them gain better insights into the actual economic impact as it affects the modern-day retail chain businesses in real terms. This must be achieved with a fit for purpose model that not only accounts for reality in practice, but one that also leads away from the inevitable loss of performance as it is obtainable with the current traditional model (thesis section 6.11.5). Therefore, taken together, the overall thesis study aim offers more empirically based insights into the relative roles (objective 1) and importance of different *performance criteria* (objectives 1, 2 and 3) across two retail business functional areas (operations and finance). The adaptation of the traditional costing technique, both to overcome these obstacles and to leverage, in the best way, the new possibilities granted, can be of paramount importance for the retail chains.

The motives for the selection of the performance variable metrics utilised for this research study are based on both their managerial implications and evidence-driven policy (objectives 1, 2 and 3). Evidence from credible research studies such as Deloitte (2019) and Brealey et al (2012) support the fact that working capital, free cash flow and stock turn (or inventory turnover) are key liquidity data points of note for retail chains. According to these and many other relevant studies (for example, Farris et al, 2010), while comprehending cash flow is crucial to retail managers, working capital gives a retail business key information regarding the firm's ability to service short-term debts and inventory turnover ratio helps managers of retail firms get a good image of how quickly inventory is sold at current sales levels, and are even availed the opportunity of looking for trends when comparing this ratio over different time periods. Deloitte (2019) has described capital deployment and cash flow management as crucial aspects of business performance for the current day retail industry. The study argues that these measures can help "*focus on what is controllable by the business, operationally relevant, and drives performance. Retail business leaders at all levels can see how their decisions have an impact on these important metrics, and industry analysts can pay more* *attention to the areas that have an impact on performance, value, and organizational health*". Retail inventory managers wish to be able to produce better forecasts for various sizes of data series and for various lapses of time both to meet certain service targets as well as to avert stockover and stockouts. The increased levels of detail subjected by these issues poses challenges (including contextual costs implication realities) for managers and practitioners, especially when they operate on multiple different levels of the business (Fildes et al, 2019). The results of this research study can enhance our understanding of how to implement mitigating inventory costs and revenue risks policies in practice (objectives 1 and 2) and should enrich the understanding, for the top supply chain business managers as well as relevant operational and financial managers at various levels within the retail chain firms, of the actual economic costs implications of forecast errors based on company contexts as well as on the forecasting strategies employed. And in particular, those managers with little or no statistical background are provided with better insights, through the proposed models, of the financial implications of statistical forecast error measures (objectives 1, 2 and 3).

8.5 Conclusions

Because one of the dominant objectives of science or statistics is to comprehend how systems and processes work rather than just to establish whether a total effect occurs and its size, techniques of quantifying and making inferences concerning indirect effects in causal models are common in the theoretical and applied statistical methods literatures. Investigations of this kind are especially valuable in mitigating risks including costs and customer risks for retail chain organisations. The current study considers the problem of managing an inventory system consisting of perishable products whose quality deteriorates over time and under financial constraint. Inventory management and control operations and its finance in terms of inventory investment under the working capital management are two topics that have been widely studied in the literature (see for example, Bendavid et al, 2017). However, according to the same authors, traditionally, these two functional areas of the retail chain organisations are explicitly considered separately, supposing that there are no interactions between them. In other words, the stock control system is studied independently of the financial system, and it is assumed that both systems have been properly modelled. Importantly, the interactions that may exist between inventory control system and working capital control system, in terms of their effects on global system performances, are not being considered.

In the current research study, an approach for evaluating these interactions is presented and assessed, based on multiple regression analysis and a comparative simulation-based optimisation test of global system costs using demand data from real retail chains in the United States of America (USA). Results of the simulation study and the empirical study show that the traditional statistical forecast error metrics cannot be considered as the only indicators for choosing between different demand forecasting models. Moreover, the results also show that the traditional inventory cost function cannot be taken as robust enough to evaluate the impacts of forecast error metrics on the global inventory control system under a firm's financial constraints. This study has also demonstrated that causal association between forecast accuracy and working capital level is mediated by inventory efficiency. It can, therefore, be reckoned from the findings of this study that optimal or better demand forecast accuracy might not only improve inventory turnover but could encourage or help enhance working capital management. The empirical data sets described in chapter 4 have been utilised to show that the moderation method is capable of helping inventory managers to identify interactions among many and competing key performance indicators, while the mediation approach can help to classify and estimate direct and indirect effects of forecast errors on working capital. And besides, it is important to note that when considered together with main effects of forecast error, working capital and free cash flow on the inventory turnover, then it fully explains the vicious cycle of effects and impacts on the productivity of the inventory management and control unit of a retail firm; and indeed, as well as on financial function.

This outcome supports the suggestion that a clear understanding of the anatomy of the role of forecast error and indeed of the financial performance metrics can be useful in the efforts of managers to improve and optimise revenue, return on investment and other business ratios for the retail organisations. In addition, this study offers empirically based insights as to the relative importance of different performance criteria used by inventory control managers as well as financial control managers to judge productivity and efficiency in their firms. Such information is clearly of relevance to a retail business when designing inventory as well as financial forecasting systems and staff training. For example, knowing that free cash flow is a major influence shaping operational efficiency for a given forecast error reduction, it could be used to justify the introduction of alternative working capital allowance strategy that may work better for the firm. Similarly, if a criterion like accuracy is found to be influenced through inventory control efficiency, alternative forecasting methods or the collection of better input data or both can be considered. Moreover, by identifying the *relative* importance of studied performance metrics, it becomes possible to set managerial preferences directly reflecting priorities for different inventory and financial performance criteria.

This study has demonstrated that forecast error is capable of impacting both the top-line sales revenue and bottom-line profit margin through its impact on working capital. This is important, not least because it reveals and quantifies further potential effects of forecast errors on business financial performances. The thesis portrays the potential capability to increase the harm working capital and other financial performance metrics (by extension) can come back to inflict on the inventory performance and ultimately on the bottom-line as well as on top-line through the indirect effect of forecast errors on them.

CHAPTER 9

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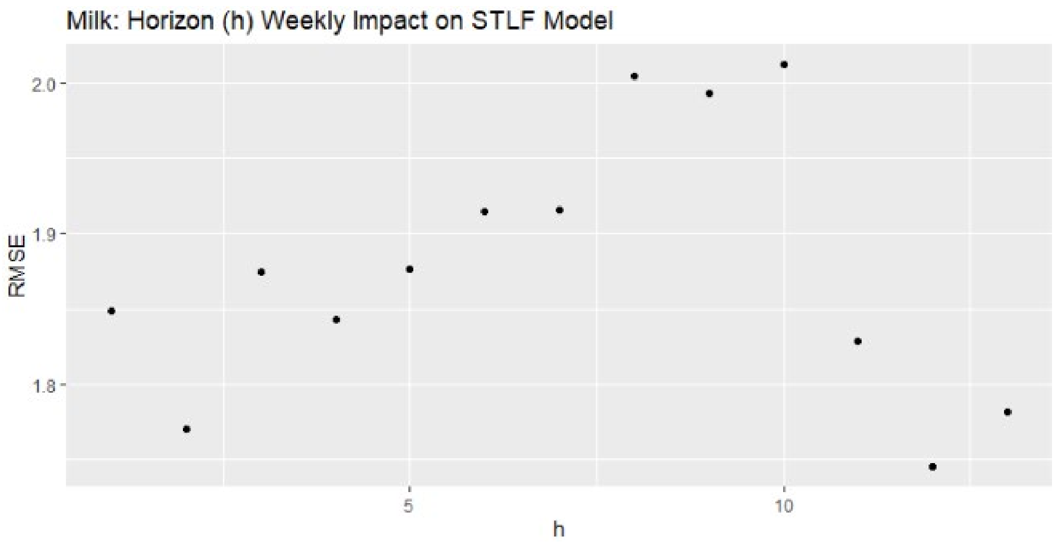
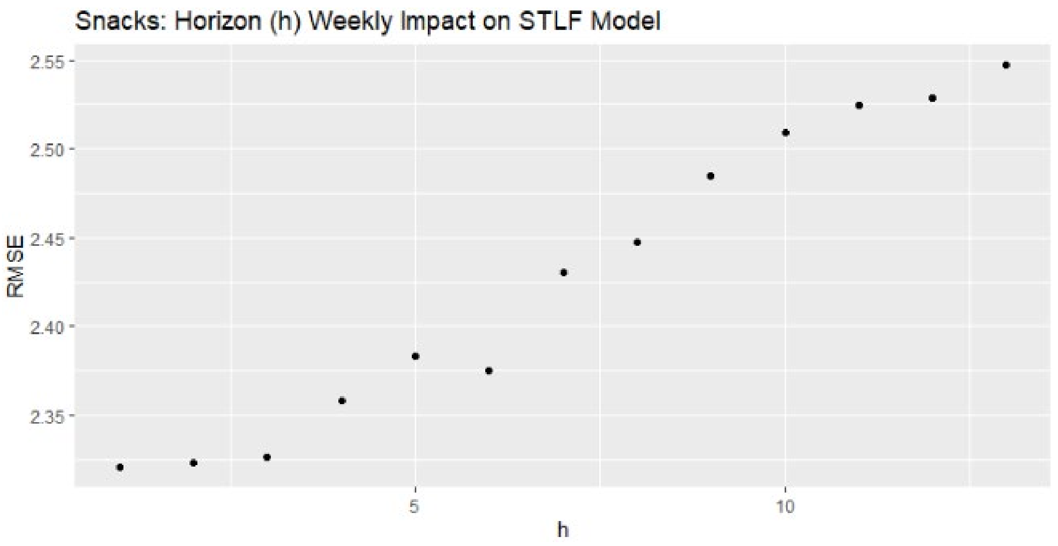
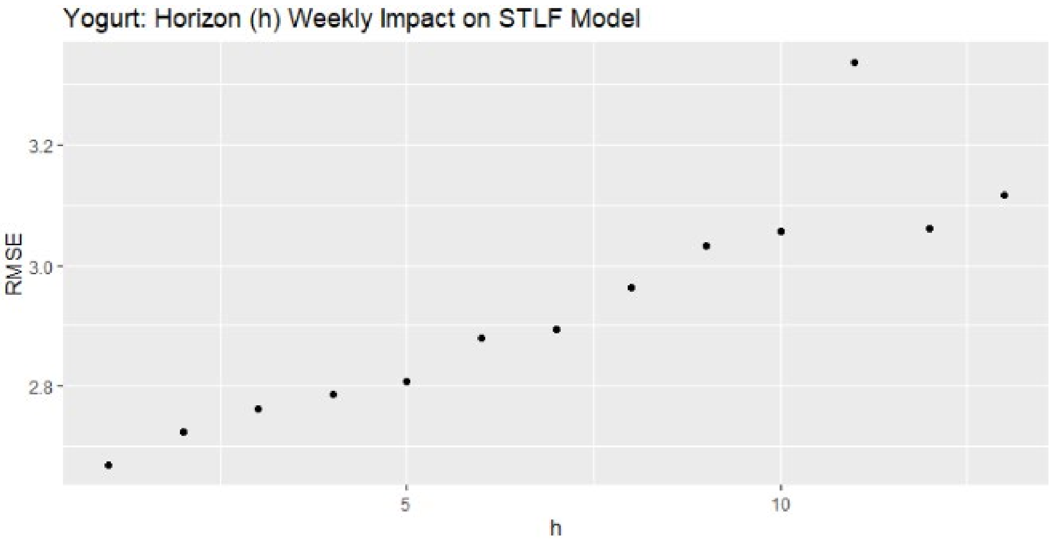
CHAPTER 10

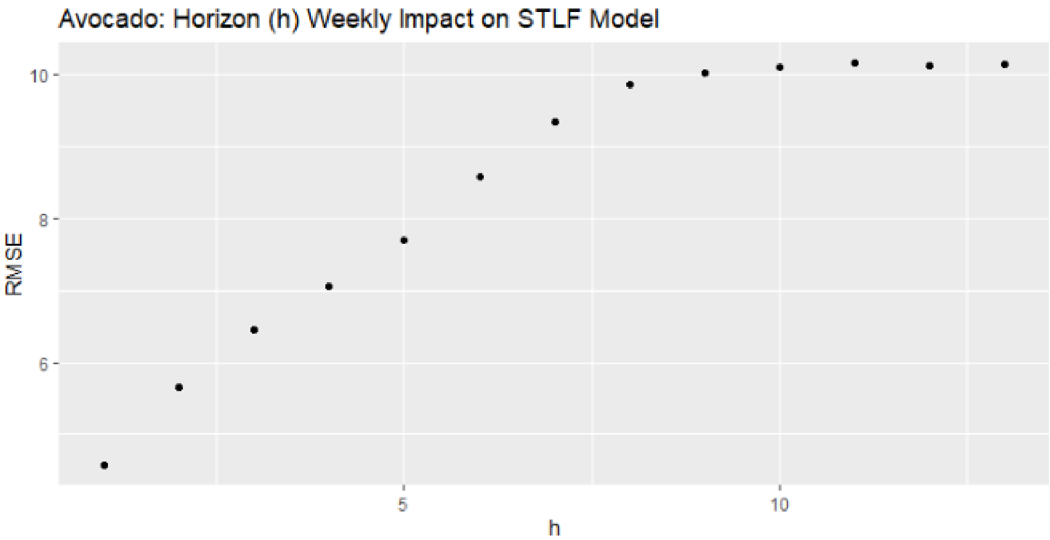
Appendices

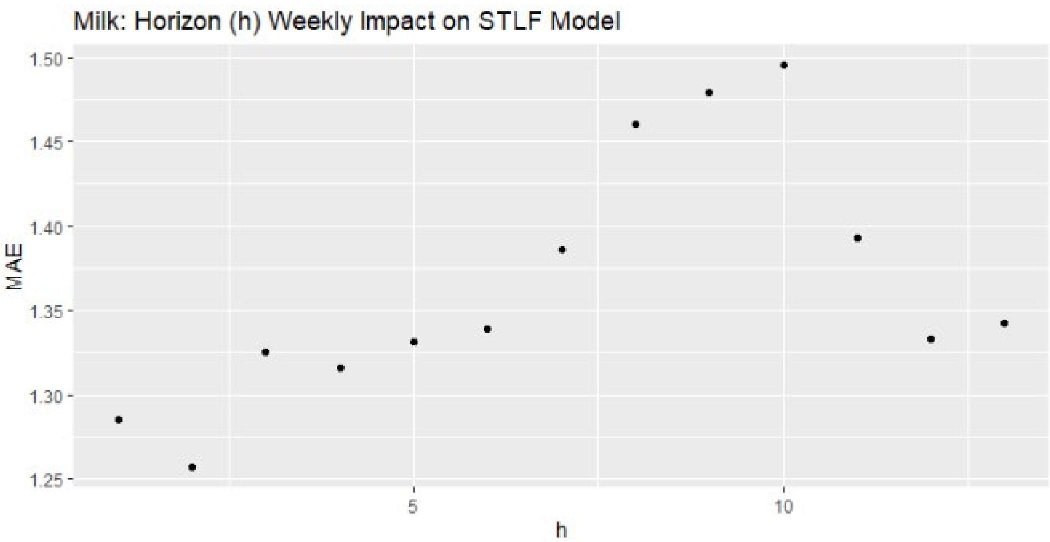
10.1 Appendix I: Horizon Impacts on Forecasting Methods (section 5.6.1.2)

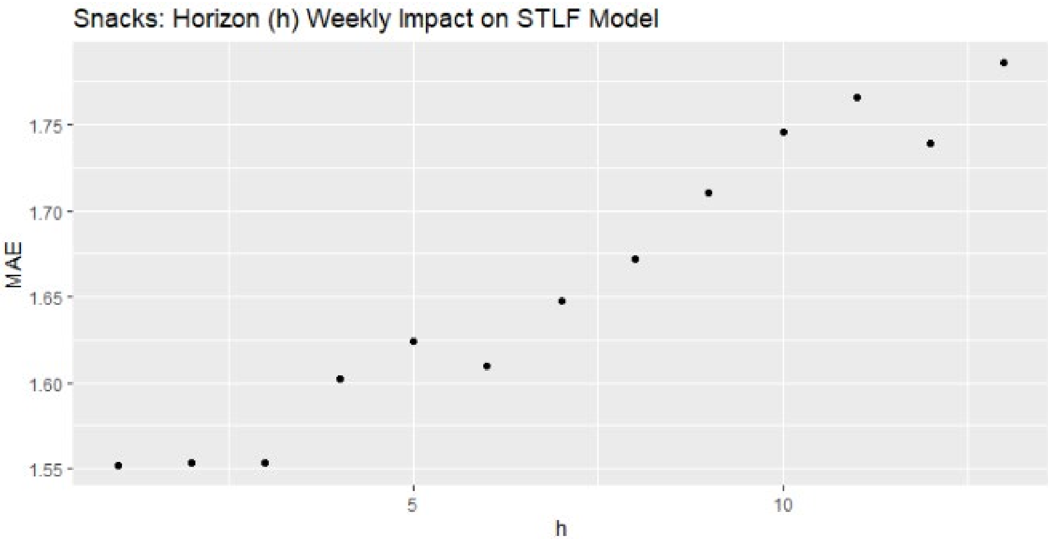




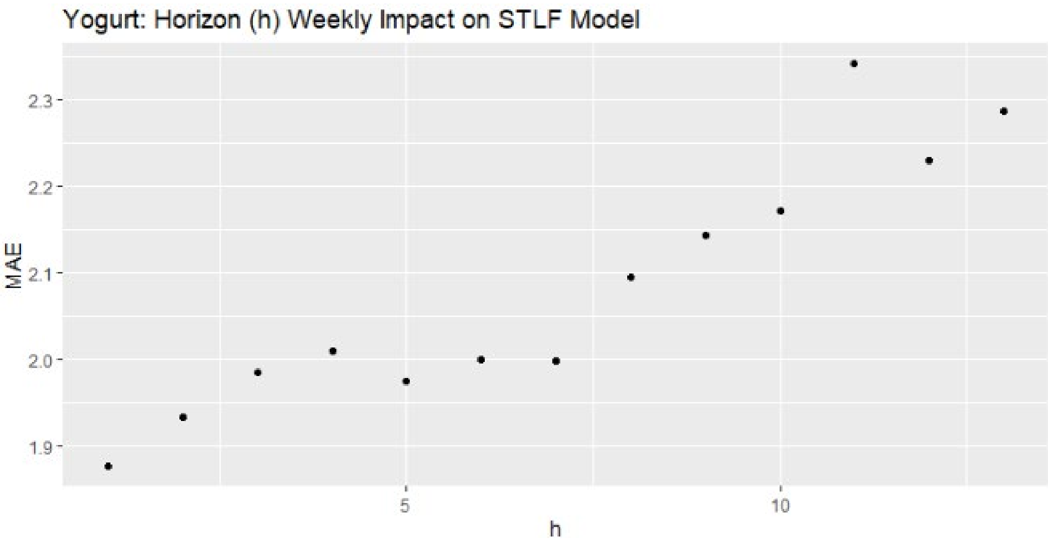

Yogurt: Horizon (h) Weekly Impact on STLF Model
RMSE
3.2
3.0
2.8
5
10
h


Avocado: Horizon (h) Weekly Impact on STLF Model
RMSE
10
8
6
5
10
h

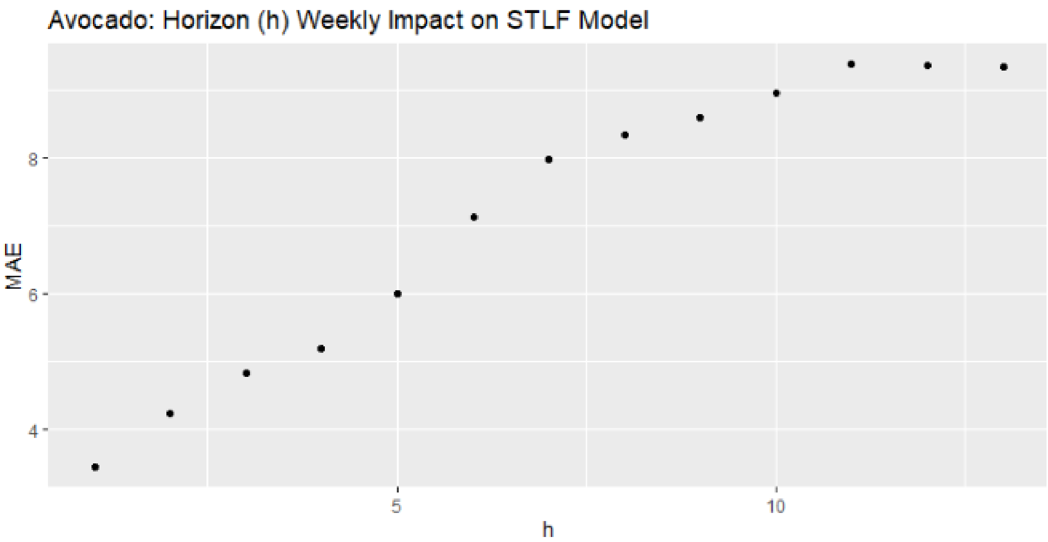

Milk: Horizon (h) Weekly Impact on STLF Model
MAE
1.50
1.45
1.40
1.35
1.30
1.25
5
10
h



Snacks: Horizon (h) Weekly Impact on STLF Model
MAE
1.75
1.70
1.65
1.60
1.55
5
10
h

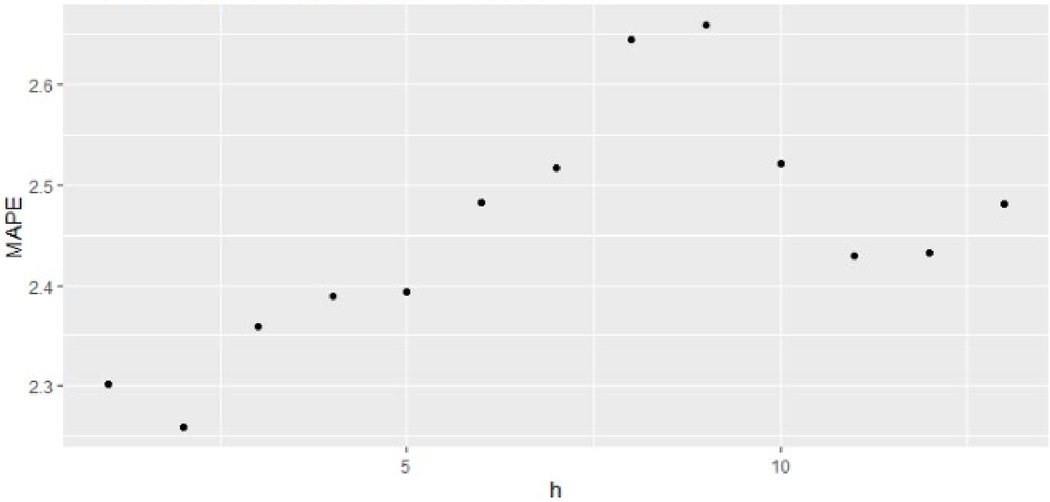


Yogurt: Horizon (h) Weekly Impact on STLF Model
MAE
2.3
2.2
2.1
2.0
1.9
5
10
h

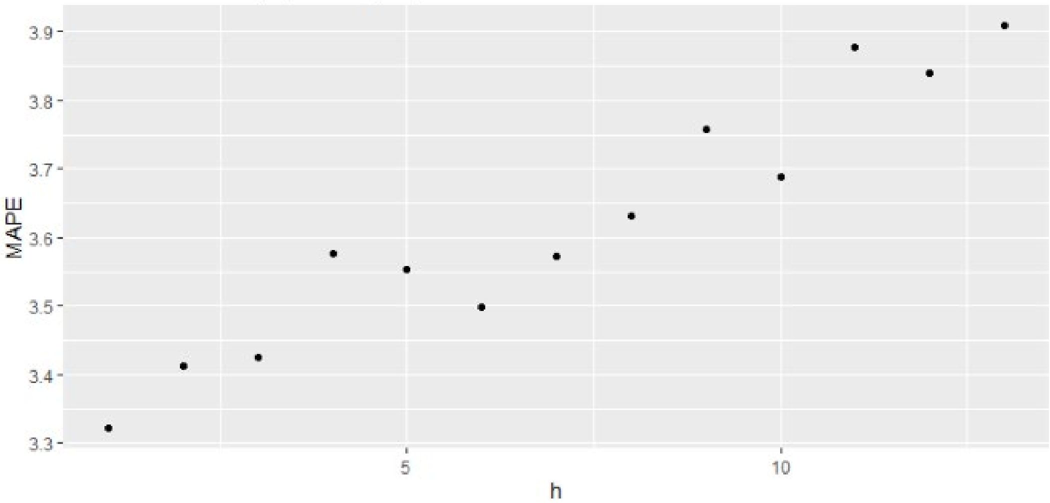


Avocado: Horizon (h) Weekly Impact on STLF Model
MAE
8
6
4
5
10
h

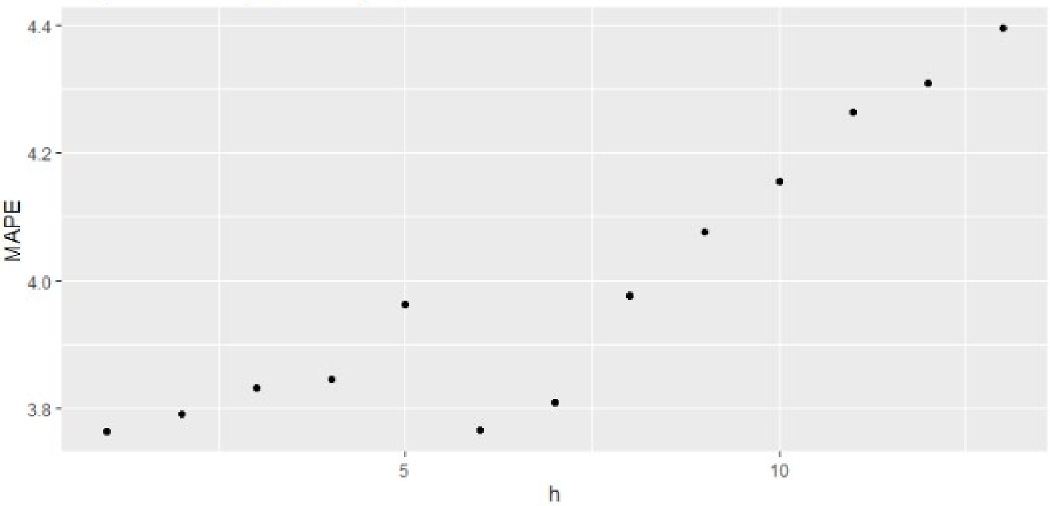
Milk: Horizon (h) Weekly Impact on STLF Model

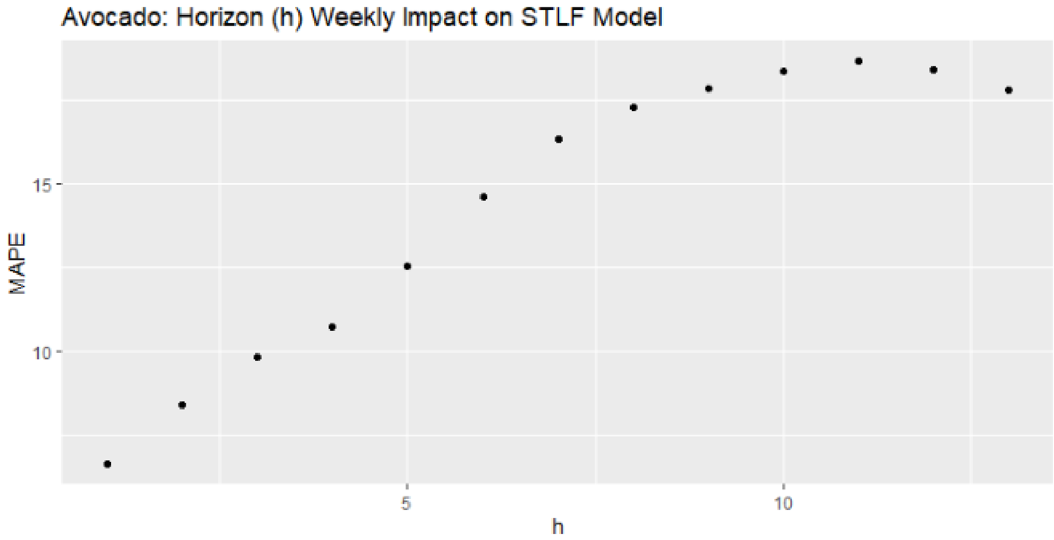


Snacks: Horizon (h) Weekly Impact on STLF Model

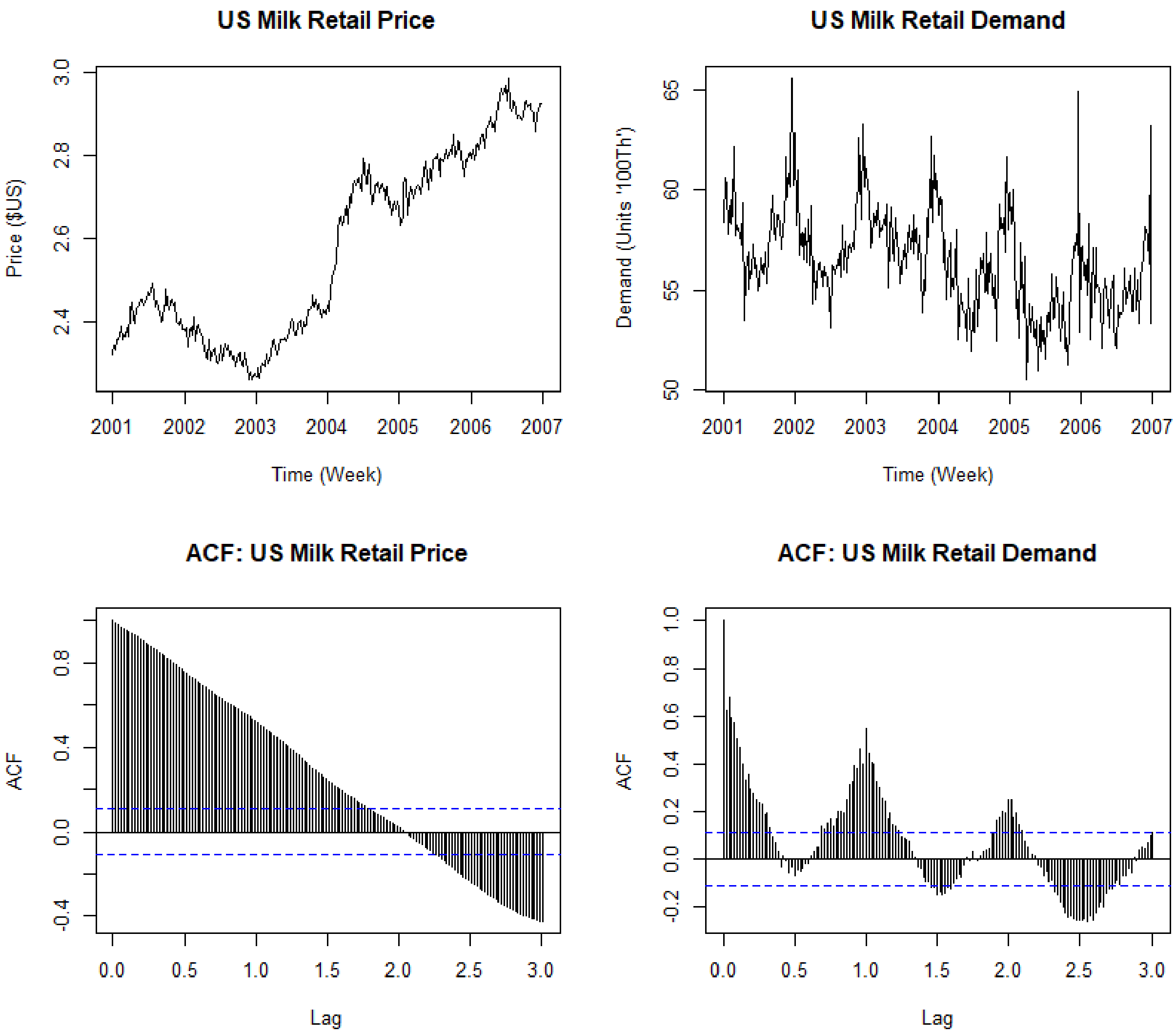


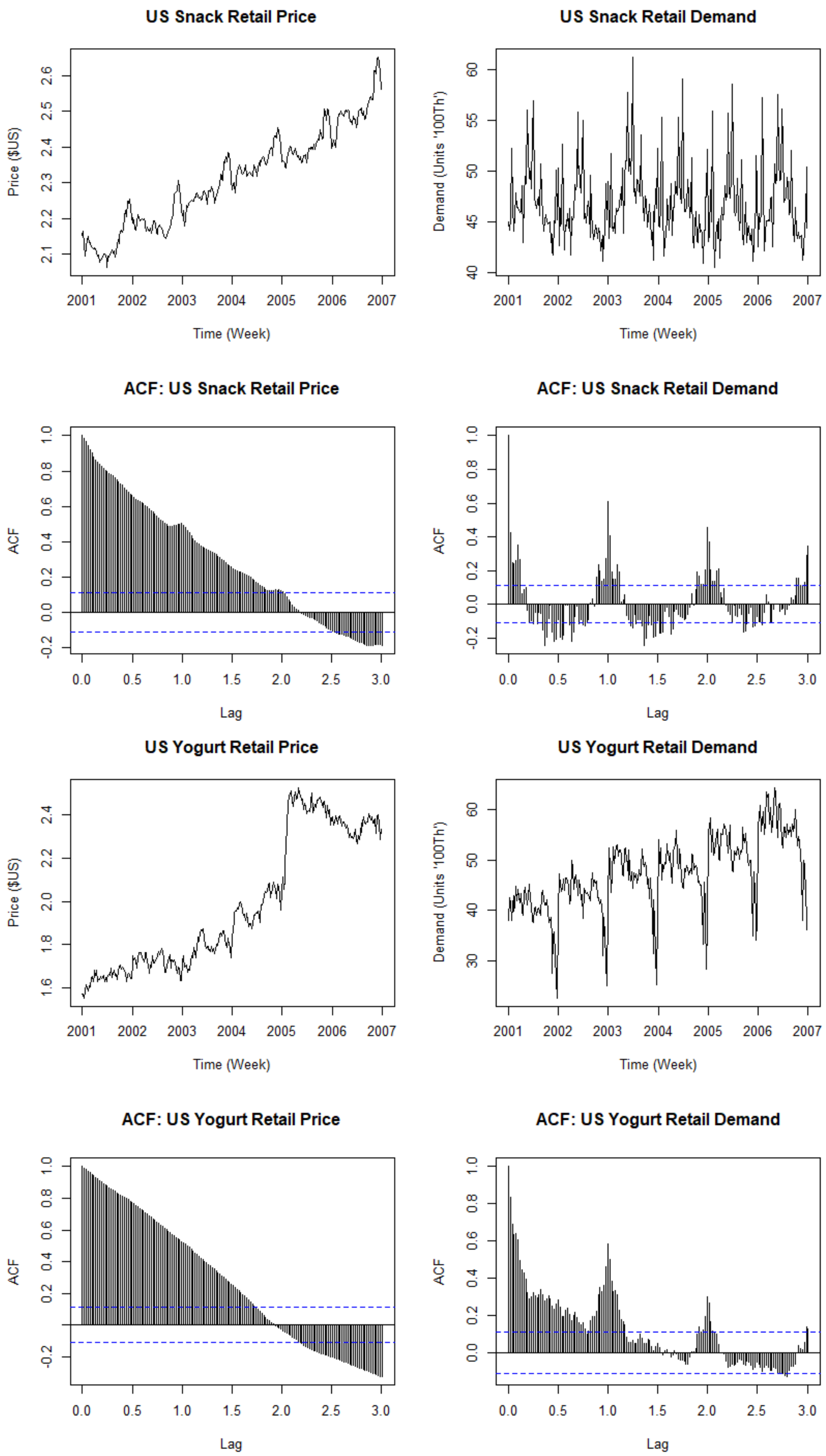
Yogurt: Horizon (h) Weekly Impact on STLF Model



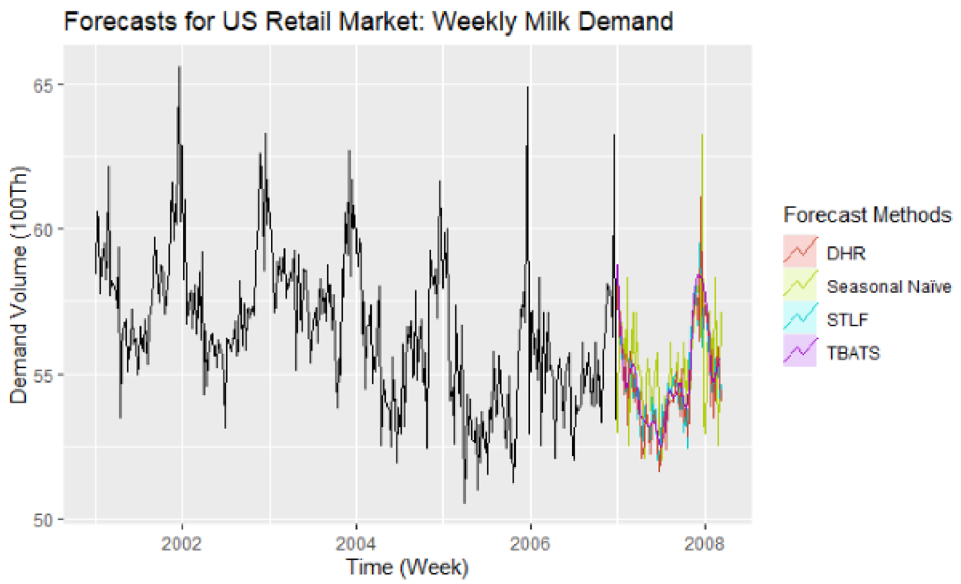

Avocado: Horizon (h) Weekly Impact on STLF Model
MAPE
15
10
5
10
h

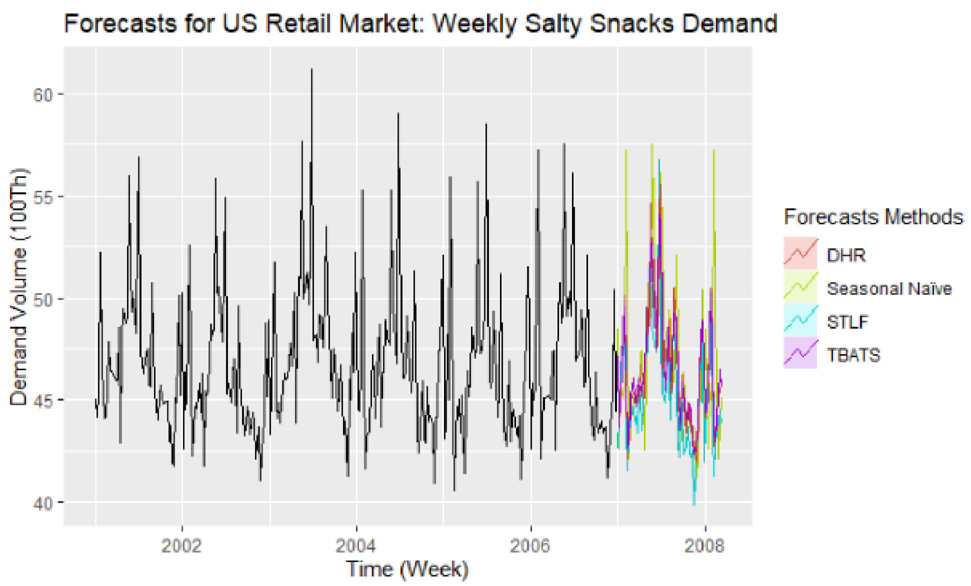
10.2 Appendix II: Exploratory Data Analysis (EDA section 5.6.3.1)

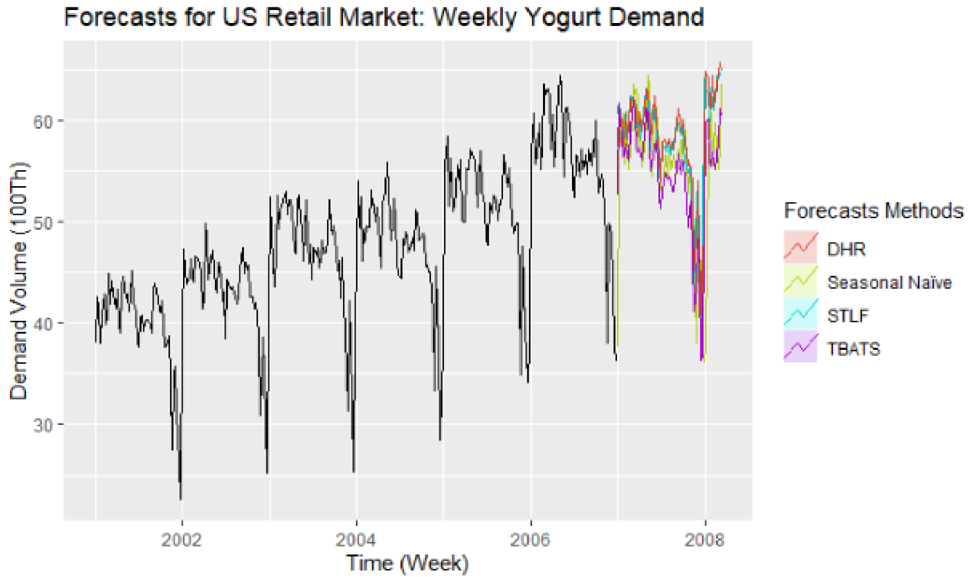


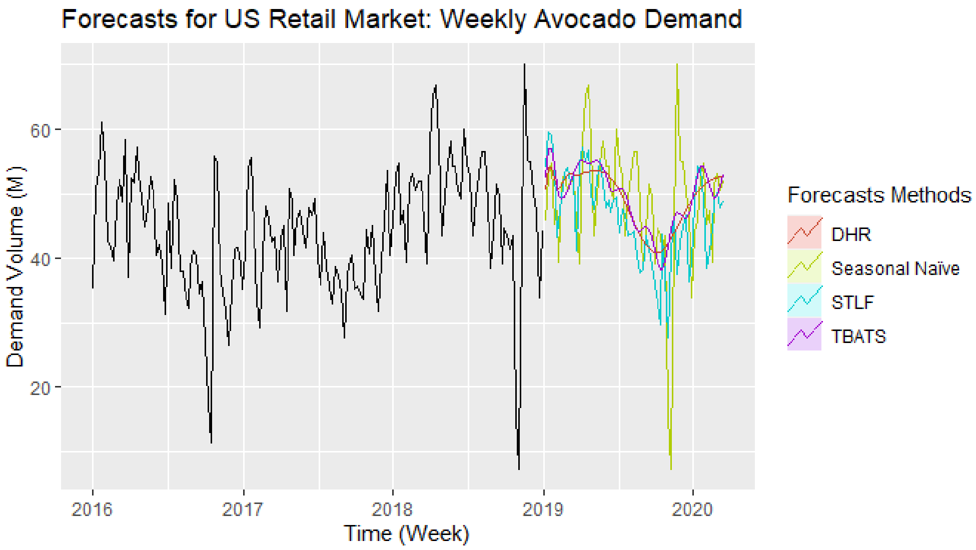

US Snack Retail Price
Price ($US)
Time (Week)
US Snack Retail Demand
Demand (Units '100Th')
Time (Week)
ACF: US Snack Retail Price
ACF
Lag
ACF: US Snack Retail Demand
ACF
Lag
US Yogurt Retail Price
Price ($US)
Time (Week)
US Yogurt Retail Demand
Demand (Units '100Th')
Time (Week)
ACF: US Yogurt Retail Price
ACF
Lag
ACF: US Yogurt Retail Demand
ACF
Lag

10.3 Appendix III: Forecasts for all four items (section 5.6.3.2)






Forecasts for US Retail Market: Weekly Yogurt Demand
Demand Volume (100Th)
60
50
40
30
2002
2004
2006
2008
Time (Week)
Forecasts Methods
DHR
Seasonal Naïve
STLF
TBATS


Forecasts for US Retail Market: Weekly Avocado Demand
Demand Volume (M)
60
40
20
2016
2017
2018
2019
2020
Time (Week)
Forecasts Methods
DHR
Seasonal Naïve
STLF
TBATS

10.4 Appendix IV: Empirical Analysis for Milk (section 5.8)


```
Call:
lm(formula = log(iTurnsmd) ~ FCFmd + WCLmd + RMSEmd + MAPEmd,
    data = myData3)

Residuals:
     Min       1Q   Median       3Q      Max 
-0.40205 -0.17089  0.01969  0.15583  0.42164 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) -6.84670    1.44465  -4.739 6.69e-05 ***
FCFmd        0.69224    0.35920   1.927   0.0649 .  
WCLmd        0.67686    0.09626   7.031 1.82e-07 ***
RMSEmd      -3.36163    0.95442  -3.522   0.0016 ** 
MAPEmd       1.74755    0.64564   2.707   0.0118 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2322 on 26 degrees of freedom
Multiple R-squared:  0.9133,	Adjusted R-squared:    0.9 
F-statistic:  68.5 on 4 and 26 DF,  p-value: 2.005e-13


ASSESSMENT OF THE LINEAR MODEL ASSUMPTIONS
USING THE GLOBAL TEST ON 4 DEGREES-OF-FREEDOM:
Level of Significance =  0.05 

Call:
 gvlma(x = Model1md) 

                    Value p-value                Decision
Global Stat        3.8417  0.4279 Assumptions acceptable.
Skewness           0.2303  0.6313 Assumptions acceptable.
Kurtosis           1.0364  0.3087 Assumptions acceptable.
Link Function      0.8525  0.3558 Assumptions acceptable.
Heteroscedasticity 1.7225  0.1894 Assumptions acceptable.
```

```
Main Effects Only Regression Results for Milk
===============================================
                        Dependent variable:
                    ---------------------------
                             Milk Model
-----------------------------------------------
FCFmd                         0.692*
                             (0.359)
WCLmd                        0.677***
                             (0.096)
RMSEmd                       -3.362***
                             (0.954)
MAPEmd                       1.748**
                             (0.646)
Constant                     -6.847***
                             (1.445)
-----------------------------------------------
Observations                    31
R2                            0.913
Adjusted R2                   0.900
Residual Std. Error      0.232 (df = 26)
F Statistic          68.495*** (df = 4; 26)
===============================================
Note:               *p<0.1; **p<0.05; ***p<0.01
```

```
Main Effects Only Regression Results for Milk
===============================================
                        Dependent variable:
                    ---------------------------
                             Milk Model
-----------------------------------------------
FCFmd                         0.692*
                         (-0.012, 1.396)
WCLmd                        0.677***
                          (0.488, 0.866)
RMSEmd                       -3.362***
                        (-5.232, -1.491)
MAPEmd                       1.748**
                          (0.482, 3.013)
Constant                     -6.847***
                        (-9.678, -4.015)
-----------------------------------------------
Observations                    31
R2                            0.913
Adjusted R2                   0.900
Residual Std. Error      0.232 (df = 26)
F Statistic          68.495*** (df = 4; 26)
===============================================
Note:               *p<0.1; **p<0.05; ***p<0.01
```

	Estimate	CI.Lower_BCa	CI.Upper_BCa
Indirect.Effect	3.2085526	2.3343166	4.8733143
Indirect.Effect.Partially.Standardized	4.3016462	3.0670933	6.0887339
Index.of.Mediation	0.4956310	0.3690510	0.6297575
R2_4.5	0.4766420	0.1695592	0.6837104
R2_4.6	0.2778260	0.1402828	0.3976303
R2_4.7	0.3393558	0.1740100	0.4464038
Ratio.of.Indirect.to.Total.Effect	0.6993974	0.4876719	0.9573751
Ratio.of.Indirect.to.Direct.Effect	2.3266516	0.7573619	11.7923071
Success.of.Surrogate.Endpoint	2.2338441	1.7514287	2.7753706
Residual.Based_Gamma	0.4306760	0.1899676	0.6032373
Residual.Based.Standardized_gamma	0.4061448	0.1795294	0.5656537
SOS	0.9491250	0.8727012	0.9964944