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# Analyzing impacts on backorders and ending inventory in MRP due to changes in lead-time, demand variability and safety stock levels

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**Analyzing impacts on backorders and ending inventory in MRP due to  
changes in lead-time, demand variability and safety stock levels**

by

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in partial fulfillment of the requirements for the degree of

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2008

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## Abstract

Global sourcing represents one of the major focuses in many industries as a means to lower costs. While global sourcing generally reduces per unit costs, the impact of global sourcing on total costs throughout the supply chain often remains unrecognized. Increased lead-time due to global sourcing represents one of the commonly unrecognized costs. Hence, the simulation model developed in this study demonstrates the impact of lead-time length and variation as well as variation in demand and safety stocks on the ending inventory and backorder levels in a two product MRP system. The results show that backorders grow at a diminishing rate as a function of lead-time while ending inventories show the opposite trend. In addition, the study shows that firms need to more carefully consider the impact of lead-time. The study demonstrates that lead-time, not just lead-time variability, represents a key cost factor.

## 1 – Introduction

Global sourcing represents one of the major focuses in many industries as a means to lower costs. According to total cost research discussed in Chapter 2, global sourcing generally reduces per unit costs, but the impact of global sourcing on total costs throughout the supply chain often remains unrecognized. In particular, costs such as purchase price and transportation are easily calculated and recorded. However, costs due to quality issues, reverse logistics and particularly increased lead-time often are unmonitored.

Costs associated with lead-time can be difficult to quantify. In general, as lead-time grows, so does lead-time variability, which negatively impacts forecast accuracy. As forecast accuracy worsens, end product and component backorders tend to increase. Moreover, low forecast accuracy tends to lead to increased system buffers in the form of inventory. The buffers due to increased lead-time come in the form of safety stock and increased batch size to achieve economies of scale and transportation. While the larger safety stocks and batch sizes keep companies at desired customer service levels, the inventory and related costs grow throughout the supply chain.

While some of the Total Cost of Ownership (TCO) literature discussed in Chapter 2 references the concept of lead-time costs, the actual quantification of the costs usually has been ignored. Hence, this research examines the impact of lead-time, lead-time variability and forecast accuracy on backorders and inventory levels throughout a two product MRP driven system. Specifically, the extensive literature search found in Chapter 2 reveals a void in research that quantifies lead-time and demand variability impacts and costs. In particular, very few research papers either in TCO or operations quantify the impacts of lead-time and stochastic demand in MRP systems. Hence, the model developed in this study demonstrates the impacts of lead-time length and variation as well as variation in demand and safety stocks on the ending inventory and backorder levels in a two product MRP system.

The study begins with a thorough search of literature (Chapter 2) on a range of studies from qualitative TCO through highly mathematical iterative optimization processes that determine lot sizing rules. In other words, the literature search includes a variety of papers that examine or optimize safety stocks, lot sizes, lead-times, inventory levels and more. However, few of the studies attempt to analyze results across multiple explanatory variables.



Chapter 3 presents the simulation model for the study. The simulation model discussion outlines the various assumptions and random distributions necessary to make a working MRP model. The structure of the MRP simulation provides a great variety of controllable parameters, which permit in-depth investigation of impacts on ending inventories and backorders for both end products and component parts/subassemblies. Chapter 3 provides details about the Bill of Materials (BOM) for the product structure, insight into the random distributions of lead-time and demand as well as details about the forecasting methodology and more.

Chapters 4, 5 and 6 present insights into the results of the simulation in intuitive terms. The various graphics offer direct, visual meaning behind the results of changing lead-time, safety stock and demand variability levels. In each Chapter, notes and conclusions give further details for the reader to grasp the meaning of the results.

Chapter 7 presents a detailed statistical analysis of the simulation's results. Chapter 7 breaks the statistical analysis into two parts. The first part examines the full model with all possible interaction terms. The second part examines only those factors and treatments that offered statistically significant changes to ending inventory and backorder levels.

Chapter 8 explores directions future research might lead as batch sizes, safety stock and lead-time variability levels change more dramatically than in the main experiment detailed in Chapters 4 through 7. The research concludes in Chapters 9 with overall findings and conclusions.

## 2 - Literature Review

This research began with a search of various Total Cost of Ownership (TCO) studies as well as other related works on similar topics, such as demand variability, lead-time variability, optimal lead-time policies and optimal inventory policies. The literature search revealed a void in research that quantifies lead-time and demand variability impacts and costs. Hence, the simulation model developed in this study demonstrates the impact of lead-time and lead-time variability as well as demand variation on the overall inventory levels as well as backorders in an MRP system. As with all studies, the assumptions of the research often dictate the general validity of the study to industry. In this study, the goal of the MRP model is to remain both tractable and valid by allowing the parameters to vary in ways that mimic real industry without excessive assumption sets. In particular, this study integrates ending inventories and backorders in MRP under various lead-time levels with differing levels of demand variability and safety stock. The results from the study reveal that global sourcing and associated long lead-times lead to ever increasing levels of inventory and backorders.

### 2.1 - Total Cost of Ownership and Lead-Time

Early TCO articles, mostly authored or co-authored by Ellram, discuss detailed conceptual TCO frameworks with little quantitative analysis (Ellram L. 1993, Ellram L. M. 1994, Ellram & Siferd 1998). Ellram (1993) focuses on using TCO to analyze supplier development (pre-transaction), purchase considerations (transaction) and supplier/material defect (post-transaction) impacts (Ellram L. , 1993). While not a part of the current research, future research will integrate the impacts of material defects. In their 1998 article, Ellram and Siferd discuss ways companies use TCO as a link to strategic cost management (Ellram & Siferd, 1998). According to the article, 73% of companies included in the case study used TCO to analyze purchases of components while 55% of companies used TCO to make raw material purchases. The article also notes the link between TCO and quality focus in 91% of the case study firms as well as use of best value (cost reduction overall) items in 82% of firms. In other words, the components and raw materials in the BOM often represent areas of focus in TCO. Unfortunately, the article does not discuss metrics to assess costs of the components or raw materials.

Relatively recent TCO articles focus on offshore sourcing and the added costs of increased lead-times. Ferrin and Plank's TCO research tries to incorporate lead-time as a cost driver but does

not indicate how lead-times impact costs, merely that costs will go up as a function of lead-time (Ferrin & Plank, 2002). Ferrin and Plank also include a large number of other cost drivers, such as purchase price, shipping, transportation and quality costs with some indication of the impact of each on the overall costs within a system. Mary Harding and Michael Harding attempt to make lead-time cost rules of thumb, such as simple percent multipliers based on total lead-time (Harding M. L. 2001, Harding M. 2007).

Most TCO articles note the common costs associated with manufacturing, such as purchase price, transportation costs and related overhead. Some of the more recent articles such as Ferrin et al. (2002) list many more cost drivers including quality, reverse logistics, lead-time, on-time delivery, storage and more. While TCO literature extensively investigates potential costs, few of the papers attempt to give metrics to quantify those costs. Thus, this research examines the impact of lead-time and lead-time variability in combination with demand variability and safety stocks on backorders and inventory levels as a step toward understanding cost structures. As already noted, this research is of particular use for firms considering long lead-time global sourcing strategies.

## **2.2 - Demand and Lead-Time Variability Studies**

A number of studies examine the impact of lead-time and demand variability. One of the earliest works in the field appeared in 1976. Whybark et al. attempt to investigate and categorize uncertainty in MRP systems (Whybark & Williams, 1976). The authors assert that timing uncertainty requires safety lead-time while quantity uncertainty requires safety stock. Future works affirm much of the early work by Whybark and Williams. For example, Maloni et al. investigate the need for special planning methods under stochastic lead-times (Maloni & Benton, 1997). In effect, lead-time variability comprises one of reasons manufacturers hold safety stock. Hence, much research attempts to understand and quantify the relationship of lead-time variability with safety stock. A later work by De Bodt et al. also confirms that safety stock represents an effective tool to manage variation in production planning and scheduling as well as maintenance of customer service levels (DeBodt & Wassenhove, 2001).

Other studies investigate the impact of external demand variability (end-product demand) as a random variable. Grubbstrom et al. discover that proper buffering requires correctly dimensioned safety stocks for the master production schedule (MPS) (Grubbstrom & Molinder, 1996). Enns notes the impact of batch size on utilization levels while moving down the Bill of

Materials (BOM) under known lead-times (Enns, 1999). Enns finds that appropriate batch sizes can lead to low work-in-process (WIP) inventory and low tardiness as well as consistent throughput given a known lead-time. Enns' later 2002 article demonstrates that performance effects due to forecast bias and demand uncertainty impact the MPS and delivery performance quite differently (Enns, 2002). Enns contends that increasing planned lead-time or safety stock will improve delivery performance [metrics] depending on the nature of the tardiness. Enns further contends that forecast bias offers no benefit over the use of safety stock. Talluri et al. discuss setting safety stock levels using well established functions based on variable demand and variable lead-time at a case study firm (Talluri, Cetin, & Gardner, 2004). Holsenback et al. employ the same well established formulas in their 2007 article on safety stock as a function of variable lead-time and demand (Holsenback & McGill, 2007).

Interestingly, demand variability is often assumed to follow a normal distribution. Benton (1991) and Vollmann et al. (2005) are only a few examples (Vollmann, Berry, Whybark, & Jacobs 2005, Benton 1991). Eppen and Martin test the normality assumption by examining two safety stock determination models with demand and lead-time as unknown, random parameters that must be estimated (Eppen & Martin, 1988). The model uses exponential smoothing for demand forecasts. From the exponential smoothing model, Eppen and Martin test for normality of the errors and find that for long periods of lead-time ( $j=5$  or  $10$ ), the normality of error assumption is not always valid when demand across periods is correlated. When the demands are roughly stationary, the normality assumption appears reasonable with five or more lead-time periods. Moreover, Eppen and Martin's experimental data shows that forecast error appears to grow as the period's lead-time increases. The research in this paper uses stationary demand with a modified exponential smoothing forecasting method (see Section 3.5).

Also, several MRP specific articles investigate safety stocks as a function of lead-times and batch/lot-sizes. One of the early and often cited works by Karmarkar notes that manufacturing lead-times depend on lot sizes as well as utilization levels (Karmarkar, 1987). An earlier work by Gupta et al. investigates the impacts of product structure, lot-sizes, position in the BOM as well as lead-time uncertainty and lead-time bias (Gupta & Brennan, 1995). The authors find that costs tend to increase as the lead-time uncertainty bias factors increase. The study also notes that uncertainty applied at high levels of the BOM has the greatest cost impact. In their 1996 paper, Zijm and Buitenhok discuss the need to integrate lead-time and capacity management in MRP systems (Zijm

& Buitenhek, 1996). In a comprehensive research paper, Koh et al. find that appropriate safety stocks, lot-sizes and rescheduling provide the best means to cope with uncertainty (Koh, Saad, & Jones, 2002). Koh et al. categorize and investigate a wide array of uncertainty sources and further categorize the research that attempts to harness or understand the uncertainty. In a 2004 article, Koh finds that unexpected lead-time increases (late delivery from suppliers) can have significant impacts throughout the BOM, which is known to cause high inventory and system costs (Koh, 2004). In addition, Koh finds that delays in a resource can ripple through the MRP system and delay all batches held in queue, which increases inventory and system costs further—a finding verified in this research. Jonsson and Mattsson discuss the need for analytically based safety stock levels in MRP (Jonsson & Mattsson, 2008). The article's survey data of PLAN companies (an affiliate of APICS) also shows that among manufacturing companies, daily regeneration MRP and reorder point systems remain the most popular inventory management systems for purchased inventory. Specifically, 61% of manufacturers used MRP for parts inventory while 63% used MRP for semi-finished items inventory. Curiously, 27% of the respondents even used MRP for distribution functions. Most importantly, Jonsson and Mattsson find that lead-time accuracy and safety stock levels are the most critical parameters for overall MRP performance. The research in this paper shows that extending lead-times for materials only compounds the manufacturing lead-time increases as well as the commensurate inventory increases.

Further studies try to quantify the penalties of shortened lead-times. Das et al. (discussed below) find that suppliers attempt to charge a higher unit price for the small lot-size, short lead-time orders (Das & Abdel-Malek, 2003). Chandra et al. argue similarly that while shortened lead-times allow a reduction of safety stock, procurement costs may increase due to increased demands on suppliers as well as increased transportation costs (expedited transportation) (Chandra & Grabis, 2008). The question of procurement costs will not be a part of the current research but may be a consideration for future research.

Demand variability and lead-time articles offer an enormous depth of research potential as seen in the myriad of articles cited above. The research in this paper picks up on the theme of understanding and harnessing knowledge about demand variability, lead-time and particularly lead-time variability. None of the previous works have integrated the idea of long lead-times in conjunction with demand variability on the backorders and ending inventories within an MRP system.

### 2.3 - Resilience, Flexibility and Lengthening Supply Chain Lead-Times

Long supply chains lead to both greater complexity and increased variability (Christopher & Peck, 2004). Christopher and Peck also assert that in-bound lead-times represent a major key for supply chain velocity as well as supplier selection. Moreover, added complexity and variability become particularly large problems when companies make decisions in isolation due to forecast rather than demand driven systems. The Christopher and Peck article also discusses the need to build a resilient supply chain that can help mitigate such risks.

Resilience can come in many forms. One often noted form is redundant or reserve suppliers, some of whom are close to the final manufacturing site or point of sale (Chopra & Sodhi, 2004). Chopra and Sodhi specifically cite Cisco Systems' use of slow, overseas suppliers for items that are fast-moving, standardized and low risk. For slower-moving, non-standardized, high risk items, Cisco uses more expensive local suppliers to achieve greater flexibility. In partial contrast, Berger and Zeng argue that better communication and stronger ties can lead to lower risk as well as more stability in the supply chain, even in the case of single sourcing or limited supplier sourcing (Berger & Zeng, 2006). Their paper goes on to model the impacts of supplier disruptions, the operating costs of multiple suppliers and the commensurate financial loss caused by all suppliers' being down. Unfortunately, the research does not identify the potential downsides of increasing lead-times even when those long lead-times are known. While integration of supply chain risk and associated probabilities of the risks are beyond the current research, future research may benefit from modeling some risk factors.

Supply chain flexibility and agility appear to tie in well with lead-time evaluation. Sharifi et al. propose that increased speed (reduced lead-time) directly improves agility (Sharifi & Zhang, 1999). Other early papers on supply chain flexibility with regard to procurement often focus on the importance of relationships between buyers and suppliers (Narasimhan, Jayram, & Carter, 2001). Another early work by Svensson argues both qualitatively and quantitatively that outsourcing appears to increase inbound material flow disruptions and related risks, both of which hurt agility (Svensson, 2001). Later papers, such as Das et al., discuss the concept of flexibility in fixed order quantity and variable lead-time supply chains (Das & Abdel-Malek, 2003). Das et al. state that order

quantities (lot-size) and lead-time tend to cause the most supply chain conflict due to a buyer's ever decreasing lead-time and smaller lot-size orders to accommodate demand variability. Moreover, the article models and defines flexibility as the ability of firms in the supply chain to mitigate procurement price increases and penalties under adverse conditions. Manzini et al. discuss the benefits of added flexibility in the supply chain to handle capability variation (product mix) and capacity variation (demand levels) in multi-cellular manufacturing systems (Manzini, Persona, & Regattieri, 2006).

Verma studies the impacts on supply chain agility in a base stock model with stochastic demand and fixed replenishment lead-time (Verma, 2006). Finally, in what may become a seminal piece in defining supply chain flexibility and agility, Swafford et al. tie the concept of flexibility and agility into multiple dimensions including procurement, manufacturing, distribution and overall supply chain adaptability (Swafford, Ghosh, & Murthy, 2006). Swafford et al. further assert that more stable lead-times could allow greater customer responsiveness.

The current study shows that increasing lead-times lead to significant increases in backorders and ending inventory, two areas that flexibility and agility try to minimize. Moreover, the findings show that increased lead-time can negatively impact a company's ability to meet customer needs. If a company also faces the potential of significant disruptions beyond the simple demand and lead-time variability investigated in this study, the results could be quite negative for overall supply chain resilience.

## **2.4 - Optimization Studies under Demand and Lead-Time Variability**

Several previous research papers focus on optimizing lead-time and safety stock. Each optimization model makes varying degrees of limiting assumptions. In a paper similar to this study, Molinder investigates optimal lot-sizes, safety stocks and lead-times (Molinder, 1997). More specifically, Molinder employs design of experiments to define various treatment levels based on stochastic demand and lead-time to evaluate the impact on optimal lot-sizes, safety stocks and safety lead-times. The study uses twelve treatment levels to investigate the impact of stochastic demand and lead-times. The stochastic impact is dramatically lessened by choosing predetermined factor/treatment combinations. Molinder also attempts to balance stockout costs with inventory holding costs. Grubbstrom et al. create one of the more broadly valid models using Laplace

transforms with Gamma distributions to make safety stock decisions (Grubbstrom & Tang, 1999). Their research shows that optimal safety stock levels tend to drop with reduced variance levels.

An early article by Yano attempts to optimize lead-time directly in a limited structure two-level subassembly system (Yano, 1987). Chu et al. also investigate and propose an iterative algorithm to minimize holding costs and backlogging costs under lead-time variability (Chu, Proth, & Xie, 1993). Other researchers investigate use of Markov models in limited contexts to achieve optimal lead-times to minimize backlogging and holding costs (Dolgui & Olud-Louly, 2002). Dolgui et al. note that the assumption set required for modeling makes validity of the Markov model for industry somewhat questionable. A much later work by Persona investigates super BOMs, modular product design and safety stock as means to control the forecasts and forecast errors (Persona, 2007). Persona demonstrates the efficacy of the model in both make-to-order (MTO) and assemble-to-order (ATO) contexts. The article also formulates a total cost of safety stock and demonstrates the potential safety stock as well as logistics cost reductions in two industrial case studies. While each of these works focuses more heavily on optimization than the current research, the field of research into understanding and controlling lead-time and lead-time variability remains quite active. Unfortunately, as Dolgui et al. note, the assumption sets to make inference can be somewhat restrictive. Hence, as already noted, the current research tries to maintain a minimal assumption set for modeling purposes.

In a loosely related paper, Sounderpandian et al. investigate optimization of order quantities under long lead-times and uncertainty in finished good demands (Sounderpandian, Prasad, & Madan, 2008). The optimization technique involves linear programming along with genetic algorithms and stochastic optimization to determine optimal order quantities. The paper demonstrates the model efficacy with an example application in the plywood industry. Sounderpandian et al. stress the impact of long lead-times within the supplier's intra-country supply chain as well as the lead-times to move the product down the chain. Moreover, the authors note that risk of loss and commensurate supply uncertainties are also higher in the developing nations.

## **2.5 - Ties to Strategic Sourcing**

In an early work, Ellram and Carr argue that for true strategic sourcing, purchasers must take an active rather than passive role in controlling material flows (Ellram & Carr, 1994). In effect, Ellram and Carr argue that strategic purchasing should incorporate purchasing departments at high



level, strategic decision points. Other related articles discuss sourcing decisions for vertical integration versus outsourcing of production under differing forms of uncertainty (Kouvelis & Milner, 2002). Talluri and Narasimhan note that firms that engage in strategic sourcing must focus on supplier capabilities such as management practices, process capabilities and more as opposed to simple metrics such as cost (Talluri & Narasimhan, 2004). In other words, though taking inventory costs as a function of lead-time and demand variability can be very useful for defining and understanding costs, strategic issues beyond costs must also be considered.

## 2.6 - Summary of Articles

A chronological summary of the articles cited above appears in table 2.6.1.

**Table 2.6.1: Summary of Cited Articles**

<b>Lead-time and Demand Variability</b>	<b>Topic</b>
Chandra and Grabis, 2008	Supplier penalties for short lead-times
Jons son and Mattsson, 2008	Criticality of analytically based safety stocks
Holsenback and McGill, 2007	Applications of established safety stock formulas
Koh, 2004	Ripple effect of material delays through the BOM
Talluri, Cetin and Gardner, 2004	Applications of established safety stock formulas
Enns, 2002	Forecast bias and demand uncertainty impact MPS
Koh, Saad and Jones, 2002	Best buffers to handle uncertainty
DeBodt and Wassenhove, 2001	Safety stock to manage planning, scheduling & service
Enns, 1999	Batch size impact on utilization through the BOM
Maloni and Benton, 1997	Planning needs to accommodate variability
Grubbstrom and Molinder, 1996	Proper safety stock buffering in the MPS
Zijm and Buitenhek, 1996	Integration of lead-time and capacity management
Gupta and Brennan, 1995	MRP cost impacts due to variability and BOM position
Benton, 1991	Safety stock levels with normally distributed demand
Eppen and Martin, 1988	Safety stock levels & normality of forecast error
Karmarkar, 1987	Lot size impacts on lead-time
Whybark and Williams, 1976	Early work in MRP uncertainty buffers
<b>Optimization Studies Related to Lead-time and Demand Variability</b>	<b>Topic</b>
Sounderpandian, Prasad, & Madan, 2008	Optimal order quantity in developing nations
Persona, 2007	Optimizing safety stocks with the SBOM and modularity
Dolgui and Olud-Louly, 2002	Markov models to reduce holding and backlog costs
Grubbstrom and Tang, 1999	Reduced variance leads to lower safety stock levels
Molinder, 1997	Optimizing lot-size, lead-time and safety stocks

Chu, Proth and Xie, 1993 Yano, 1987	Optimization of costs under lead-time variability Optimal lead-times in two-level subassemblies
<b>Resilience, Flexibility and Lengthening Supply Chain Lead-Times</b> Berger and Zeng, 2006 Manzini, Persona and Regattieri, 2006 Swafford, Ghosh and Murthy, 2006 Verma, 2006 Christopher and Peck, 2004 Chopra and Sodhi, 2004 Das and Abdel-Malek, 2003 Narasimhan, Jayram and Carter, 2001 Svensson, 2001 Sharifi and Zhang, 1999	<b>Topic</b>  Optimizing number of suppliers SC flexibility to handle capacity and capability variance Defining flexibility and agility in the supply chain Supply chain agility in the face of variability Resilience and dangers of longer supply chains Supply chain risks and industry reactions Flexibility in lot-size & lead-time buyer/supplier conflict Flexibility of supplier relations Outsourcing disruptions for inbound material flows Relation of lead-time to supply chain agility
<b>Strategic Sourcing Links</b> Talluri and Narasimhan, 2004 Kouvelis and Milner, 2002 Ellram and Carr, 1994	<b>Topic</b> Monitor and understand supplier capabilities Modeling impacts of outsourcing versus integration Lit review of strategic sourcing methods/research
<b>TCO and TCO with Lead-Time</b> Harding M. , 2007 Ferrin and Plank, 2002 Harding M. L., 2001 Ellram and Siferd, 1998 Ellram L. M., 1994 Ellram L. , 1993	<b>Topic</b> Discussion of practical lead-time cost metrics Exhaustive list of TCO cost factors Simple cost metrics related to lead-time TCO implementation in strategic cost management Standard vs. Unique TCO models Framework for pre, post and transactions in TCO
<b>Textbooks</b> Vollmann, Berry, Whybark, & Jacobs, 2005	<b>Topic</b> Manufacturing Planning and Control Systems in SCM

## 2.7 - Summary of Literature Search Findings

The literature search reveals that demand variability and lead-time studies are plentiful and span multiple topic areas. Supply chain agility, flexibility, resilience, planning, optimization as well as MRP represent some of the many areas that note the various impacts due to lead-time on costs, inventory levels, supply chain responsiveness and customer service. However, few of the papers attempt to directly quantify the impact of excessively long lead-times due to global sourcing. TCO papers sometimes note lead-time as a cost but only give minimal guidance on calculating the cost. In resilience, flexibility and agility papers, increased lead-time throughout a supply chain emerges as a negative factor for the flexibility, resilience and agility. MRP research focuses include finding

optimal safety stock levels, transportation methods and costs given set levels of lead-time. Yet, little of the existing research attempts to model ever increasing lead-times due to global sourcing. In particular, the current literature lacks investigation of ending inventories and backorders in MRP under various lead-time levels with differing levels of demand variability and safety stock.

### 3 - The Simulation Model

The model employs a two product structure with shared and unique components. Moreover, the model uses symmetrical and asymmetrical components as well as unique components to discern potential backorder and ending inventory differences. Further, distributional assumptions came from various works cited in Chapter 2 of this work. For instance, many research papers and supply chain texts generally assume that demand variability follows the normal distribution (Vollmann, Berry, Whybark, & Jacobs 2005, Benton 1991). The following sections discuss the experimental factors, batch sizes, steady state levels, forecasting methods, bill of materials, MRP regeneration and other facets of the simulation model.

#### 3.1 – Bill of Materials

The bill of materials (BOM) contains two end products (parents) and four component inputs. Component C is a common component with symmetric requirements of 4 pieces per unit of end product. Component D is unique to end product A with a requirement of one unit per unit of end product A. Component F is unique to end product B with a requirement of four units per unit of end product B. Component E is another common component with asymmetric requirements. End product A requires one unit of component E while end product B requires four units of component E. The different quantity and symmetry in components should provide both more validity and information about potentially different ending inventory and backorder levels. Table 3.1.1 and Figure 3.1.1 display the BOM in tabular and graphical form, respectively.

Table 3.1.1: Bill of Materials

Level 0	Level 1	Quantity Per Parent
Product A	Component C	4
	Component D	1
	Component E	1
Product B	Component C	4
	Component F	4
	Component E	4

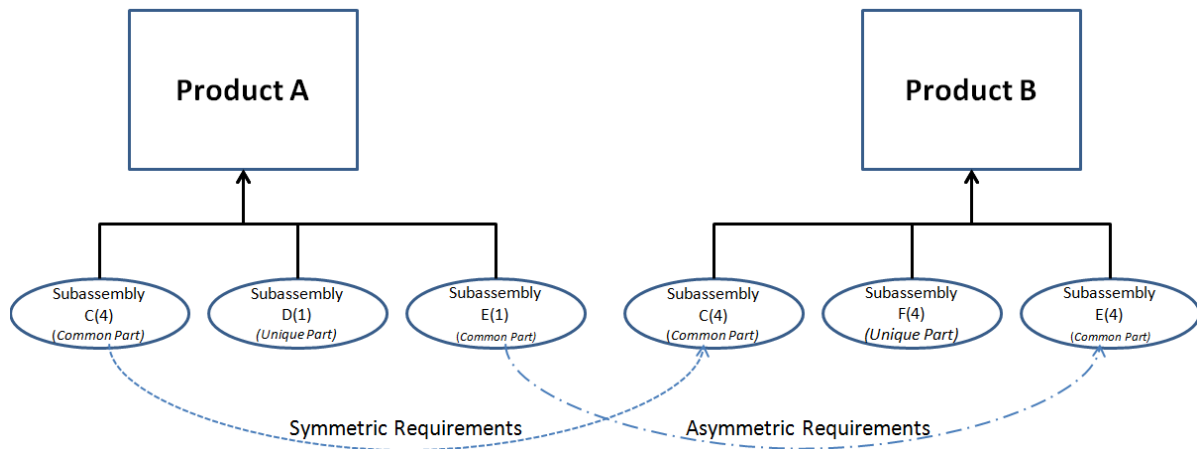


Figure 3.1.1: Bill of Materials Graphical Depiction

### 3.2 - Capacity and Daily Regeneration

The simulation models companies in an assemble-to-order (ATO) environment. Orders arrive daily. Additionally, the MRP system regenerates daily. When orders for end products arrive, the companies promise delivery 5 days out. In the simulation, production capacity is always adequate to meet demand when component parts are available. The daily regeneration of the MRP allows frequent determination of production requirements, demand levels and forecasts. Hence, the error due to regeneration should be minimal when compared to a weekly or longer MRP regeneration cycle. However, the planned order receipts created in a day freeze into the future for the length of the lead-time (no change orders are allowed within the lead-time period). In other words, the planned order receipts within the lead-time will always be zero – the manufacturer cannot alter orders within the lead-time. In practical terms, once a shipment leaves a supplier, a supplier cannot insert more components into the shipment. Since MRP is a forecast driven system, the freeze period length can have a great impact on the overall performance of the MRP system. Any demand changes within the lead-time that increase requirements beyond the predicted on hand inventory generate additional backorders.

### 3.3 - Backorders

The simulation also runs under the assumption that no orders are lost. In other words, customers will choose to indefinitely backorder end products rather than seek a different supplier.

A complete stockout of any one component required to make an end product generates a backorder for the end product. To exemplify, if component E is entirely stocked out (on backorder), the manufacturer can produce neither end product A nor B.

Further, when the supply of a component is not sufficient to meet the full demand for end products, the shortage splits proportionally between products A and B. For example, assume end product A has demand for 100 units while end product B also has demand for 100 units. However, only 400 units of component E are available while all other component stocks are sufficient to meet demand. The BOM shows that demand for 100 units of end product A leads to gross requirements of 100 units of component E. Furthermore, the BOM shows that demand for 100 units of end product B leads to gross requirements of 400 units of component E. Hence, component E has total gross requirements of 500 units but only 400 units available. Since the requirements will be split proportionally among products and  $400/500$  or 80% of the components required are available,  $0.8 \times 400$  or 320 units of component E will be assigned to produce end product B while  $0.8 \times 100$  or 80 units of component E will be assigned to produce end product A. In terms of finished goods, the manufacturer will create 80 units of end product A and 80 units of end product B. In other words, when X% of a component's gross requirements are available, the manufacturer will produce X% of the demand for end products A and B.

### 3.4 - Demand Distribution

The simulation models end product demand as normally distributed with a mean of 100 and two standard deviation levels of 10 and 15. Mathematically,

$$Demand \sim N(\mu, \sigma)$$

s.t.

$$\mu = 100$$

$$\sigma_{Low} = 10$$

$$\sigma_{High} = 15$$

All random numbers were created in PROModel simulation package and rounded to the nearest integer in Excel to create the required random vector of demand. Since the demand follows a truly random distribution, no built-in cyclical/seasonality exists.

### 3.5 - Forecast Methodology

The adaptive-response-rate single exponential smoothing (ADRES) appears to be a relatively well behaved forecasting model for the randomly generated demand data (Wilson & Keating, 2002). The ADRES adapts to the data to provide automatic adjustments for frequent changes in demand, particularly when the model forecasts demand that is roughly symmetric around a mean value. Forecasting a demand based on  $N(100, \text{sigma})$ , where sigma is 10 or 15, the ADRES represented an easy choice. The ADRES in mathematical form:

$$F_{t+1} = \alpha_t X_t + (1 - \alpha_t) F_t, \text{ s.t.},$$

$$\alpha_t = \left| \frac{S_t}{A_t} \right|, \text{ where}$$

$$S_t = \beta e_t + (1 - \beta) S_{t-1} \text{ and } A_t = \beta |e_t| + (1 - \beta) A_{t-1}$$

$$e_t = X_t - F_t$$

Hence, alpha is a dynamic value based on the past period smoothed error ( $S_t$ ) and absolute smoothed error ( $A_t$ ).

The ADRES model forecasts one period forward. Hence, since the data has no trend or seasonality, the forecast for demand in day X is also the forecasted demand for every day through the length of the lead-time. Thus, for a 42 day lead-time, the MRP system will generate requirements based on a forecast schedule X+42 days into the future. Thus, if the forecast is particularly far from the true demand for the period, the forecast error will carry through the entire MRP freeze period.

The tracking signal provided a check of the biases of the forecasts. The tracking signal divides the running sum of forecast errors (RSFE), a measure of bias, by the mean absolute deviation (MAD), a measure of error, to give a picture of the true bias (in terms of MAD) in the system. To hold the tracking signal within roughly desired bounds of +/-5, the ADRES forecasting held beta

constant at 0.2 with alpha varying as needed. A summary of the tracking signals for each forecasting vector appears in Table 3.5.1.

**Table 3.5.1: Tracking Signals on Forecast Error**

<b>Tracking Signal N(100,10)</b>										
<b>Run (Product - Run#)</b>	A-1	B-1	A-2	B-2	A-3	B-3	A-4	B-4	A-5	B-5
<b>Average Tracking Signal</b>	-0.7	1.1	-0.1	2.9	2.0	-2.9	9.0	3.2	2.4	1.1
<b>Count Beyond +/-5</b>	292	51	39	648	180	352	1224	313	238	291
<b>Percent Beyond +/-5</b>	19%	3%	3%	43%	12%	23%	82%	21%	16%	19%
<b>Tracking Signal N(100,15)</b>										
<b>Run (Product - Run#)</b>	A-1	B-1	A-2	B-2	A-3	B-3	A-4	B-4	A-5	B-5
<b>Average Tracking Signal</b>	-0.6	1.6	0.4	3.5	1.6	-2.2	8.8	3.3	2.2	0.6
<b>Count Beyond +/-5</b>	260	78	45	686	124	248	1231	340	213	278
<b>Percent Beyond +/-5</b>	17%	5%	3%	46%	8%	17%	82%	23%	14%	19%

Since the MRP followed a daily regeneration, forecasting also occurred daily and only one day into the future. Random error showed up as quite large in some demand vectors and relatively small in others—just as it would in real companies. For instance, A-4 and B-2 show particularly large tracking signals in both the levels of demand variability. On the other hand, A-2 and B-1 show very small tracking signals at both levels of demand variability. Hence, the simulation covers scenarios from excellent forecasts down to poor, highly biased forecasts for greater general validity. While discussion of various alternative forecasting methods is beyond the scope of this research, a real company would be unlikely to achieve forecast accuracy significantly better than A-2 and B-1 or worse than A-4 and B-2.

### 3.6 - Lead-Time Distribution

The simulation models the maximum early lead-time (MELT) as a gamma distribution. MELT represents that maximum number of days early that a shipment can arrive for each potential lead-time. As a conservative assumption, orders were only allowed to arrive early as a ratio of LT/7. In other words, the maximum amount an order could arrive early was one day for a seven day lead-time while a forty-two day lead-time could have an order arrive up to six days early. In reality, the variability of arriving early could be larger. As for arriving late, the gamma distribution has a right skewed tail that allows orders to be significantly late but only rarely. All random digits were created as vectors in PROModel and rounded to the nearest integer to create a vector of lead-times in Excel. A summary of the results appears in Table 3.6.1. Mathematically,



$MaxEarlyLeadTime(MELT) \sim Gamma(\alpha, \beta)$  or  $\Gamma(\alpha, \beta)$

s.t.

$$\alpha = \frac{\mu_{MELT}^2}{\sigma_{MELT}^2} \text{ while } \beta = \frac{\sigma_{MELT}^2}{\mu_{MELT}}$$

Thus,

$$E(MELT) = \alpha\beta = \mu_{MELT}$$

and

$$V(MELT) = \alpha\beta^2 = \sigma_{MELT}^2$$

$\alpha$  and  $\beta$  take on values to set the coefficient of variation equal to 0.3

$$CV = \frac{\sigma}{\mu} = \frac{\sqrt{V(MELT)}}{E(MELT)} = \frac{\sqrt{\alpha\beta^2}}{\alpha\beta} = \alpha^{-1/2} = 0.3$$

Thus,  $\alpha^{-1/2} = 0.3$  or  $\alpha = 11.1111$

Hence, the  $\beta$  takes on values such that the expected values are

$$E(MELT) = \alpha\beta =$$

1 for 7 day LT,  $\alpha = 11.1111$ ,  $\beta = 0.09$

2 for 14 day LT,  $\alpha = 11.1111$ ,  $\beta = 0.18$

3 for 21 day LT,  $\alpha = 11.1111$ ,  $\beta = 0.27$

4 for 28 day LT,  $\alpha = 11.1111$ ,  $\beta = 0.36$

5 for 35 day LT,  $\alpha = 11.1111$ ,  $\beta = 0.45$

6 for 42 day LT,  $\alpha = 11.1111$ ,  $\beta = 0.54$

and the standard deviations are

$$SD(MELT) = \sqrt{V(MELT)} = \sqrt{\alpha\beta^2} =$$

0.3 for 7 day LT

0.6 for 14 day LT

0.9 for 21 day LT

1.2 for 28 day LT

1.5 for 35 day LT

1.8 for 42 day LT

**Table 3.6.1: Summary of Lead-Time Distribution Means and Variances**

<u>LT Days</u>	<u>Alpha</u>	<u>Beta</u>	<u>Beta^2</u>	<u>E(MELT)</u>	<u>V(MELT)</u>	<u>SD(MELT)</u>
7	11.11111	0.09	0.0081	1	0.09	0.3
14	11.11111	0.18	0.0324	2	0.36	0.6
21	11.11111	0.27	0.0729	3	0.81	0.9
28	11.11111	0.36	0.1296	4	1.44	1.2
35	11.11111	0.45	0.2025	5	2.25	1.5
42	11.11111	0.54	0.2916	6	3.24	1.8

The coefficient of variation remains at 0.3 for all calculations.

In effect, the mean of the Gamma distribution positions at the expected lead-time in days. The Gamma distribution models the variance around the expected lead-time. The higher the lead-time, the wider the gamma distribution becomes as a function of the CV. Of course, the gamma distribution truncates at zero but skews on infinitely at higher values. In other words, the expected lead-time is the original lead-time in days while MELT represents the maximum number of days an order can arrive early, which truncates at zero. The standard deviation of the MELT follows the right skewed tail of the Gamma distribution. Hence, there is no direct truncation on the number of days an order can be late.

### 3.7 - Steady State

As noted in the forecasting section, the adaptive-response single exponential smoothing forecasting system was set to hold beta constant at 0.2 with alpha varying as needed. Each simulation replication generated 1000 days of data. To allow steady state to take effect, each experimental run removed the first 150 observed days. Many simulation runs achieved steady state much earlier than 150 days. Yet, consistency of the sample size and conservative estimates were fortunate benefits from the data loss. Steady state was checked graphically for every treatment level of the simulation. Law and Kelton's text on simulation modeling describes the method employed (Law & Kelton, 2000). Figures 3.7.1 and 3.7.2 show examples of output of twenty period moving averages for various responses in the simulation.

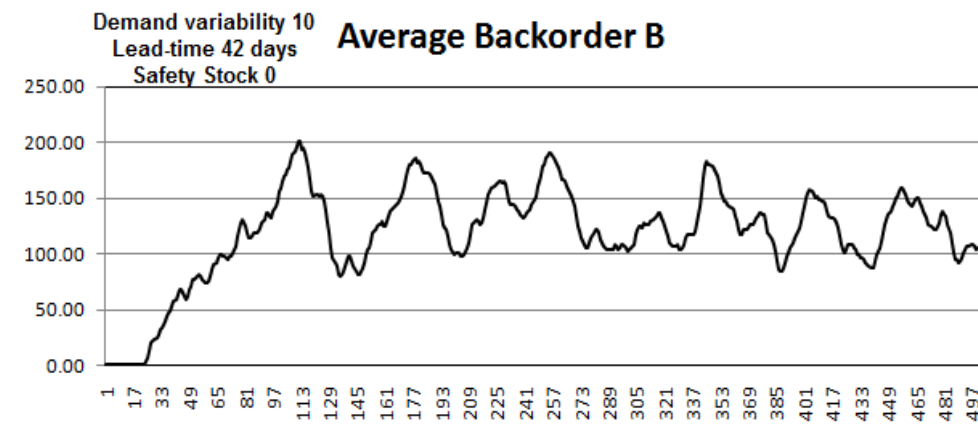


Figure 3.7.1: Sample steady state graph for DV10, LT42, SS0 on Average Backorders of End Product B

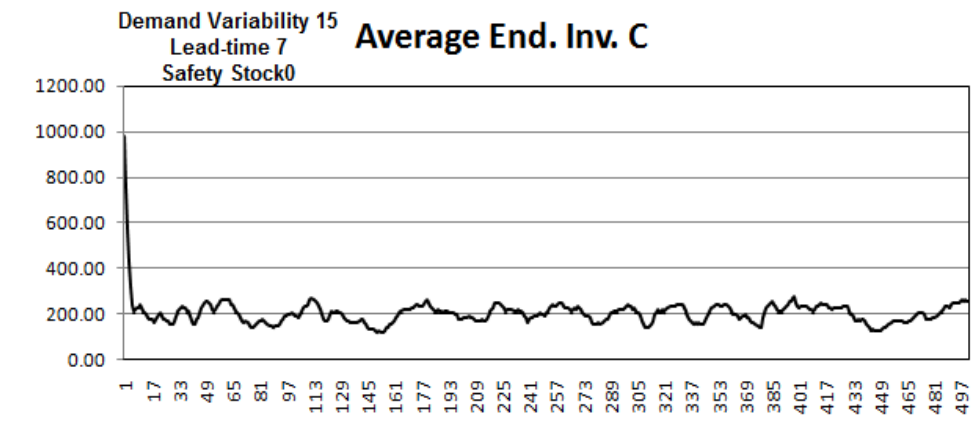


Figure 3.7.2: Sample steady state graph for DV15, LT7, SS0 on Average Ending Inventory on Component C

### 3.8 - Safety Stock

Safety stock had no distributional assumptions. Instead, two main effect factor levels were set with one additional pilot study level. The main effect levels were no safety stock and 20% of daily demand. The pilot study level held safety stock at 40% of daily demand to observe the impact of ever increasing safety stock levels on both backorders and ending inventory.

### 3.9 - Batch Size

The experiment held batch sizes fixed. While batch size was not part of the main experiment, experimental subsets test the impact of batch size at extremes of lead-time (e.g., 7 and 42 days). Batch size for the main experiment was always lot-for-lot (L4L). As noted, orders could occur in each period to meet forecast demand for the length of the lead-time.

### 3.10 - Final Experimental Models

The experiment's main effects at the factor level:

- **Lead-Time (LT):** Lead-time at factor levels 7, 14, 21, 28, 35 and 42 days [6 levels]
  - Lead-time variance follows a Gamma distribution.
  - As noted in the Lead-time distribution section, the coefficient of variation for lead-time remained constant at 0.3.
- **Demand Variability (DV):** Demand variability had factor levels 10 and 15 [2 levels]
  - Demand was modeled using a normal distribution with mean 100.
- **Safety Stock (SS):** Safety stock was set at either 0% or 20% of average daily gross requirements for each component under the ratios described in the BOM. For example, component C has gross average daily requirements of 800 units. Hence, safety stock at 20% of average daily gross requirements leads to a safety stock of 160 units. [2 levels]

Treatment levels (combinations of the factor levels):

- **LT = 7, DV = 10, SS = 0**
- **LT = 14, DV = 10, SS = 0**

- 
- 
- **LT = 35, DV = 15, SS = 20%**
- **LT = 42, DV = 15, SS = 20%**

Hence, the main effects consisted of 24 treatment levels ( $LT \cdot DV \cdot SS = 6 \cdot 2 \cdot 2 = 24$ ). Each treatment level had  $n=5$  replicates.

Other effects examined in subsequent experiments include zero lead-time variability, higher safety stock levels and larger batch sizes. Each of these other effects contains between four and twelve experimental runs.

- **Zero Lead-Time Variability:** Additional experimental runs investigate the impact of zero lead-time variability at each lead-time and demand variability level. [12 additional runs]
- **Safety Stock:** Another set of additional runs investigates a 40% safety stock level at 7 and 42 days of lead-time with demand variability at sigma equal 10 and 15. [4 additional runs]
- **Batch Size:** An additional set of experimental runs investigates the impact of increasing batch size to two weeks (14 days) of average demand or simply  $100 \cdot 14 = 1,400$  units multiplied by the appropriate BOM multiplier for each component. [8 additional runs]

The total experiment contains 48 experimental runs with 240 replicates. 120 replicates were used in the main experiment for the first 24 experimental runs. The remaining 24 experimental runs split replicates across the additional questions of interest.

The responses of interest include end product backorders, component backorders and component ending inventory. Each of these requires examination for statistical as well as practical importance.

## 4 – Simulation Results and Findings

Chapter 4 focuses on the practical significance of the experimental results. All main effects are statistically significant. Many interaction effects are not statistically significant. A full statistical analysis appears in Chapter 7.

While the experiment/simulation tries to isolate the impacts of the main effects (lead-time, safety stock and demand variability), the forecasting method (ADRES) and random error also cause some of the effects seen. Most of the impact of the forecasting error should appear as random error. Yet, while the simulation gives guidance on the general pattern due to main effects, other impacts could make significant performance differences for real world manufacturers. The potential exists that forecasting error added to the extremely poor results in terms of backorders and ending inventory at the highest lead-times. Interestingly, the company with the very poor forecasting (tracking signal average of 8.8 indicating bias) did not show up as consistently high or low in terms of backorders or ending inventory. In other words, the MRP system appears to have smoothed the biased forecast by adjusting requirements dynamically at each level of lead-time. In any case, *as with any simulation, validity is highest when the modeling assumptions (outlined in detail in Chapter 3) are met.*

### 4.1 – Graphical Analysis

The responses of interest in the experiment include end product backorders, component backorders and component ending inventories. As noted in the simulation model section, the main effect experimental variables include safety stock, lead-time and demand variability. The trends across lead-time in each of these responses can be seen most easily through graphical analysis. In each case, the examined isolated effect is calculated as an average across all other effects.

The first set of graphs show that as lead-time grows, the level of end product backorders grows. Likewise, as lead-time grows, the backorders and ending inventory of components also grow. See Figures 4.1.1 – 4.1.3 to examine end product backorders, component backorders and component ending inventories, respectively.

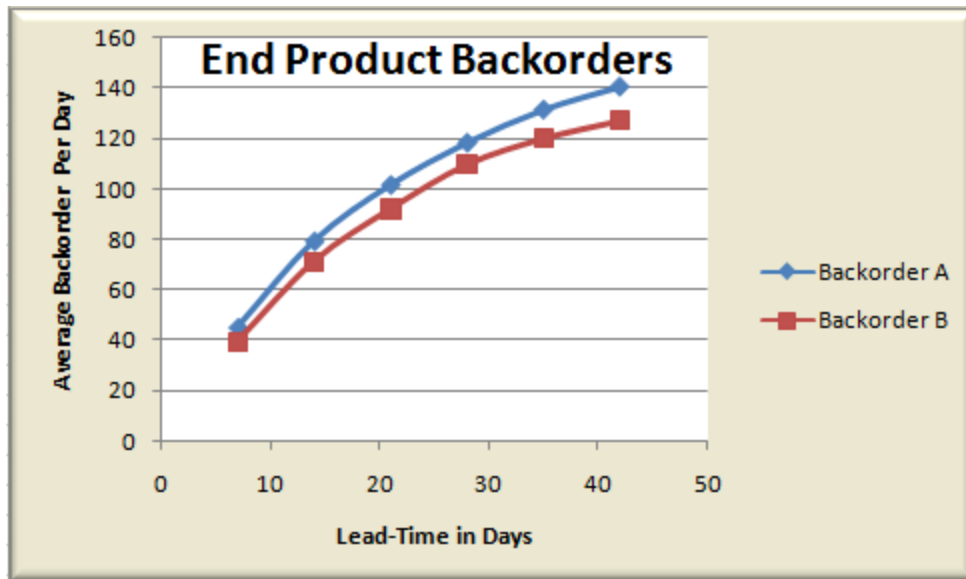


Figure 4.1.1: Average End Product Backorders across Lead-Time in Days

Figure 4.1.1 displays that end product backorders grow at a diminishing rate as lead-time grows. Of course, other experimental factors generate different impacts on the growth of backorders and ending inventory as discussed in Chapters 5 and 6. Another note is that backorders of end product A appear to grow at a faster rate than the backorders of end product B, which appears to be in part due to the more linear rate of increase in backorders for component D. At a lead-time of 7 days, the difference between the two backorders averages only 5 units and grows to 13 units at a lead-time of 42 days. Since each end product has an average daily demand of approximately 100, the difference could be significant for some firms.

As already noted, the average demand for each end product is approximately 100 units per day. In other words, at 21 days of lead-time, the average backorders per day for end product A exceed average daily demand. Likewise, end product B backorders exceed average daily demand at approximately 24 days of lead-time. In other words, the systems are not serving customer needs well at relatively short lead-times. Chapters 5 and 6 analyze the impact of safety stock and demand variability potential causes behind the poor backorder performance of the system.

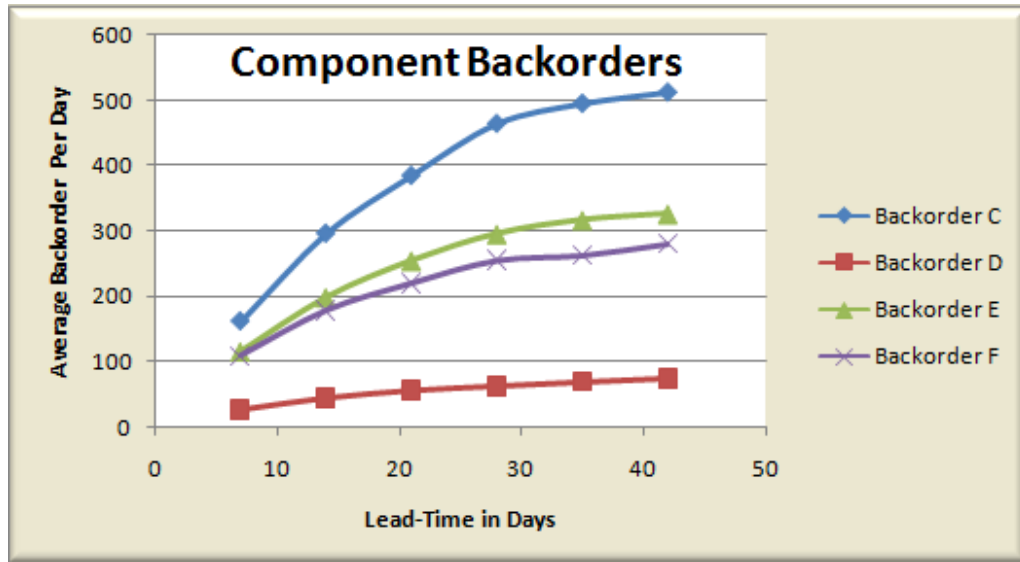


Figure 4.1.2: Average Component Backorders across Lead-Time in Days

The BOM (section 3.1) shows that end item C has symmetric requirements of four units per unit of end product A and four units per unit of end product B. Thus, the total gross requirements for end product C are the highest of any component part in the experiment. As figure 4.1.2 displays, backorders for component C represent the largest magnitude backorders of any component, as expected. Both end products A and B require component E but asymmetrically. Figure 4.1.2 shows the impact of the lessened requirements for component E. End product B requires four units of component F per unit of end product B. End product A requires one unit of component D per unit of end product A. Hence, the total backorders for D and F are the lowest among the backorders.

Each of the backorders shows a diminishing growth rate overall. However, the symmetrically required component C average backorders grow faster than any other component average backorder and do not appear to level off as quickly. Moreover, component D shows a slower rate of diminishing returns in relative proportion to the other components.



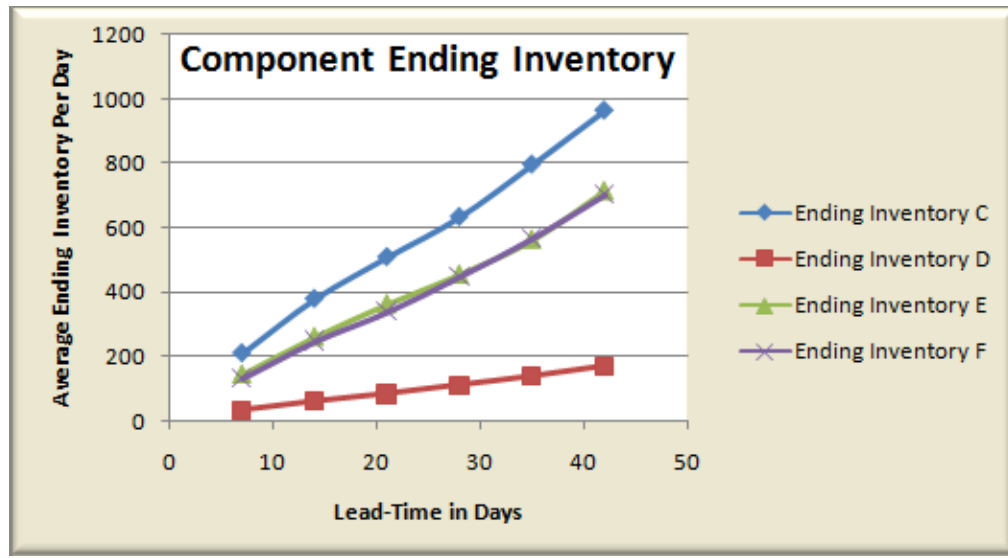


Figure 4.1.3: Average Component Ending Inventory across Lead-Time in Days

Unlike backorders, which show diminishing growth rates, ending inventory appears to continue growth at an accelerating rate as lead-time grows. Due to the product structure (see section 3.1), the ending inventory for component C grows the fastest while component D grows the slowest, which helps explain the less dramatic growth rate in backorders for component D observed in Figure 4.1.3.

Unexpected are the nearly identical ending inventories for components E and F. Component F is an asymmetrically shared component while component E is unique to end product B. Gross requirements are similar at 500 units per day of F and 400 units per day of E. However, the nearly identical results, both in magnitude and trend, still represent somewhat of a surprise.

Quantitatively, ending inventory of component C grows from an average of approximately 200 units at a lead-time of seven days to nearly 1000 units at a lead-time of forty-two days. In percentage terms, ending inventory for component C grows by nearly 500%. Other inventories show similar percent gains at lower raw inventory levels.

## 4.2 – Discussion of Results

The overall results show that as lead-time grows, ending inventories and backorders of component parts grow. As the backorders of component parts grow, so do the backorders of end products. Backorders grow at diminishing rates while inventories grow at accelerating rates. Of course, both higher backorders and higher inventories lead to higher costs for the firms.

Two interesting notes emerge from the overall experimental picture. First, at only 21-24 days of lead-time, average end product backorders exceed average daily demand. In other words, the system fails to keep backorder levels below demand at approximately a three week lead-time. The result demonstrates that companies engaging in relatively long lead-time global sourcing should exercise caution or at least recognize the potential for customer service issues. Second, average ending inventories for a jointly, asymmetrically required component are nearly identical to the average ending inventories of a lower gross requirement component required for only one end product. In other words, the impact of asymmetry in component requirements does not appear to have a major impact in the ending inventories. The gross requirements, rather than common parts or symmetry of requirements, seem to have the largest impact on ending inventory levels.

Sections 5 and 6 discuss the impacts on ending inventory and backorders due to safety stock and demand variability levels across lead-times. Each section breaks down the impacts of demand variability and safety stock in isolation and then in combination.

## 5 - Analysis of Backorders

Chapter 4 notes that average end product backorders exceed average daily demand at only 21-24 days of lead-time. Chapter 5 analyzes some of the potential causes of the breakdown as well as investigates other points of interest in the backorder patterns for both end products and components.

### 5.1 - Lead-Time Impact on End Products and Components

In the overall system, backorders exceed average demand at 21-24 days of lead-time and beyond. The following sections analyze the impacts of demand variance and safety stocks on backorder levels at the various lead-times.

### 5.2 - Demand Variance Impact on End Products across Safety Stock Levels

Figures 5.2.1 and 5.2.2 show the average backorder level per day (averaged across safety stock levels) for end products A and B, respectively. In each graph, two lines appear showing the trend for demand variability at standard deviations 10 and 15. As discussed in section 3.4, end product demand is modeled under a normal distribution with mean 100 and standard deviations of 10 and 15 units. In general, higher demand variability should lead to higher backorders. Figures 5.2.1 and 5.2.2 verify the intuition that greater demand variability leads to higher average levels of backorders.

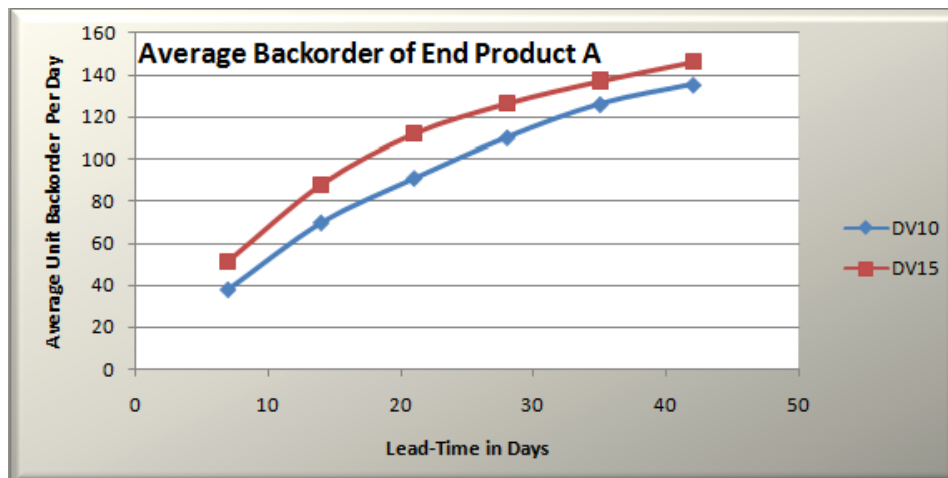


Figure 5.2.1: Average Backorder of End Product A at Demand Variability 10 and 15 across Lead-Time in Days

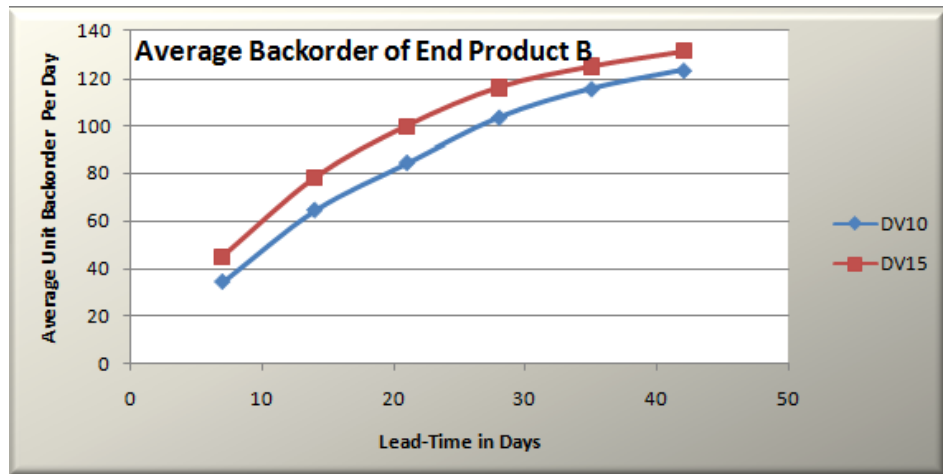


Figure 5.2.2: Average Backorder of End Product A at Demand Variability 10 and 15 across Lead-Time in Days

Both Figures 5.2.1 and 5.2.2 show very similar diminishing growth patterns for the average backorder levels. The impact of increased demand variability on average backorder level is somewhat consistent at each level of lead-time until a convergence at high lead-times. While the end products do not show the convergence pattern as strongly as the components (discussed below), the average backorder level starts to converge between the two demand variability levels at the highest levels of lead-time. Hence, companies that are concerned about the demand variability in their industry, something that is often regarded as outside an individual company's control, can see that increased lead-time worsens backorder levels but at a diminishing and somewhat consistent amount for short and fairly long lead-times with a potential convergence at the longest investigated lead-times.

### 5.3 - Demand Variance Impact on Components

Figures 5.3.1 through 5.3.4 show the average backorder level per day for components C, D, E and F, respectively. In each graph, two lines appear showing the changes in trend due to end product demand variability at standard deviations 10 and 15. End product demand variability directly impacts component demand as shown in the BOM (see section 3.1).

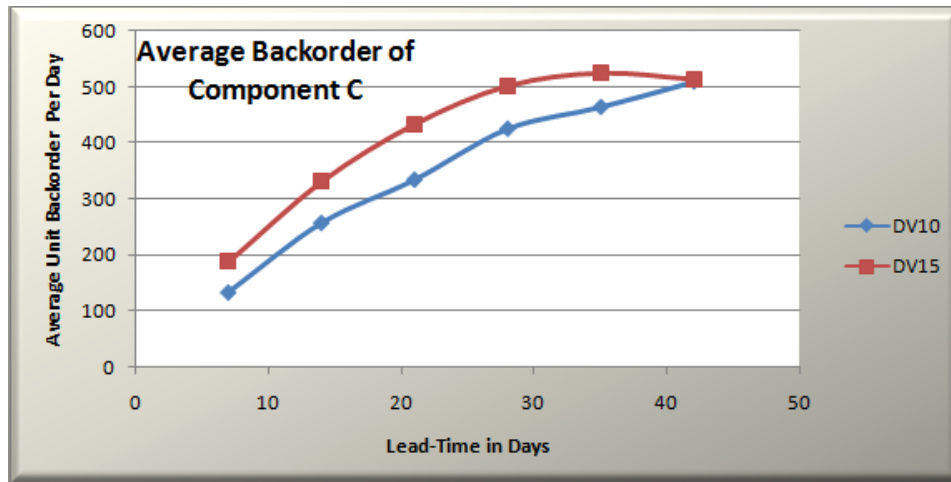


Figure 5.3.1: Average Backorder of Component C at Demand Variability 10 and 15 across Lead-Time in Days

Figure 5.3.1 shows a diminishing growth rate of average component C backorders with a convergence at the highest level of lead-time (42 days). Examination of the standard deviations of demand at 10 and 15 shows that demand variability 15 grows average backorders at a faster rate than demand variability 10 until a sudden drop and convergence of the average backorder levels after 35 days of lead-time.

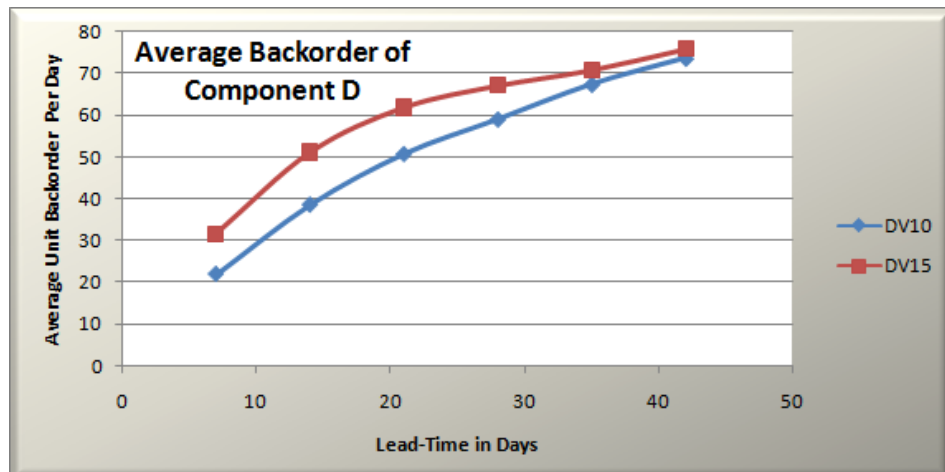


Figure 5.3.2: Average Backorder of Component D at Demand Variability 10 and 15 across Lead-Time in Days

Figure 5.3.2 shows a diminishing growth rate of average component D backorders with another convergence at the highest level of lead-time (42 days). The convergence at 42 days of

lead-time could be cause for modeling longer lead-times in the future to see if some sort of demand variability cancelation occurs at very high lead-times.

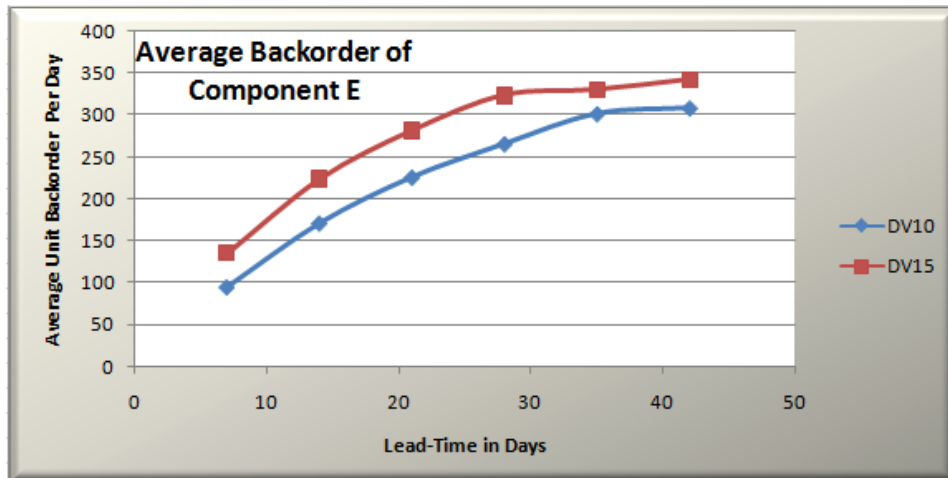


Figure 5.3.3: Average Backorder of Component E at Demand Variability 10 and 15 across Lead-Time in Days

Figure 5.3.3 once again shows a diminishing growth rate of average component E backorders. Component E shows little convergence at the highest lead-times.

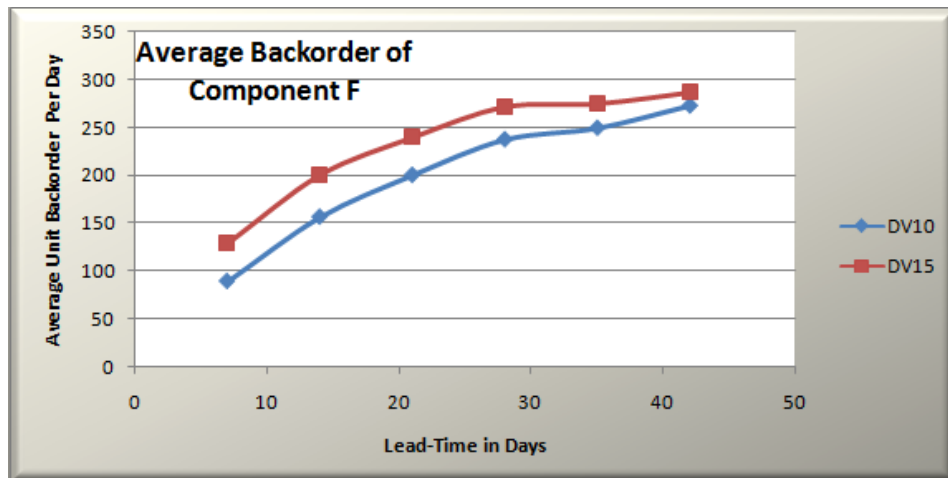


Figure 5.3.4: Average Backorder of Component F at Demand Variability 10 and 15 across Lead-Time in Days

Figure 5.3.4 shows that component F follows a pattern similar to the other components with a diminishing growth rate in average component backorders. Once again, component F shows convergence of the two demand variability levels at the highest level of lead-time (42 days).

The convergence in three of the four components at 42 days of lead-time appears to be worth future investigation. The result could be due to random error or some other factor. None the less, future simulations likely should model longer lead-times to see if some sort of demand variability cancelation occurs at very high lead-times.

#### 5.4 - Safety Stock Impact on End Products across Demand Variability Levels

Figures 5.4.1 and 5.4.2 show the average backorder level per day across both levels of demand variability for end products A and B, respectively. In each graph, two lines appear showing the trend for safety stock levels of 0% and 20% of average gross daily requirements for components. In other words, safety stock is not modeled for end products in the simulation since the manufacturers produce and ship orders within the five day promised lead-time window (when component stock is available). Figures 5.4.1 and 5.4.2 verify the commonly held notion that lower component safety stock levels lead to higher average backorder levels for end products.

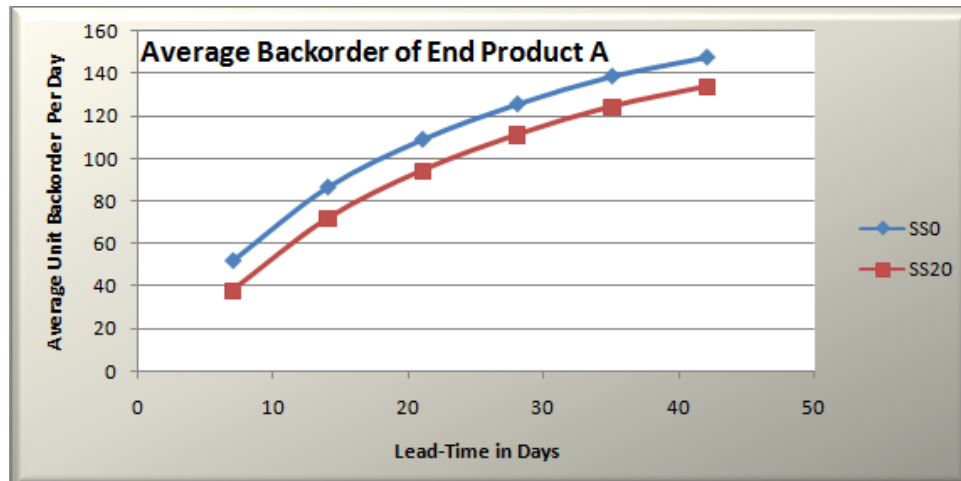


Figure 5.4.1: Average Backorder of End Product A at Component Safety Stocks 0% and 20% of Gross Daily Requirements across Lead-Time in Days

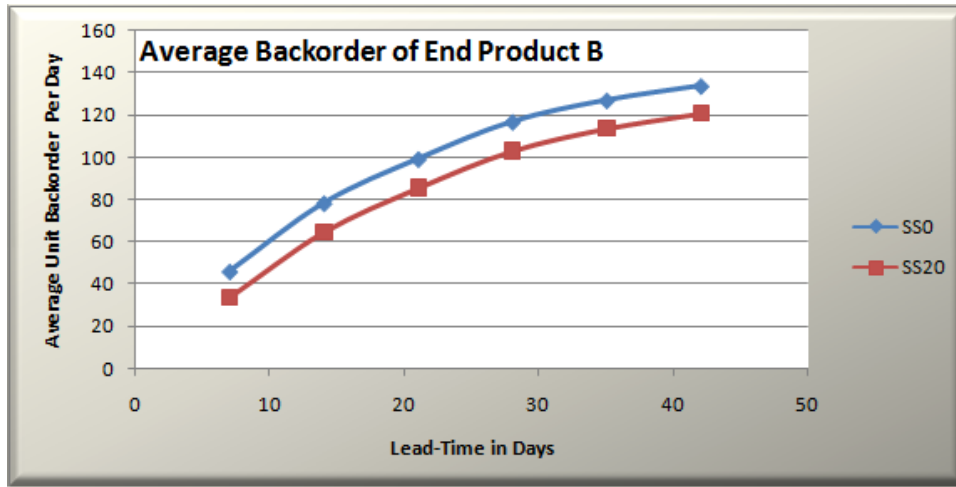


Figure 5.4.2: Average Backorder of End Product B at Component Safety Stocks 0% and 20% of Gross Daily Requirements across Lead-Time in Days

Figures 5.4.1 and 5.4.2 show very similar diminishing growth patterns for the average backorder levels across the two safety stock levels of 0% and 20% of gross daily component requirements. The lines move in an almost perfectly parallel fashion, showing that the impact of increased safety stock on average backorder level is roughly constant at each level of lead-time. In fact, the difference between average backorders due to safety stock levels at each lead-time is approximately constant at 14 units for end product A and 13 units for end product B. In effect, safety stock simply reduces backorder levels by a roughly constant amount no matter the lead-time level. Chapter 6 shows that the price for the diminishing backorder levels is actually a growing rate of daily ending inventory.

## 5.5 - Safety Stock Impact on Components

Figures 5.5.1 through 5.5.4 graphically display the average backorder level per day for components C, D, E and F, respectively. In each graph, two lines appear displaying the trend for safety stock levels of 0% and 20% of gross daily requirements.



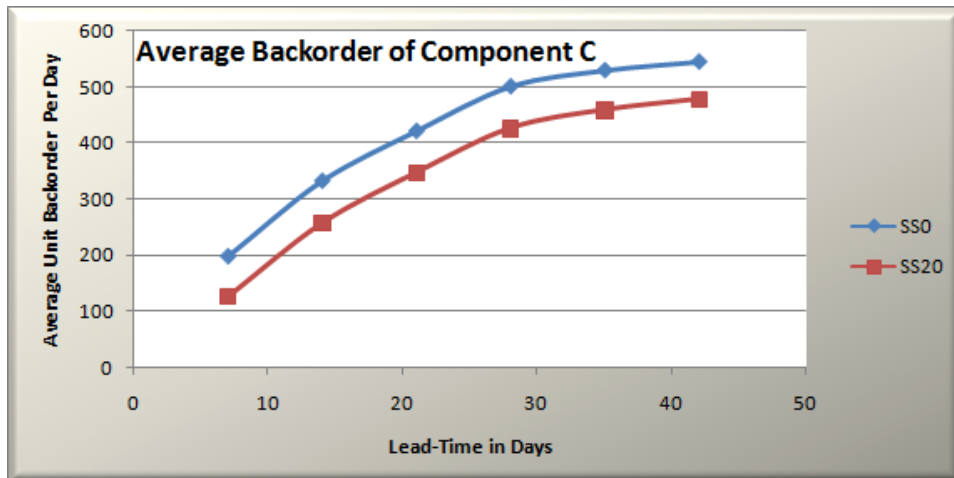


Figure 5.5.1: Average Backorder of Component C at Safety Stocks 0% and 20% of Gross Daily Requirements across Lead-Time in Days

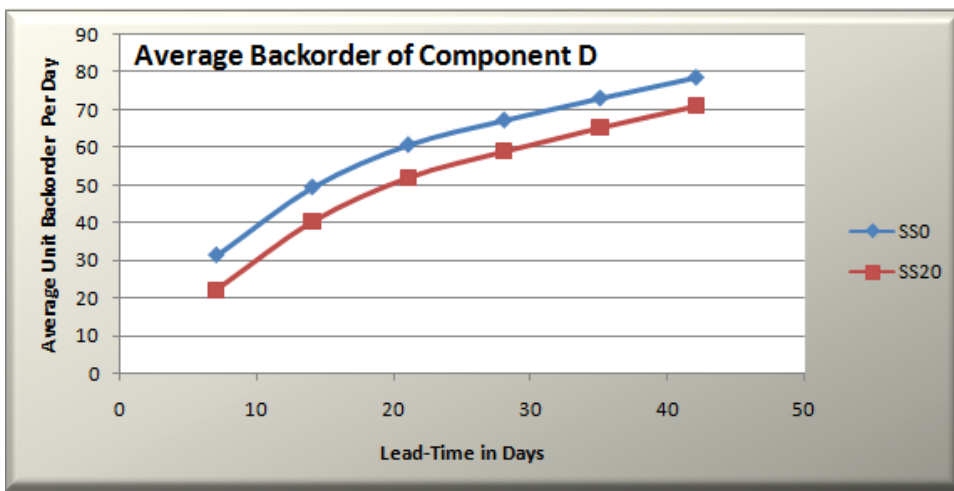


Figure 5.5.2: Average Backorder of Component D at Safety Stocks 0% and 20% of Gross Daily Requirements across Lead-Time in Days

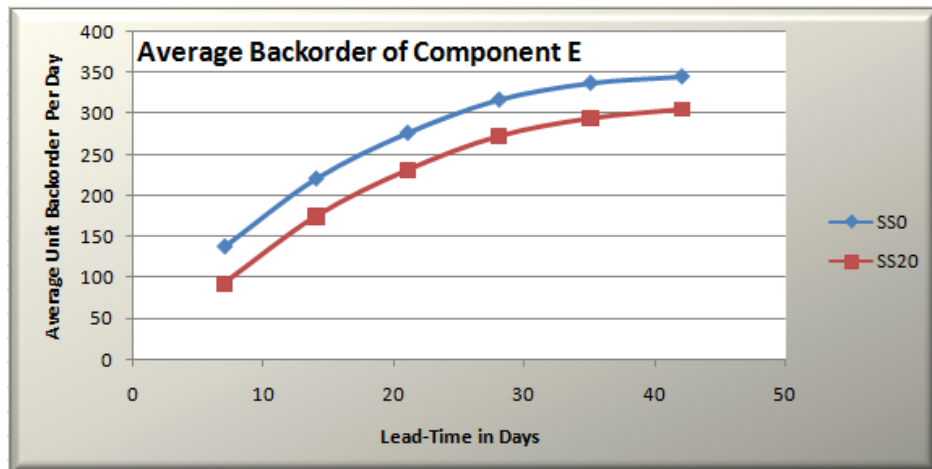


Figure 5.5.3: Average Backorder of Component E at Safety Stocks 0% and 20% of Gross Daily Requirements across Lead-Time in Days

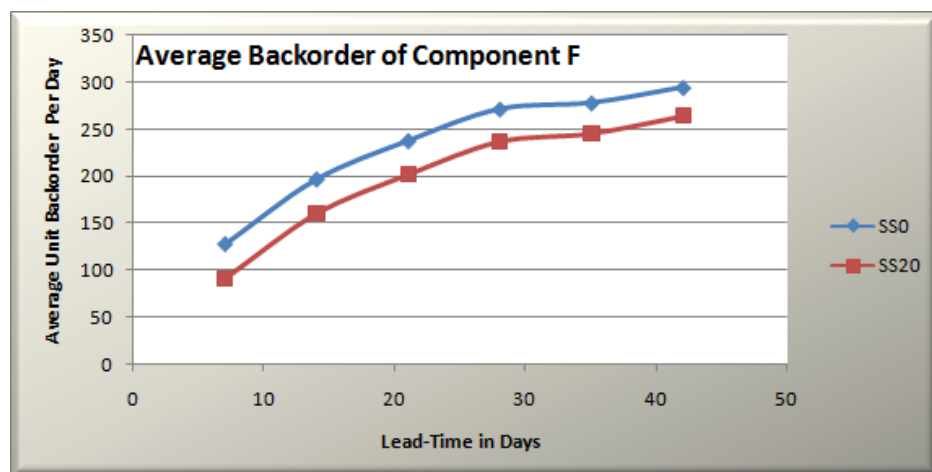


Figure 5.5.4: Average Backorder of Component F at Safety Stocks 0% and 20% of Gross Daily Requirements across Lead-Time in Days

Figures 5.5.1 through 5.5.4 all show roughly the same result—safety stock has a nearly constant impact on the average backorder level across each level of lead-time. Unlike the average backorder levels seen at different levels of demand variability, the average backorder levels at each safety stock level do not converge or even change in pattern as a function of lead-time.

## 5.6 – Backorder Analysis for Components Combined Analysis

Figures 5.6.1 through 5.6.6 graphically display impacts on backorders due to changes in both demand variability and safety stock level combinations.

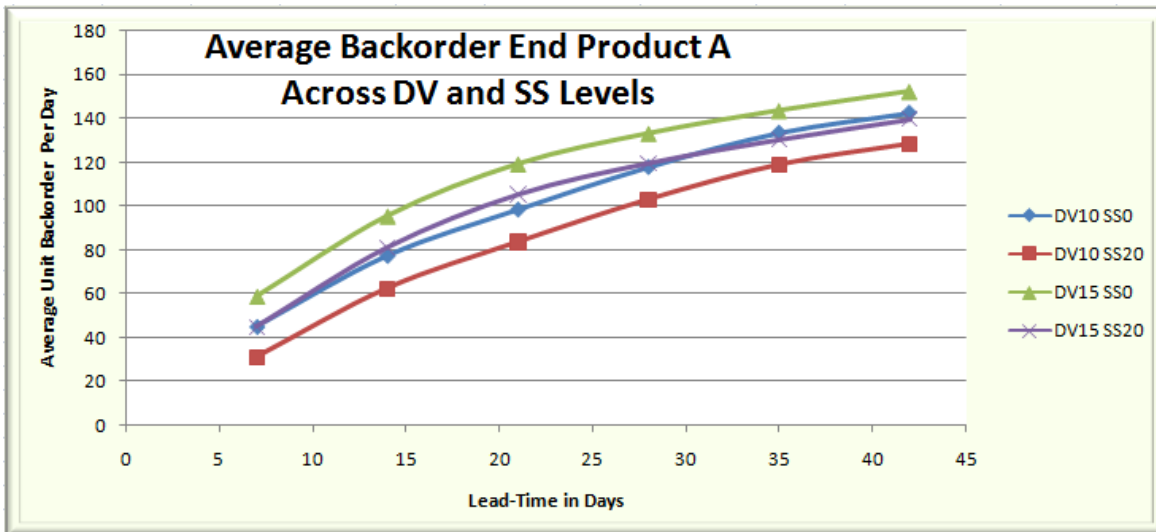


Figure 5.6.1: Average Backorder of End Product A at all Safety Stock and Demand Variability Levels across Lead-Time in Days

Figure 5.6.1 shows that DV10-SS0 and DV15-SS20 appear to be approximately the same. All trends are nearly the same.

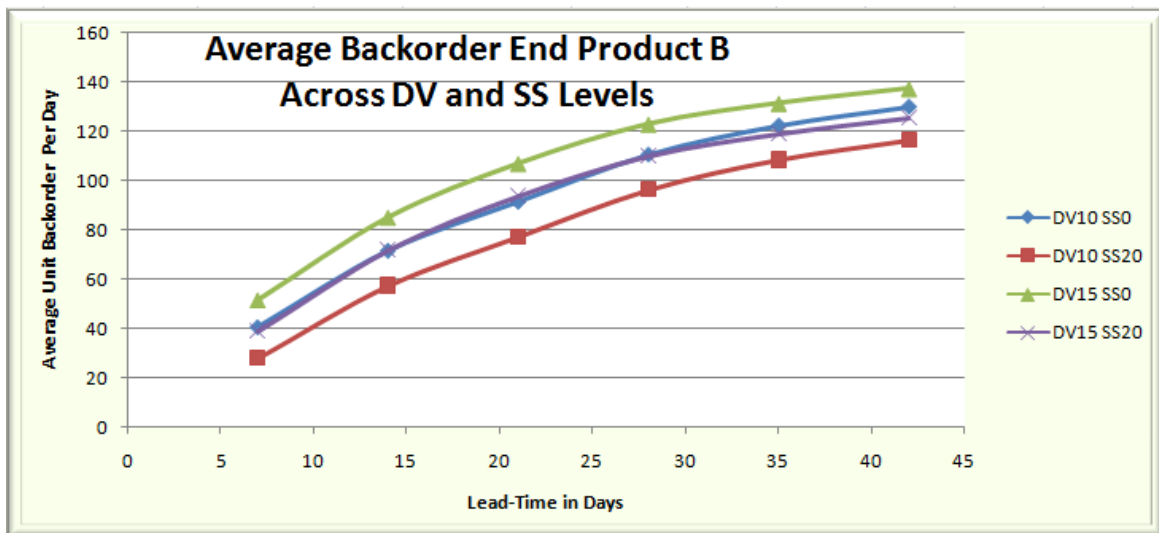


Figure 5.6.2: Average Backorder of End Product B at all Safety Stock and Demand Variability Levels across Lead-Time in Days

Figure 5.6.2 once again shows that DV10-SS0 and DV15-SS20 appear to be approximately the same at each mean level. As with end product A, all trends are nearly the same for every treatment level.

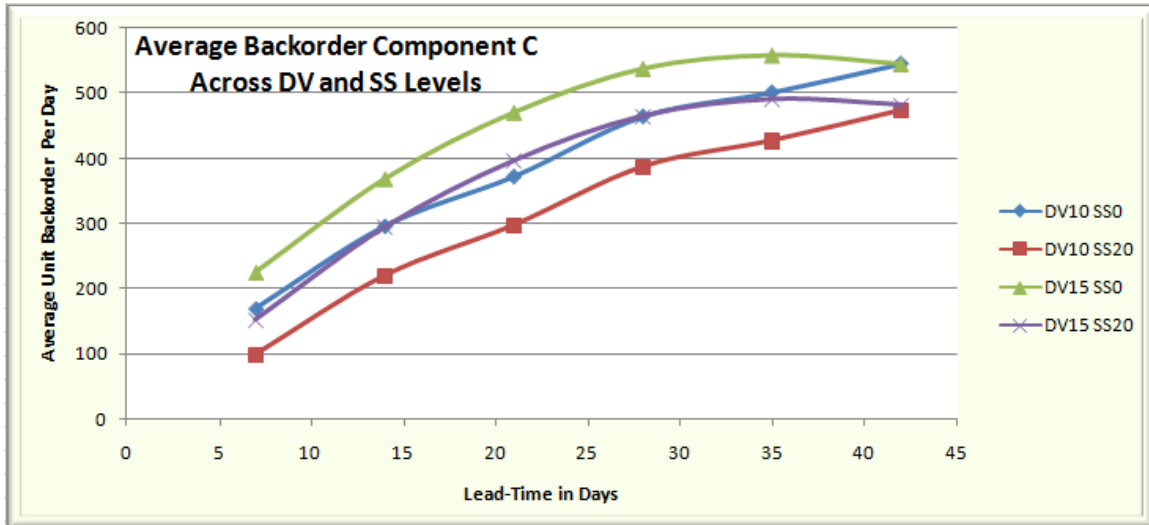


Figure 5.6.3: Average Backorder of Component C at all Safety Stock and Demand Variability Levels across Lead-Time in Days

Figure 5.6.3, the graphic for component C, shows that DV10-SS0 and DV15-SS20 appear to be similar at low lead-times but diverge at high lead-times. The trends in the treatment levels show some variability, particularly at the longest lead-times.

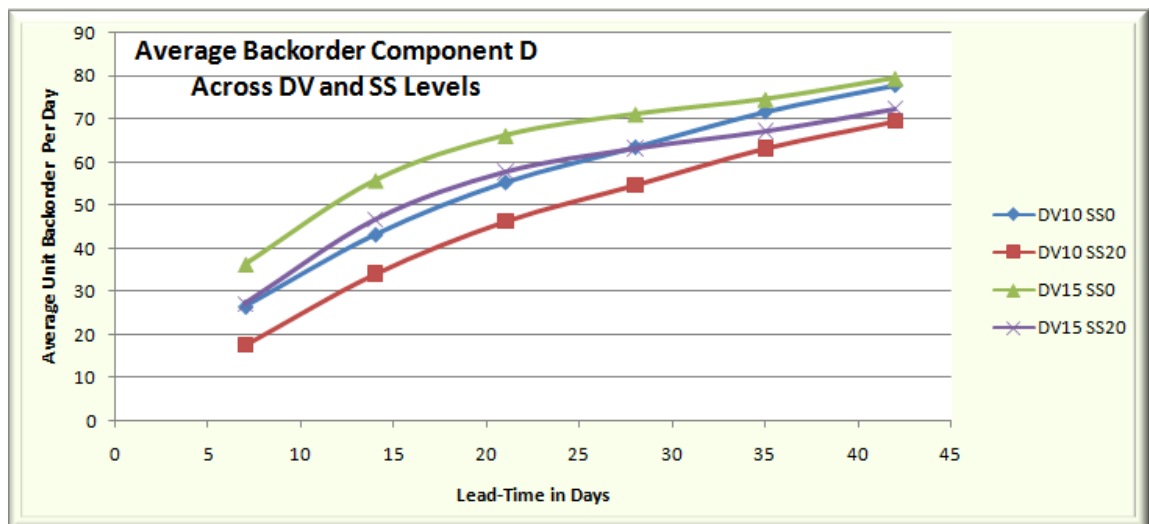


Figure 5.6.4: Average Backorder of Component D at all Safety Stock and Demand Variability Levels across Lead-Time in Days

Figure 5.6.4 for component D shows somewhat less variability than Figure 5.6.3 (component C). DV10-SS0 and DV15-SS20 appear similar at low lead-times but diverge at high lead-times.

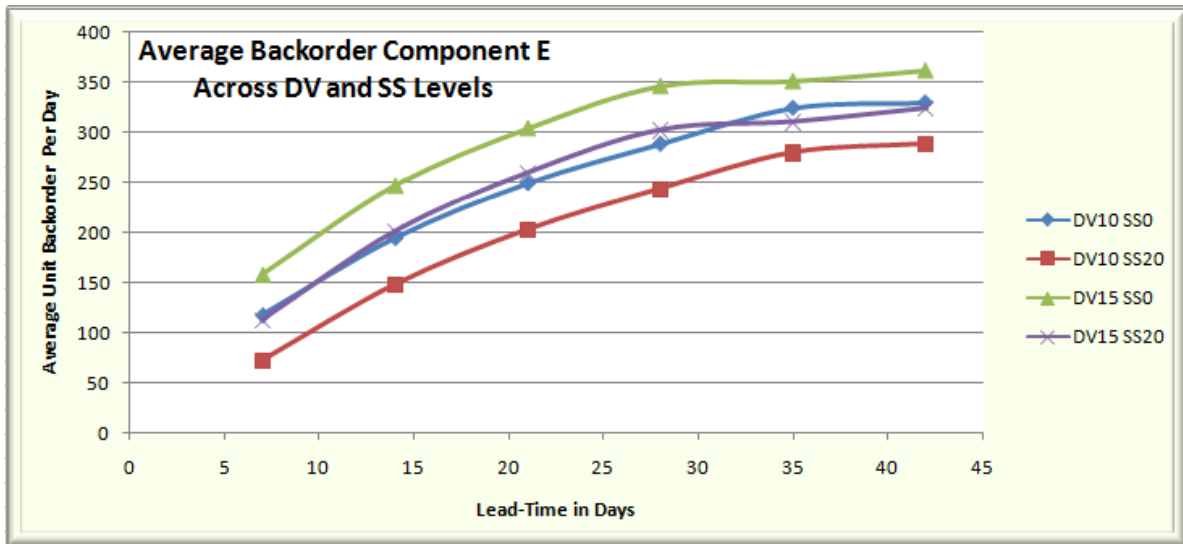


Figure 5.6.5: Average Backorder of Component E at all Safety Stock and Demand Variability Levels across Lead-Time in Days

Figure 5.6.5 for component E shows somewhat less variability than Figure 5.6.3 (component C) but more variability than 5.6.4 (component D). The added variability likely stems from the joint requirements by both end products for components C and E. Yet again, DV10-SS0 and DV15-SS20 appear to be similar at low lead-times but diverge at high lead-times.

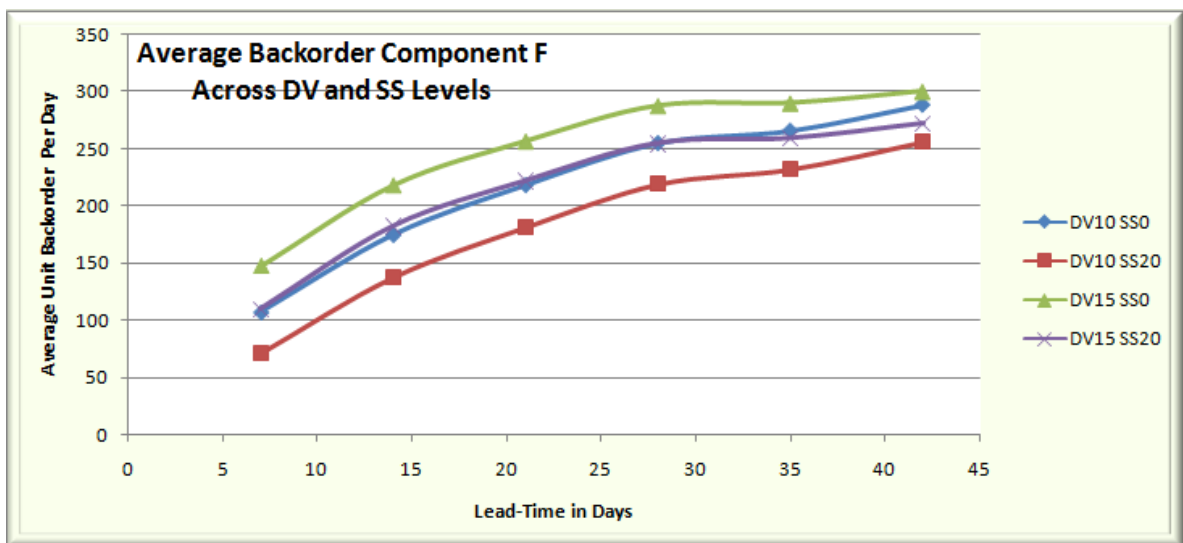


Figure 5.6.6: Average Backorder of Component F at all Safety Stock and Demand Variability Levels across Lead-Time in Days

Figure 5.6.6 for component F shows somewhat less variability than Figures 5.6.3 and 5.6.5 (component C and E) and similar variability to 5.6.4 (component D). The added variability likely stems from the joint requirements by both end products for components C and E. Yet again, DV10-SS0 and DV15-SS20 appear to be similar at low lead-times but diverge at high lead-times.

The results show similar patterns for both end products and the component parts. For instance, both components and end products show that DV10-SS20 (low demand variability and high safety stock) consistently performs the best in terms of backorders (i.e., has the lowest average backorder levels at each lead-time) while DV15-SS0 (high demand variability and low safety stock) performs the worst. For both end products and components, the treatment levels DV10-SS0 and DV15-SS20 show nearly identical results at low lead-time levels with some divergence at higher lead-times. In addition, components C and E show higher overall variability in terms of trend changes and spreads at each treatment level when compared to components D and F. The shared requirements for both C and E in end products A and B represent the most likely explanation for the difference in behavior of the different components.

## 5.7 – Conclusions about Backorders

One of the most important notes on backorders occurs in Chapter 4: backorders exceed average demand after 21-24 days of lead-time for both end products. Chapter 5 displays how demand variability causes interesting convergence in component and end product backorder levels at the longest investigated lead-times. On the other hand, Chapter 5 also displays how safety stock levels have a nearly constant impact on average backorder levels for both components and end products.

The experiment demonstrates that longer lead-times tend to lead to higher average backorder levels. Higher levels of safety stock help mitigate the average backorder levels by a relatively constant amount. When analyzed together as treatment combinations, the simulation shows that high demand variability and low safety stocks lead to the highest average backorder levels at every lead-time while low demand variability and high safety stocks do the opposite. Interestingly, low safety stock with high demand variability and high safety stock with high demand variability appear to yield roughly the same overall average backorder levels.

In quantitative terms, average component and end product backorders often grow by 300% or more as lead-time moves from seven to forty-two days. For instance, the average backorder level for end product A with demand variability 10 and safety stock of 20% of gross daily component requirements grows from an average backorder level of 31 units per day at a lead-time of seven days to 128 units at a forty-two day lead-time – a 410% increase in average backorders due to lead-time.

In sum, manufacturers in relatively high demand variability industries do face even more potential of backorders, but the pattern shows a strongly diminishing rate of backorder growth as lead-time increases. Moreover, safety stocks do appear to help mitigate overall average backorder levels by an approximately constant amount no matter the length of the lead-time. Thus, companies may be able to set safety stock levels independently of lead-time if they face similar conditions to those modeled (e.g., no lost orders, MRP freezes for the length of the lead-time, etc.).

## 6 - Analysis of Ending Inventories

As noted in Chapter 4, average ending inventories for a jointly, asymmetrically required component are nearly identical to the average ending inventories of a component required for only one end product. Chapter 6 will investigate whether safety stock, demand variability or simple random error causes the observed result. Chapter 6 will also display the impacts of demand variability and safety stock levels on ending inventories for end products as well as components.

### 6.1 - Lead-Time Impact on End Products and Components

The general pattern observed in Chapter 4 shows that ending inventories grow as a function of lead-time for both end products and components. The following sections breakdown the impacts of demand variability and safety stocks on ending inventory levels at the lead-times from seven to forty-two days.

### 6.2 - Demand Variance Impact on Components Across Safety Stock Levels

Figures 6.2.1 through 6.2.4 display the average ending inventory level per day for components C, D, E and F. In each graph, the two trend lines show the changes in trend due to end product demand variability at standard deviations 10 and 15. End product demand variability directly impacts component demand as shown in the BOM (see section 3.1).

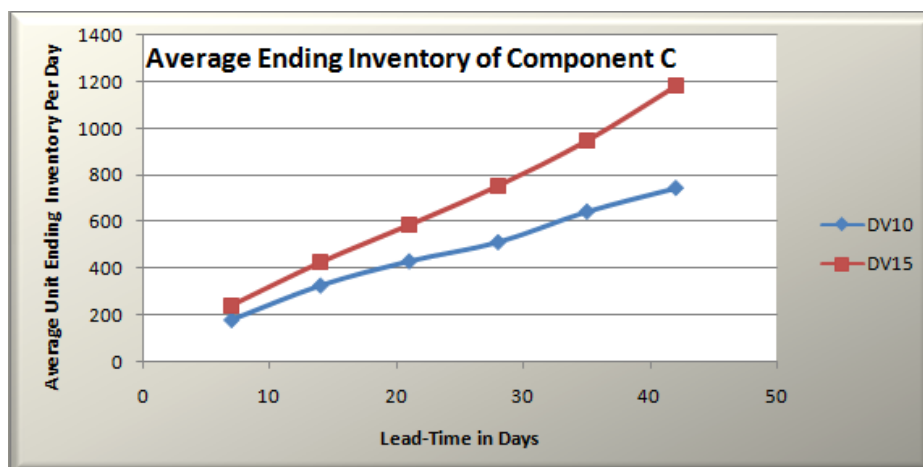


Figure 6.2.1: Average Ending Inventory of Component C at Demand Variability 10 and 15 across Lead-Time in Days



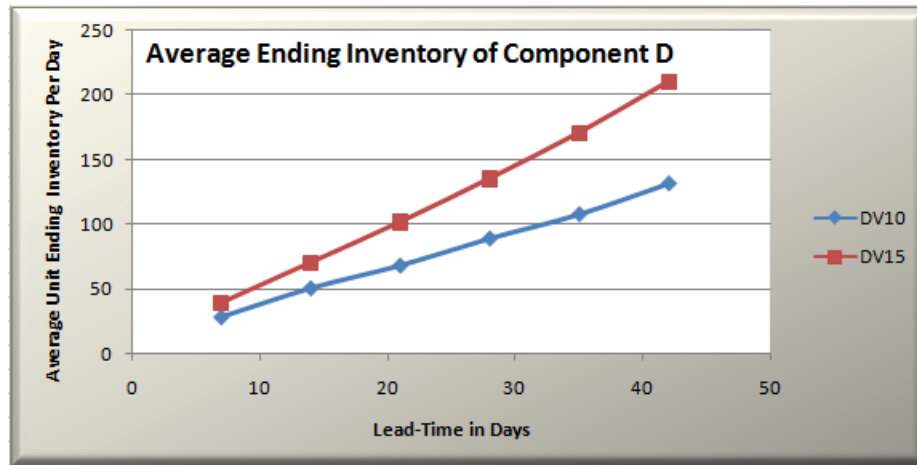


Figure 6.2.2: Average Ending Inventory of Component D at Demand Variability 10 and 15 across Lead-Time in Days

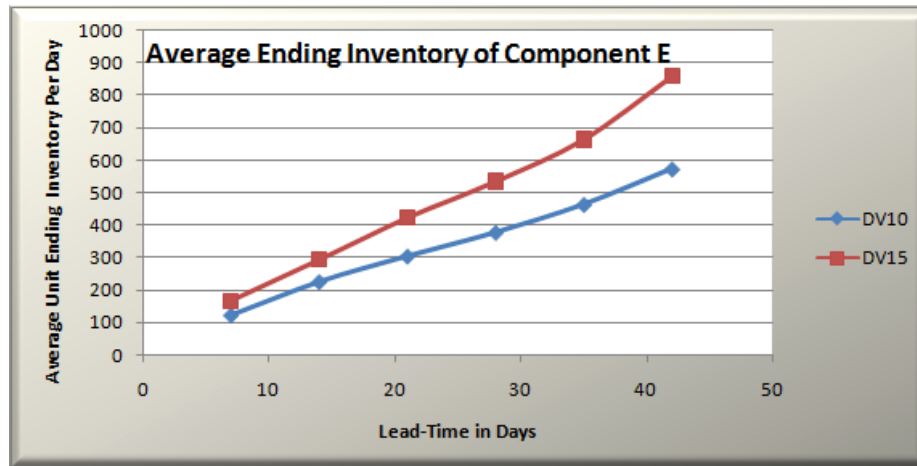


Figure 6.2.3: Average Ending Inventory of Component E at Demand Variability 10 and 15 across Lead-Time in Days

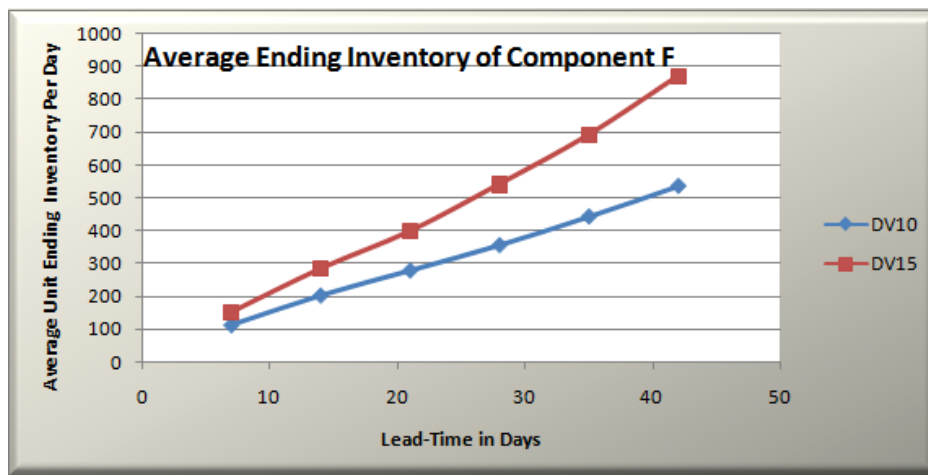


Figure 6.2.4: Average Ending Inventory of Component F at Demand Variability 10 and 15 across Lead-Time in Days

Figures 6.2.1 through 6.2.4 all display the same general pattern. At a lead-time of seven days, the difference in average ending inventory due to demand variability level is very small. As lead-time grows, the difference between the average ending inventory due to changes demand variability grows at every lead-time level. While both demand variability 10 and 15 show continued acceleration in the growth of average ending inventory, demand variability 15 shows a much faster rate of acceleration. For example, the average ending inventory of component F grew from 113 at a seven day lead-time to 537 units at a forty-two day lead-time at a demand variability of 10. At demand variability 15, the average ending inventory of component F grows from 153 units at a seven day lead-time to 871 units at a forty-two day lead-time. In percentage terms, average ending inventory grows by 376% and 469% for demand variability 10 and 15, respectively.

While the present data cannot demonstrate whether the growth rate is exponentially growing forever, the pattern within the investigated seven to forty-two day lead-time certainly indicates worsening inventory levels as a function of lead-time. High demand variability simply exacerbates an already severe inventory growth problem.

### 6.3 - Safety Stock Impact on Components across Demand Variability Levels

Figures 6.2.1 through 6.2.4 display the average ending inventory level per day for components C, D, E and F at each safety stock levels of 0% and 20% of average gross daily requirements.

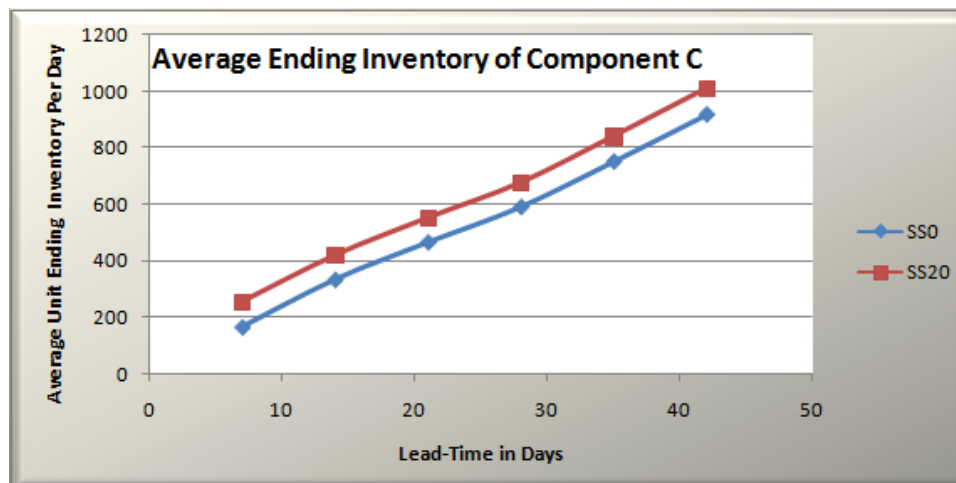


Figure 6.3.1: Average Ending Inventory of Component C at Safety Stocks 0% and 20% of Gross Daily Requirements

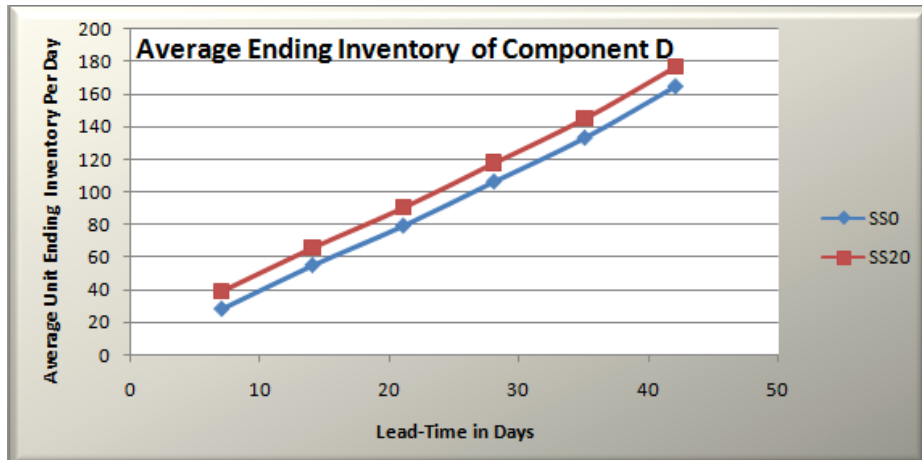


Figure 6.3.2: Average Ending Inventory of Component D at Safety Stocks 0% and 20% of Gross Daily Requirements

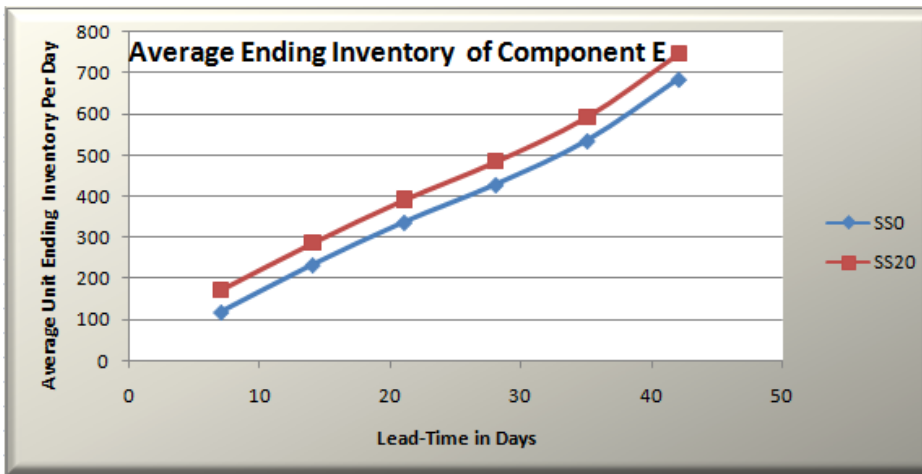


Figure 6.3.3: Average Ending Inventory of Component E at Safety Stocks 0% and 20% of Gross Daily Requirements

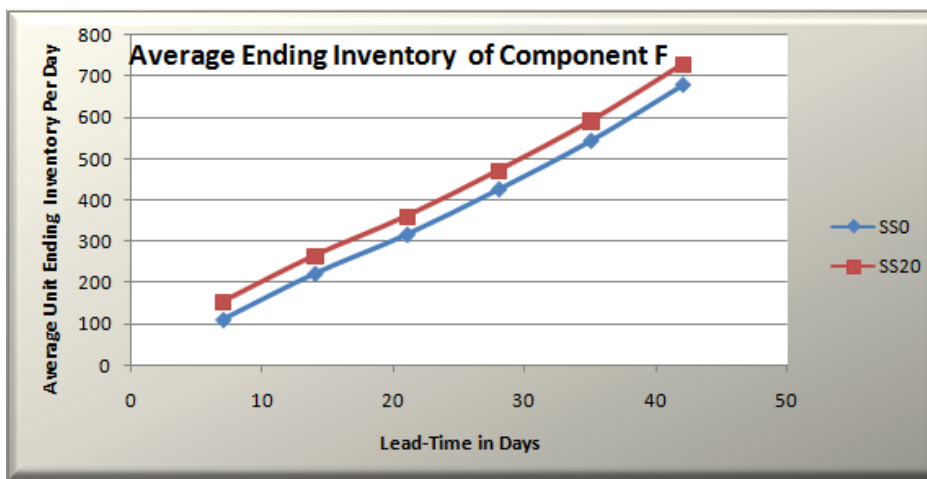


Figure 6.3.4: Average Ending Inventory of Component F at Safety Stocks 0% and 20% of Gross Daily Requirements

Safety stock appears to generate a constant increase in average ending inventory at every level of lead-time. Average backorder levels show a similar magnitude reduction due to increased levels of safety stock in section 5.5. Of course, the impact of increased safety stock is an increase in component inventory levels, which directly lowers the chance of a backorder for the component—the classic cost trade-off between inventory and backorders/lost sales.

In contrast to average ending inventory pattern of divergence at different levels of demand variability seen in section 6.2, the average ending inventory levels at each safety stock level neither converge nor diverge. Once again, demand variability causes different rates of growth at different lead-times while safety stock has a nearly constant effect at each lead-time.

## 6.4 – Ending Inventory Analysis for Components

Figures 6.4.1 through 6.4.4 graphically display impacts on backorders due to changes in both demand variability and safety stock level combinations.

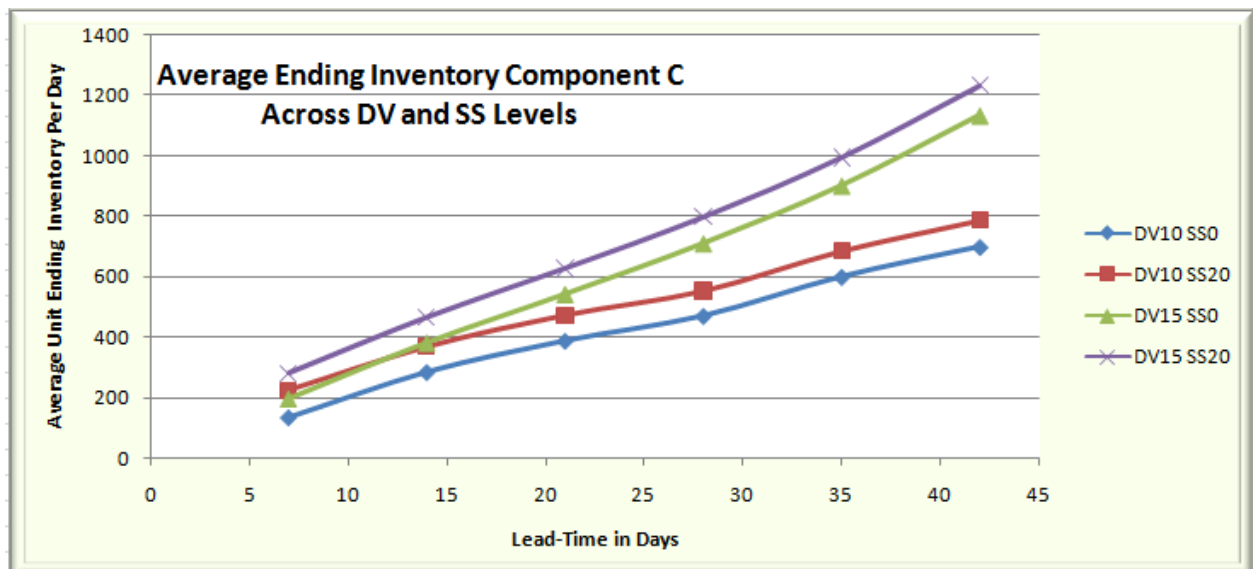


Figure 6.4.1: Average Ending Inventory of Component C at all Safety Stock and Demand Variability Levels across Lead-Time in Days

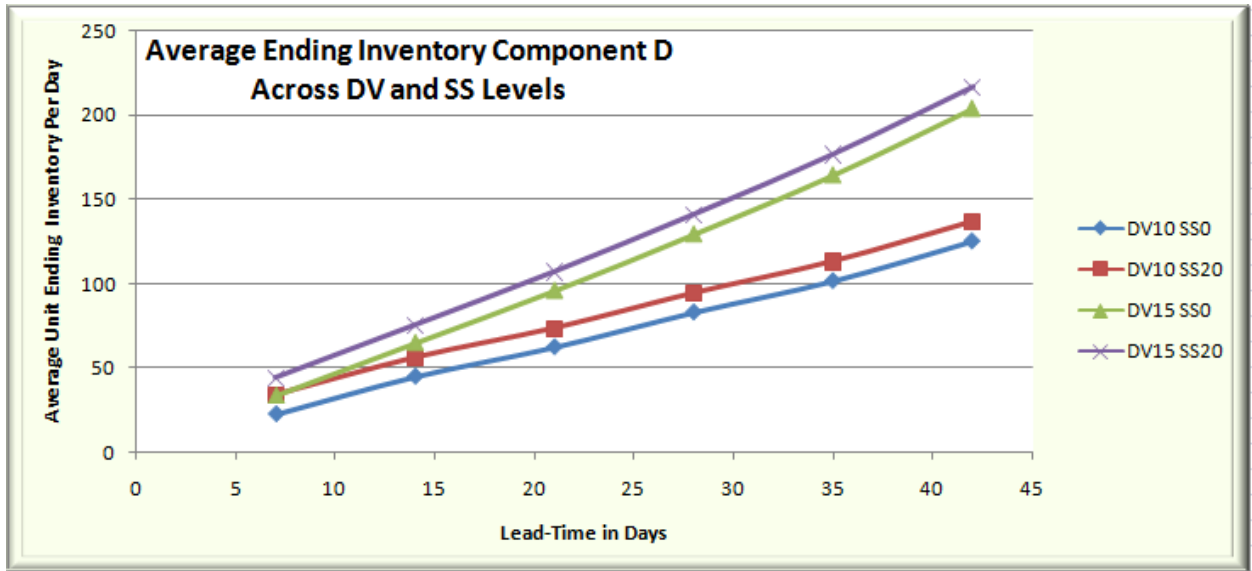


Figure 6.4.2: Average Ending Inventory of Component D at all Safety Stock and Demand Variability Levels across Lead-Time in Days

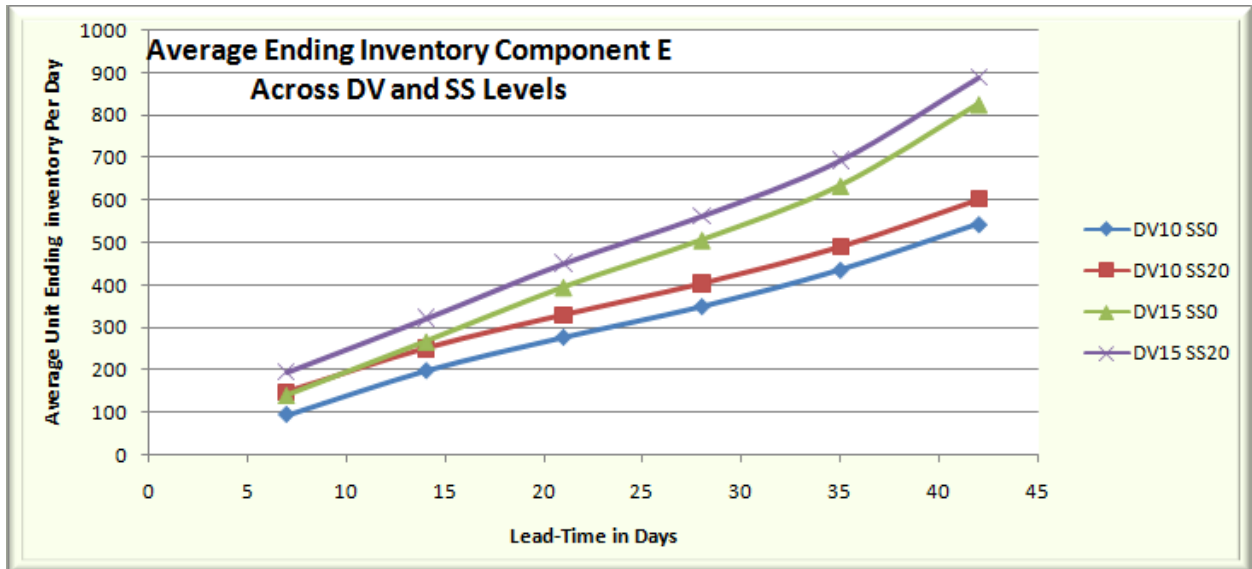


Figure 6.4.3: Average Ending Inventory of Component E at all Safety Stock and Demand Variability Levels across Lead-Time in Days

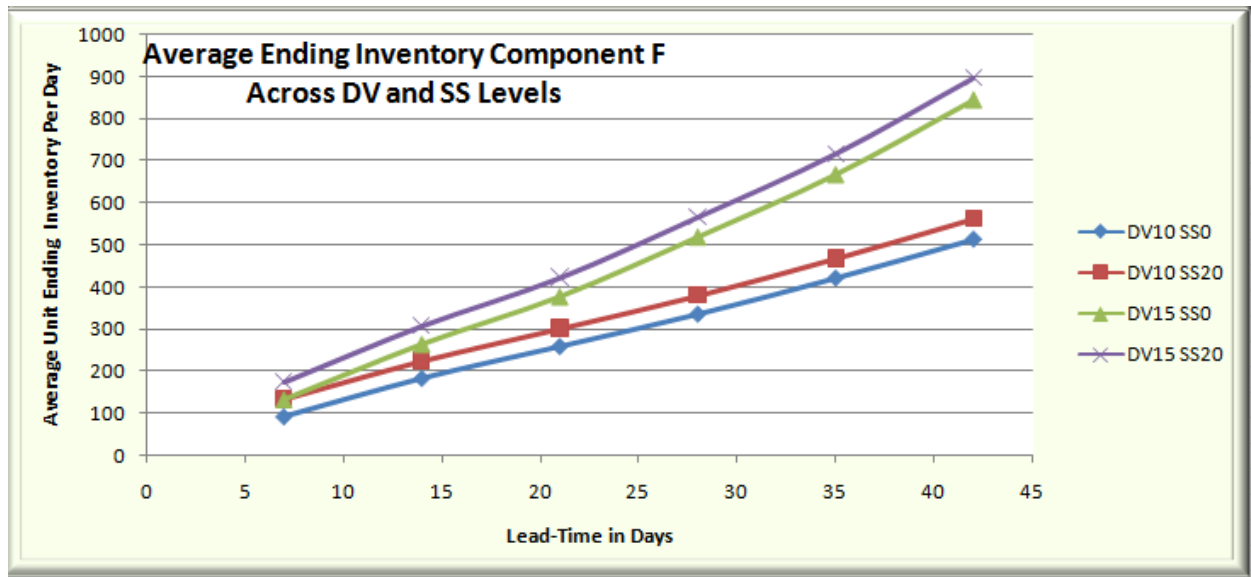


Figure 6.4.4: Average Ending Inventory of Component F at all Safety Stock and Demand Variability Levels across Lead-Time in Days

Unlike the average backorder levels, which show convergence of some treatment levels, the ending inventories display no such convergence. In fact, all ending inventories grow as lead-time grows. The difference is one of growth rate. Demand variability appears to be a major driving force behind the growth rate of ending inventory levels no matter the safety stock level. Safety stock does appear to provide a buffer but only by a roughly constant amount. Hence, once again, safety stock determination appears to be somewhat independent of lead-time under the simulation's assumptions.

## 6.5 – Conclusions about Ending Inventories

The results of Chapters 5 and 6 distinctly show the trade-off between ending inventories and backorders. While backorders show diminishing growth rates as a function of lead-time, the ending inventories show the opposite trend. Ending inventories consistently grow as a function of lead-time regardless of safety stock levels or demand variability. Increased safety stock and demand variability merely increases the growth of ending inventory. As noted in section 6.4, the demand variability directly causes accelerated growth rates of ending inventory while safety stock adds a roughly constant amount at each level of lead-time.

Quantitatively, component average ending inventories often grow by 400% or more as lead-time grows. For instance, the average ending inventory for component C with demand variability 10

and safety stock of 0% of gross daily component requirements grows from an average ending inventory level of 134 units per day at a lead-time of seven days to 699 units at a forty-two day lead-time – a 422% increase in average ending inventory due to lead-time.

In sum, manufacturers in relatively high demand variability industries do face even more potential of high ending inventories. Unlike the average backorder levels of Chapter 5, the average ending inventory levels do not diminish in growth rate. To the contrary, average ending inventory shows a pattern of accelerating growth as a function of increasing lead-times. Additionally, safety stocks only increase the average ending inventory by a relatively constant amount at each lead-time level. Thus, once again, companies may be able to set safety stock levels independently of lead-time if they face similar conditions to those modeled (e.g., no lost orders, MRP freezes for the length of the lead-time, etc.).

## 7 - Formal Statistical Analysis of Lead-Time, Demand Variability and Safety Stock Main Effects

Chapters 4 through 6 of this research focus on the practical meaning of the simulation results. Chapter 7 focuses on the statistical significance of the simulation's main effects experiment. In each of the following sections, an analysis of the statistically significant results appears as output from JMP (a JAVA based program from the SAS Corporation).

### 7.1 – Overall Model Analysis – Significant Effects and Interactions

Before each least-squares means level can be examined thoroughly, the full model with all possible interactions must be checked. Section 7.1 details the full factorial ANOVA models for each response from backorders of end products through ending inventories of components. In each case, a full factorial model shows the overall results followed by a reduced model with insignificant effects removed. Interactions without highly significant p-values (i.e., p-values < 0.001) are removed.

#### 7.1.1 – Backorder of End Product A

The full model adjusted  $R^2$ , F-statistic and individual significance tests appear in figure 7.1.1.1.

Summary of Fit				
RSquare		0.982894		
RSquare Adj		0.978796		
Root Mean Square Error		5.072637		
Mean of Response		102.6796		
Observations (or Sum Wgts)		120		

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	23	141936.81	6171.17	239.8279
Error	96	2470.24	25.73	Prob > F
C. Total	119	144407.05		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	262.0894	<.0001*
Lead-Time	1000.781	<.0001*
Demand Var*Lead-Time	3.4827	0.0062*
Safety Stock	232.2891	<.0001*
Demand Var*Safety Stock	0.1261	0.7233
Lead-Time*Safety Stock	0.0269	0.9997
Demand Var*Lead-Time*Safety Stock	0.0165	0.9999

Figure 7.1.1.1: Backorder of End Product A Fit and Effects Significance Full Model

The adjusted  $R^2$  of 97.8% and F-statistic of 239.83 with accompanying p-value < 0.0001 indicate that at least some factors are highly significant in explaining the variability in average backorder level for end product A. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. The interaction of demand variability with lead-time is also fairly significant with a p-value of 0.0062 but



not enough for inclusion against a required p-value of less than 0.001. A reduced model appears in Figure 7.1.1.2.

Summary of Fit					Effect Tests		
RSquare					Source	F Ratio	Prob > F
RSquare Adj					Demand Var	258.0423	<.0001*
Root Mean Square Error					Lead-Time	985.3275	<.0001*
Mean of Response					Safety Stock	228.7022	<.0001*
Observations (or Sum Wgts)							
Analysis of Variance							
Source	DF	Sum of Squares	Mean Square	F Ratio			
Model	7	141479.90	20211.4	773.3403			
Error	112	2927.14	26.1	Prob > F			
C. Total	119	144407.05		<.0001*			

Figure 7.1.1.2: Backorder of End Product A Fit and Effects Significance Reduced Model

The adjusted  $R^2$  barely changed while the F-statistic improved. The reduced model appears to be highly statistically significant for explaining variability in average backorders for end product A.

## 7.1.2 – Backorder of End Product B

The full model adjusted  $R^2$ , F-statistic and individual significance tests appear in figure 7.1.2.1.

Summary of Fit					Effect Tests		
RSquare					Source	F Ratio	Prob > F
RSquare Adj					Demand Var	109.4857	<.0001*
Root Mean Square Error					Lead-Time	564.4964	<.0001*
Mean of Response					Demand Var*Lead-Time	1.0578	0.3887
Observations (or Sum Wgts)					Safety Stock	134.4247	<.0001*
					Demand Var*Safety Stock	0.1492	0.7002
Analysis of Variance							
Source	DF	Sum of Squares	Mean Square	F Ratio	Lead-Time*Safety Stock	0.0365	0.9993
Model	23	120066.01	5220.26	133.5680	Demand Var*Lead-Time*Safety Stock	0.0103	1.0000
Error	96	3751.98	39.08	Prob > F			
C. Total	119	123817.99		<.0001*			

Figure 7.1.2.1: Backorder of End Product B Fit and Effects Significance Full Model

The adjusted  $R^2$  of 96.2% and F-statistic of 133.6 with accompanying p-value < 0.0001 indicate that at least some factors are highly significant in explaining the variability in average backorder level for end product B. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. None of

the interaction effects show any statistically significant effects. A reduced model appears in Figure 7.1.2.2.

Summary of Fit				
RSquare				0.967907
RSquare Adj				0.965901
Root Mean Square Error				5.956433
Mean of Response				93.46985
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	119844.33	17120.6	482.5551
Error	112	3973.66	35.5	Prob > F
C. Total	119	123817.99		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	120.6076	<.0001*
Lead-Time	621.8396	<.0001*
Safety Stock	148.0799	<.0001*

Figure 7.1.2.2: Backorder of End Product B Fit and Effects Significance Reduced Model

Both the adjusted  $R^2$  and F-statistic improved. The reduced model appears to be highly statistically significant for explaining variability in average backorders for end product B.

### 7.1.3 – Backorder and Ending Inventory of Component C

The backorder's full model adjusted  $R^2$ , F-statistic and individual significance tests for average backorder of component C appear in figure 7.1.3.1.

Summary of Fit				
RSquare				0.953992
RSquare Adj				0.942969
Root Mean Square Error				32.79989
Mean of Response				384.8724
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	23	2141554.5	93111.1	86.5479
Error	96	103279.9	1075.8	Prob > F
C. Total	119	2244834.5		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	104.7716	<.0001*
Lead-Time	343.5869	<.0001*
Demand Var*Lead-Time	4.7524	0.0006*
Safety Stock	143.7103	<.0001*
Demand Var*Safety Stock	0.0584	0.8095
Lead-Time*Safety Stock	0.0453	0.9988
Demand Var*Lead-Time*Safety Stock	0.0277	0.9996

Figure 7.1.3.1: Backorder of Component C Fit and Effects Significance Full Model

The adjusted  $R^2$  of 94.3% and F-statistic of 86.5 with accompanying p-value < 0.0001 indicate that at least some factors are highly significant in explaining the variability in average backorder level for component C. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. The interaction of

demand variability with lead-time is also statistically significant with a p-value of 0.0006. A reduced model appears in Figure 7.1.3.2.

Summary of Fit				
RSquare		0.953789		
RSquare Adj		0.948607		
Root Mean Square Error		31.13665		
Mean of Response		384.8724		
Observations (or Sum Wgts)		120		

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	12	2141098.9	178425	184.0398
Error	107	103735.5	969	Prob > F
C. Total	119	2244834.5		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	116.2638	<.0001*
Lead-Time	381.2743	<.0001*
Safety Stock	159.4737	<.0001*
Demand Var*Lead-Time	5.2737	0.0002*

Figure 7.1.3.2: Backorder of Component C Fit and Effects Significance Reduced Model

The adjusted  $R^2$  reduced slightly while the F-statistic improved. All factors and interactions appear to be highly statistically significant for explaining variability in average backorders for component C.

The ending inventory full model adjusted  $R^2$ , F-statistic and individual significance tests for average ending inventory of component C appear in figure 7.1.3.3.

Summary of Fit				
RSquare		0.978755		
RSquare Adj		0.973665		
Root Mean Square Error		46.94709		
Mean of Response		580.6577		
Observations (or Sum Wgts)		120		

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	23	9747655.5	423811	192.2892
Error	96	211586.8	2204	Prob > F
C. Total	119	9959242.3		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	635.1960	<.0001*
Lead-Time	690.7655	<.0001*
Demand Var*Lead-Time	45.5015	<.0001*
Safety Stock	105.9139	<.0001*
Demand Var*Safety Stock	0.0285	0.8663
Lead-Time*Safety Stock	0.0221	0.9998
Demand Var*Lead-Time*Safety Stock	0.0135	0.9999

Figure 7.1.3.3: Ending Inventory of Component C Fit and Effects Significance Full Model

The adjusted  $R^2$  of 97.3% and F-statistic of 192.3 with accompanying p-value < 0.0001 indicate that at least some factors are highly significant in explaining the variability in average ending inventory level for component C. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. The interaction of

demand variability with lead-time is also statistically significant with a p-value of less than 0.0001. A reduced model appears in Figure 7.1.3.4.

Summary of Fit				
RSquare				0.978709
RSquare Adj				0.976321
Root Mean Square Error				44.51635
Mean of Response				580.6577
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	12	9747199.9	812267	409.8827
Error	107	212042.4	1982	Prob > F
C. Total	119	9959242.3		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	706.4577	<.0001*
Lead-Time	768.2615	<.0001*
Safety Stock	117.7962	<.0001*
Demand Var*Lead-Time	50.6063	<.0001*

Figure 7.1.3.4: Ending Inventory of Component C Fit and Effects Significance Reduced Model

Both the adjusted  $R^2$  and the F-statistic improved. All factors and interactions in the reduced model appear to be highly statistically significant for explaining variability in average ending inventory for component C.

#### 7.1.4 – Backorder and Ending Inventory of Component D

The backorders full model adjusted  $R^2$ , F-statistic and individual significance tests for average backorder of component D appear in figure 7.1.4.1.

Summary of Fit				
RSquare				0.960434
RSquare Adj				0.950955
Root Mean Square Error				3.899757
Mean of Response				55.85684
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	23	35440.087	1540.87	101.3192
Error	96	1459.978	15.21	Prob > F
C. Total	119	36900.065		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	121.8887	<.0001*
Lead-Time	407.1649	<.0001*
Demand Var*Lead-Time	5.8488	<.0001*
Safety Stock	142.5917	<.0001*
Demand Var*Safety Stock	0.1504	0.6990
Lead-Time*Safety Stock	0.0987	0.9921
Demand Var*Lead-Time*Safety Stock	0.0299	0.9995

Figure 7.1.4.1: Backorder of Component D Fit and Effects Significance Full Model

The adjusted  $R^2$  of 95.1% and F-statistic of 101.3 with accompanying p-value  $< 0.0001$  indicate that at least some factors are highly statistically significant in explaining the variability in average backorder level for component D. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. The

interaction of demand variability with lead-time is also statistically significant with a p-value of 0.0001. A reduced model appears in Figure 7.1.4.2.

Summary of Fit				
RSquare				0.960107
RSquare Adj				0.955633
Root Mean Square Error				3.709098
Mean of Response				55.85684
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	12	35428.022	2952.34	214.5996
Error	107	1472.043	13.76	Prob > F
C. Total	119	36900.065		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	134.7417	<.0001*
Lead-Time	450.0997	<.0001*
Safety Stock	157.6277	<.0001*
Demand Var*Lead-Time	6.4655	<.0001*

Figure 7.1.4.2: Backorder of Component D Fit and Effects Significance Reduced Model

Both the adjusted  $R^2$  and the F-statistic improved. All remaining factors and interactions appear to be highly statistically significant for explaining variability in average backorders for component D.

The ending inventory full model adjusted  $R^2$ , F-statistic and individual significance tests for average ending inventory of component D appear in figure 7.1.4.3.

Summary of Fit				
RSquare				0.978935
RSquare Adj				0.973888
Root Mean Square Error				8.618793
Mean of Response				100.0469
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	23	331404.19	14408.9	193.9712
Error	96	7131.22	74.3	Prob > F
C. Total	119	338535.42		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	714.2698	<.0001*
Lead-Time	693.2938	<.0001*
Demand Var*Lead-Time	45.4091	<.0001*
Safety Stock	53.3911	<.0001*
Demand Var*Safety Stock	0.0308	0.8611
Lead-Time*Safety Stock	0.0202	0.9998
Demand Var*Lead-Time*Safety Stock	0.0061	1.0000

Figure 7.1.4.3: Ending Inventory of Component D Fit and Effects Significance Full Model

The adjusted  $R^2$  of 97.4% and F-statistic of 193.9 with accompanying p-value  $< 0.0001$  indicate that at least some factors are highly significant in explaining the variability in average ending inventory level for component D. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. The interaction of demand variability with lead-time is also statistically significant with a p-value of less than 0.0001. A reduced model appears in Figure 7.1.4.4.

Summary of Fit				
RSquare				0.978899
RSquare Adj				0.976533
Root Mean Square Error				8.170662
Mean of Response				100.0469
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	12	331392.13	27616.0	413.6628
Error	107	7143.29	66.8	Prob > F
C. Total	119	338535.42		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	794.7686	<.0001*
Lead-Time	771.4286	<.0001*
Safety Stock	59.4083	<.0001*
Demand Var*Lead-Time	50.5267	<.0001*

Figure 7.1.4.4: Ending Inventory of Component D Fit and Effects Significance Reduced Model

Both the adjusted  $R^2$  and the F-statistic improved. All factors and interactions in the reduced model appear to be highly statistically significant for explaining variability in average ending inventory for component D.

### 7.1.5 – Backorder and Ending Inventory of Component E

The backorder's full model adjusted  $R^2$ , F-statistic and individual significance tests for average backorder of component E appear in figure 7.1.5.1.

Summary of Fit				
RSquare				0.943796
RSquare Adj				0.930331
Root Mean Square Error				22.05363
Mean of Response				250.6253
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	23	784051.87	34089.2	70.0901
Error	96	46690.82	486.4	Prob > F
C. Total	119	830742.69		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	124.3401	<.0001*
Lead-Time	272.3244	<.0001*
Demand Var*Lead-Time	1.5632	0.1778
Safety Stock	117.8971	<.0001*
Demand Var*Safety Stock	0.0265	0.8710
Lead-Time*Safety Stock	0.0625	0.9973
Demand Var*Lead-Time*Safety Stock	0.0117	1.0000

Figure 7.1.5.1: Backorder of Component E Fit and Effects Significance Full Model

The adjusted  $R^2$  of 93.0% and F-statistic of 70.0 with accompanying p-value < 0.0001 indicate that at least some factors are highly statistically significant in explaining the variability in average backorder level for component E. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. No interaction effects show statistically significant results. A reduced model appears in Figure 7.1.5.2.

Summary of Fit				
RSquare				0.938988
RSquare Adj				0.935174
Root Mean Square Error				21.2732
Mean of Response				250.6253
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	7	780057.21	111437	246.2424
Error	112	50685.48	453	Prob > F
C. Total	119	830742.69		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	133.6306	<.0001*
Lead-Time	292.6720	<.0001*
Safety Stock	126.7061	<.0001*

Figure 7.1.5.2: Backorder of Component E Fit and Effects Significance Reduced Model

Both the adjusted  $R^2$  and the F-statistic improved. All remaining factors and interactions appear to be highly statistically significant for explaining variability in average backorders for component E.

The ending inventory full model adjusted  $R^2$ , F-statistic and individual significance tests for average ending inventory of component E appear in figure 7.1.5.3.

Summary of Fit				
RSquare				0.98182
RSquare Adj				0.977464
Root Mean Square Error				31.71531
Mean of Response				417.0338
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	23	5214935.8	226736	225.4152
Error	96	96562.6	1006	Prob > F
C. Total	119	5311498.4		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	635.4422	<.0001*
Lead-Time	852.3815	<.0001*
Demand Var*Lead-Time	38.5072	<.0001*
Safety Stock	94.4726	<.0001*
Demand Var*Safety Stock	0.0128	0.9101
Lead-Time*Safety Stock	0.0302	0.9995
Demand Var*Lead-Time*Safety Stock	0.0056	1.0000

Figure 7.1.5.3: Ending Inventory of Component E Fit and Effects Significance Full Model

The adjusted  $R^2$  of 97.7% and F-statistic of 225.4 with accompanying p-value  $< 0.0001$  indicate that at least some factors are highly significant in explaining the variability in average ending inventory level for component E. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. The interaction of demand variability with lead-time is also statistically significant with a p-value of less than 0.0001. A reduced model appears in Figure 7.1.5.4.



Summary of Fit					Effect Tests		
RSquare		0.981784			Source	F Ratio	Prob > F
RSquare Adj		0.979741			Demand Var	706.8390	<.0001*
Root Mean Square Error		30.07092			Lead-Time	948.1531	<.0001*
Mean of Response		417.0338			Safety Stock	105.0873	<.0001*
Observations (or Sum Wgts)		120			Demand Var*Lead-Time	42.8337	<.0001*
Analysis of Variance							
Source	DF	Sum of Squares	Mean Square	F Ratio			
Model	12	5214742.6	434562	480.5717			
Error	107	96755.8	904	Prob > F			
C. Total	119	5311498.4		<.0001*			

Figure 7.1.5.4: Ending Inventory of Component E Fit and Effects Significance Reduced Model

Both the adjusted  $R^2$  and the F-statistic improved. All factors and interactions in the reduced model appear to be highly statistically significant for explaining variability in average ending inventory for component E.

### 7.1.6 – Backorder and Ending Inventory of Component F

The backorder's full model adjusted  $R^2$ , F-statistic and individual significance tests for average backorder of component F appear in figure 7.1.6.1.

Summary of Fit					Effect Tests		
RSquare		0.904774			Source	F Ratio	Prob > F
RSquare Adj		0.88196			Demand Var	61.3854	<.0001*
Root Mean Square Error		22.95048			Lead-Time	155.4528	<.0001*
Mean of Response		217.1451			Demand Var*Lead-Time	1.1845	0.3225
Observations (or Sum Wgts)		120			Safety Stock	67.1354	<.0001*
Analysis of Variance							
Source	DF	Sum of Squares	Mean Square	F Ratio			
Model	23	480442.57	20888.8	39.6579			
Error	96	50565.55	526.7	Prob > F			
C. Total	119	531008.12		<.0001*			
					Demand Var*Safety Stock	0.0695	0.7927
					Lead-Time*Safety Stock	0.0626	0.9973
					Demand Var*Lead-Time*Safety Stock	0.0085	1.0000

Figure 7.1.6.1: Backorder of Component F Fit and Effects Significance Full Model

The adjusted  $R^2$  of 88.1% and F-statistic of 39.7 with accompanying p-value < 0.0001 indicate that at least some factors are highly statistically significant in explaining the variability in average backorder level for component F. Interestingly, component F average backorder represents the only response to achieve less than a 90% adjusted  $R^2$ . The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than 0.0001. No interactions proved statistically significant. A reduced model appears in Figure 7.1.6.2.



Summary of Fit					Effect Tests		
RSquare		0.898478			Source	F Ratio	Prob > F
RSquare Adj		0.892133			Demand Var	67.1745	<.0001*
Root Mean Square Error		21.93927			Lead-Time	170.1130	<.0001*
Mean of Response		217.1451			Safety Stock	73.4668	<.0001*
Observations (or Sum Wgts)		120					
Analysis of Variance							
Source	DF	Sum of Squares	Mean Square	F Ratio			
Model	7	477098.97	68157.0	141.6009			
Error	112	53909.15	481.3	Prob > F			
C. Total	119	531008.12		<.0001*			

Figure 7.1.6.2: Backorder of Component F Fit and Effects Significance Reduced Model

Both the adjusted  $R^2$  and the F-statistic improved. All remaining factors and interactions appear to be highly statistically significant for explaining variability in average backorders for component F.

The ending inventory full model adjusted  $R^2$ , F-statistic and individual significance tests for average ending inventory of component F appear in figure 7.1.6.3.

Summary of Fit					Effect Tests		
RSquare		0.984514			Source	F Ratio	Prob > F
RSquare Adj		0.980803			Demand Var	919.3820	<.0001*
Root Mean Square Error		30.42648			Lead-Time	958.0738	<.0001*
Mean of Response		406.3278			Demand Var*Lead-Time	65.0895	<.0001*
Observations (or Sum Wgts)		120			Safety Stock	67.5818	<.0001*
					Demand Var*Safety Stock	0.0395	0.8428
Analysis of Variance							
Source	DF	Sum of Squares	Mean Square	F Ratio	Lead-Time*Safety Stock	0.0356	0.9993
Model	23	5649998.4	245652	265.3488	Demand Var*Lead-Time*Safety Stock	0.0049	1.0000
Error	96	88874.0	926	Prob > F			
C. Total	119	5738872.4		<.0001*			

Figure 7.1.6.3: Ending Inventory of Component F Fit and Effects Significance Full Model

The adjusted  $R^2$  of 98.1% and F-statistic of 265.34 with accompanying p-value  $< 0.0001$  indicate that at least some factors are highly significant in explaining the variability in average ending inventory level for component F. In contrast to the low adjusted  $R^2$  for the average backorder levels of component F, the adjusted  $R^2$  for the average ending inventory for component F is among the highest of all adjusted  $R^2$  values. The individual effect F-tests show that demand variability, lead-time and safety stock are all highly statistically significant with p-values less than

0.0001. The interaction of demand variability with lead-time is also statistically significant with a p-value of less than 0.0001. A reduced model appears in Figure 7.1.6.4.

Summary of Fit				
RSquare				0.984475
RSquare Adj				0.982733
Root Mean Square Error				28.8564
Mean of Response				406.3278
Observations (or Sum Wgts)				120

Analysis of Variance				
Source	DF	Sum of Squares	Mean Square	F Ratio
Model	12	5649774.4	470815	565.4128
Error	107	89098.0	833	Prob > F
C. Total	119	5738872.4		<.0001*

Effect Tests		
Source	F Ratio	Prob > F
Demand Var	1022.151	<.0001*
Lead-Time	1065.168	<.0001*
Safety Stock	75.1362	<.0001*
Demand Var*Lead-Time	72.3653	<.0001*

Figure 7.1.6.4: Ending Inventory of Component F Fit and Effects Significance Reduced Model

Both the adjusted  $R^2$  and the F-statistic improved. All factors and interactions in the reduced model appear to be highly statistically significant for explaining variability in average ending inventory for component F.

### 7.1.7 – Conclusions from Full Models

Every response shows statistically significant results. In only one model did the adjusted  $R^2$  fall below 90%--a surprisingly high figure given the unaccounted for error due to poor forecasting. The reduced models all contained the main effects of demand variability, lead-time and safety stock.

On the other hand, the only interaction term that shows significant results in some of the models is demand variability by lead-time. The interaction of demand variability by lead-time is observed by the diverging lines in the graphics of sections 5.2 and 6.2. In most cases, the interaction effect of demand variability by lead-time has smaller F-statistics than the main effects. Interpretation of the interaction is actually fairly simple. The interaction shows that while backorders and ending inventory grow as a function of lead-time, they actually grow faster when demand variability is high than when demand variability is low (i.e., at demand variability has a standard deviation 15 instead of 10).

## 7.2 – Significant Effects Impact on End Products

Lead-time, demand variability and safety stock level all prove highly statistically significant in helping to explain variability in average backorder levels and average ending inventory levels for

every end product and component (see section 7.1). Each of the following subsections of section 7.2 contains a breakdown of the least-squares means (i.e., the average impact on the mean due to each experimental factor) for each response backorder and ending inventory level of end products and components.

### 7.2.1 – Backorder of End Product A

Statistical analysis of average backorders of end product A shows that lead-time, demand variability and safety stock are all highly statistically significant. The interaction of demand variability and lead-time is also somewhat statistically significant but not enough for inclusion in this discussion.

Lead-time LSMeans for end product A appear in Figure 7.2.1.1.

Least Squares Means Table			LSMeans Differences Tukey HSD	
Level	Least Sq Mean	Std Error	Level	Least Sq Mean
07	44.80388	1.1431364	42	A 140.70899
14	79.01669	1.1431364	35	B 131.56610
21	101.59971	1.1431364	28	C 118.38226
28	118.38226	1.1431364	21	D 101.59971
35	131.56610	1.1431364	14	E 79.01669
42	140.70899	1.1431364	07	F 44.80388

α= 0.050 Q= 2.89966  
Levels not connected by same letter are significantly different.

Figure 7.2.1.1: Lead-time LSMeans of Backorders for End Product A

The Tukey Honestly Significant Difference (Tukey HSD) shows that every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. The increase in average backorder level due to lead-time grows at a diminishing rate.

Demand variability LSMeans for end product A appear in Figure 7.2.1.2.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	95.18294	0.65999010	95.183
15	110.17626	0.65999010	110.176

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98137$		
Level	Least Sq Mean	
15	A	110.17626
10	B	95.18294

Levels not connected by same letter are significantly different.

Figure 7.2.1.2: Demand Variability LSMMeans of Backorders for End Product A

As already shown by the F-statistic in section 7.1.1, the different levels of demand variability are statistically significantly different. On average, a move from demand variability 10 to demand variability 15 causes approximately a 15 unit jump in the average backorders of end product A.

Safety stock LSMMeans for end product A appear in Figure 7.2.1.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	109.73721	0.65999010	109.737
0.2	95.62199	0.65999010	95.622

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98137$		
Level	Least Sq Mean	
0	A	109.73721
0.2	B	95.62199

Levels not connected by same letter are significantly different.

Figure 7.2.1.3: Safety Stock LSMMeans of Backorders for End Product A

Once again, as already shown by the F-statistic in section 7.1.1, the different levels of safety stock are statistically significantly different. On average, moving from a safety stock of 0% to 20% of gross daily component requirements causes an approximately 14 unit drop in the average backorders of end product A.

Overall, the LSMMeans for lead-time have by far the largest impact on average backorders of end product A as shown by the dramatically increasing LSMMeans at each level of lead-time. Demand variability and safety stock have relatively similar magnitude LSMMeans impacts on the average backorder level of end product A.

## 7.2.2 – Backorder of End Product B

Examination of average backorders of end product B shows that lead-time, demand variability and safety stock are all highly statistically significant. No interactions are close to statistically significant.

Lead-time LSMeans for end product B appear in Figure 7.2.2.1.

Least Squares Means Table		
Level	Least Sq Mean	Std Error
07	39.67897	1.3318990
14	71.37397	1.3318990
21	92.29101	1.3318990
28	109.90752	1.3318990
35	120.28878	1.3318990
42	127.27885	1.3318990

LSMeans Differences Tukey HSD		
$\alpha = 0.050$ $Q = 2.89966$		
Level		Least Sq Mean
42	A	127.27885
35	B	120.28878
28	C	109.90752
21	D	92.29101
14	E	71.37397
07	F	39.67897

Levels not connected by same letter are significantly different.

Figure 7.2.2.1: Lead-time LSMeans of Backorders for End Product B

The Tukey Honestly Significant Difference (Tukey HSD) shows that every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. As is the case for end product A, the increase in average backorder level due to lead-time grows at a diminishing rate for end product B.

Demand variability LSMeans for end product B appear in Figure 7.2.2.2.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	87.498355	0.76897222	87.4984
15	99.441344	0.76897222	99.4413

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98137$		
Level		Least Sq Mean
15	A	99.441344
10	B	87.498355

Levels not connected by same letter are significantly different.

Figure 7.2.2.2: Demand Variability LSMeans of Backorders for End Product B

As already shown by the F-statistic in section 7.1.2, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 12 unit jump in the average backorders of end product B.

Safety stock LSMeans for end product B appear in Figure 7.2.2.3.

The screenshot displays two Minitab output windows. The first window, titled 'Least Squares Means Table', shows the following data:

Level	Least Sq Mean	Std Error	Mean
0	100.08658	0.76897222	100.087
0.2	86.85311	0.76897222	86.853

The second window, titled 'LSMeans Differences Student's t', shows the following data:

Level	Least Sq Mean
0 A	100.08658
0.2 B	86.85311

Below the second table, it states: 'Levels not connected by same letter are significantly different.'

Figure 7.2.2.3: Safety Stock LSMeans of Backorders for End Product B

Once again, as already shown by the F-statistic in section 7.1.2, the different levels of safety stock are statistically significantly different. On average, moving from a safety stock of 0% to 20% of gross daily component requirements causes approximately a 13 unit drop in the average backorders of end product B.

In sum, the LSMeans for lead-time have by far the largest impact on average backorders for end product B as shown by the dramatically increasing LSMeans at each level of lead-time. Demand variability and safety stock have similar magnitude LSMeans impacts on the average backorder level of end product B.

## 7.3 – Significant Effects Impact on Components

### 7.3.1 – Backorder of Component C

Analysis of average backorders of component C shows that lead-time, demand variability and safety stock are all highly statistically significant. Moreover, the interaction between demand variability and lead-time is statistically significant.

Lead-time LSMeans for component C appear in Figure 7.3.1.1.

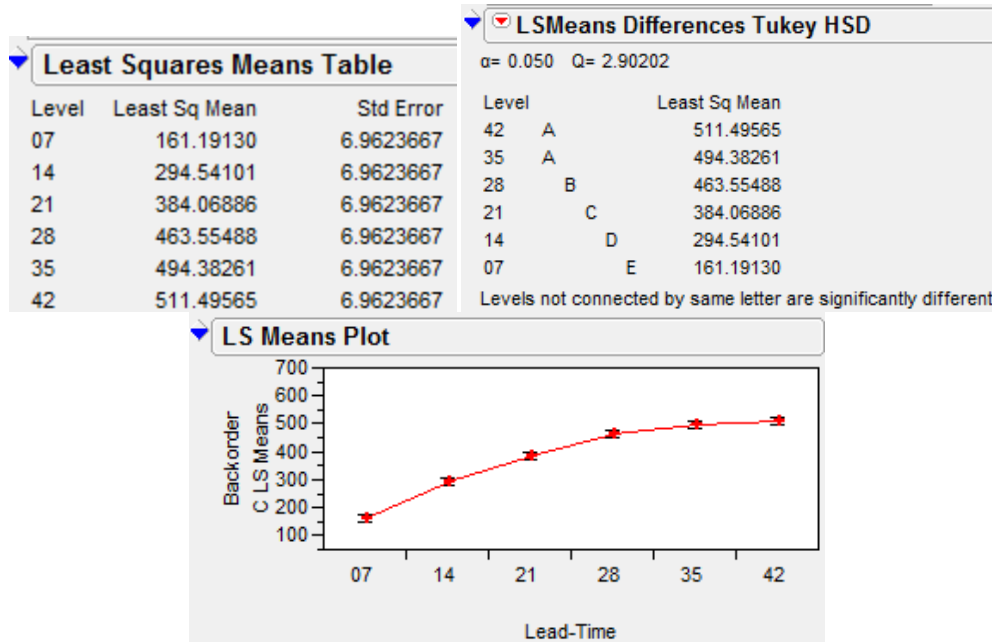


Figure 7.3.1.1: Lead-time LSMeans of Backorders for Component C

Even under a Tukey Honestly Significant Difference (Tukey HSD), almost every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. At the highest lead-times of 35 and 42 days, the LSMeans are too close to be statistically significantly different. As is the case for end products A and B, the increase in average backorder level due to lead-time grows at a diminishing rate for component C.

Demand variability LSMeans for component C appear in Figure 7.3.1.2.

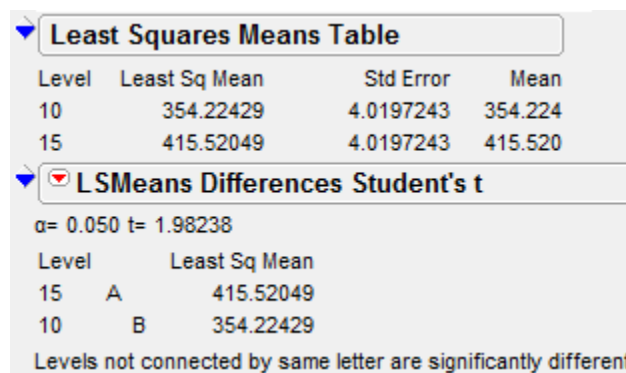


Figure 7.3.1.2: Demand Variability LSMeans of Backorders for Component C

As already shown by the F-statistic in section 7.1.3, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 61 unit jump in the average backorders of component C.

Safety stock LSMMeans for component C appear in Figure 7.3.1.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	420.76671	4.0197243	420.767
0.2	348.97807	4.0197243	348.978

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level		Least Sq Mean
0	A	420.76671
0.2	B	348.97807

Levels not connected by same letter are significantly different.

Figure 7.3.1.3: Safety Stock LSMMeans of Backorders for Component C

As expected due to the F-statistic in section 7.1.3, the different levels of safety stock are statistically significantly different. On average, moving from a safety stock of 0% to 20% of gross daily component requirements causes approximately a 72 unit drop in the average backorders of component C.

Demand variability and lead-time interactions LSMMeans for component C appear in Figure 7.3.1.4.



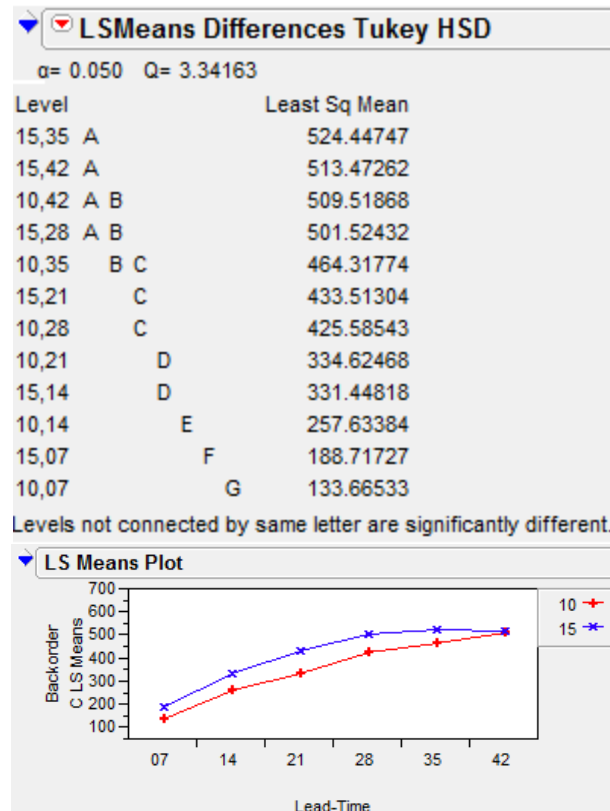


Figure 7.3.1.4: DV\*LT LSMMeans of Backorders for Component C

Not all levels of the interaction combinations are statistically significantly different. At high levels of lead-time, the LSMMeans tend to become too close to distinguish statistically. In contrast, lower levels of lead-time show statistically significant differences regardless of demand variability. In other words, lead-time is the prime driving force in the difference of the LSMMeans while demand variability plays some role in changing the LSMMeans when the lead-time sits in the range of 21-42 days (also seen by the differing slopes past 21 days in the LSMMeans plot). Demand variability plays less of a role in increasing the LSMean backorder level at higher levels of lead-time.

As was the case with the end products, lead-time has by far the largest LSMMeans impact on average backorders for component C as shown by the dramatically increasing LSMMeans at each level of lead-time other than the highest two lead-time levels. Demand variability and safety stock have somewhat similar magnitude LSMMeans impacts on the average backorder level of component C. Interaction between demand variability and lead-time does play a statistically significant role in accounting for the variability in average backorder levels. The LSMMeans plot in figure 7.3.1.4 (and

figure 5.3.1) shows as lead-time grows the slope of the higher demand variability curve decreases at a more rapid rate than the slope of the low demand variability curve.

### 7.3.2 – Ending Inventory of Component C

Analysis of average ending inventory of component C shows that lead-time, demand variability and safety stock are all highly statistically significant. Moreover, the interaction between demand variability and lead-time is statistically significant.

Lead-time LSMeans for component C appear in Figure 7.3.2.1.

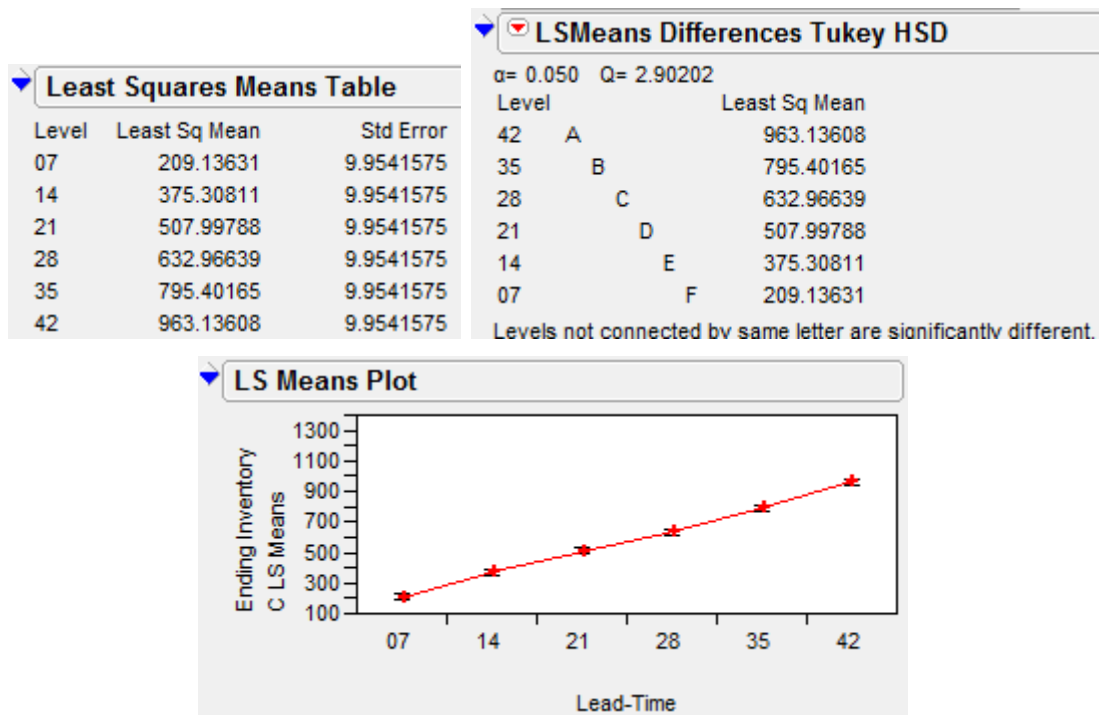


Figure 7.3.2.1: Lead-time LSMeans of Ending Inventory for Component C

The Tukey HSD shows that every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. The increase in average ending inventory level due to lead-time grows at a nearly constant rate for component C.

Demand variability LSMeans for component C appear in Figure 7.3.2.2.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	472.64575	5.7470355	472.646
15	688.66972	5.7470355	688.670

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level		Least Sq Mean
15	A	688.66972
10	B	472.64575

Levels not connected by same letter are significantly different.

Figure 7.3.2.2: Demand Variability LSMMeans of Ending Inventory for Component C

As already shown by the F-statistic in section 7.1.3, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 216 unit jump in the average ending inventory of component C.

Safety stock LSMMeans for component C appear in Figure 7.3.2.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	536.55206	5.7470355	536.552
0.2	624.76342	5.7470355	624.763

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level		Least Sq Mean
0.2	A	624.76342
0	B	536.55206

Levels not connected by same letter are significantly different.

Figure 7.3.2.3: Safety Stock LSMMeans of Ending Inventory for Component C

As expected due to the F-statistic in section 7.1.3, the different levels of safety stock are statistically significantly different. On average, moving from a safety stock of 0% to 20% of component requirements causes an approximately 88 unit increase in the average ending inventory of component C.

Demand variability and lead-time interactions LSMMeans for component C appear in Figure 7.3.2.4.

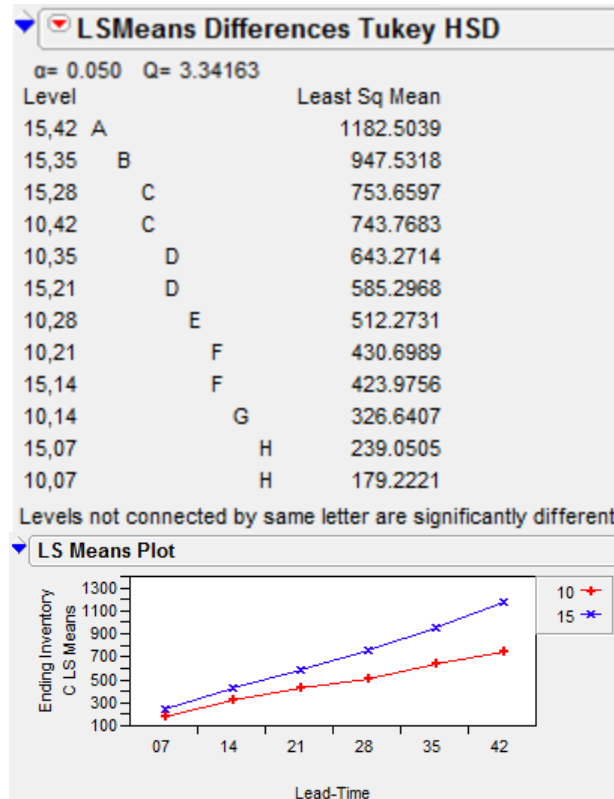


Figure 7.3.2.4: DV\*LT LSMMeans of Ending Inventory for Component C

Not all levels of the interaction combinations are statistically significantly different. The lack of Tukey HSD differences appears to scatter throughout the interaction levels. In other words, lead-time remains the prime driving force in the difference of the LSMMeans. The interaction really shows that as lead-time grows, higher demand variability leads to a faster overall LSMean growth rate.

Once again, as is the case with the end products, lead-time has by far the largest LSMMeans impact on average ending inventory for a component as shown by the dramatically increasing LSMMeans at each level of lead-time. Demand variability and safety stock have somewhat similar magnitude LSMMeans impacts on the average ending inventory level of component C. Interaction between demand variability and lead-time does play a statistically significant role in accounting for the variability in average ending inventory levels. The LSMMeans plot in figure 7.3.2.4 (and figure 6.2.1) shows as lead-time grows the slope of the higher demand variability curve increases at a more rapid rate than the slope of the low demand variability curve. In other words, increased demand variability plays more of a role in increasing the LSMMeans at higher levels of lead-time.

### 7.3.3 – Backorder of Component D

Analysis of average backorders of component D shows that lead-time, demand variability and safety stock are all highly statistically significant. Moreover, the interaction between demand variability and lead-time is statistically significant.

Lead-time LSMeans for component D appear in Figure 7.3.3.1.

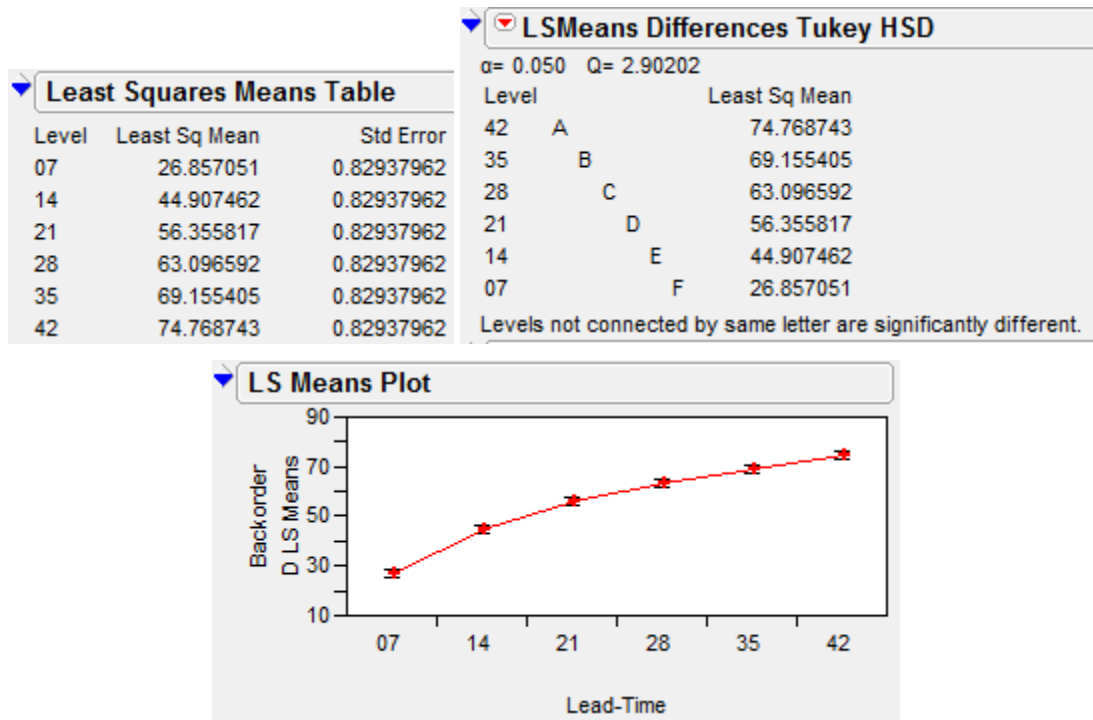


Figure 7.3.3.1: Lead-time LSMeans of Backorders for Component D

The Tukey HSD shows that every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. As is the case for component C, the increase in average backorder level due to lead-time grows at a diminishing rate for component D.

Demand variability LSMeans for component D appear in Figure 7.3.3.2.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	51.926518	0.47884255	51.9265
15	59.787172	0.47884255	59.7872

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level		Least Sq Mean
15	A	59.787172
10	B	51.926518

Levels not connected by same letter are significantly different.

Figure 7.3.3.2: Demand Variability LSMMeans of Backorders for Component D

As already shown by the F-statistic in section 7.2.4, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 9 unit jump in the average backorders of component D.

Safety stock LSMMeans for component D appear in Figure 7.3.3.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	60.107873	0.47884255	60.1079
0.2	51.605817	0.47884255	51.6058

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level		Least Sq Mean
0	A	60.107873
0.2	B	51.605817

Levels not connected by same letter are significantly different.

Figure 7.3.3.3: Safety Stock LSMMeans of Backorders for Component D

As expected due to the F-statistic in section 7.2.4, the different levels of safety stock are statistically significantly different. On average, moving from a safety stock of 0% to 20% of gross daily component requirements causes an approximately 8 unit drop in the average backorders of component D.

Demand variability and lead-time interactions LSMMeans for component D appear in Figure 7.3.3.4.

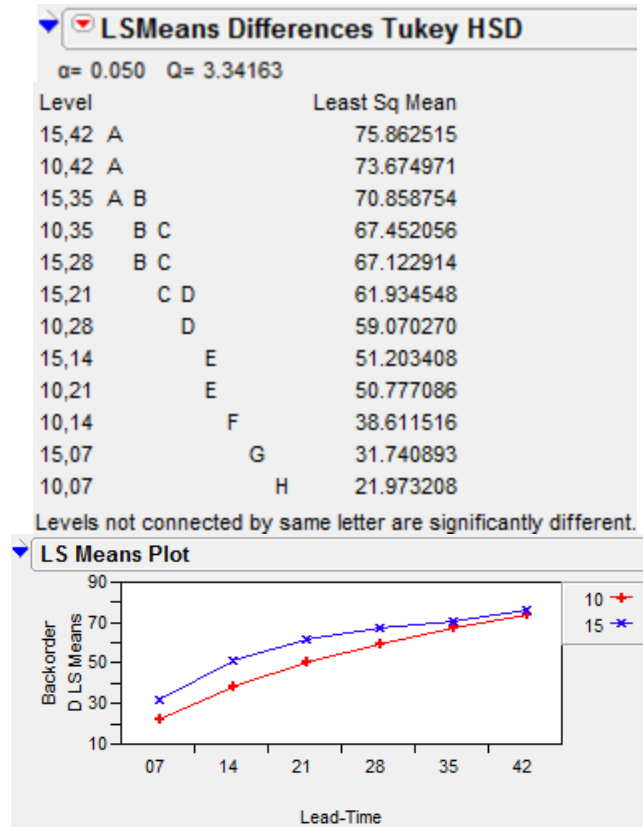


Figure 7.3.3.4: DV\*LT LSMeans of Backorders for Component D

Not all levels of the interaction combinations are statistically significantly different—a similar result to that seen for component C. At high levels of lead-time, the LSMeans tend to become too close to distinguish statistically under a Tukey HSD. In contrast, lower levels of lead-time show statistically significant differences regardless of demand variability. In other words, lead-time is the prime driving force in the difference of the LSMeans while demand variability plays some role in changing the LSMeans when the lead-time sits in the range of 21-42 days (also seen by the differing slopes past 21 days in the LSMeans plot). In other words, demand variability plays less of a role in increasing the LSMeans backorder level at higher levels of lead-time.

In sum, lead-time once again has by far the largest LSMeans impact on average backorders for component D as shown by the dramatically increasing LSMeans at each level of lead-time. Demand variability and safety stock have fairly different magnitude LSMeans impacts on the average backorder level of component D. In fact, demand variability appears to cause a nearly 2.5 fold greater rise in the LSMeans of ending inventory levels for component C when compared to the LSMeans impact of safety stock. Interaction between demand variability and lead-time does play a

statistically significant role in accounting for the variability in average backorder levels of component D. The LSMeans plot in figure 7.3.3.4 (and figure 5.3.2) displays that the slope of the higher demand variability curve decreases at a more rapid rate than the slope of the low demand variability curve as lead-time grows.

### 7.3.4 – Ending Inventory of Component D

Analysis of average ending inventory of component D shows that lead-time, demand variability and safety stock are all highly statistically significant. Moreover, the interaction between demand variability and lead-time is statistically significant.

Lead-time LSMeans for component D appear in Figure 7.3.4.1.

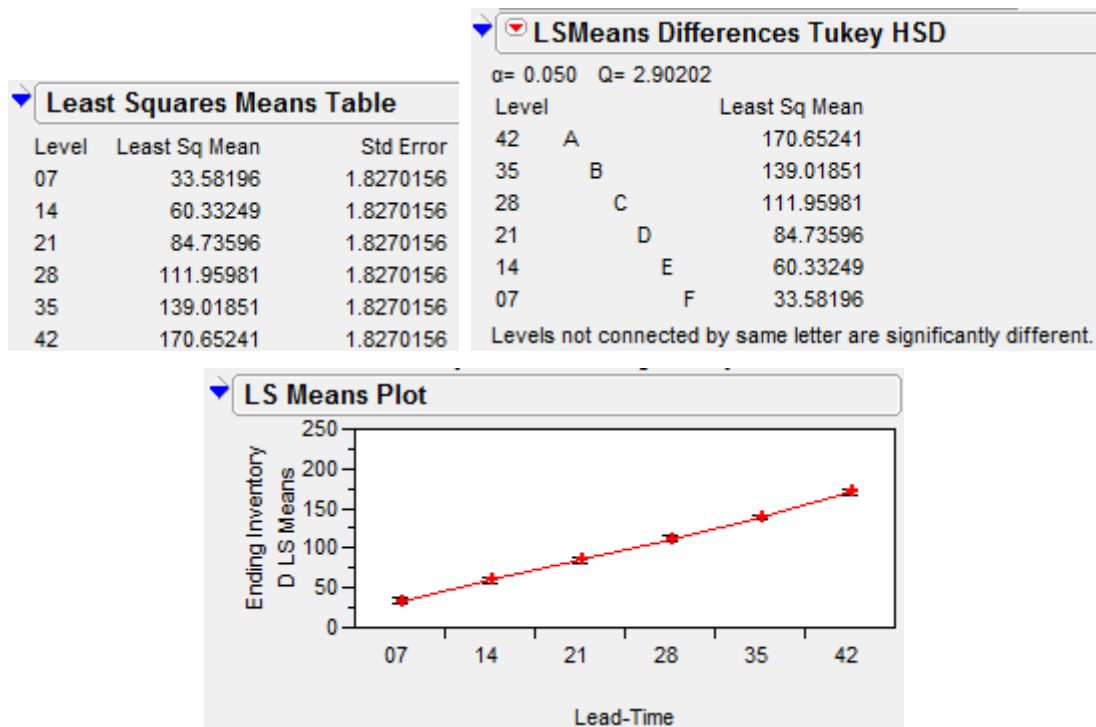


Figure 7.3.4.1: Lead-time LSMeans of Ending Inventory for Component D

The Tukey HSD shows that every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. The increase in average ending inventory level due to lead-time grows at a nearly constant or slightly increasing rate for component D.

Demand variability LSMeans for component D appear in Figure 7.3.4.2.



Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	79.01939	1.0548279	79.019
15	121.07432	1.0548279	121.074

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level		Least Sq Mean
15	A	121.07432
10	B	79.01939

Levels not connected by same letter are significantly different.

Figure 7.3.4.2: Demand Variability LSMMeans of Ending Inventory for Component D

As already shown by the F-statistic in section 7.2.3, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 42 unit increase in the average ending inventory of component D.

Safety stock LSMMeans for component D appear in Figure 7.3.4.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	94.29788	1.0548279	94.298
0.2	105.79583	1.0548279	105.796

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level		Least Sq Mean
0.2	A	105.79583
0	B	94.29788

Levels not connected by same letter are significantly different.

Figure 7.3.4.3: Safety Stock LSMMeans of Ending Inventory for Component D

As expected due to the F-statistic in section 7.2.3, the different levels of safety stock are statistically significantly different. On average, moving from a safety stock of 0% to 20% of gross daily component requirements causes an approximately 12 unit jump in the average ending inventory of component D.

Demand variability and lead-time interactions LSMMeans for component D appear in Figure 7.3.4.4.

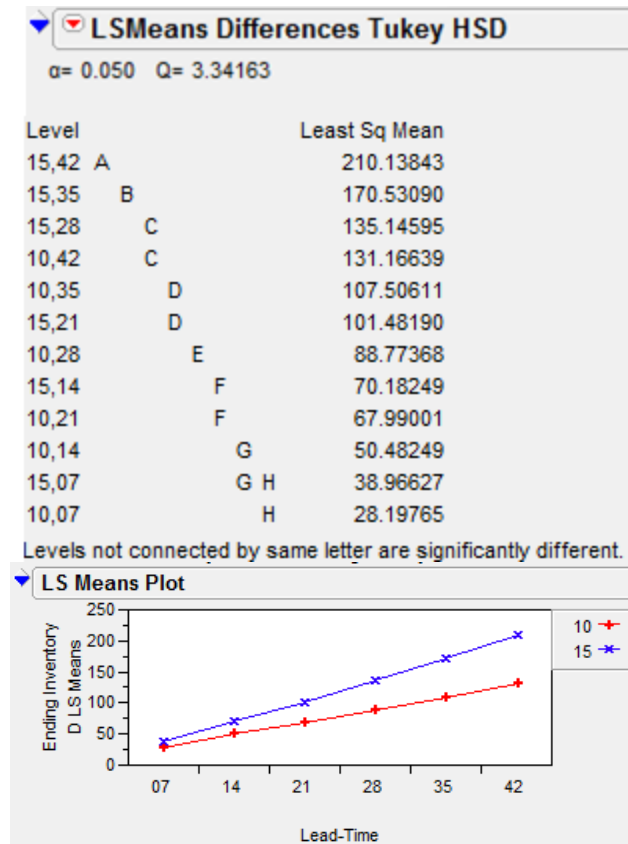


Figure 7.3.4.4: DV\*LT LSMMeans of Ending Inventory for Component D

Not all levels of the interaction combinations are statistically significantly different. The lack of Tukey HSD differences appears to scatter throughout the interaction levels. In other words, lead-time remains the prime driving force in the difference of the LSMMeans. The interaction does display that as lead-time grows, higher demand variability leads to a faster overall LSMean growth rate.

As is the case for component C's ending inventories, lead-time has by far the largest LSMMeans impact on average ending inventory for component D as shown by the dramatically increasing LSMMeans at each level of lead-time. Analysis shows that demand variability has approximately double the impact of safety stock on the LSMMeans of ending inventory of component D. Only end product A requires component D (see section 3.1). Apparently, the demand variability of end products has a larger impact than safety stock buffers on ending inventories for the uniquely required component. Interaction between demand variability and lead-time does play a statistically significant role in accounting for the variability in average ending inventory levels. The LSMMeans plot in figure 7.3.4.4 (and figure 6.2.2) clearly displays that higher demand variability (i.e., demand

variability 15 instead of 10) leads to accelerating ending inventory growth as lead-time grows. In other words, increased demand variability plays an increasing role in accelerating the growth of the LSMeans at higher levels of lead-time.

### 7.3.5 – Backorder of Component E

Analysis of average backorders of component E shows that lead-time, demand variability and safety stock are all highly statistically significant. Further, no interaction effects appear to be statistically significant.

Lead-time LSMeans for component E appear in Figure 7.3.5.1.

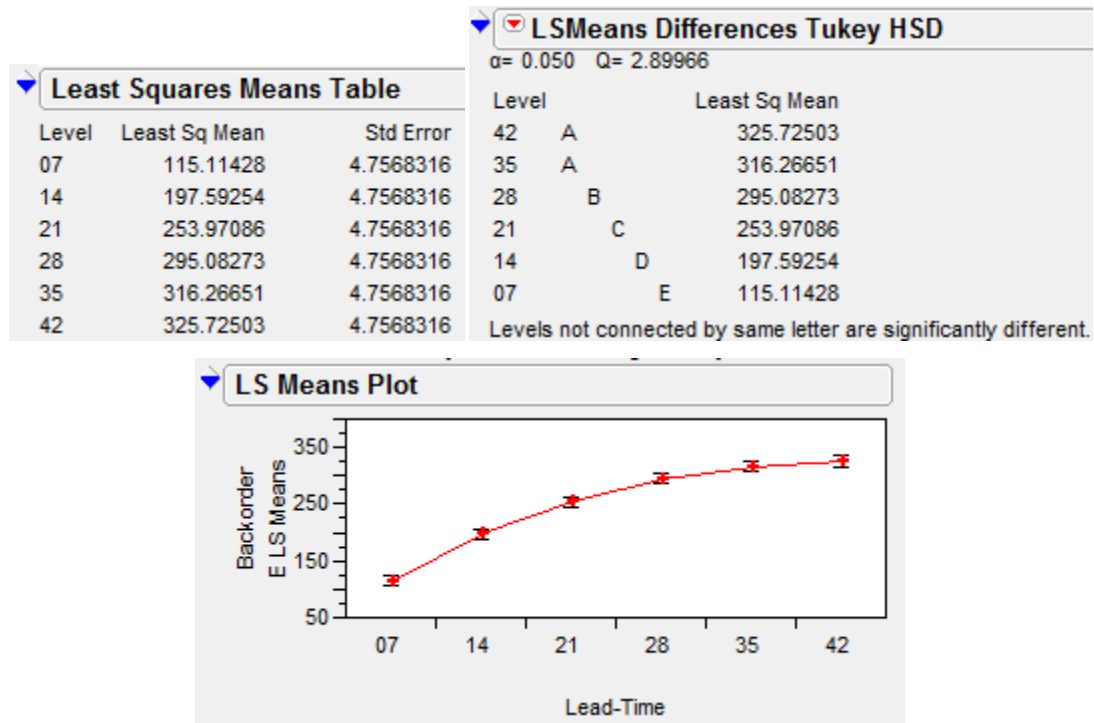


Figure 7.3.5.1: Lead-time LSMeans of Backorders for Component E

The Tukey HSD shows that almost every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. At the highest lead-times of 35 and 42 days, the Tukey HSD fails to find a statistically significant difference. In other words, the growth rate of average backorders due to lead-time levels off too much for the LSMeans at the highest lead-times to show a statistically significant difference.

Demand variability LSMeans for component E appear in Figure 7.3.5.2.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	228.17642	2.7463580	228.176
15	273.07423	2.7463580	273.074

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98137$		
Level		Least Sq Mean
15	A	273.07423
10	B	228.17642

Levels not connected by same letter are significantly different.

Figure 7.3.5.2: Demand Variability LSMMeans of Backorders for Component E

As already shown by the F-statistic in section 7.2.5, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 45 unit increase in the average backorders of component E.

Safety stock LSMMeans for component E appear in Figure 7.3.5.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	272.48486	2.7463580	272.485
0.2	228.76579	2.7463580	228.766

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98137$		
Level		Least Sq Mean
0	A	272.48486
0.2	B	228.76579

Levels not connected by same letter are significantly different.

Figure 7.3.5.3: Safety Stock LSMMeans of Backorders for Component E

As expected due to the F-statistic in section 7.2.5, the different levels of safety stock are statistically significantly different. On average, moving from a safety stock of 0% to 20% of gross daily component requirements causes approximately a 44 unit drop in the average backorders of component E.

As has consistently been true for both the end products and other components, lead-time has by far the largest LSMMeans impact on average backorders for component E. Figure 7.3.5.1 shows the increasing LSMMeans at each level of lead-time other than the highest two lead-time levels.

Demand variability and safety stock have nearly identical magnitude LSMean impacts on the average backorder level of component E.

### 7.3.6 – Ending Inventory of Component E

Analysis of average ending inventory of component E shows that lead-time, demand variability and safety stock are all highly statistically significant. Moreover, the interaction between demand variability and lead-time is statistically significant.

Lead-time LSMean for component E appear in Figure 7.3.6.1.

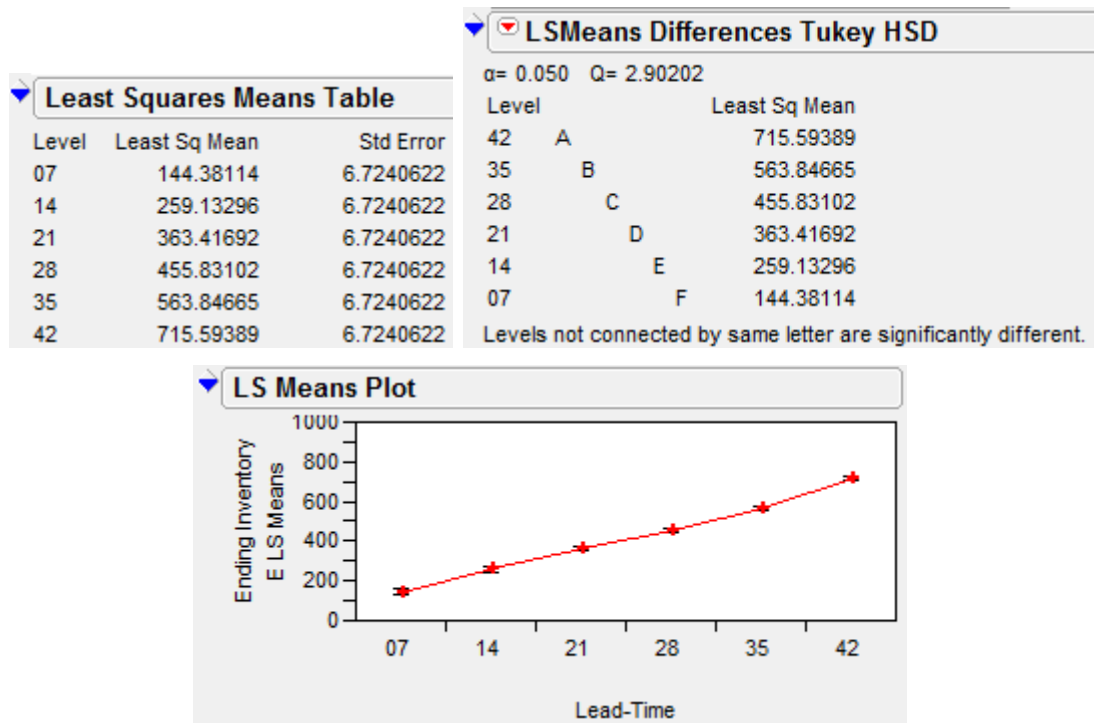


Figure 7.3.6.1: Lead-time LSMean of Ending Inventory for Component E

The Tukey HSD shows that every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. The increase in average ending inventory level due to lead-time grows at a nearly constant or slightly increasing rate for component E.

Demand variability LSMean for component E appear in Figure 7.3.6.2.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	344.05166	3.8821391	344.052
15	490.01586	3.8821391	490.016

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level	Least Sq Mean	
15	A	490.01586
10	B	344.05166

Levels not connected by same letter are significantly different.

Figure 7.3.6.2: Demand Variability LSMMeans of Ending Inventory for Component E

As already shown by the F-statistic in section 7.2.5, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 146 unit jump in the average ending inventory level of component E.

Safety stock LSMMeans for component E appear in Figure 7.3.6.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	388.89330	3.8821391	388.893
0.2	445.17423	3.8821391	445.174

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98238$		
Level	Least Sq Mean	
0.2	A	445.17423
0	B	388.89330

Levels not connected by same letter are significantly different.

Figure 7.3.6.3: Safety Stock LSMMeans of Ending Inventory for Component E

As expected due to the F-statistic in section 7.2.5, the different levels of safety stock are statistically significantly different. On average, moving from a safety stock of 0% to 20% of gross daily component requirements causes approximately a 56 unit increase in the average ending inventory level of component E.

Demand variability and lead-time interactions LSMMeans for component E appear in Figure 7.3.6.4.

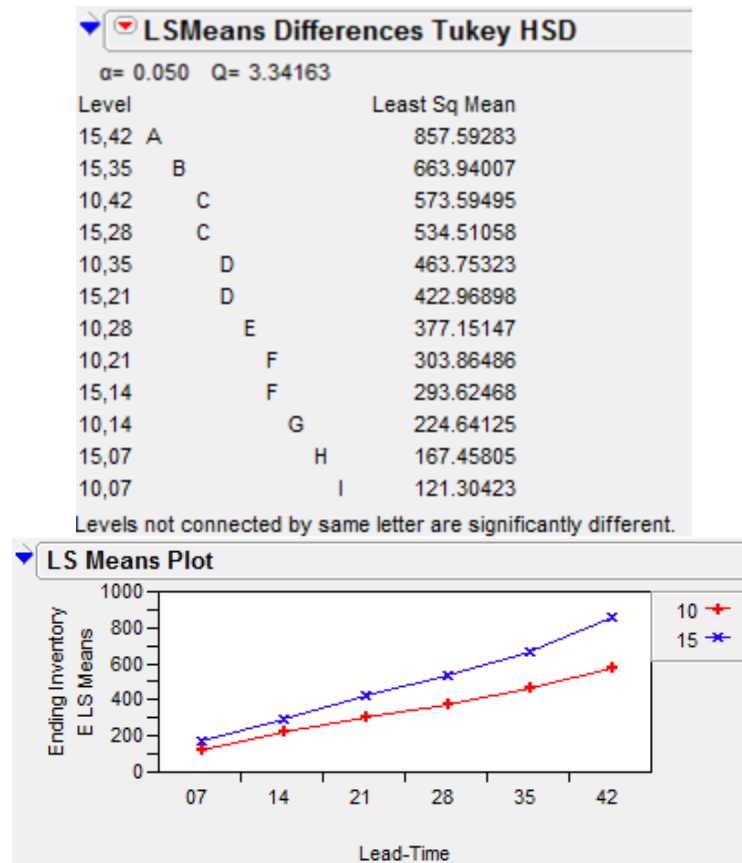


Figure 7.3.6.4: DV\*LT LSMMeans of Ending Inventory for Component E

Interestingly, most interaction combinations are statistically significantly different. The Tukey HSD differences appear throughout the interaction levels. The interaction plot in Figure 7.3.6.4 (and Figure 6.2.3) displays that as lead-time grows, higher demand variability leads to a faster overall LSMean growth rate.

Once again, as is true for both components C and component D ending inventory levels, lead-time has by far the largest LSMMeans impact on average ending inventory for component E as shown by the generally large increases in the LSMean ending inventory levels at each level of lead-time. Further, the analysis shows that demand variability causes more than double the impact of safety stock on the LSMMeans of ending inventory for component E. As seen in the ending inventories for other components, the demand variability of end products has a larger impact than safety stock buffers on ending inventories for required components. As has been the case for other component parts, interaction between demand variability and lead-time does play a statistically significant role in accounting for the variability in average ending inventory levels. The LSMMeans plot in figure

7.3.6.4 (and figure 6.2.3) clearly displays that higher demand variability (i.e., demand variability 15 instead of 10) leads to accelerating ending inventory growth as lead-time grows. Yet again, increased demand variability plays a role in accelerating the growth of the LSMeans at higher levels of lead-time.

### 7.3.7 – Backorder of Component F

Analysis of average backorders of component F shows that lead-time, demand variability and safety stock are all highly statistically significant. Further, no interaction effects appear to be statistically significant.

Lead-time LSMeans for component F appear in Figure 7.3.7.1.

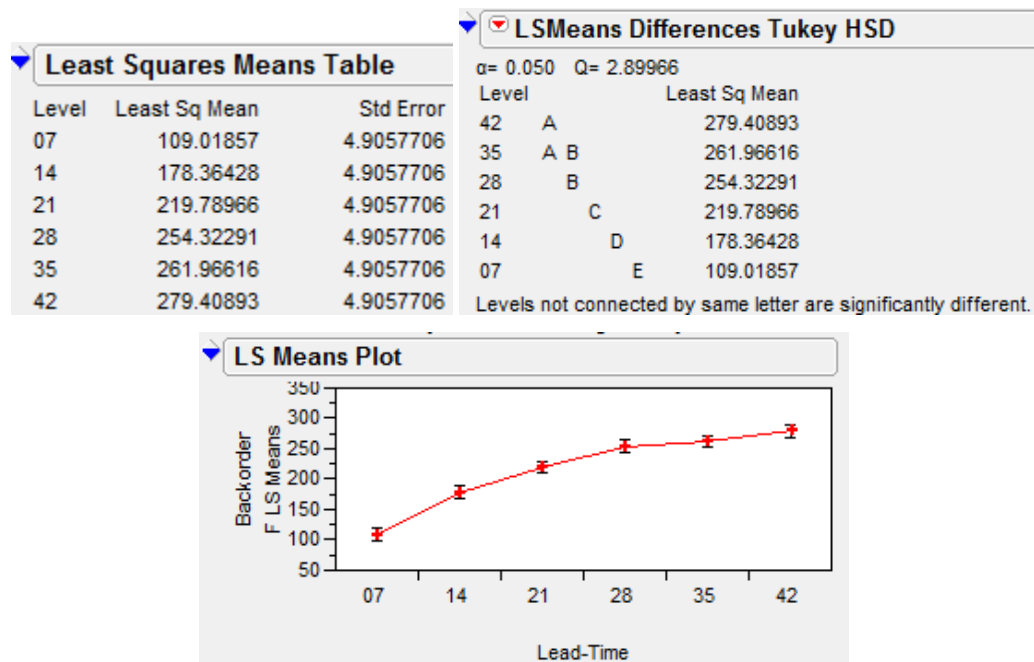


Figure 7.3.7.1: Lead-time LSMeans of Backorders for Component F

The Tukey HSD shows that most levels of lead-time are statistically significantly different from other levels with an overall alpha error rate of 0.05 or 5%. At the highest lead-times of 35 and 42 days as well as 28 and 35 days, the Tukey HSD fails to find a statistically significant difference (i.e., the Tukey individual alpha error rate is too small to allow statistical significance for those pairs). In other words, the growth rate of average backorders due to lead-time levels off too much for the LSMeans at the highest two pairs of lead-times to show a statistically significant difference. Of



course, as with all other average backorders of components and end products, the general pattern of the LSMeans plot is upward with a diminishing growth rate.

Demand variability LSMeans for component F appear in Figure 7.3.7.2.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	200.73036	2.8323480	200.730
15	233.55981	2.8323480	233.560

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98137$		
Level		Least Sq Mean
15	A	233.55981
10	B	200.73036

Levels not connected by same letter are significantly different.

Figure 7.3.7.2: Demand Variability LSMeans of Backorders for Component F

As already shown by the F-statistic in section 7.2.6, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 33 unit increase in the average backorders of component F.

Safety stock LSMeans for component F appear in Figure 7.3.7.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	234.31140	2.8323480	234.311
0.2	199.97877	2.8323480	199.979

LSMeans Differences Student's t		
$\alpha = 0.050$ $t = 1.98137$		
Level		Least Sq Mean
0	A	234.31140
0.2	B	199.97877

Levels not connected by same letter are significantly different.

Figure 7.3.7.3: Safety Stock LSMeans of Backorders for Component F

As expected due to the F-statistic in section 7.2.6, the different levels of safety stock are statistically significantly different. On average, moving from a component safety stock of 0% to 20% of gross daily requirements causes approximately a 34 unit drop in the average backorders of component F.

As has consistently been the true for both the end products and other components, lead-time has by far the largest LSMeans impact on average backorders for component F. Figure 7.3.4.1

shows the increasing LSMeans at each level of lead-time other than the highest two lead-time levels. Demand variability and safety stock have nearly identical LSMeans impacts on the average backorder level of component F.

### 7.3.8 – Ending Inventory of Component F

Analysis of average ending inventory of component F shows that lead-time, demand variability and safety stock are all highly statistically significant. Moreover, the interaction between demand variability and lead-time is statistically significant.

Lead-time LSMeans for component F appear in Figure 7.3.8.1.

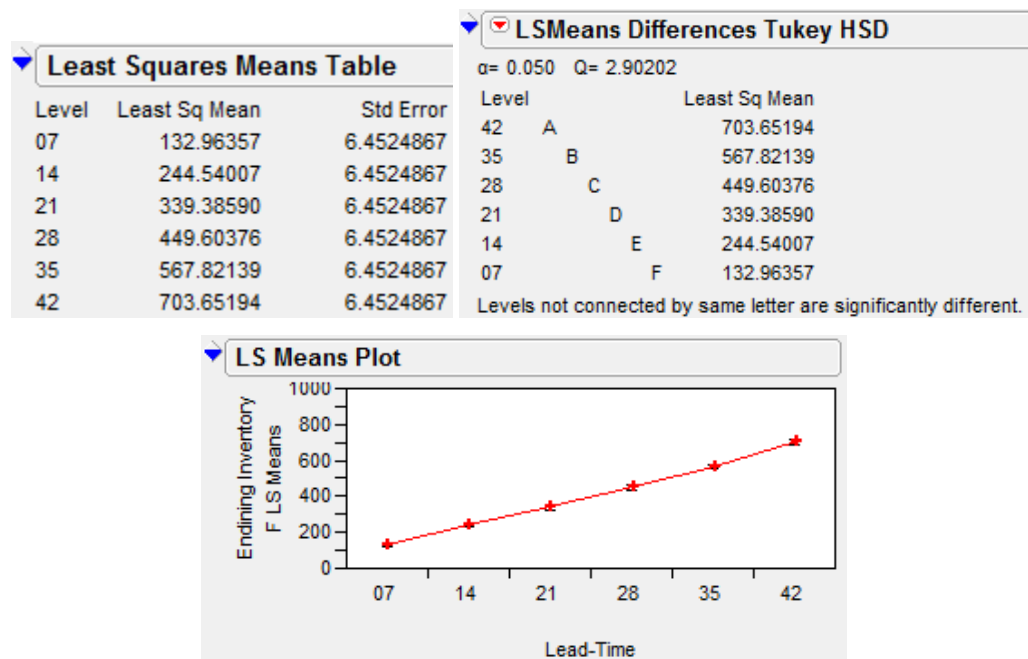


Figure 7.3.8.1: Lead-time LSMeans of Ending Inventory for Component F

The Tukey HSD shows that every level of lead-time is statistically significantly different from all others with an overall alpha error rate of 0.05 or 5%. The increase in average ending inventory level due to lead-time grows at a nearly constant or slightly increasing rate for component F.

Demand variability LSMeans for component F appear in Figure 7.3.8.2.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
10	322.10897	3.7253449	322.109
15	490.54657	3.7253449	490.547

LSMeans Differences Student's t			
$\alpha = 0.050$ $t = 1.98238$			
Level		Least Sq Mean	
15	A	490.54657	
10	B	322.10897	

Levels not connected by same letter are significantly different.

Figure 7.3.8.2: Demand Variability LSMMeans of Ending Inventory for Component F

As already shown by the F-statistic in section 7.2.6, the different levels of demand variability are statistically significantly different. On average, the move from demand variability 10 to demand variability 15 causes approximately a 179 unit increase in the average ending inventory level of component F.

Safety stock LSMMeans for component D appear in Figure 7.3.8.3.

Least Squares Means Table			
Level	Least Sq Mean	Std Error	Mean
0	383.49409	3.7253449	383.494
0.2	429.16146	3.7253449	429.161

LSMeans Differences Student's t			
$\alpha = 0.050$ $t = 1.98238$			
Level		Least Sq Mean	
0.2	A	429.16146	
0	B	383.49409	

Levels not connected by same letter are significantly different.

Figure 7.3.8.3: Safety Stock LSMMeans of Ending Inventory for Component F

As expected due to the F-statistic in section 7.2.6, the different levels of safety stock are statistically significantly different. On average, moving from a component safety stock of 0% to 20% of gross daily requirements causes an approximately 46 unit rise in the average ending inventory level of component F.

Demand variability and lead-time interactions LSMMeans for component F appear in Figure 7.3.8.4.

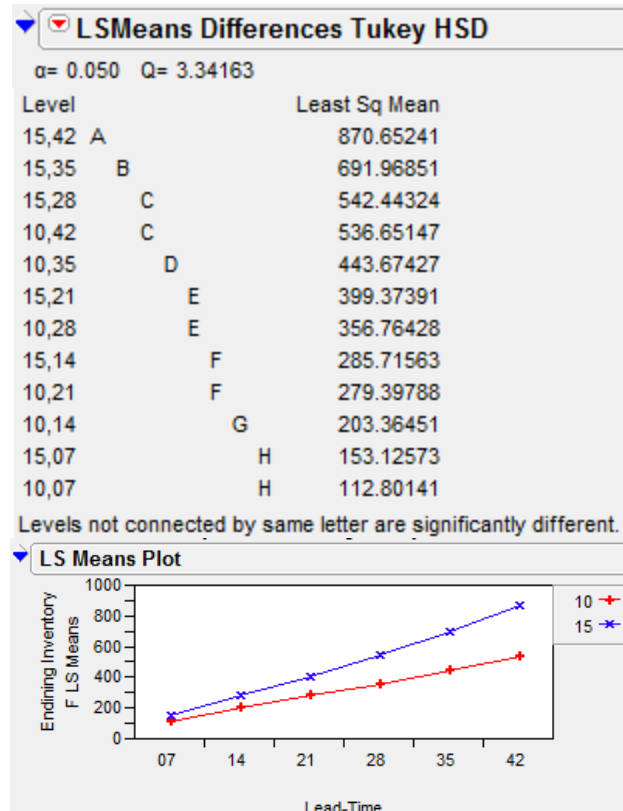


Figure 7.3.8.4: DV\*LT LSMMeans of Ending Inventory for Component F

Most interaction combinations are statistically significantly different. As is the case for most component ending inventory LSMean interaction levels, the insignificant Tukey HSD differences appear to scatter throughout the interaction levels. The interaction plot in Figure 7.3.8.4 (and Figure 6.2.4) displays that as lead-time grows, higher demand variability leads to a faster overall LSMean growth rate.

As is the case for components C, D and E ending inventory levels, lead-time has by far the largest LSMean impact on average ending inventory for component F as shown by the generally large increases in the LSMean ending inventory levels at each level of lead-time. Moreover, the output shows that demand variability has more than triple the impact of safety stock on the LSMean of ending inventory for component F. As seen in the ending inventories for other components, the demand variability on end products has a larger impact than safety stock buffers on ending inventories for required components. Component F is similar to component C in that both components feed into end products A and B (see section 3.1 for details).

As has been the case for other component parts, interaction between demand variability and lead-time does play a statistically significant role in accounting for the variability in average ending inventory levels. The LSMeans plot in figure 7.3.8.4 (and figure 6.2.4) clearly displays that higher demand variability (i.e., demand variability 15 instead of 10) leads to accelerating ending inventory growth as lead-time grows. Once again, increased demand variability plays a role in accelerating the growth of the LSMeans at higher levels of lead-time.

## 7.4 – Final Results of Statistical Examinations

Every full model in section 7.1 shows statistically significant results for every response. In each model, the main effect variables, lead-time, demand variability and safety stock, are statistically significant. In some of the models, the interaction term of lead-time crossed with demand variability is also statistically significant even at an alpha error rate of 0.001. In addition, all but one of the models displays an adjusted  $R^2$  well over 90%. In other words, the models appear to do a very good job of explaining the variation in their respective responses—average ending inventories and backorders.

Every model shows that the largest LSMeans impact on both average ending inventory levels and average backorder levels derives from lead-time. At the highest levels of lead-time, the differences between LSMeans levels sometimes lack significance in a Tukey HSD test. The simulation models longer lead-times with higher standard deviations as discussed in section 3.6. Hence, the likelihood of the larger random error's causing lowered statistical significance was built into the model to keep validity high.

Models for average backorder levels generally show similar magnitude LSMeans impacts due to changes in demand variability and safety stock level. In contrast, models for average ending inventory levels generally show that demand variability has a 200%-300% greater impact on LSMeans than safety stock levels. Chapters 5 and 6 note this pattern as a faster growth rate in the average ending inventories due to higher demand variability as opposed to nearly constant additions to the ending inventory due to higher safety stock levels – the same pattern that emerges from the interaction effects of demand variability with lead-time.

Overall, lead-time appears to have the greatest impact on both backorders and ending inventory. Demand variability and safety stock levels have different impacts depending on the response of interest. High demand variability causes large growths in LSMeans of ending inventories

but relatively small growths in the LSMeans of average backorder levels. High safety stocks tend to cause relatively small growth in the LSMeans of average ending inventories and commensurate decreases in average backorders.

## 8 – Examining Zero Lead-Time Variability, Higher Levels of Safety Stock and Larger Batch Sizes

Chapter 8 focuses on isolating the effects of zero lead-time variability, safety stocks at 40% of gross daily component requirements and different lot sizing rules with larger batch sizes. Each of these factors goes beyond the scope of the original experiment. The examination of each factor focuses on the practical perspective. Factors are also checked statistically when feasible. Full statistical analysis would require more runs at each factor/treatment level to understand the true impacts beyond the extremes investigated below.

### 8.1 – Zero Lead-Time Variability

To isolate the impact of the lead-time variability in the experiment, the simulation generated 12 extra runs with zero lead-time variability. Safety stock is set to zero in every run. Demand variability includes both sigma equal to 10 and 15. Lead-time varies from seven to forty-two days in increments of seven. In every case, the full model for every response, from backorders of end products/components to ending inventories of components, shows statistically significant results.

Specifically, every model (except ending inventory for component D) shows that lead-time variability plays a statistically significant role in explaining variability in the responses. Component D shows a p-value of slightly more than 0.01 for the lead-time variability factor. Lead-time and demand variability are also statistically significant in every model. Some interactions are significant in the various models. In particular, lead-time crossed with lead-time variability as well as demand variability crossed with lead-time tend to be statistically significant in many models.

Figures 8.1.1 and 8.1.2 display the impact of lead-time variability across all lead-times in terms of average backorders for the end products.

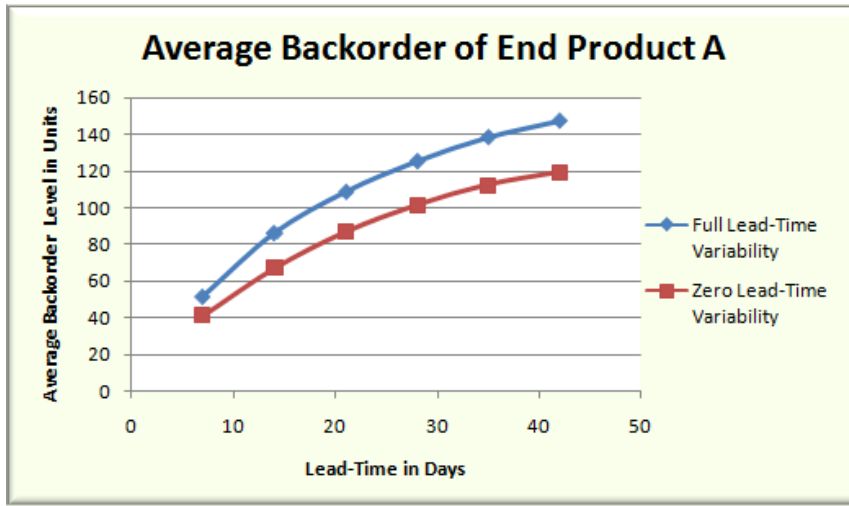


Figure 8.1.1: End Product A Backorders Full vs. Zero Lead-Time Variability across Lead-Times

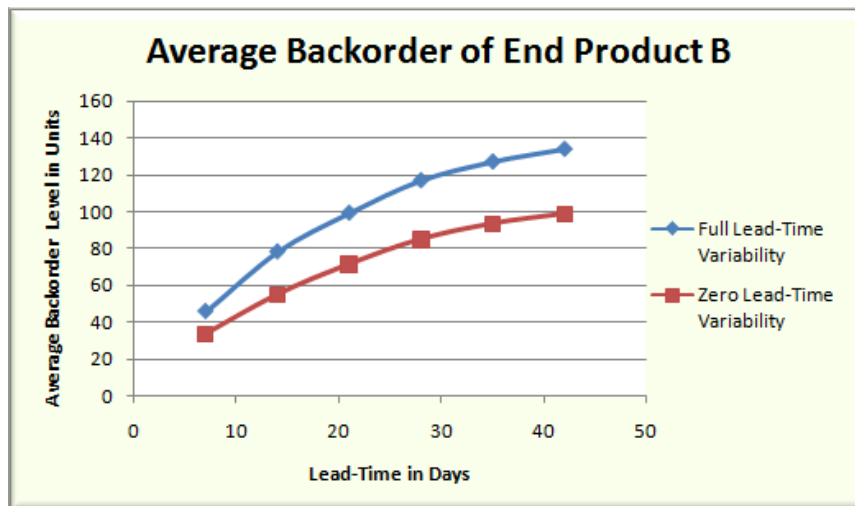


Figure 8.1.2: End Product B Backorders Full vs. Zero Lead-Time Variability across Lead-Times

Both Figures 8.1.1 and 8.1.2 show distinctly higher levels of average backorders for end products at every lead-time level when lead-time variability is present. Moreover, the growth rate of average backorders is faster when lead-time variability is present.

Figure 8.1.3 summarizes the average backorder levels for each component with both levels of lead-time variability across all lead-times.



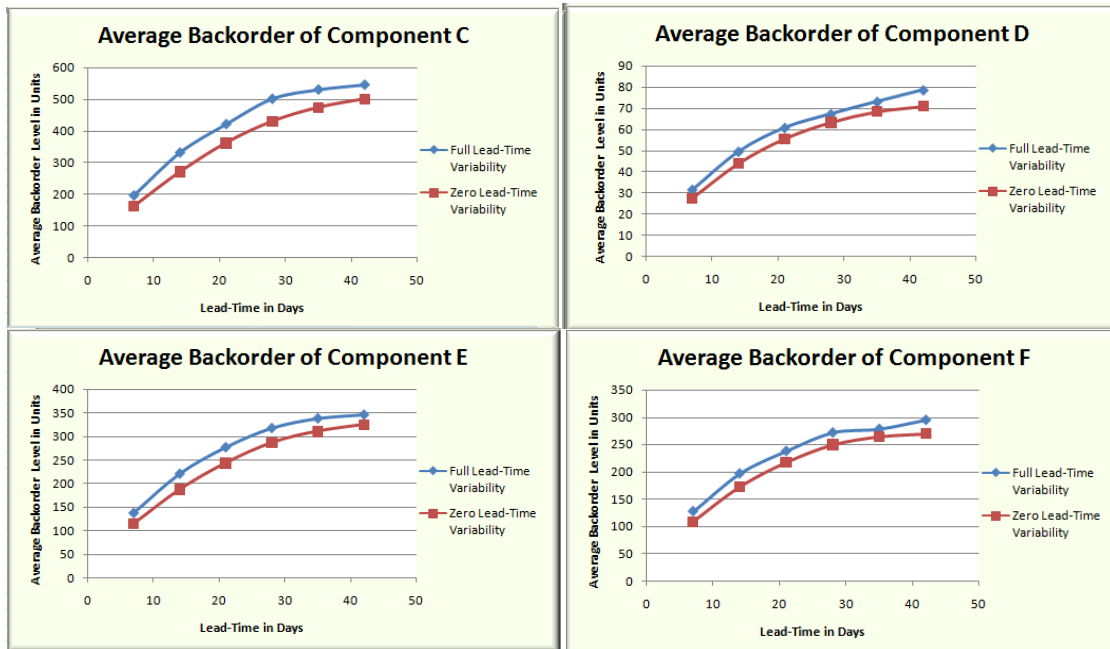


Figure 8.1.3: Component Backorders Full vs. Zero Lead-Time Variability across Lead-Times

The pattern in each graph of Figure 8.1.3 is roughly the same. The average backorder level grows slightly faster for components with the inclusion of full lead-time variability. Even without lead-time variability, the average backorder level grows as a function of lead-time.

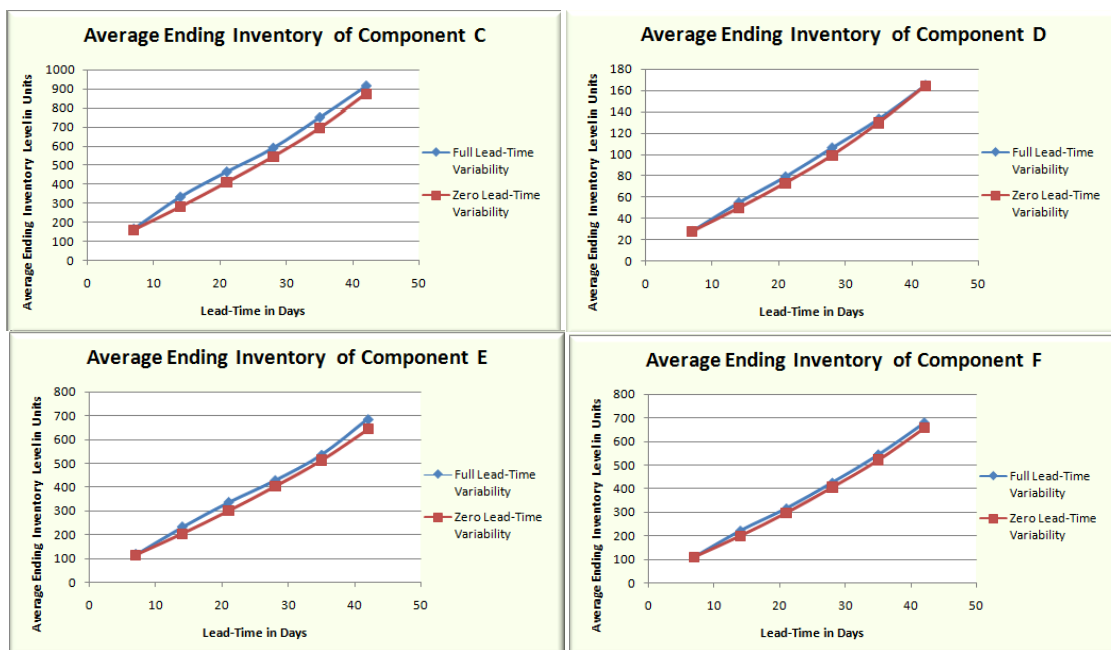


Figure 8.1.4: Component Ending Inventory Full vs. Zero Lead-Time Variability across Lead-Times

The average ending inventory levels show slight increases when moving from zero to full lead-time variability. In fact, the amount of increase due to lead-time variability appears nearly constant at each level of lead-time. The growth patterns are nearly identical for all components.

Figure 8.1.5 summarizes the LSMeans of backorders for each response.

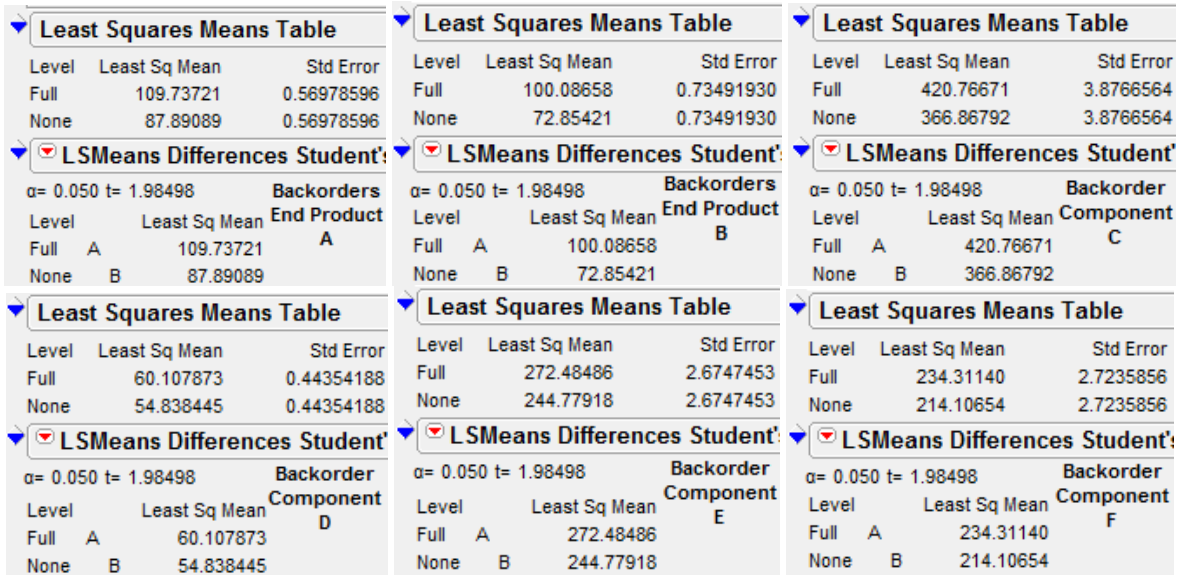
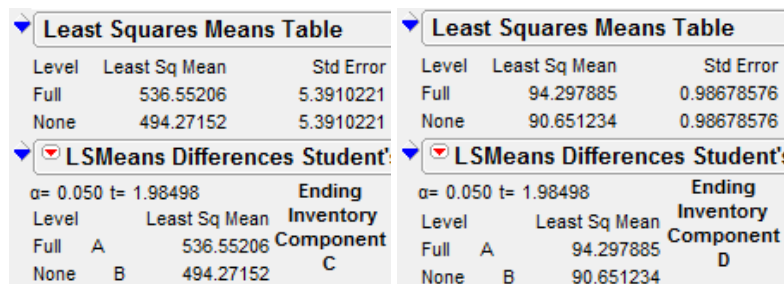


Figure 8.1.5: Lead-Time Variability LSMeans of Backorders

The range of LSMeans impacts goes from only a 5 unit or 9.7% change in the backorders of component D (only required for product A in a 1:1 ratio) to a 49 unit or 14.7% change in the backorders of component C (required for both products A and C in a 4C:1A and 4C:1B ratio). Both the quantity of components per end-item and the joint/non-joint requirement for both end products seem to impact the raw size of the LSMeans for the backorders.

Figure 8.1.6 summarizes the LSMeans of ending inventory for each component response.



Least Squares Means Table			Least Squares Means Table		
Level	Least Sq Mean	Std Error	Level	Least Sq Mean	Std Error
Full	388.89330	3.5106410	Full	383.49409	3.2427728
None	363.66022	3.5106410	None	365.68155	3.2427728

LSMeans Differences Student's			LSMeans Differences Student's		
$\alpha = 0.050$ $t = 1.98498$			$\alpha = 0.050$ $t = 1.98498$		
Level	Least Sq Mean	Ending Inventory Component	Level	Least Sq Mean	Ending Inventory Component
Full A	388.89330	E	Full A	383.49409	F
None B	363.66022		None B	365.68155	

Figure 8.1.6: Lead-Time Variability LSMeans of Ending Inventory

Ending inventories do not change greatly in raw terms due to the inclusion/removal of lead-time variability. Ending inventory for component D shows LSMeans growth of approximately four units or 4% due to inclusion of full lead-time variability. Ending inventory for component C grows by approximately 42 units or 8.5% due to the inclusion of full lead-time variability.

## 8.2 – Exploring Component Safety Stock at 40% of Gross Daily Requirements

The main experiment examines only two levels of safety stock—0 and 20% of gross daily component requirements. Hence, the simulation generated 4 extra runs with component safety stock set to 40% of average gross daily requirements. Lead-time sits at two levels—seven days and forty-two days. Demand variability includes sigma equal to both 10 and 15. The full factorial model for every response (i.e., backorders of end products and components as well as ending inventory for components) shows highly statistically significant results with very large F-statistics and adjusted  $R^2$  above 90% in every model.

Not every factor/treatment level shows significance. Each model shows that safety stock level plays a statistically significant role in explaining variability in the responses (all p-values < 0.0001). Lead-time and demand variability are also statistically significant in every model. Only the interaction between demand variability and lead-time shows significance in some of the models.

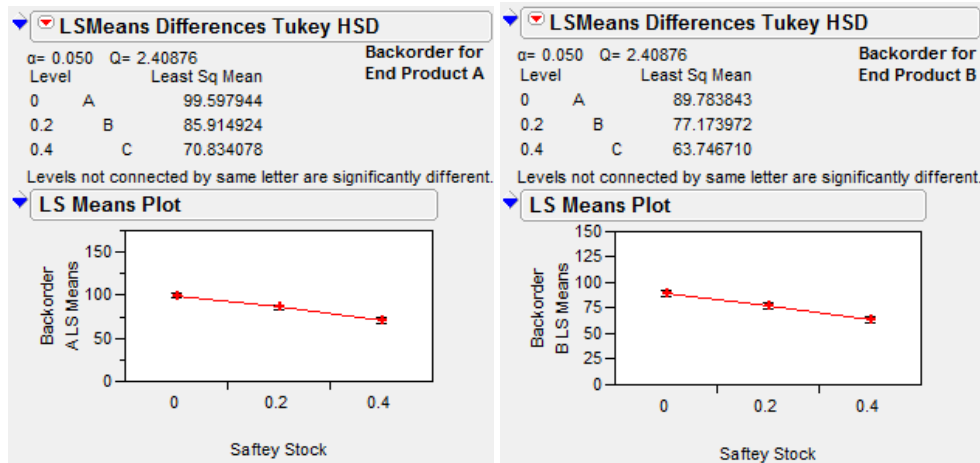
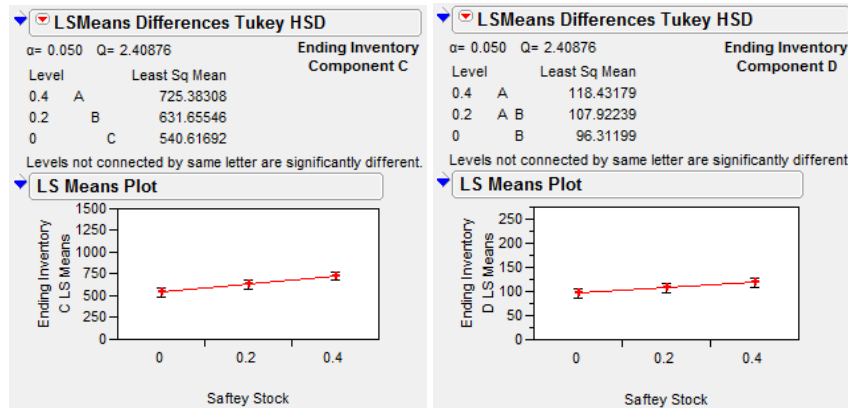


Figure 8.2.1: Safety Stock Level Impact on LSMeans of End Product Backorders

Each increase in the level of safety stock lowers the overall level of backorders by a Tukey HSD significant amount. In terms of the LSMeans, moving from zero safety stock to forty percent of gross daily component requirements lowered end product A average backorders from 100 to 71 units or a 29% drop. End product B saw a similar LSMeans drop in average backorders from 90 to 64 or a 29% drop. In other words, the impact of increasing safety stock appears to be proportional in both end product average backorder levels. The pattern was similar for all component backorder levels.

Figure 8.2.2 displays the statistical results on component ending inventory levels.



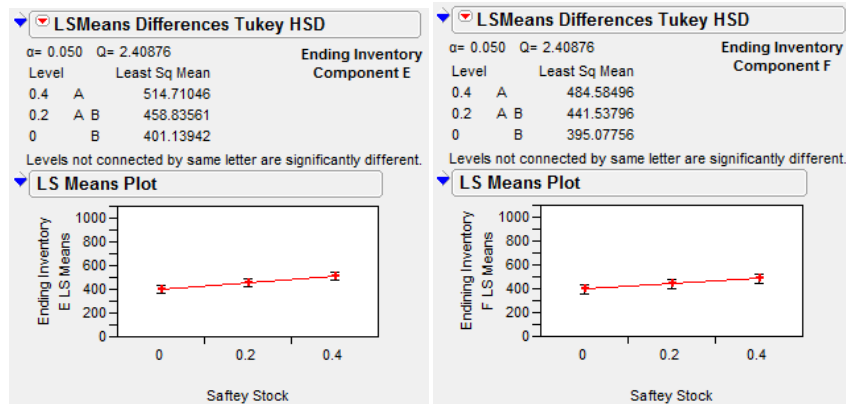


Figure 8.2.2: Safety Stock Level Impact on LSMeans of Component Ending Inventory

Only component C shows a Tukey HSD statistically significant result at each level of safety stock. The other components show statistically significant differences when moving from a component safety stock of 0% to 40% of gross daily requirements. In each case, the general trend is for greater levels of ending inventory in each component as safety stock rises.

### 8.3 – Component Batch Size at Two Weeks of Gross Daily Requirements

The main experiment uses the L4L batch sizing rule. Hence, to check what happens to backorders and component ending inventories, 8 extra simulation runs show the impact of increasing the batch size to two weeks of gross daily requirements for each component. Lead-time sits at two levels—seven days and forty-two days. Demand variability includes sigma equal to both 10 and 15. Lead-time variability of zero or full is also included in these runs. The full factorial to degree two model for every response (i.e., backorders of end products and components as well as ending inventory for components) shows statistically significant results with very large F-statistics and adjusted  $R^2$  above 90% in every model.

Not every factor or interaction level shows significance. Each model shows that lot size plays a statistically significant role in explaining variability in the responses (all p-values < 0.0001). Lead-time and demand variability are also statistically significant in every model. Lead-time variability is usually statistically significant. Various interaction terms show significance in different models. However, no interaction terms are significant across all models. Hence, for ease of examining this extension, all interactions are temporarily ignored.

Least Squares Means Table			Least Squares Means Table		
Level	Least Sq Mean	Std Error	Level	Least Sq Mean	Std Error
14days	11.089924	3.0325284	14days	9.284959	2.8373943
1day	89.868184	3.0325284	1day	77.977615	2.8373943

LSMeans Differences Student's t			LSMeans Differences Student's t		
α= 0.050 t= 1.9921		Backorder	α= 0.050 t= 1.9921		Backorder
Level	Least Sq Mean	End Product A	Level	Least Sq Mean	End Product B
1day A	89.868184		1day A	77.977615	
14days B	11.089924		14days B	9.284959	

Figure 8.3.1: Lot Size Impact on LSMeans of End Product Backorders

The drop in end product backorders due to the larger lot size appears to be dramatic. Both products see an average backorder drop rate of over 87%. Specifically, the average end product backorder rate for end product A drops by 87.7% while end product B experiences an 88.5% drop. Components experience even larger percentage drops in average backorder levels. Of course, end products become backordered when any component required for the product is backordered. Hence, the end product backorder rate is worse than the component backorder rate. All component backorder rates fall by at least 90%. As suspected, ending inventories rise dramatically to cause such a result as shown in Figure 8.3.2.

Least Squares Means Table			Least Squares Means Table		
Level	Least Sq Mean	Std Error	Level	Least Sq Mean	Std Error
14days	5870.9267	21.963799	14days	753.35508	4.4446769
1day	528.4637	21.963799	1day	96.22241	4.4446769

LSMeans Differences Student's t			LSMeans Differences Student's t		
α= 0.050 t= 1.9921		Ending Inventory	α= 0.050 t= 1.9921		Ending Inventory
Level	Least Sq Mean	Component C	Level	Least Sq Mean	Component D
14days A	5870.9267		14days A	753.35508	
1day B	528.4637		1day B	96.22241	

Least Squares Means Table			Least Squares Means Table		
Level	Least Sq Mean	Std Error	Level	Least Sq Mean	Std Error
14days	3739.6558	16.967729	14days	3053.5834	17.182902
1day	390.3692	16.967729	1day	389.5451	17.182902

LSMeans Differences Student's t			LSMeans Differences Student's t		
α= 0.050 t= 1.9921		Ending Inventory	α= 0.050 t= 1.9921		Ending Inventory
Level	Least Sq Mean	Component E	Level	Least Sq Mean	Component F
14days A	3739.6558		14days A	3053.5834	
1day B	390.3692		1day B	389.5451	

Figure 8.3.2: Lot Size Impact on LSMeans of Ending Inventory of Components

While backorders drop by 87% or more for both end products and components, ending inventories rise by as much as 1012% or a ten-fold increase in ending inventories. The results dramatically display the classic issue of balancing inventories with service level.

#### **8.4 – The Exploratory Summary**

Increased safety stocks and batch sizes both lead to lower average backorder levels at the expense of higher inventory levels. A world with always on-time deliveries (i.e., no lead-time variability) leads to lower backorders and lower ending inventory. Interestingly, zero lead-time variability has more of an impact on reducing backorders than affecting inventory. In contrast, increased batch sizes increase average inventory levels enormously while also having potentially large impacts in reducing average backorder levels. Safety stock at 40% of gross daily requirements shows less dramatic LSMean impacts on backorders and component ending inventories. None the less, increasing safety stocks is one of the most common steps firms take to enhance the service level. The findings show that safety stocks do indeed provide the desired buffer to lower overall average backorder levels—something future research may wish to examine further.

## 9 – Conclusions

The results of Chapters 5 and 6 show the trade-off between ending inventories and backorders. While backorders show diminishing growth rates as a function of lead-time, the ending inventories show the opposite trend. Intuitively, as lead-time and lead-time variability increase, firms rationalize the requisite increase in batch sizes and inventory as a means to enhance economies of scale in purchasing and transportation. The reality is that firms have no choice but to hold more inventory as lead-time increases regardless of discounts or economies of scale and scope.

The graphics of Chapter 4 display how lead-time plays a large role in increasing the rate of backorders while simultaneously increasing the ending inventory levels. In other words, lead-time causes both backorders and inventories to rise dramatically. Demand variability and safety stock levels both have impacts on backorders/ending inventories to varying degrees. Safety stock tends to cause fairly constant increases in ending inventory and somewhat varied impacts on backorders as a function of lead-time.

The statistical analyses of Chapter 7 display in numbers how the results of Chapters 4 through 6 emerge as statistically significant in ANOVA least squares means analysis. Just as seen in the graphics of Chapters 4 through 6, lead-time appears to have the largest impact of any of the experimental factors. High demand variability appears to cause fairly large growths in ending inventories but relatively small growths in the average backorder levels. High safety stocks tend to cause relatively small growth in average ending inventories and commensurate decreases in average backorders.

Chapter 8 shows the same pattern of trade-offs between backorder rates and ending inventories in the more extreme cases. When batch sizes become large, the ending inventories grow to extreme levels while the backorders diminish markedly. Safety stocks also promote decreased backorders but at the cost of higher ending inventories. In the extreme case of zero lead-time variability, both backorders and ending inventories fall. Interestingly, while the impact of zero lead-time variability on backorders is fairly significant, the impact on ending inventories is somewhat minimal under the L4L batch size rules and no safety stock.

As stated at the beginning of this research, global sourcing represents one of the major focuses in many industries as a means to lower costs. The costs associated with global sourcing and associated long lead-times have been difficult to quantify. This paper gives guidance through simulation to help ascertain the impact of lead-time, lead-time variability under different levels of



safety stock and demand variability on inventories and backorders—two major sources of costs for firms.

In sum, the results of the experiment show that firms do need safety stocks or large batch sizes of component parts to prevent excessive backorders. High ending inventories represent the trade-off for the safety stocks and large batch sizes. The research also demonstrates that firms need to consider a factor not often investigated—lead-time. In many cases, firms seem to assume that lead-time variability, not raw lead-time, represents a key factor in creating excess costs. The results of this research call that assumption into question.

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