Quantifying the Impact of Customer Allocations on Supply Chain Performance

by
Neel Sheth

B.S. Computer Engineering
University of Illinois Urbana-Champaign, 2004

SUBMITTED TO THE MIT SLOAN SCHOOL OF MANAGEMENT AND THE DEPARTMENT OF ELECTRICAL ENGINEERING AND COMPUTER SCIENCE IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREES OF

MASTER OF BUSINESS ADMINISTRATION
AND
MASTER OF SCIENCE IN ELECTRICAL ENGINEERING AND COMPUTER SCIENCE

IN CONJUNCTION WITH THE LEADERS FOR GLOBAL OPERATIONS PROGRAM AT THE MASSACHUSETTS INSTITUTE OF TECHNOLOGY

JUNE 2012

Signature of Author ______________________________
Department of Electrical Engineering and Computer Science
MIT Sloan School of Management
May 11, 2012

Certified by ______________________________
Donald Rosenfield, Thesis Advisor
Director, Leaders for Global Operations Program
Senior Lecturer, MIT Sloan School of Management

Certified by ______________________________
Tomàs Palacios, Thesis Advisor
Emmanuel E. Landsman Associate Professor
Department of Electrical Engineering and Computer Science

Accepted By ______________________________
Leslie A. Kolodziejski, Graduate Officer
Professor of Electrical Engineering and Computer Science

Accepted By ______________________________
Maura Herson, Director of MBA Program
MIT Sloan School of Management

This page intentionally left blank

Quantifying the Impact of Customer Allocations on Supply Chain Performance

by

Neel Sheth

Submitted to the MIT Sloan School of Management and Department of Electrical Engineering and Computer Science on May 11, 2012 in partial fulfillment of the requirements for the degrees of Master of Business Administration and Master of Science in Electrical Engineering and Computer Science

Abstract

This project investigates the impact that customer allocations have on key cost and service indicators at Intel Corporation. Allocations provide a method to fill orders during constrained supply, when total demand for a given product exceeds available supply. It is hypothesized that allocations increase inventory levels since customers may not always take the supply that is reserved for them in allocations. Also, if the total number of allocation groupings could be reduced, it is thought that the total inventory needed to adequately service the same customer base could be reduced due to the increased potential for pooling.

To test these hypotheses, historical data on allocations and product shipments were analyzed to assess how much inventory on hand could be attributed to using allocations. A model was built to calculate safety stock using historical allocations data as a demand indicator. Using this model, we simulate how much safety stock would be sufficient to meet expected demand as we reduce the number of allocations groups and pool risk across larger groups of customers. We also interview various supply managers to understand the impact allocations has on headcount, factoring in the geographical differences in managing allocations across a global supply chain.

The results suggest that customer allocations are a complex yet necessary process at a large manufacturing firm. A moderate amount of extra inventory is carried since there is no penalty to customers for inflating forecasts, but relative to safety stock already kept on hand it is nominal. Strategically reducing allocations groupings in key product lines that are likely to be significantly constrained can provide a way to operate efficiently with less inventory on hand. Longer term, products can feasibly be taken off allocations when it is determined that supply is healthy enough to do so, but a robust process needs to be in place to handle this.

Thesis Advisor:	Donald Rosenfield
Title:	Director, Leaders for Global Operations Program Senior Lecturer, MIT Sloan School of Management
Thesis Advisor:	Tomàs Palacios
Title:	Emmanuel E. Landsman Associate Professor Department of Electrical Engineering and Computer Science

This page intentionally left blank

Acknowledgements

I would like to acknowledge the Intel Corporation for sponsoring my internship, and the many individuals who helped make it a rewarding experience. Specifically, I would like to thank my project supervisor, Carlos Mazariegos, for his guidance throughout my time at Intel, and his dedication to both my personal and professional development. I would also like to thank Sean Cunningham and Tony Romeo, for their timely advice and overall support of the work. I am grateful for the many insights derived from colleagues who took time to bring me up to speed on the inner workings of a complex supply chain – thank you to Adam Bush, Pat Mastrantonio, Tom Sanger, Carol Taylor, and the entire SPIA team. Neelesh Pai and Ryan Lester also ensured a smooth onboarding at Intel, and their counsel helped eliminate numerous roadblocks.

From MIT I thank my faculty advisors, Donald Rosenfeld and Tomàs Palacios, whose expertise improved the study immensely and gave the work a broader perspective. The Leaders for Global Operations program and its tireless staff have created an amazing environment to learn, and I am thankful for everything they have done for us. I must also thank my LGO 2012 classmates, who continually inspire me and have made the past two years an unforgettable experience.

Finally, to my family, who has given everything in their power to see me succeed, I am forever grateful.

This page intentionally left blank

Table of Contents

List of Figures

List of Tables

1. Introduction

The research presented here was conducted with the Intel Corporation over a six-month period in 2011. The intent was to investigate the potential for customer allocations process improvements, including understanding the historical use of allocations, modeling costs and potential benefits of potential changes, and providing strategic recommendations to enable future competitiveness in the semiconductor market. The analysis considers business, cultural, and technical implementation factors which provide insight into the practice of allocations management that could be relevant to any large manufacturing firm. Note that throughout this report, raw data as collected are not presented. Instead, masked figures are used that preserve the intent and conclusions of the analysis but refrain from divulging sensitive proprietary information about Intel Corporation.

1.1. Problem Overview

Semiconductor products typically require long manufacturing lead times as compared to relatively short ordering lead times that customers expect. Additionally, the markets in which these products are traded are very dynamic with constantly changing customer needs. Manufacturers such as Intel must forecast how much supply to produce and keep in inventory, an imperfect process that can put them at risk of their supply not being flexible enough to meet changes in demand. Capacity expansion is not always a feasible way to deal with uncertainty, as it can be too costly or time consuming to deal with short-term demand swings. Forecasting is further complicated by Intel's broad portfolio of products, which reach a diverse set of customers each of whom may have different service expectations. For instance, high volume customers of mainstream desktop and mobile microprocessors require different service levels and lead times than customers that Intel is attempting to attract in high-growth Smartphone and Tablet markets.

Given these dynamic market forces, supply and demand for a particular product may periodically shift between periods of high demand/low supply where customers order more product than can be filled (constrained supply) and lower demand/higher supply where enough supply exists for all customer orders to be filled (unconstrained supply). One can visualize that over the lifecycle of a product, supply can oscillate between constrained and unconstrained states as various supply side and demand side market effects occur.

The process of customer allocations was primarily designed to determine how to fill orders in the constrained supply scenario. The process seeks to ration limited supply quantities to the set of orders that arrived, potentially taking into account past sales data, forecast accuracy, contractual obligations, and other factors. This decision of how many units of product to allocate to a given customer group must happen during each planning window. An allocations process designed to manage these decisions not only helps the supplier deal with constraints, but it gives customers assurance that they will receive some portion of a high-demand product. Customers also expect good service overall, and allocations can help create a healthier customer ecosystem so that one customer cannot unfairly buy up supply to block out competitors. However, the process also adds additional planning complexity for the supplier, including additional labor, IT tools, and time to successfully fill customer orders.

It is generally agreed that an allocation process is unnecessary for products that have become 'healthy' and unconstrained. If enough supply exists to cover all incoming orders, then simply agreeing to ship all orders as they arrive is the quickest and cheapest order fulfillment policy. However, new products are generally in high demand and constrained. Once an allocations process is put into place to handle that, it can be logistically difficult from a tools and process standpoint to change methods. It is also difficult to concretely define when a product has become 'healthy' enough to potentially stop using allocations. Moreover, there is not clear insight into how much of an impact the allocation process has on important cost drivers and service measures.

It is hypothesized that allocation drives higher inventory levels and headcount levels. Extra inventory is likely carried due to the nature of the allocations planning process. Customers give weekly updates on how much of a given product they expect to need in each of the following two to three months, but they are not penalized if they decide to take a different amount when that week actually arrives. Therefore, customers have an incentive to inflate forecasts to stockpile future allocations, and then taking what they truly need when committing to an order. As a result, extra supply is built up to meet expected demand, but true demand is typically not as high and excess inventory is carried. From a headcount perspective, it is known that numerous dedicated roles within Sales and Planning organizations are defined to handle allocations management. But a detailed analysis on how much time is spent on allocations, and exactly how additional allocation complexity influences headcount needs has not been performed.

It is also hypothesized that reducing the number of actively managed allocation buckets will yield lower overall inventory levels due to increased pooling across groups of customers. Allocations effectively negate the benefit of pooling, since a certain amount of supply is reserved for a particular customer even though they may not eventually commit to take all of it. Over time, Intel's expanding portfolio has created a large number of allocations buckets, atomizing the total supply base into smaller buckets of products that may not be as flexibly redistributed across its customer base. If buckets are grouped together to consolidate the total number, pooling could increase and therefore a smaller total supply could be necessary to meet all customer demand. It is thought that this is a viable way to reduce the total amount of inventory needed, but the total amount of reduction and whether appreciable service levels can be preserved have yet to be determined.

1.2. Key Questions and Thesis Outline

In seeking a better understanding of allocations and its impact at Intel, this analysis will consider the following key questions:

How are customer allocations used at Intel and what purpose does it serve?

Allocations are a firmly entrenched process at Intel, the origins of which began over 20 years ago. Its history and past effectiveness are important to understand before attempting to suggest ways to augment it. Allocations are also used in many other industries, and a survey of these methods was performed to provide insight into the broader use cases of these processes. In Chapter 2, background research on the Intel supply chain, order fulfillment, supply constraints, and allocations management lay the groundwork for this study. Chapter 3 provides deeper analysis of the process at Intel, and includes an assessment of the business implications of using allocations.

What are the Inventory driven costs of using allocations?

Though it is thought that allocations drive additional inventory costs at Intel, no formal assessment has been done to quantify how much. We construct a methodology to perform such an analysis using available historical orders data. In Chapter 4, two separate analyses were performed to provide insight into how much extra inventory is carried and how much potential benefit there could be if allocations were simplified. To answer the first question, we define the concept of excess allocations as extra inventory carried due to the allocations process that was not taken by final customer orders. We quantify this value by matching past allocations to actual shipment records in key product segments and discuss the discrepancies. For the second question, a model was built to estimate how much inventory would be needed if a simple safety stock methodology was used. This model was then used to simulate the needed safety stock if we were to vary the size of allocation groupings. This model tests the effects of pooling customers into larger buckets to see if the potential savings in inventory are significant. This portion of the analysis concludes with a discussion of how much inventory is needed to meet the needs of customers as the number of allocation buckets changes, and includes a graphical representation of the impact of allocation group size on inventory levels.

What are the Labor driven costs of using allocations?

Similar to inventory costs, there had not been a formal investigation into the labor driven costs of allocations. Allocations processes add complexity to order fulfillment, and typically requires additional heads to manage. In addition, many allocation decisions rely on the tacit knowledge of analysts who best understand their customers and current market conditions. In Chapter 5 we discuss the results of interviews performed to collect data from all major geographic regions of Intel's supply chain to give a preliminary view the number of heads needed to manage allocations. Furthermore, a simple model provides demonstration of analyses that can be performed to quantitatively analyze headcount needs. Such a model complements the inventory analysis, and as the number of allocation buckets increases we might know how many additional heads are needed to support it.

What are the most promising applications for a simplified allocations process?

Given the previous discussion and analysis, a summary of the potential impact of allocations reform is discussed with next steps and future suggested investigations outlined. Chapter 6 summarizes the key findings and how improvements to customer allocations might be achieved. Chapter 7 provides some suggestions for follow on research.

2. Background

2.1. Intel Corporation

Intel is a leading producer of semiconductor products with a broad portfolio, including microprocessors, chipsets, motherboards, connectivity solutions, and the platforms necessary to integrate these components into complete computing solutions. Founded in 1968, the company has grown to become the largest semiconductor firm in the world based on revenues of over $54 Billion in 2011. Intel has over 100,000 employees and supplies over 80% of PC microprocessors worldwide (New York Times, 2011).

Intel has historically been a key driver of the computing industry, and the number of products in its portfolio has increased dramatically over the years as the company has broadened its reach. This includes the ongoing refinement of its core *Integrated Circuit* (IC) products, including microprocessors and chipsets, but also its expansion into complementary products that reinforce core businesses, including platforms and software systems that together provide complete computing solutions (Figure 1). Historically thought of as an 'ingredient' brand that other companies built solutions around, Intel has recently undertaken a strategic initiative to transform into a company that provides complete solutions across the "compute continuum", a vision that includes Intel designed hardware and software working together to seamlessly and securely provide consumers with the digital experiences they desire (Intel Corporation, 2011). In accordance, the customers that Intel attracts have evolved and now represent a very diverse set of needs across many industries. Simultaneously, a cultural shift is in process to transition from a core mission centered on technological innovation towards enabling transformative customer experiences. Intel's ability to continue serving legacy customers while simultaneously attracting new ones in growing markets will be a key challenge to its long-term success.

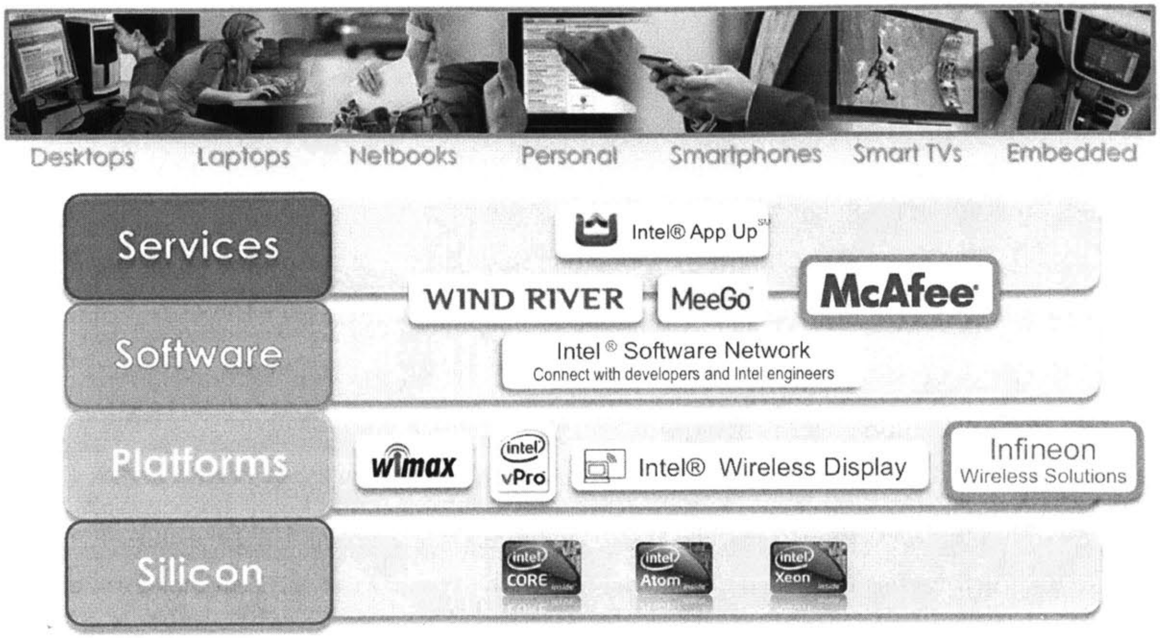

Figure 1 - Intel's Evolving Portfolio

2.2. The Semiconductor Market

The semiconductor industry is dynamic, as illustrated by rapidly changing technology, frequent new product introductions, and short product lifecycles. Fine suggests the notion of industry 'clockspeed' and uses semiconductors as a prime example. *Process Technology,* as measured by the obsolescence rate of capital equipment, and *Product Technology*, as measured by the rate of new product introductions, are both considered to define how quickly a company must respond to change in order to stay competitive. A firm's ability to continually adapt and create a series of temporary competitive advantages is crucial for success in fast clockspeed environments (Fine, 1996). The Semiconductor Market is also unique in that it enables broader economic growth, enabling numerous other high technology industries with estimated value in the trillions of dollars.

2.2.1. Customers

Intel products and platforms comprise the building blocks that enable other manufacturers to achieve high performing, reliable computing systems. They include *Original Equipment Manufacturers* (OEMs) and *Original Design Manufacturers* (ODMs) that build computer systems, phones, tablets, telecommunications systems, and other devices that require computing. A few of these OEMs form global companies that are as large or larger than Intel itself, and directly compete with one another despite all relying on Intel platforms at the heart of their products. In 2010, Hewlett-Packard Company accounted for 21% of Intel's net revenue (21% in 2009 and 20% in 2008) and Dell Inc. accounted for 17% (17% in 2009 and 18% in 2008), both of whom compete directly with one another on many of their products (Intel Corporation, 2011). Board level PC products and networking components are sold to individuals, small and large businesses, and service providers through a large network of distributors, resellers, retail, and OEM channels (Intel Corporation, 2012). Intel products compete on performance, energy efficiency, features, price, quality, reliability, brand recognition, and availability.

2.3. The Intel Supply Chain

Intel has become a dominant player in the industry by developing expertise in semiconductor design, manufacturing, distribution, and marketing. The supply chain is an important component in the company's success and has been admired as one of the top supply chains of any manufacturer (Gartner, 2011). Intel's diverse portfolio can require unique optimizations in the supply chain that are tailored to a particular product family, hence each business unit may have specific practices in place to meet the unique needs of their customer base. Standardization of processes is continually considered for potential cost and response time benefits, but in many cases each business unit is allowed to tailor operations to its specific needs. Of particular interest is the supply chain for Intel microprocessors, which comprise the majority of Intel's annual revenues.

2.3.1. Intel Microprocessors

Intel's success is largely driven by the success of the microprocessor business, accounting for 76% of its revenue (Grimes, 2012). Intel microprocessors carry out the fundamental instructions necessary for computing systems in a single integrated circuit. Commonly thought of as the 'brains' of a computer, Intel pioneered this class of device with the first commercially available microprocessor, the Intel 4004, in 1971. It continued to innovate in the space and currently is considered among the foremost leaders in microprocessor design and manufacturing. Intel microprocessors are being developed for four primary market segments, as seen in Table 1.

Segment	Typical Devices
PC Client	Desktop PCs, Laptops, Netbooks
Data Center	Servers, Data Centers
Other Intel Architecture	Embedded Applications, Consumer Electronics, Tablets
Mobile	Handheld Devices, Cellular Phones

Table 1 - Intel Microprocessor Market Segments (Intel Corporation, 2011)

2.3.2. Microprocessor Build Strategy

Integrated circuit manufacturing is extremely complex, requiring significant technological expertise and vast amounts of capital. Semiconductor companies spend 25 cents of every dollar of revenue on capital investments, and a modern fabrication plant (fab) costs 5-8 billion dollars and requires more than two years to construct and configure before it can become operational (Gartner, 2011). Maximizing the utilization of the fabs becomes a key concern of a semiconductor manufacturer, as the depreciation of capital equipment can be significant especially when new process technologies will likely replace the equipment in a short time. A *make to stock* (MTS) strategy is commonly used to keep utilization high and alleviate relatively long cycle times (Sun, Fowler, & Shunk, 2007). In an MTS system, forecasting is necessary to drive the production schedule since appropriate stock needs to be ready to handle expected demand. This differs from *made-to-order* (MTO) systems where customer orders can directly drive production activities. In the semiconductor market, an MTS environment is necessary due to typical lead-times of 6-16 weeks to replenish finish goods inventory. High-technology customers typically cannot afford to wait so long for orders to be filled, so supply chain efficiency becomes an important factor to minimize missed business opportunities, limit excess inventory, and preserve key performance indicators.

2.3.3. Microprocessor Manufacturing

The Microprocessor supply chain can roughly be divided into three major phases as seen in Figure 2 (Ng, Sun, & Fowler, 2010). *Wafer Fabrication and Sort* (WF) is the collection of processes that produce silicon die from raw materials. An initial test is also done to sort out die that meet quality standards, and then these units are held in *Assembly Die Inventory* (ADI). Units are drawn from ADI inventory to the *Assembly and Test* (AT) process, which is where microprocessors are packaged and assembled into functioning units and then tested. At this stage, each die is 'committed' to a specific configuration, and is the final stage of postponement before the units are distributed to customers. Finished goods are stored in *Component Warehouses* (CW) until they are shipped out to customers in the final stage. Also of interest is the final configuration prior to shipment can take on one of two forms. Large Original Equipment Manufacturers (OEMs) and Original Design Manufacturer (ODMs) who use Intel microprocessors as components in own products are shipped these items in *Tray Form*, which are bulk packaged and then immediately integrated into other products. Distributors and retailers who look to sell directly to consumers or small businesses will purchase Intel microprocessors in *Box Form,* which are the same products packaged with a fan and heatsink and localized to the market in which they are sold. Each of the high level phases of the process maps to a critical decision point in which supply must be matched to demand. This must be done in order to minimize the costs of either not having enough supply to meet demand or carrying more supply than needed to meet demand (see Section 2.5.1 Allocation Decisions in the Semiconductor Industry).

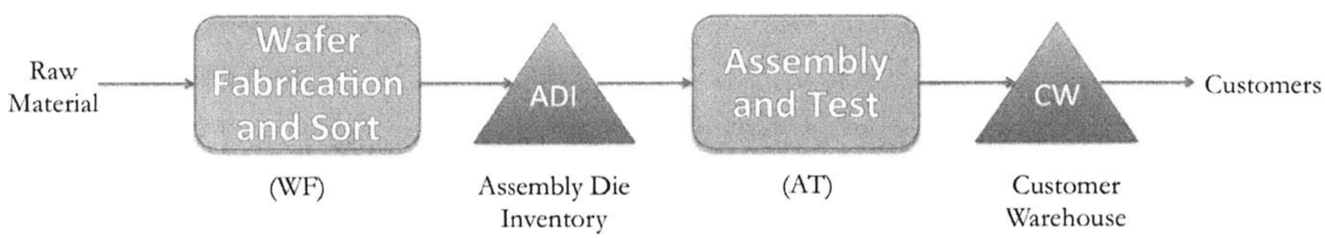

Figure 2 – Microprocessor Manufacturing Process Overview

2.3.4. Supply Chain Transformation

Intel's supply chain is structured to help achieve key strategic initiatives (Figure 3). Two primary goals include growth enablement to attract customers in new markets, and increasing agility to respond to changing customer needs while keeping costs low. Growth into new markets requires an understanding of the differing service expectations of those customers and preparing to produce and distribute products to meet new customer needs. Initiatives have assessed the potential for supporting tiered service levels and ways to improve response time through reducing the number of touches on an order. As the product base expands, the supply chain must also adapt to deal with a more complex product mix. Supply chain segmentation is being explored as a viable way to meet the varying needs of multiple customer bases without alienating any individual group. Growth in portfolio complexity can lead to increased cost and slower response times, so the second major thrust of the transformation has included methods to combat these tendencies. Efforts to improve velocity have assessed tools and processes to decrease ordering and planning cycle times, and methods to improve information visibility and end-to-end collaboration through digital supply chain initiatives.

Given the need to attract and retain new customers while remaining cost efficient, opportunities arise to refine existing processes to better manage the supply chain. Balancing the tension between successfully adding new customers with different service expectations and the added cost and complexities of managing an expanding product portfolio underscore many of the supply chain challenges that Intel faces.

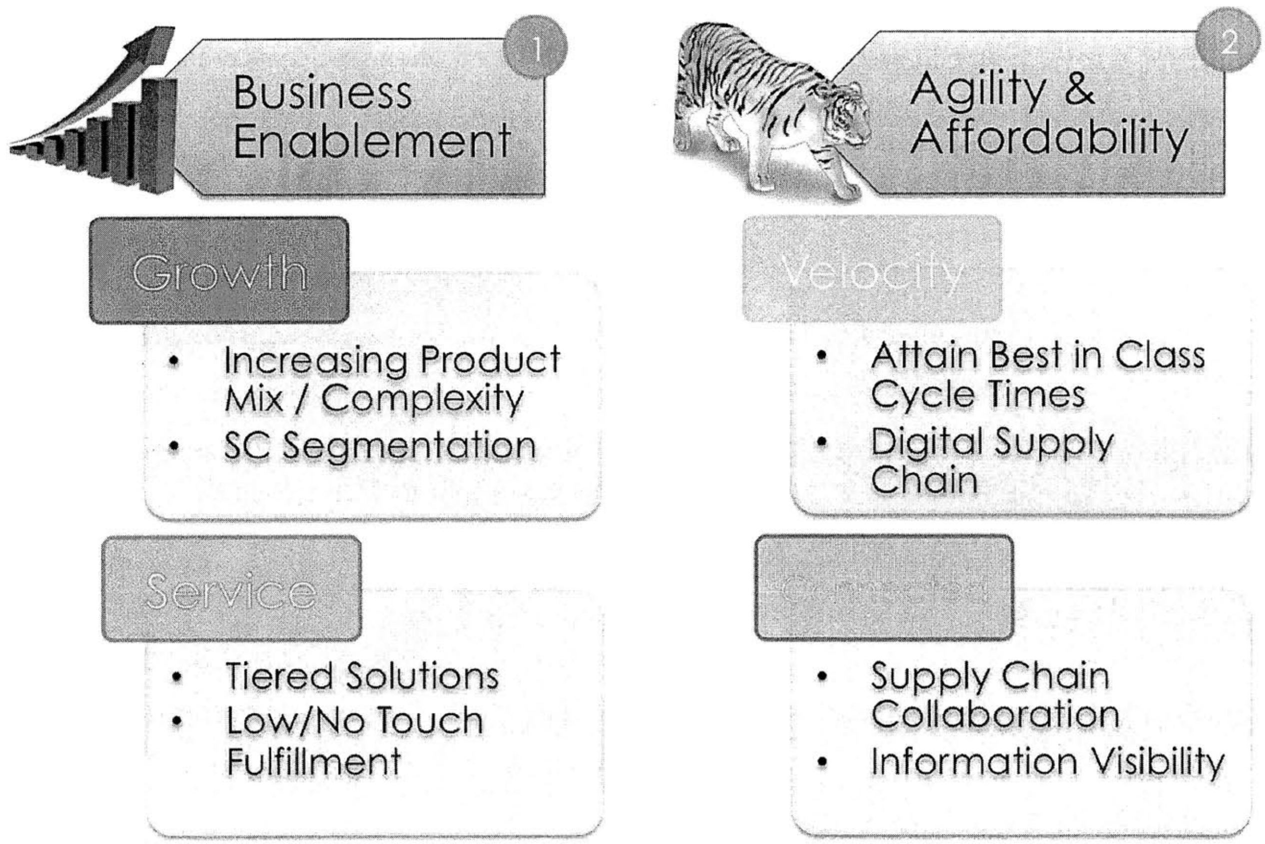

Figure 3 - Supply Chain Transformation Initiatives

2.4. Demand Fulfillment

Supply chain planning systems play an important role in balancing supply with demand to optimize inventories and distribution plans, helping provide good customer service while keeping costs low. An important supply chain planning function involves determining how demand is fulfilled. Broadly, this involves all activities necessary to respond to and ship product in response to a customer order, including order processing, promising/commitment, and execution. The ability to accurately and rapidly respond to customer inquiries is a source of competitive advantage for many manufacturers. Customers expect a reasonable turnaround time for an order to be fulfilled, and the fulfillment process has a direct impact on Key Performance Indicators (KPI) such as lead times and on time deliveries (Kilger & Meyr, 2008).

An incoming order will typically need to be 'confirmed' or 'promised' by the manufacturer to let the customer know when they can expect the order to be filled. This is due to inevitable variations in supply and demand that may make it infeasible for the manufacturer to fill every order. Simplistic planning systems may take the approach of confirming orders against inventory on hand, and then any orders that exceed inventory on hand will be quoted a delivery time equal to the production lead-time. Since this does not take into account capacity, material, or other potential supply constraints, this method may occasionally result in accepting customer orders that are not feasible (Kilger & Meyr, 2008). Most advanced planning systems generate a plan for future supply that includes production, purchasing and incoming demand signals, factoring in data from suppliers and the factory before confirming orders. The pool of current and future supply from which incoming orders can be confirmed is commonly known as *'Available to Promise'* (ATP) in modern ERP systems (Kilger & Meyr, 2008). The ability of a planning system to accurately assess ATP inventory directly affects its on-time delivery metrics, since it drives the assignment of committed orders to actually available inventory.

The design of the order promising process is tailored to a particular firm's master plan. ATP can be structured around products, time, customers, region, and many other dimensions (Kilger & Meyr, 2008). Additionally, when promising ATP to customer orders, a firm may choose to use *batch processing,* where all orders in a given time frame are batched and assigned ATP together in one pass. Alternatively, a firm could choose *single order processing*, where orders are confirmed in real-time as they arrive (Ng, Sun, & Fowler, 2010).

2.4.1. Unconstrained and Constrained Supply

A particular product being supplied to customers can be thought of in one of two supply modes. If the total amount of supply that a firm carries exceeds the total number of units demanded by its customers, the product is *supply unconstrained* (or *demand constrained).* If the total amount of demand exceeds the total amount that can be supplied, the product is *supply constrained.*

A product that is supply unconstrained is one that is currently creating excess supply that is not likely to be consumed by customers in the short-term (and in some cases also in the long-term). In this mode, the supply chain is likely carrying some excess cost (e.g. inventory, capacity) that may be an area in which the supply chain could strive to remove. From a planning point of view, any given customer order can simply be confirmed as there is enough ATP supply on hand to meet all demand, so the optimal order fulfillment process becomes trivial. There may be some pressure to remove the inefficiencies in excess supply to save on costs, eventually driving the supply chain towards the supply constrained mode by cutting supply or stimulating demand (Kilger & Meyr, 2008).

A product that is constrained, however, presents a more complicated planning scenario. In this mode, total demand exceeds supply and a decision must be made on how to meet incoming orders. Supply might be constrained due to one of many different supply or demand side effects. Supply disruptions may occur due to supplier performance, raw material shortages, natural disasters, or many other unforeseen events. On the demand side, the unpredictability of consumer demand in industries with fast clockspeed means that demand may quickly change as market conditions warrant. Once the situation arises in which a manufacturer receives more orders for a product than they can possibly fill, the product has become constrained.

Moreover, a product can move between constrained and unconstrained states over time, as seen in Figure 4. As an example, new product introductions are assumed to be supply constrained since true demand for a new SKU is hard to predict. Eventually after a few ordering periods, demand will likely taper off and supply will build up such that it is eventually unconstrained. At a later time, a materials shortage could hamper production, causing a supply shortage and a constrained situation, though eventually once corrected the supply can fill in and meet the excess demand until the unconstrained state is once again achieved. Since the supply mode can shift over time, the question arises about how to manage order fulfillment as a particular product moves in and out of being constrained.

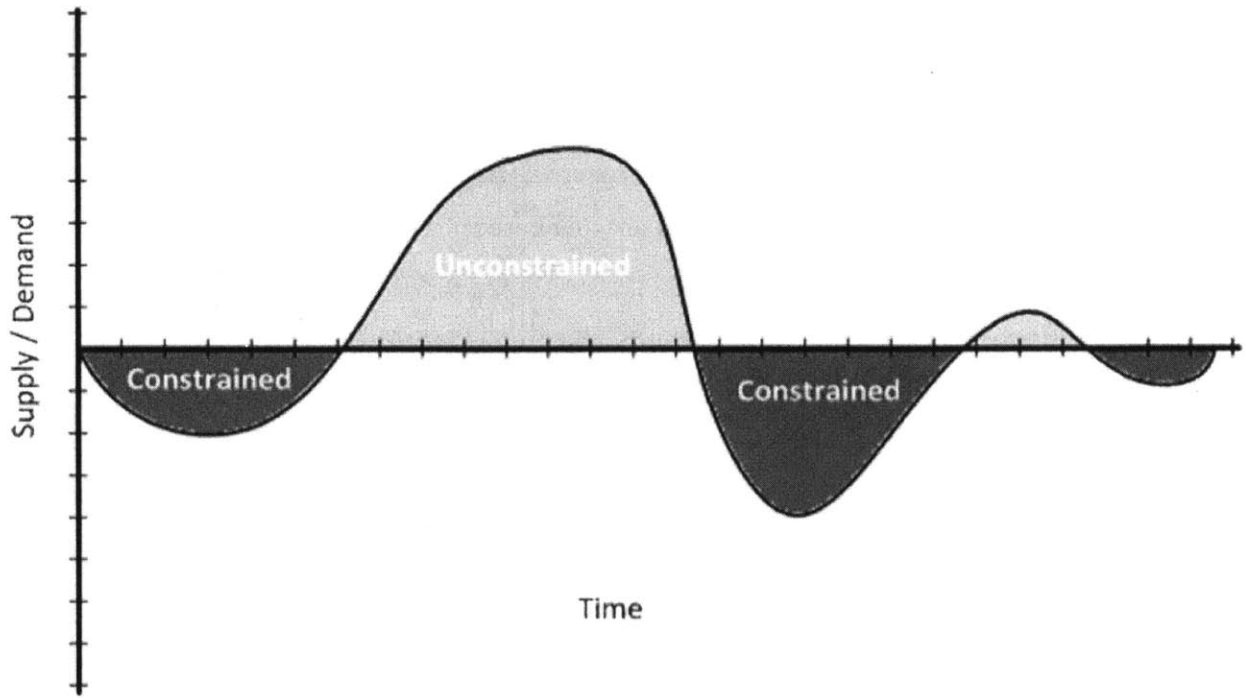

Figure 4 - Shifting Between Constrained and Unconstrained States

2.4.2. Fulfillment Under Supply Constraints

Managing order fulfillment in the constrained supply state requires fundamental decisions on how to handle incoming orders, whether to attempt to increase product supply, or if demand can be influenced. For semiconductor companies, as discussed in Section 2.3.2, increasing capacity through additional manufacturing capabilities requires significant time and capital investments. As a result, it is not always feasible from a cost or time perspective to expand capacity when supply constraints occur. This inflexibility in production makes it harder to adjust supply to meet demand changes in numerous industries, shifting emphasis to planning processes to seek out ways to manage constraints (Talluri & Van Ryzin, 2005). Demand could potentially be influenced through price adjustments, though the long-term health of customer relationships may be at risk. For many industries, the order fulfillment strategy becomes an important tool in managing constrained environments.

With a *first-come-first-served policy* (FCFS) fulfillment strategy, orders are confirmed as they arrive without regard to the price, customer, or if that order was one that was expected from forecasts (Kilger & Meyr, 2008). This policy is simple, fast, and in many cases can be fully automated. It is a viable fulfillment strategy in the unconstrained supply scenario since all incoming orders can be filled with ATP supply, but in the constrained scenario it can result in a number of undesirable consequences. Profitability of each order is not accounted for, and since existing contracts might give favorable pricing to some customers, total profit may not be maximized under FCFS. Important customers could be alienated if another customer happens to submit an order before them, since FCFS does not have a concept of customer priority. Some customers could be blocked entirely from receiving any supply if another greedy and potentially malicious customer decides to place an early order for all product stock. In Intel's case, some customers might not agree to do business with them if guarantees were not in place to prevent this scenario from occurring. Moreover, Intel's customer base is largely comprised of manufacturers who are competing amongst one another in computing or consumer electronics industries. Cultivating a healthy ecosystem from Intel's products to reach consumers is an important reason why FCFS is not a sustainable method to managing constrained supply.

More sophisticated methods can be envisioned by analogies to other restricted supply scenarios. Generally, they fall into either *price-driven* mechanisms that directly influence demand, or *quantity-driven* mechanisms that ration limited quantities to select groups of customers (Talluri & Van Ryzin, 2005). These methods are commonly used in *revenue management* applications, which seek to maximize total revenues by optimizing product pricing and availability to capitalize on differences in customers' willingness to pay (Quante, Meyr, & Fleischmann, 2009). Price driven decisions are frequently seen in retail demand planning, where the price of an item is adjusted over a particular season as demand for the product varies. Quantity driven methods formed the basis of the initial airline management systems, attempting to optimize the quantity of different seat classes available to customers of differing willingness to pay.

2.5. Customer Allocations

One category of methods to handle the constrained supply scenario is to put customers on "allocation", rationing units of limited supply to individual or groups of customers (Cachon & Lariviere, 1999). This is a quantity-based mechanism that attempts to segment the customer base into different groups and allocate available ATP quantities according to a set of rules. Consider if Intel only had 2,250 units of a product to ship out in a given ordering window. If the sum of all units ordered totals more than 2,250, Intel must decide how much of the limited supply would go to which individual or groups of customers. Each group can be thought of an allocation 'bucket', which represents a subset of total supply that is reserved for that specific customer group in a specific time period (Figure 5).

A strategy for allocating units to customers may take into account a number of factors to optimize across service and cost factors. Customer prioritizations can be created to ensure important customers are given allocations first, which can additionally be contractually based to give important customers supply assurance. Therefore, allocations can be used to increase revenues by optimizing the allocation of units to customer segments who generate higher margins (Meyr, 2009). Costs can also be prioritized to allocate units to customers from locations that minimize transportation costs or taxes. In many cases the prioritization scheme takes on a hierarchical form in which customers of varying relationships are grouped together (discussed further in Section 3.2). Past sales history can also be a predictor of future demand and is frequently used as a factor in determining how to 'judge' future customer orders in order to determine allocations. For instance, 'turn and earn' schemes are used in the automobile industry to allocate limited supplies of cars to the best performing dealers, in an effort to incentivize them to make sales in order to have higher future allocations (Cachon & Lariviere, 1999).

Also important is the effect that allocations decisions may have on customer behavior. Over time, a customer may alter their firm's strategy given current market realities and the value proposition offered by the manufacturer with given supply constraints. Models of customer memory have been included in some allocation policies. For instance, future customer orders may be impacted by the fill rates they have seen in the past, and customers may eventually decide to seek alternate suppliers if they are not being adequately serviced (Adelman & Mersereau, 2010). These 'neglected' customers may eventually become important future customers if market conditions change, and this factor can be modeled in a firm's allocation policy. Demand distortions have also been noted in many allocations based environments due to the fact that customers may be incentivized to inflate orders to increase future allocations and hedge the risk of potential supply constraints (Krishnan, Kleindorfer, & Heching, 2007). These distortions have the potential to impact the future accuracy of allocations planning, and may become an important factor in the inventory efficiency of an allocations based planning system.

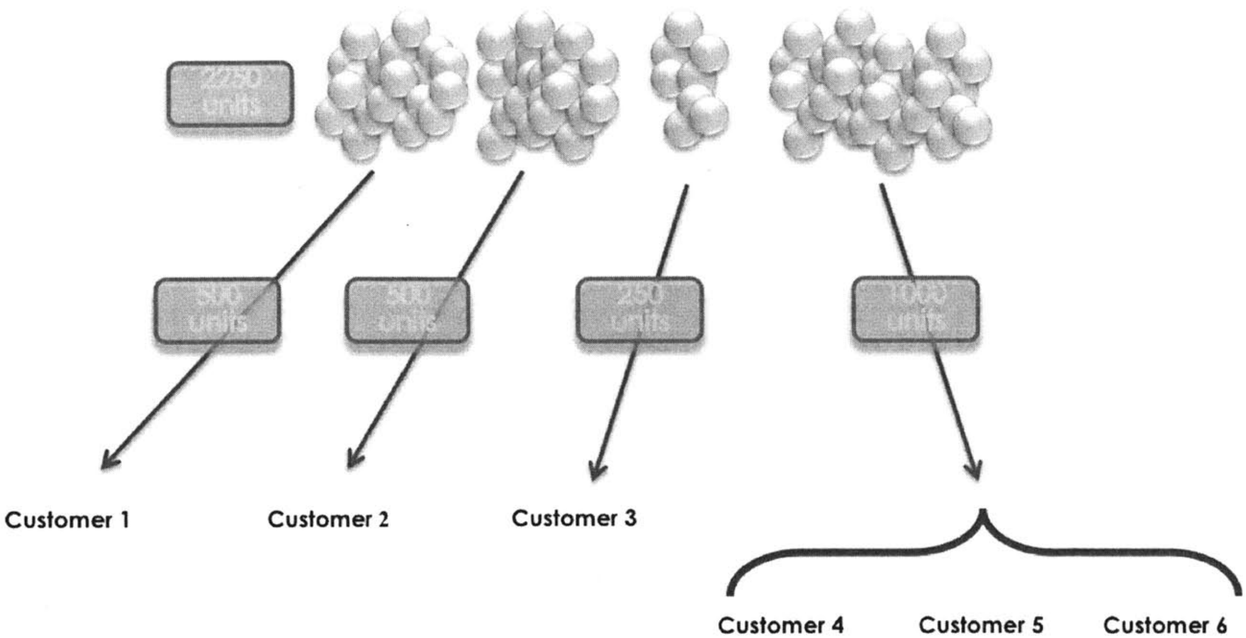

Figure 5 - Customer Allocations Example

2.5.1. Allocation Decisions in the Semiconductor Industry

The idea of matching supply to demand is relevant at many stages in a firm's supply chain. Figure 6 provides an overview of the semiconductor supply chain overlaid with the allocation decisions that typically need to be made at different stages. At the Finished Goods level, current and expected inventory in Component Warehouses and regional hubs are assigned to firm customer orders, resulting in shipments being sent out. At Assembly and Test, lots of ADI are matched to forecasted customer orders to determine how many units to push into Assembly and Test. Finally, at the Fabrication facilities, a decision on how many raw wafers to start is made against internal orders typically made by product planners (Ng, Sun, & Fowler, 2010). In each case, supply is being matched to demand such that the production process is being driven by the demand being seen up the chain. This investigation will focus on customer allocations at the Finished Goods level, though many of the insights derived from studying finished good allocations can be applied to decisions in earlier stages.

Factors inherent in the semiconductor industry make allocation decisions challenging. Long lead times and uncertainty in semiconductor yields can make long term planning of ATP difficult, potentially requiring decisions to be made on intuition. Sun et al. discuss the results of a survey across semiconductor firms that found allocations decisions to be made predominantly with tacit knowledge of experts, especially in the later stages of the supply chain (Sun, Feller, Shunk, Fowler, Callarman, & Duarte, 2007). The human element in decisions impacts response time, requires additional costs in labor, and makes standardization of an allocations process across an organization more difficult. Demand volatility for semiconductor products also makes it difficult to accurately allocate for long horizons, suggesting that shorter or close to real-time allocations decisions are necessary. Survey data suggest that weekly allocations decisions are the most commonly used in practice (Sun, Fowler, & Shunk, 2007). The need for frequent allocations decisions with humans in the loop suggests that allocations can potentially be a costly endeavor.

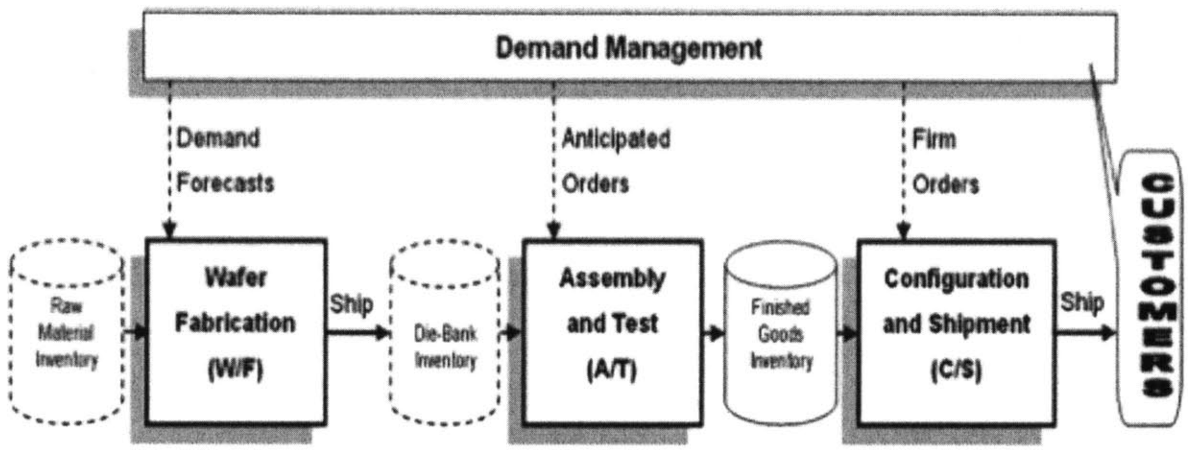

Figure 6 - Allocation Decisions in the Semiconductor Supply Chain (Ng, Sun, & Fowler, 2010)

This page intentionally left blank

3. Allocations at Intel

The need to deal with constraints and manage supply down to the level of individual or groups of customers has been present at Intel for many years. The tools and methodologies used have evolved as enabled by new technology, but the fundamental problem has largely remained the same. We review some of the key facets and implications of this process to better understand how it can affect the company's ability to serve its customers.

3.1. Customer Drivers for Allocations

In Chapter 2 we discussed general use cases for allocations, but it is important to discuss the specific drivers for Intel. A supply chain must manage the tension between achieving efficient operations and attaining excellent customer service, and the allocations process sits at the center of these two goals.

From the customer's perspective, continued access to the *latest products* is a recurring need. The companies integrating Intel products compete in very dynamic markets, and it is important to have access to the latest products in order to stay competitive. The semiconductor industry moves at a fast 'clockspeed', where both process and product technologies are moving at a very fast pace that both Intel and its customers must keep up with in order to stay competitive (Fine, 1996). As new products are released, they are likely to be highly sought after. Combined with potentially limited supplies when using new process technology, new product introductions are typically supply constrained. Gaining access to constrained product therefore becomes a key concern of Intel customers in order for them to stay competitive, which allocations can directly address. They can be used to provide direct *supply assurance* to a customer such that they can be sure that some supply will be provided to them, though not necessarily all that they ask for. Consider a customer that is seeking to stay on the cutting edge of technology, and must stay competitive with other manufacturers who are also looking to create products with the latest technology. These customers would place a high value on having some assurance from their supplier that at least some portion of the latest and greatest products is reserved for them. In some cases, the lack of supply assurance might make a buyer reconsider purchasing Intel products, as they may not be willing to take the risk of designing a system around an Intel part that could potentially have future supply disruptions. Without protections, a malicious customer could conceivably place an order to hoard stock of a product and prevent competitors from gaining access to it. Finally, to continue to stay competitive customers will always prefer *lowest cost* for the same level of quality. As discussed in Section 2.4, price is a potential lever in dealing with supply constraints and could be raised or lowered to actively influence demand for products. However, a fulfillment process centered on price manipulations in response to changes in supply may again engender displeasure from customers. Allocations provide a way to deal with constraints using a quantity driven approach, such that frequent price fluctuations are not interpreted as stock being auctioned off to the highest bidder. For Intel, maintaining a healthy *customer ecosystem* is paramount to sustained business, and allocations can be an important way to help foster goodwill. S*upply chain efficiency* is of course a continuing goal in order to ensure that Intel keeps its business running as smoothly as possible. Keeping *inventory levels* optimized, responding to customer inquiries with a fast *response time*, and ensuring that the supply it has actually makes it out to customers are key measures of success. Allocations may create challenges in meeting some of the cost goals, but those tradeoffs may be considered acceptable in order to create more effective customer relationships.

3.2. Hierarchical Allocation Rules

As mentioned in Section 2.5, a customer allocation scheme will typically use a hierarchical system in order to determined allocation quantities. Figure 7 shows an example of the allocation hierarchy used at Intel, structured geographically where the higher tiers represent broader business territories while lower tiers represent individual customers or subsidiaries. Each bubble on the lowest tier represents a specific customer or group to which product can be allocated, while higher tiers represent aggregations of the tiers below it. A customer may purchase multiple SKUs, and an allocation decision needs to be made for each product SKU-customer combination. We term this quantity an *allocation bucket*, and the total number of allocation buckets will relate to both the number of divisions in the hierarchy and the total number of SKUs a given customer is actively purchasing.

Kilger & Meyr (2008) discuss specific *allocation rules* that can be applied using a hierarchical customer ordering to determine the sizes of allocation buckets. *Rank Based* priority would order the set of allocation buckets on a given tier, such that when taking the total pool of supply the policy goes in rank order to assign available ATP. This allows customer or regional prioritization to ensure strategic concerns are accounted for. Another strategy uses the total forecasts submitted by customers to allocate proportionally to all customers given their stated needs. This *per-committed* strategy effectively gives each customer their 'fair share' of the total available supply given their stated needs. However, this method can easily be skewed by inflated customer forecasts as already discussed. A *fixed-split* policy dedicates predefined fractions of available supply to buckets at a given tier. Customer forecasts are still used to derive aggregated supply needs, but a pre-determined percentage of available supply is dedicated to individual customers or groups each week. In addition to these simple allocation strategies, special buckets can be used to allow added flexiblity to deal with demand uncertainty. These extra buckets are sized and assigned ATP, but then planners can strategically move those quantities to specific customers or groups, creating a sort of safety stock within the allocations system. *Free for all* (FFA) buckets are safety stock buckets that can be assigned to any allocation bucket within its tier, using a first come first serve approach.

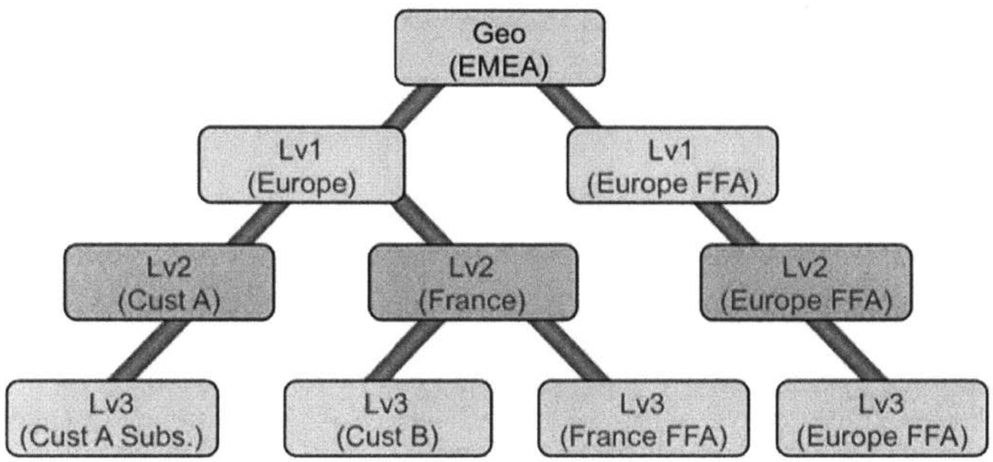

Figure 7 - Example Intel Allocation Hierarchy

At Intel, these decisions are dependent on both the business unit that the particular product falls under as well as the geographic region (Geo) in which the product is being distributed. For many families of products, allocations may not even be used as discussed in Section 3.4.1. Moreover, the Geo in which the product is sold will drive the allocations strategy used. In some geographies supply assurance is extremely valuable to customers and so allocations is widely used. In such Geos we would expect a large number of allocations buckets and a larger workforce required to maintain the process. In other Geo's, customers are more comfortable without having direct supply assurance through allocations. In these areas, we expect to see fewer total allocation buckets, and those in use are higher tiers buckets that represent a large pool of stock to be distributed amongst a group of customers.

3.3. Allocations Planning at Intel

At Intel, allocations planning occurs weekly, using a batched process to match available ATP to customer demand. Each week, forecasts and allocations are updated for each week in the planning horizon, which can be 8-12 weeks depending on the product. Customer orders can be confirmed (e.g. available ATP is promised) to orders within the upcoming 2 weeks of the current planning period. Available supply is tabulated hierarchically, starting with an assignment of product supply for a Geographic region, and then breaking this down to lower levels as exemplified in Figure 8. When supply at the Geo level is defined for a time period, allocations can then be made to Level 1 buckets. Once those are defined, allocations of those quantities can be mapped to lower level buckets. Each of these decisions is led by an analyst responsible for a particular stage in the allocations process for a specific set of products.

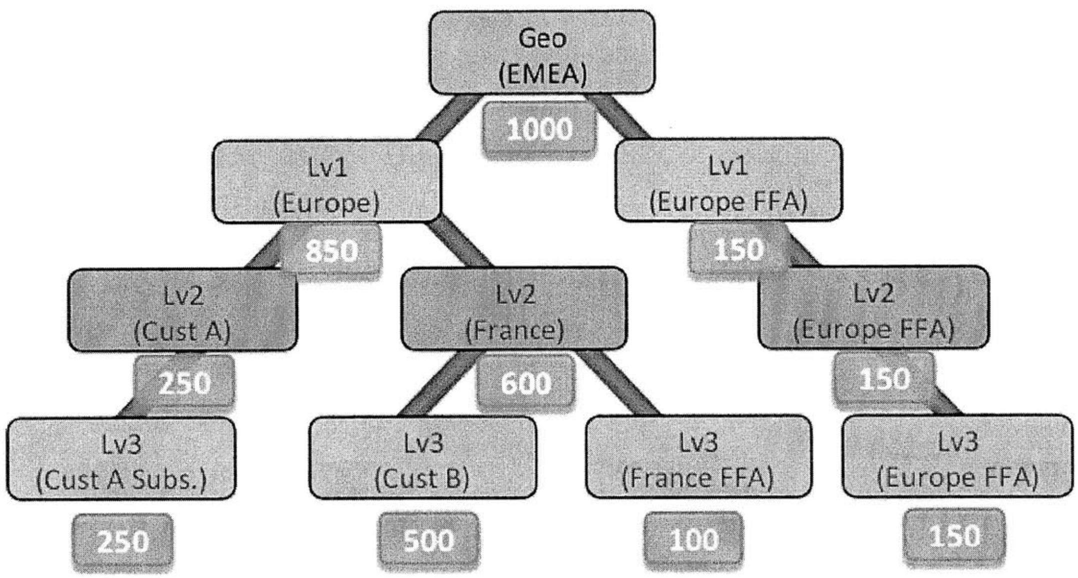

Figure 8 - Hierarchical Allocation Assignments

Given information for the available supply to work with, analysts consider customer demand in the form of weekly forecasts to make allocations decisions. An analyst may have the ability to remix allocations across the same level of the hierarchy. For instance, if a customer updates a forecast in the current planning period, the change may allow the analyst to adjust the allocation for the customer accordingly. *Remixing* is a key task that analysts can use to manage the volatility in the allocations process, but it isn't always able to completely rebalance allocations perfectly. If a customer decides that they no longer wish to receive a shipment, there may not be another customer willing to take that product. As discussed later in Section 3.4.4, these may be contributing to extra inventory being carried.

During this weekly process, customer representatives may also be engaged in order to best determine current and future needs, and confirm allocation decisions. After allocations quantities are finalized, the set of current orders can be reconfirmed against the updated picture of available supply, and those orders that are confirmed can be prepared for fulfillment.

3.4. Challenges with Allocations

3.4.1. Multiple Interpretations

The concept of allocations can have different interpretations across a large enterprise. As already mentioned in Section 2.5.1, multiple stages in the supply chain require allocation decisions to be made. Furthermore, at Intel, each business unit may take some liberties to design an order fulfillment process that best suits their products, supply chain constraints, and customer needs. Standardization is pursued as much as possible, but differences can and do emerge as needed. For instance, in one business unit, allocations have been widely used since Intel invested in the tools to support them. Here, every product is sold using the allocations based process, regardless of whether a product is constrained. This is partially attributed to customer expectations of supply assurance during severe supply constraints. But it is also due to the difficulty in updating existing processes in which allocations based planning is tightly integrated. Allocations quantities are used in formulating tactical demand estimates, supply response decisions, and as a build signal to determine how much additional supply will be needed in the future. As such, organizational inertia keeps the allocations process firmly in place. In contrast, another business unit does not rely so much on allocations except as a way to segregate supply on hand to incoming customer orders. In fact, about half of the products in this business unit do not use allocations at all, and instead use a fully 'off-allocations' process that matches customers orders to available supply as they come in. In other business units, no form of allocations is used whatsoever. These discrepancies are noted because certain business realities will affect the choices an organization may make pertaining to order fulfillment. While an investigation into cost savings measures or a refined process may suggest potential improvement, other factors may prevent one or more business units from fully adopting any change. Our analysis will reside within the first business unit, where allocations are used for all products and no functioning 'off-allocations' process exists. This business unit represents a high potential environment for allocations reform opportunities.

3.4.2. Added Complexity

Customer allocations add a layer of complexity to the planning process that can impact Key Performance Indicators such as order response time. Allocation quantities must be considered and updated in each iteration of the planning cycle and require the judgment of a supply analyst. Customers are frequently consulted to negotiate allocation remixes that require approval. Intel does this on a weekly basis, batching orders and committing them to available ATP and then tracking forecasted orders for future weeks. This must be done per SKU and per customer, requiring a large number of decisions each week. And a complex set of IT tools must be supported and continually updated to ensure the process can feasibly be executed.

3.4.3. Labor Intensive Processes

The complexity of allocations drives the need for dedicated personnel to oversee the process and make critical decisions in the planning cycle. Decision support tools can give insight into the current state of the supply chain, but a supply planner is tasked with making the final assignments. These individuals have responsibility over customers or groups of SKUs and reconcile past history of customer activity, future forecasts, upstream supply issues, current market conditions, adjusting overflow or 'free for all' buckets, and other factors to make these decisions. Such decisions are unlikely to be completely automated as they directly impact service seen by customers and must resolve a significant number of factors to make the right choices. We look closer at how much labor is involved in allocations management in Chapter 5.

3.4.4. Excess Inventory

It has been hypothesized that inventory levels are driven up as a result of using customer allocations. Consider that when customers expect supply to be constrained, they might alter their ordering strategy if they believe they are at risk of not receiving all of the supply they seek. The customer might decide to increase future forecasts without any intention of actually making firm orders for those forecasted quantities, in an effort to try and reserve larger future allocations. Cachon and Lariviere (1999) discuss a number of allocation policies and how customers seeking to gain a larger share of rationed supply can manipulate them. Furthermore, the true picture of demand as seen at the supplier can become distorted over time as customers begin inflating forecasts in an attempt to secure higher future allocations (Krishnan, Kleindorfer, & Heching, 2007). Given that customers are not directly penalized for having forecasted a quantity they don't actually take, there is more reason to believe that over-forecasting is occurring. This phenomenon was seen in the mid 1990's during microprocessor supply shortages, resulting in production being increased due to the supposed increase in demand, and then eventually a situation of excess supply as the artificial bubble resulted (Gonçalves, 2003). It is thought that the current structure of the allocations process incentivizes over-forecasting and may contribute to added forecast inaccuracies. The result is that the upstream supply chain prepares extra inventory for demand that does not eventually materialize. We attempt to investigate to what extent this is occurring in Section 4.1 and estimate how much inventory can be attributed to this phenomenon.

3.4.5. Proliferation of Allocation Buckets

Another challenge is that over time, Intel has seen a large increase in the number of allocations buckets it must manage. Recall that an allocation bucket is an amount of inventory of a particular SKU that is reserved for a specific customer in a given order window. The growth trend can be attributed to growth in the total number of SKUs under management, the number of different customers buying product, expansion into new markets, and market competition requiring increased levels of customer assurance that allocations can provide. This reliance on allocations has created an increasingly large management task, requiring more allocation decisions to be made on order quantities and adding complexity to order fulfillment. Also, *supply flexibility* is reduced due to the fact that allocation buckets create artificial restrictions on how supply can be applied to incoming customer orders. Consider that for a supplier to meet a particular forecasted amount of supply in a given week, it needs to build up supply ahead of time. An allocation reserves a portion of that supply base for a future customer order, and until customer forecasts are updated or a finalized customer order arrives, that supply may not be applied to another customer's order. Intel takes the risk for customer demand not materializing from phantom ordering, and allocations reduce its ability to flexibly assign supply across its customer base when dealing with uncertain demand. It is hypothesized that reducing the number of total allocation buckets could allow Intel to reduce the total amount of inventory it must carry. This would result from being able to pool risk over larger groups of customers at the expense of being able to give individual customers direct supply assurance guarantees. In Chapter 4 we create a model to explore this claim and attempt to quantify any potential inventory benefits of such a strategy.

3.5. Key Stakeholders

Allocations have a strong impact on both customer satisfaction and supply chain efficiency. Due to the current organizational structure at Intel, decisions on allocations reform impact multiple organizations. Intel is strategically broken into functional groups, which then internally break down into teams that focus on specific product or customer segments. Any successful reforms to the process will need to satisfy the interests of two parties:

1. Technology Manufacturing Group (TMG) – This group oversees manufacturing, logistics and distribution of Intel products. It focuses on ensuring low cost, high quality, and high responsiveness, enabling Intel to have a competitive advantage in manufacturing and supply chain excellence. The Customer Fulfillment, Planning and Logistics Group (CPLG) under TMG is responsible for optimizing the supply chain, with goals to increase speed and simplification to improve customer experience. The group is judged first by customer service metrics, such as 'Customer Excellence', order confirmation lead-time, and 'perfect orders'. This group is technical and quantitative by design in order to seek out and test the most effective ways to bring Intel products to customers.
2. Sales and Marketing Group (SMG) – This group is focused on understanding customer needs and tailoring Intel's products to meet them. SMG is divided into Geographic regions (Geo's), as different physical locations will have differing sales mechanisms and market needs. Geos are primarily driven by customer service and retention. There is also a high level Corporate Marketing Group (CMG) that defines Intel's overall branding and communications strategy that all Geo's align to. This group has significant quantitative efforts in market analysis but is primarily designed to ensure customer needs are met, so much of the organization is set up to ensure Intel can understand and relate to its diverse customer base.

4. Allocations Impact on Inventory

The previous chapter highlighted a number of challenges that Intel faces when dealing with Allocations based fulfillment. Inventory is a particularly important cost metric due to the rapid product cycles typical of the semiconductor industry. Multiple analyses were performed to better understand how inventories are impacted by the use of allocations at Intel. Recall that all data as presented in this report use masked figures to protect proprietary information about the Intel Corporation, but preserve the intent and conclusions of the analysis.

4.1. Excess Allocations

In Section 3.4.4 we discussed the hypothesis that extra inventory is being carried as a result of inflated customer forecasting in the allocations process. Though Intel believes this may be occurring, it is not clear how much of the inventory that Intel stores can be directly attributed to this. To test this hypothesis, we analyze historical data within a single business unit in which allocations are used for all products. First, we define the concept of *excess allocations* as inventory carried due to the allocations process that did not end up being shipped out against a firm customer order. As discussed in Section 3.3, the weekly planning process creates allocations using customer forecasts. The allocations are updated weekly as new forecasts come in, and in the current process customers are allowed to make updates to their requested quantities at any time in the process. However, Intel is using the forecasts and updating allocations values to build up and distribute supply to the customer base. At a certain point in time, allocations become a *supply commitment* from the manufacturer, who is incurring cost to make product available to the customer. Our goal is to understand the discrepancy between the number of units that Intel commits to customers via allocations, and the number that actually ship to customers in confirmed orders. That discrepancy represents extra inventory being carried that ended up not being required to meet the customer demand that materialized. Some of this difference can be considered acceptable in helping deal with the unpredictability of demand, but our goal is to quantify the amount of excess.

4.1.1. Data Sources

Customer order fulfillment data was provided by Intel to analyze for this project. This data comes from the master database of an IT toolset that Intel uses to manage its supply chain. It therefore provides an accurate record of customer demand and how Intel was able to respond to it.

The data covered a period of 23 continuous weeks in 2011, and includes the majority of product SKUs for a single Intel business unit. To analyze excess allocations, two key data sets are used. One includes each customer allocation that was finalized during the weekly planning process, while the other records each shipment that leaves an Intel facility to fulfill a committed order. There is no strict link defined in the system between a shipment and an allocation that led up to the shipment occurring. Therefore, we define a methodology to match these in the next section. Each database entry stores a large amount of information about the product, customer, and order details, but the primary fields used for this analysis are:

1. *Transaction Date* – the working week (WW) in which this allocation is being recorded
2. *Need Date* – The working week in which the material needs to ship from Intel's warehouse to arrive at the customer's desired receipt date
3. *Quantity* – The quantity of units required to be shipped to the customer by the need date
4. *SKU* – The unique Stock Keeping Unit identifier of the product being allocated.
5. *Customer Code (Geo, L1, L2, L3)* – A unique identifier to designate the customer for which this allocation is being made. Each level of the customer hierarchy (see Figure 7) has a separate field, with Geo being the broadest and Level 3 (L3) being the most specific.

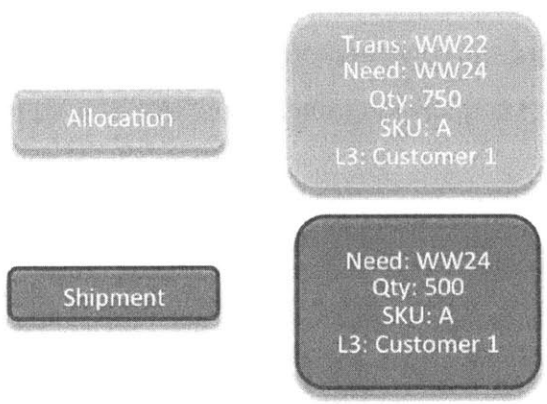

Figure 9 – Key Data Types

Shipments do not have a Transaction Date, as the entry is recorded during the week the item is shipped. Given these data sets, we must define a method to link allocations to shipments across the entire data set.

4.1.2. Matching Methodology

To quantify how much supply can be considered excess, we must match allocations to actual shipment records in key product segments and resolve discrepancies. A shipment of a product to a customer must match up with an allocation of product to that customer at some point in the past, but there is no formal link defined in the current database structure. We propose a method to create matches between allocations and shipments in which the Need Date, SKU, and Customer Codes match. Discrepancies can therefore occur in the Quantities, i.e. the number actually shipped may not match the number allocated to that customer. Additionally, to accurately link a shipment to an allocation, we must determine an appropriate *stagger* of time that is the offset between the allocation and the shipment. Intuitively we can think of the stagger as the lead time a manufacturer requires to prepare stock to ship to the customer by the requested date, i.e. point in time that an allocation becomes a supply commitment for the manufacturer.

To determine an appropriate stagger for this analysis, we determined that the primary factors that influence the amount of time needed to prepare finished goods supply for shipment include the time to execute the planning process, and the time needed to move finished goods inventory to the correct location to make the shipment. As discussed before, the process runs on a weekly cadence, so the planning time (also known as the '*review period*') requires 1 week. All activities necessary to prepare finished good inventory for customer shipment are aggregated into a *throughput time* (TPT), which depends on the particular customer, SKU, and exact inventory configuration at the time an allocation is made. We make an assumption that the average finished good TPT is 1 week, acknowledging that certain SKU-customer combinations may be ready in less than one week, while some may take longer. These two combined suggest a stagger of 2 weeks would be a realistic estimate of the time needed for Intel to make a supply commitment. From the data set, records that match a 2-week stagger are those in which the difference between the Transaction Date and the Need Date equals 2 weeks.

Figure 10 diagrams an example of the matching process, in which a shipment of 500 units of SKU A went to Customer A in week 24 of the planning period. Using a 2-week stagger, an allocation was found in week 22, to ship 750 units of SKU A to Customer A in week 24. We would therefore tally 250 units of excess allocations for the match, which represents the typical matching case for the analysis. We call all cases in which this matching occurs successfully as a *Matched Allocation.*

Given that we make an assumption about the average stagger time across all SKUs, the analysis must account for additional situations in addition to the typical match case above. The two-week supply commitment is not a hard deadline, and some mechanisms do exist to help make supply flexible to meet some of the last minute demand changes. We may find a match between a shipment and allocation using the two-week stagger, but the shipment could actually be larger than the allocation. This is due to the customer increasing the quantity needed less than two weeks before they expected to receive it, but extra supply was located and applied to meet the revised order. It could have been reallocated from a "Free-for-all" bucket purposely designed by planners to serve as safety stock, or leftover from another customer who adjusted their forecasts down for that week. We tally the surplus shipped units as *excess shipments*, which are units shipped despite not having had an explicit allocation 2 weeks prior. These balance out excess allocations, as they represent the amount of inventory that was flexible enough to still meet customer demand changes inside the stagger.

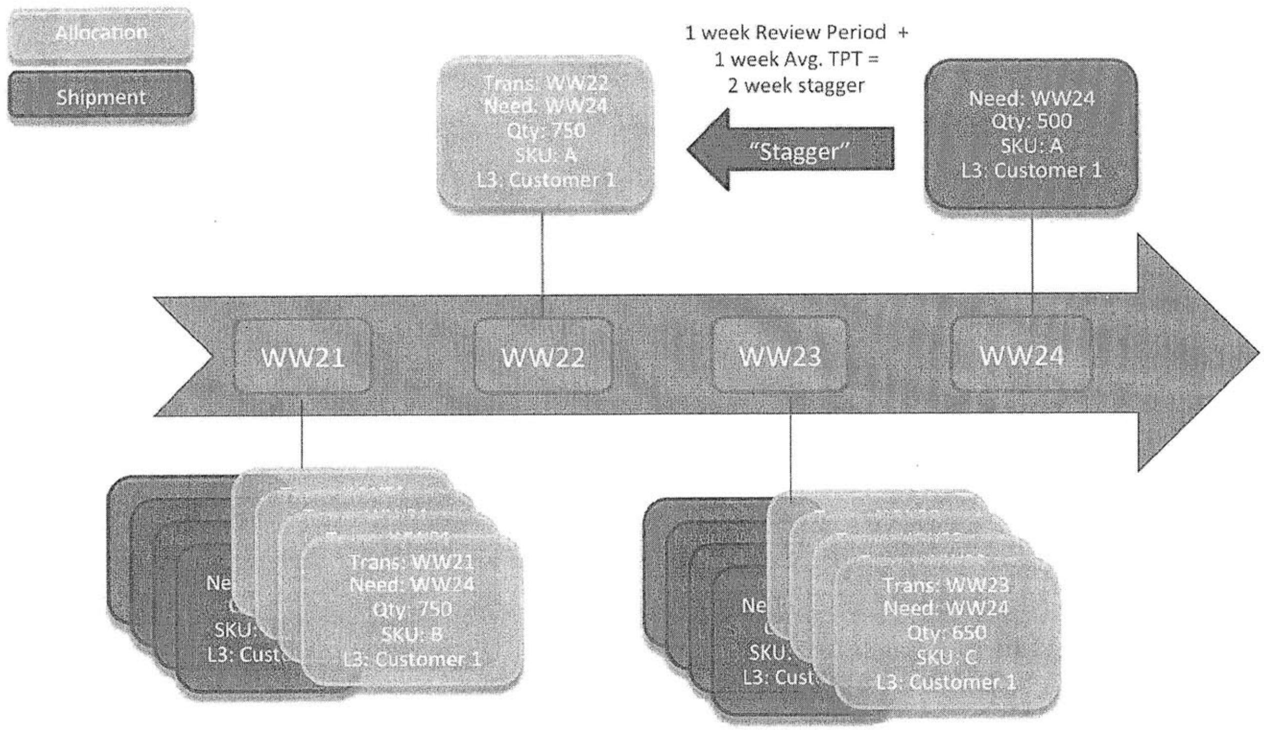

Figure 10 - Matching a Shipment to an Allocation

There are also cases where allocations and shipments do not match up to one another using a given stagger. Recall that we are using a two-week stagger to match allocations to shipments, and not every unit actually ships exactly two weeks after an allocation is made. Allocation records with no matching shipment could be orders in which customers changed their forecasts and the units are no longer needed in that week, so no shipment goes out. Alternatively, these orders could have been shipped to the customers in a different week, so a shipment record could be found before the need date or after the need date. In these cases, multiple unmatched allocations and shipment records result that cannot reliably be associated to one another using the previous methodology. Similar to the excess shipments case, we consider these cases as indicative of the variations inherent in the ordering habits of customers. *Unmatched Allocations* and *Unmatched Shipments* are tallied as units allocated and units shipped respectively. This is conservative, in that it assumes all unmatched shipments eventually offset an allocation made for a future date, but this assumption helps factor in some of the flexibility that is possible in the allocations process.

4.1.3. Matching Results

The matching methodology described above was used to process all records over 23 weeks. We first filter out allocations so that only the records with a 2-week stagger remain, and then we attempt to match the remaining records to shipments. The resulting tallies are listed in Table 2. Of interest is the breakdown of units between the type of match, and the difference between the number of units allocated vs. shipped. For the majority of records, a successful match was made between an allocation for product to be shipped in two weeks, and a shipment record in the targeted week (81% of allocations and 87% of shipments are accounted for in Matched Allocations).

Total Allocations (in units) *Over 23 Weeks in 2011, Using 2-Week Stagger*		
	Allocated	**Shipped**
Matched Allocations	24,382,558	20,526,219
Unmatched Allocations	5,617,442	
Unmatched Shipments		2,946,812
Total Units	30,000,000	23,473,030

Table 2 – Total Allocations Rollup
(Data disguised at the request of Intel Corp.)

The discrepancy between the number of units allocated and the number of units shipped indicate excess allocations. Table 3 provides a summary of these differences, both on an aggregate level over the entire time period and on a weekly basis. The total number units allocated differed notably from the number shipped, as summarized in the 'Total Allocations' column. 6.5 million units, or 21.8% of units allocated, were not shipped out within 2 weeks, suggesting that a non-trivial number of orders are altered within the two-week stagger. To judge how much of a problem this may be for Intel, we compare the total amount of excess allocations to the total ending on hand inventory we expect Intel to carry. Doing this allows us to estimate, at any given time, how much of the total EOH Inventory can be attributed to the allocations process. Note that these estimates of excess inventory are driven solely from allocations data, which are made using finished goods inventory. Order inflation can also cause additional wafer starts or units assembled as mentioned in Figure 6, but these are not directly taken into account with this estimate.

Excess Allocations (in units) *Over 23 Weeks in 2011, Using 2-Week Stagger*		
	Total Allocations	*Weekly Allocations*
Total Units Allocated	**30,000,000**	**1,304,348**
Total Units Shipped	**23,473,030**	**1,020,567**
Total Excess Units	**6,526,970**	**283,781**
% Allocated, not Shipped	21.8%	

Table 3 - Excess Allocations
(Data disguised at the request of Intel Corp.)

To make this estimate, we first calculate excess allocations on a weekly basis as seen in the 'Weekly Allocations' column of Table 3, which is simply dividing the total allocations data by the 23 weeks of the analysis. Doing this results in an expected 283,781 units of excess allocations each week. Next, from proprietary inventory data not presented here we found that over the time period analyzed, Intel carried an average of 7,190,831 units of ending inventory on hand for the product line under analysis. This means that, in any given week during the 23 weeks under analysis, we would expect Intel to be carrying 7.2 million units of product in this particular business unit, inclusive of all safety stock Intel carries to manage demand volatility.

Finally, we can make the comparison between the expected weekly amount of excess allocations and the total expected EOH inventory that Intel is carrying. Recall that we assumed a 2-week stagger, and therefore must account for a 2-week lead-time in our estimates of excess allocations. Since inventory must be held to cover the lead-time, we would expect two weeks worth of excess allocations to be held in inventory at any time, since inventory is building up in preparation for the expected customer orders over the lead time. Therefore, we translate excess allocations into excess inventory by multiplying the expected weekly excess allocations figure by the lead-time, in weeks. Table 4 summarizes these calculations, which result in the expectation that 7.9% of EOH Inventory can be attributed to the inflation of customer orders in the allocations process. Note that this is still a somewhat conservative estimate, as the ending inventory on hand could also include past customer forecasts that may also have been inflated. However, we would require direct links between an allocations record and a shipment record to more accurately calculate excess allocations over the entire planning horizon, so instead for this study we stick with our presented matching methodology and an average expected amount of excess allocations.

Excess Allocations vs Average EOH Inventory (in units) *Over 23 Weeks in 2011, Using 2-Week Stagger*	
Avg Expected EOH Inventory	**7,190,831**
Avg Weekly Allocations	**1,304,348**
Avg Weekly Shipments	**1,020,567**
Excess per Week	**283,781**
Excess over 2 week Lead Time	**567,563**
% Avg EOH that is Excess	7.9%

Table 4 - Excess Allocations as Compared to EOH Inventory
(Data disguised at the request of Intel Corp.)

4.1.4. Implications

The following key findings summarize the implications of the excess allocations study.

1. Forecast Inflation and Order Volatility– The data show that almost 22% of orders allocated to be shipped to customers within 2 weeks do not end up being confirmed. This suggests that customers and Intel analysts who generate the forecasts are likely keeping them inflated above true demand until the last minute, when demand can be updated without penalty. It gives some credibility to the theory that customers tend to over-forecast when using allocations, and in this case looks to represent a sizable percentage of incoming orders. The number of unmatched allocations, unmatched shipments, and total discrepancies between allocations made and shipments sent suggest that customers are frequently changing orders at the last minute. This volatility inside the 2-week stagger makes it harder to know the true demand that ought to be planned for. In total, these findings suggest that buyers are using the customer centric nature of the allocations process to their advantage, but at a cost to Intel.
2. Excess Inventory is Nominal compare to EOH – Though the large percentage of allocations not shipping to confirmed orders is at first alarming, the total number of excess allocation units represents a nominal portion (< 8%) of the total inventory Intel keeps on hand to manage demand volatility. Viewed in this light, the cost of handling extra inventory could be considered worth the benefits of providing customer assurance during supply constraints. Given that allocations do provide a number of benefits to Intel customers, this could conceivably be an acceptable cost to establish and preserve customer relationships. At the same time, it is still inventory that could potentially be saved, which becomes even more important if a particular product is constrained. Though for Intel these costs may not be a large issue, for other firms a similar amount of excess inventory may be prohibitive.

4.2. Reducing Allocation Buckets

In Section 3.4.5, we discussed that another ongoing challenge of managing allocations is dealing with an increasing number of allocations buckets over time. A larger number of allocation buckets requires more labor to manage and reduces the ability of planners to flexibly move supply around to meet changes in demand. With reduced flexibility, it is thought that a higher overall level of inventory is necessary to compensate for forecast errors in order to satisfy customer demand. Conversely, by improving supply flexibility through a reduction in the number of allocation buckets, it is thought that total customer demand could be sufficiently met using a lower total amount of inventory. The most direct method to reducing the number of buckets is by reorganizing the customer hierarchy to have fewer allocation groups to which SKUs are allocated.

The goal of this portion of the analysis is to quantify the benefits, if any, there are when simplifying the allocation hierarchy to reduce the total number of buckets. It was not possible within the timeframe of this study to alter the formal process and investigate the effects on real orders, so instead we model the scenario to simulate the effects. The model is devised to reasonably estimate the amount of safety stock needed to meet customer demand as we vary the number of allocation buckets. With a smaller number of buckets, we can expect inventory savings due to pooling uncertainty amongst groups of customers whose demand fluctuations can cancel each other out.

4.2.1. Estimating Necessary Inventory

We seek a simple algorithm that can estimate needed inventory given the data we have access to, and can generate realistic values under different allocation bucket configurations. Inventory levels can strategically be determined by using past customer forecasts and actual orders to estimate future needs. The total amount inventory to keep depends both on the expected number of units that customers will require, and assessing how variable this quantity is to ensure adequate coverage for volatility. The former component represents how much *cycle stock* is necessary to keep on hand, while the latter determines the amount of *safety stock*.

Allocations provide insight into customer demand since they are based on forecasts that customers must make about future product needs. We previously demonstrated the use of historical allocations data to match a shipment to a particular forecast. We can similarly utilize matched allocations as a way to measure variability in demand, which can then be used to predict safety stock.

This requires analyzing the discrepancies in units shipped vs. units allocated to devise an indicator of variability, and then calculating an amount of safety stock given those indicators.

We first devise a method to estimate how much inventory a supplier might keep given demand as seen in the data sets. By interpreting allocations data as forecasts, we base the model using forecast errors to estimate variability and then inventory. Initially, we determine how much inventory a supplier would need using the current allocation bucket configuration as used at Intel. We compare the model's output to actual inventory levels managed by Intel's current process as a means to assess its validity. Then, we vary the number of allocation buckets and simulate the inventory needed in different allocation scenarios.

4.2.1.1. Data Sources

We consider an allocation akin to a customer forecast, and a customer shipment as actual demand consumed. When doing so, we can use the data sets used to estimate excess allocations for inventory analysis. For any given matched allocation, we can utilize the difference between the allocation and actual shipment to derive an indicator for variation of a product, customer, or other factors. Given that we require an actual consumption of demand to determine forecast accuracy, we specifically use the set of matched allocations resulting from a 2 week stagger (see Section 4.1.1) to build the model.

4.2.1.2. Safety Stock

When determining supplier inventory with uncertain demand, if demand is large a stockout may occur, or if demand is low inventory is carried and costs are incurred. Safety Stock is kept in addition to base stock to allow the supplier to avoid a stockout. We use a customer service based approach to calculating safety stock, in which various service levels drive inventory levels to meet a certain percentage of expected customer demand. Safety stock can be calculated by multiplying two factors (Silver, Pyke, & Petersen, 1998):

$$SS = k\sigma_L \qquad \text{EQ1}$$

where

k is the safety factor
σ_L is the standard deviation of the errors of forecasts of total demand over the replenishment lead team L

By selecting a safety factor, as determined by choice of service level, and estimating the potential error in the incoming forecasts for a product, we can derive an amount of inventory to provide the desired amount of coverage to avoid a stockout.

4.2.1.3. Forecast Errors

Forecast errors are inevitable as demand prediction is by nature imperfect. The amount of forecast error a particular supplier sees can be characterized and used to measure demand variability. Consider that over a given period of n time units, we can record a forecasted value of supply needed in a future time unit and the actual amount of demand seen at that time. We consider $a_{t-2,t}$ to be a customer allocation made in time period $t-2$ for time period t as a forecast with a 2-week stagger. We then consider s_t to be a customer shipment in time period t as the actual materialized demand. The error in forecast for a shipment in time period t, from a forecast in time period $t-2$ can be defined as the difference between these (Kilger & Wagner, 2008):

$$e_{t-2,t} = a_{t-2,t} - s_t \qquad \text{EQ2}$$

This basic definition is simplistic but provides the basis for many different forecast error metrics. In our data set, different customer orders may have weekly variations in quantities over the total time period, and we might expect to see seasonality in demand over a period of time. A metric that is insensitive to the magnitude of the order quantities between observations is preferable, or there is a risk of a very large order in one week dominating a forecast error calculation. Therefore, we use the percentage error between the forecast and shipment:

$$PE_{t-2,t} = \frac{e_{t-2,t}}{a_{t-2}} \qquad \text{EQ3}$$

We can use the percentage error in past observations as a predictor of future forecast variance in order to estimate σ_L, as we assume that the variation seen in past demand is indicative of future demand. To calculate σ_F, we use the standard deviation of an observed group of percentage forecast error, and multiply by the square root of the total lead time necessary to replenish stock (Kilger & Wagner, 2008). However, $PE_{t-2,t}$ does not resolve to an actual number of inventory units since it is as percentage. So we must also factor in an expected number of SKU units that the group under consideration needs for a hypothetical week:

$$\sigma_L \approx \sigma_F = stdev(PE_{t-2,t}) * \mu_t * \sqrt{L} \qquad \text{EQ4}$$

where

μ_d is the derived expected number of units of a SKU demanded by a specific group in time period t
$\sqrt{L}$ is the square root of the replenishment lead team L

Note that EQ4 assumes that individual forecasts are independent of one another. As discussed earlier, we assumed that the average lead-time for replenishing product within this business unit was 2 weeks. We calculate our estimate for μ_t by using past data to derive an expected amount of demand from a specific customer, for a specific SKU, in a hypothetical week. Since our data sets record activity every week, we average the total amount of product demanded in each of the recorded weeks of interest. The key for our analysis is using the estimator of demand volatility for a single or group of customers, so that our model can derive a reasonable amount of safety stock. With this in place, we are able to produce simulations of safety stock calculations using different allocation bucket sizes, each with a safety stock value predicted by the demand volatility of that group in past observations.

4.2.2. Pooling

Risk Pooling is a common technique for managing variability in a supply chain, in which demand is aggregated across different locations (Simchi-Levi, Kaminsky, & Simchi-Levi, 2008). The larger the pool, the more likely it is that high demand from one customer can offset low demand from another customer. As a result, lower safety stock levels are needed to maintain the same service level, and overall inventory levels are reduced (Simchi-Levi, Kaminsky, & Simchi-Levi, 2008). In this study, reducing the number of allocation groups in use is a method to increase pooling, as supply analysts are able to plan for a single allocation that spans multiple customers. We would therefore expect lower total inventory levels as the number of allocations grouping is reduced.

4.2.3. Simulation Methodology

Using the method defined in the Section 4.1.1, we can calculate a predicted amount of safety stock to hold given a set of forecasts and demand consumptions. First, we translate each allocation decision into a safety stock calculation. An allocation decision is made for every SKU ordered by each customer group, so we can generate a safety stock value for each of these allocation buckets. This is done by grouping matched allocations by each customer-SKU combination, and calculating a safety stock for each one using the history of orders and a chosen service level. After summing up the predicted number of units to keep in safety stock for each bucket, we have an aggregate amount of inventory that the model predicts is sufficient to meet demand for a given service level. Initially, we simulate the predicted amount of safety stock for the current set of allocation buckets. After, we can use larger allocation groupings and rerun the simulation to see the effects of pooling risk over larger groups of customers.

4.2.3.1. Model Plausibility

The first simulation predicts the amount of inventory to hold using the current allocation configuration used at Intel. Allocations are made for every L3 customer code, so the allocation buckets are defined as each SKU-L3 Customer Code pairing. Table 5 shows a summary of the predicted safety stock levels for each of three service levels:

	Level 3 100% groups, 100% buckets)
95% SL Safety Stock	4,744,369
98% SL Safety Stock	5,926,856
99% SL Safety Stock	6,719,987

Table 5 – Simulated Safety Stock using Customer Level 3 Allocation Buckets (Data disguised at the request of Intel Corp.)

These results compare favorably to actual inventory levels seen over the time period of analysis. Recall that total inventory levels will include cycle stock and safety stock, so we should expect the predicted safety stock plus cycle stock to reasonably estimate true inventory levels. Over the 23-week period the data covers, we can calculate the average ending on hand (EOH) inventory levels (though cannot disclose the actual figure). However, the predicted 98% Service Level safety stock does reasonably estimate true inventory levels, so the model is producing values that can estimate realistic safety stock values.

4.2.3.2. Bucket Reductions

Given that the model predicts reasonable safety stock levels, we now wish to use the model to simulate how much safety stock to store when the total number of allocation buckets is reduced. A convenient way to segment the data is using the already defined customer codes. As discussed in Section 3.2 - Hierarchical Allocation Rules, the allocation scheme is inherently structured hierarchically and provides a simple way to group allocation buckets together. These divisions of the customer base provide one potential way to group customers into larger sized buckets to exploit pooling. We therefore take advantage of this structure and simulate pooling across customer level hierarchies as means to test whether reducing the total number of allocation buckets under management can reduce expected inventory levels. Note that in a real implementation, supply analysts could create more strategic customer groups based upon tacit knowledge about customer demand patterns, calculated demand volatilities, and numerous other factors.

We simulate safety stock for Customer Level 2 (L2), Customer Level 1 (L1), and Geography (Geo), using the allocation hierarchy as the method to segment customers into larger pools. All demand for a particular SKU is rolled up for the group under analysis, a measure of volatility is calculated, and a predicted amount of safety stock is calculated for each SKU-Customer Group bucket. In addition, we include a simulation of a Global pool, where safety stock is calculated for each SKU regardless of which individual or group of customers placed an order for it.

The results of these simulations are tabulated in Table 6. Note that as we move up the hierarchy, the total number of allocation groups and buckets are reduced. Table 6 denotes the number of allocation groups and buckets at a particular level of the hierarchy as a percentage of the total number of groups and buckets found in the data sets. Therefore, at Level 3 we are using 100% of the buckets and groups, at Level 2 we are using 43.5% of the stored allocation groups and 66% of the stored allocation buckets, and so on. This is done to shield the total number of allocation groups and buckets in use at the business unit under analysis.

	Level 3 100% groups, 100% buckets)	Level 2 43.5% groups, 66% buckets)	Level 1 25.4% groups, 54.5% buckets)	Geo (3.3% groups, 27% buckets)	Global (.5% groups, 9% buckets)
95% SL Safety Stock	4,744,369	4,029,938	3,784,440	2,102,546	1,003,146
98% SL Safety Stock	5,926,856	5,034,360	4,727,674	2,626,585	1,253,170
99% SL Safety Stock	6,719,987	5,708,058	5,360,331	2,978,075	1,420,869

Table 6 - Safety Stock Simulations Summary
(Data disguised at the request of Intel Corp.)

4.2.4. Results

4.2.4.1. Inventory Unit Savings

Given the final simulated safety stock values, we now look to interpret how much of an impact reductions in allocations group or buckets can have on the total number of inventory units needed to adequately meet customer demand at different service levels. We plot Table 6 on a single chart to assess the downward trend in total inventory as the total number of allocation buckets is reduced, as seen in Figure 11.

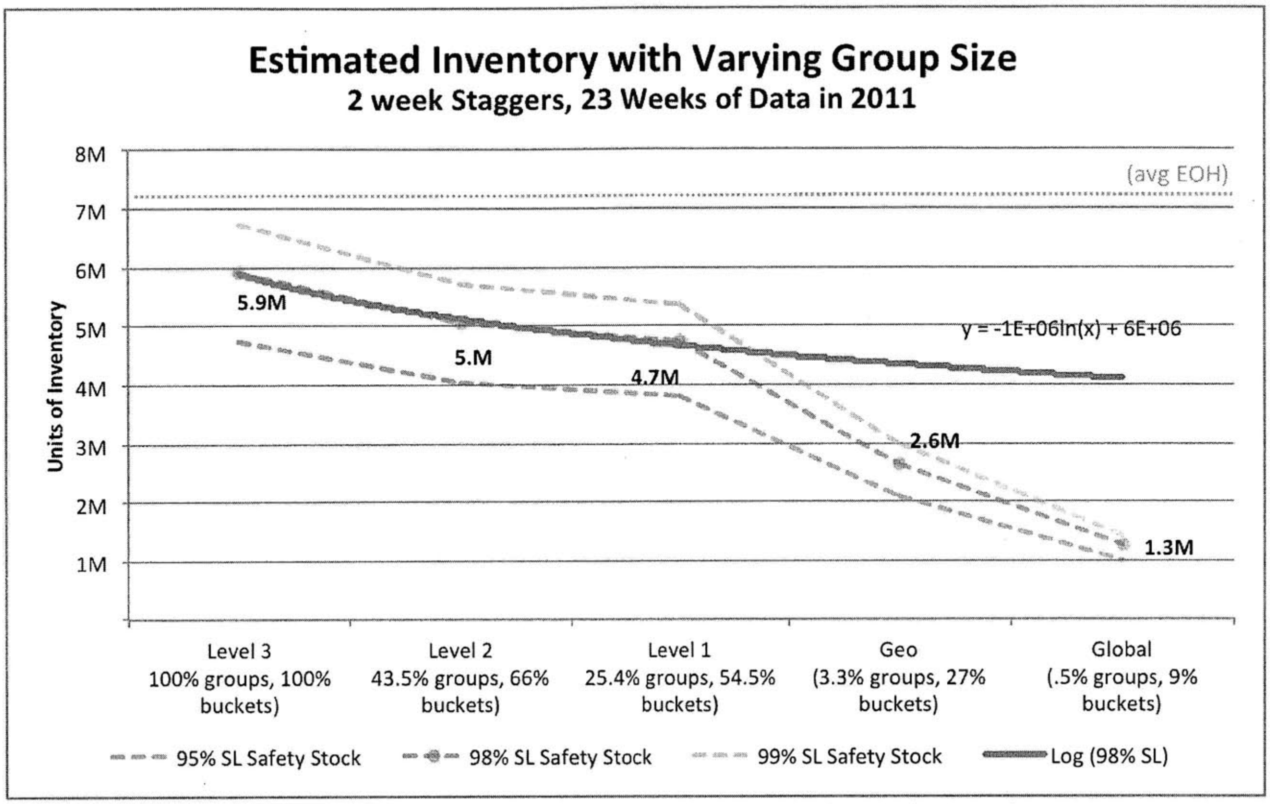

Figure 11 – Estimated Inventory when Reducing Allocation Buckets (Data disguised at the request of Intel Corp.)

A few points on this chart are notable. First, the dotted orange line represents the average ending on hand inventory for the business unit under analysis, calculated over the 23 weeks of interest as discussed in Table 4. As discussed in Section 4.2.3.1, total inventory can be broken down into cycle stock and safety stock. We therefore attribute the difference between the Level 3 Predicted 98% Service Safety Stock and the dotted line to the cycle stock. The overall downward trend in inventory agrees with our original hypothesis, and there are potentially significant reductions in total inventory when the number of allocation buckets is reduced.

Also interesting is the sharp drop between Level 1 and Geo level pooling. We see a significant drop in inventory levels when pooling at the Geography level, and another large drop when pooling globally. We attribute these large drops to the effects of averaging past demand over a large number of customers to determine an expected average unit of SKUs per EQ4. Managing allocations at the Geography or Global level would also likely incur numerous additional costs that are not accounted for, such as transportation costs to route inventory across Geo's in order to facilitate remixing to account for demand volatility. As a result, we consider the curve between Level 3 and Level 1 to be a better indicator of realistic expectations for the inventory savings trend as allocations buckets are reduced. The applied trend line follows the guide of the first three predicted safety stock values at the 98% Service Level.

4.2.4.2. Cost Savings due to Inventory

For the inventory reductions above, we estimate a cost savings using a standard translation defined by Intel. This proprietary formula translates the inventory savings predicted by the model into dollars by taking into account the costs of an average product, capital costs, the risk that extra inventory may eventually be left unsold and have to be scrapped, and other factors. We consider the Level 3 prediction to be the baseline configuration, and any reduction in inventory as compared to the baseline contributes to inventory cost savings. We also make the same assumption that the first 3 data points provide a more realistic overall cost savings trend due to the added costs of making Geographic or Global pooling feasible. These values are then annualized, and the results are shown in Figure 12.

4.2.5. Implications

The modeling efforts resulted in estimates for total inventory and cost savings that result from reducing allocation groups. We use the 98% Service Level as the baseline for estimating savings as it is a good estimate of desired Service Level for this business unit.

1. Moderate Inventory Savings – The model suggests that moderate benefits can be achieved by taking advantage of pooling opportunities through consolidating allocation groups. For instance, by rolling up allocations from Level 3 to Level 2 Customer Codes, a 56% reduction in allocation groups would have resulted in a 15% reduction in total inventory over the 23 week period. Given the demand profile under analysis, continued reductions in allocations groupings would result in further savings, but there are diminishing returns. When increasing pooling from Level 2 to Level 1 customer groups, a 42% reduction in allocation groups results in only a 6% decrease in Inventory. Assuming future demand is similar to past demand, we would expect similar inventory reductions in the future by reducing allocation groups.
2. Moderate Cost Savings – The cost savings purely from inventory are noticeable. Consolidating all Level 3 Groups into Level 2 results in an estimated savings of $24.9M. The consolidation of Level 2 to Level 1 results in an additional $8.5M in savings, for a total of $33.4M. In addition, these savings would be expected every year in which the simplified allocations process is used, so the long-term benefits can add up over time. However, in comparison to the total revenue

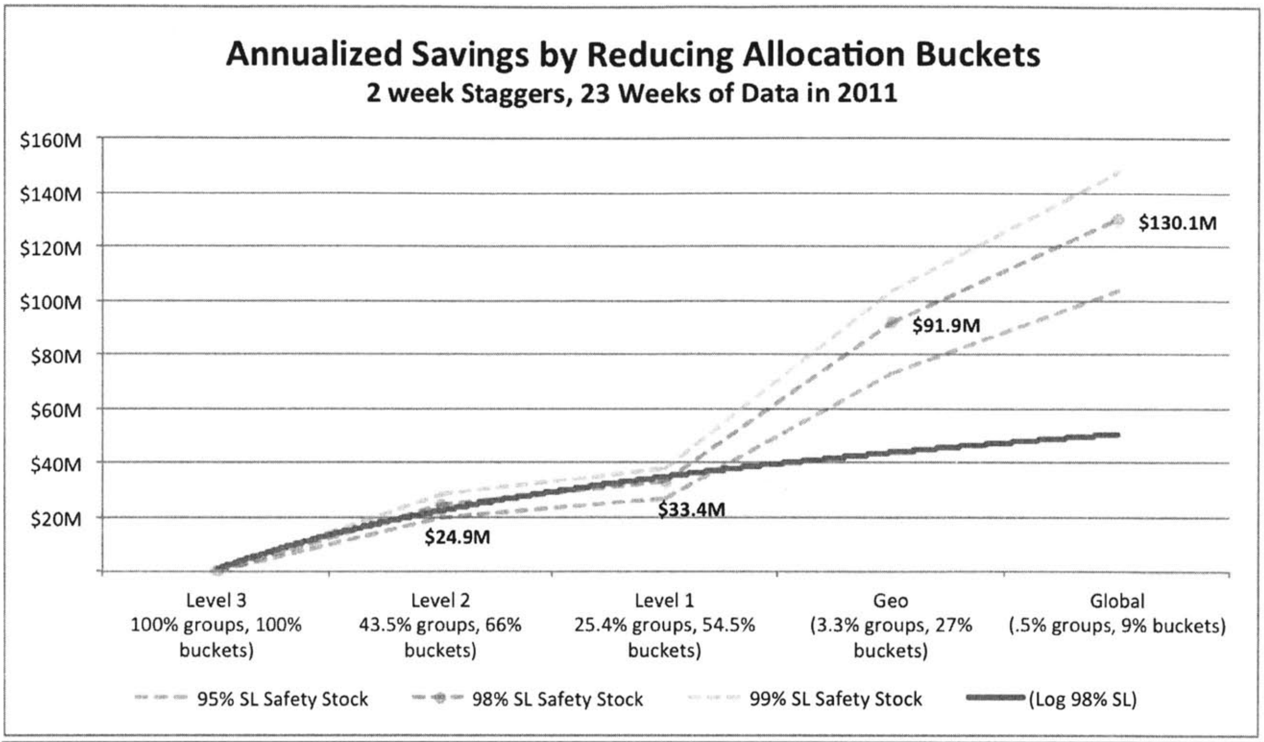

Figure 12 – Annualized Savings by Reducing Allocation Buckets
(Data disguised at the request of Intel Corp.)

generated by this business unit, these estimated cost savings are less enticing. Major customers, some of whom appreciate and expect the assurances that allocations provide them, have a much more significant impact on total revenues. Therefore, the risk of potentially missing important orders due to a lack of supply assurance may outweigh the potential cost benefits.

3. Inventory Flexibility – Though the impact of the cost savings may be debatable, additional supply flexibility is another key potential benefit. Reducing the number of allocations groups can allow the system to adequately meet customer demand with fewer units of inventory on hand. This is especially important for severely constrained products, which are in very short supply. Allocations were created to manage this supply scenario, but the proliferation of allocation groups prevents inventory from moving between customers to account for demand volatility. Simplifying the customer hierarchy can realistically allow the same group of customers to be served with less overall inventory. The data collected suggest that a 40% reduction in allocation groups could save an additional ½ week of inventory from the supply network.

5. Allocations Impact on Headcount

In sections 3.4.2 and 3.4.3 we discussed the hypothesis that the added complexity of allocations drives higher headcount levels due to the need for more people to manage allocations decisions. We investigate this by collecting data on the number of heads required to manage allocations across multiple geographies in a large business unit at Intel. Then, similar to the analysis performed for inventory, we attempt to create a model that can help understand how changing the number of allocation groupings used would affect necessary headcount. Once again, figures presented in this section are masked to protect proprietary data from the Intel Corporation, but preserve the intent and conclusions of the analysis.

5.1. Approach

Formal data on the number of people directly dedicated to managing allocations is not maintained at Intel. Finding an accurate overall measure of labor dedicated to allocations is challenging, as it spans multiple functional units across Sales and Marketing (SMG) and Technology and Manufacturing (TMG) groups. In addition, geographical differences in customer expectations require different organizational structures to manage customer accounts, so these cultural differences greatly affect how labor is organized to manage allocations in a global supply chain. Finally, data pertaining to the workload of individuals or a group is sensitive, and it can be difficult to acquire accurate numbers due to fears over perceived repercussions of any sort of labor analysis. We first attempt to collect data on the number of man-hours dedicated to managing allocations by surveying supply managers in each of the major geographies of the Intel business unit under analysis. We focus on SMG, consisting of geographically distributed teams designed to service their local markets, in order to gain more insight into complexities of managing allocations in a global supply chain. Both qualitative and quantitative data were used to design a headcount model that can estimate how many heads are needed to manage allocations for a particular geography for a given level of complexity as driven by the number of allocation groups under management.

5.2. Survey Results

Representatives for each of 5 major geographic regions in SMG were interviewed for their perspectives. During the interviews it became clear that the strategies used to manage allocations were not standardized across geographies, so notes were taken on the different methodologies. In addition to this qualitative information, estimates of the actual number of heads needed to manage the process were requested. These numbers are the best guess of the person interviewed and are not formally quantified, but they provide a good initial estimate for our analysis. The differences between geographies were notable in a few categories, which are discussed below.

5.2.1. Complexity

Due to the different business environments that they serve, each Geo has different characteristics that can make managing allocations more complex. Recall that in managing allocations, an analyst must make decisions regarding how much of a particular product will be allocated to a specific customer or group. We correlate the total number of allocations decisions being made as an indicator of the complexity of managing allocations, and expect a more complex allocation arrangement to require higher headcount. *SKU Volume* can vary widely across geographies due to differing market sizes, seasonal patterns, and numbers of customers. Geos that have to manage larger total product volumes are likely to need additional headcount in order to manage supply as there are likely more customers vying for product, and an allocation decision needs to be made for each customer group. Markets with a broader or more diverse customer base may also need to handle a larger number of SKUs. *SKU Complexity* increases the need for headcount since a higher number of different SKUs being managed will need a higher number of allocation decisions. Finally, the total number of *allocation groups* that the Geo decides to use will impact how much time must be spent managing the process.

Geo Characteristics *Over 23 Weeks in 2011*					
	Level 1 Allocation Buckets	**Level 2 Allocation Buckets**	**Level 3 Allocation Buckets**	**Number of SKUs**	**Total SKU Volume (units)**
Geo 1	14	18	74	187	12,819,037
Geo 2	10	10	19	140	2,508,832
Geo 3	10	27	67	118	5,489,800
Geo 4	12	12	23	150	839,259
Geo 5	8	24	36	114	3,759,588

Table 7 – Complexity Characteristics by Geo
(Data disguised at the request of Intel Corp.)

5.2.2. Roles

There are three job roles that typically handle allocations related tasks, but it was found that each had a slightly different definition within a geography. All of these roles are different forms of Supply Analysts, who are generally responsible for managing supply of a portion of products for a set of customers. In some cases, a person was responsible for managing the entire relationship with a single customer, which included managing supply of multiple products for a limited customer segment. In other cases, an entire product line was assigned to a person, who would then be responsible for determining how all customer needs in the geography could be resolved by the supply available to them. These varying ways of defining what a person's job tasks affect the headcount analysis, since a single head of a particular job role in one geography may spend a different amount of time on allocations that the same role in another country.

5.2.3. Market Factors

Each Geo is given the freedom to tailor service to the needs of their customers, which changes their strategies for managing allocations. In some markets, allocations can impact a Geo's ability to maintain customer satisfaction. For instance, in one Geo, customers place a high value on having supply assurance, as this is the expectation for most businesses in this market. As discussed in Section 3.1, supply assurance is a key need that allocations fills, and Intel could be at risk for losing business without providing this type of supply assurance in some markets. As a result, this Geo is organized to ensure each individual customer has an allocation specifically for them, and in aggregate we see a large total number of allocation groups and quantity decisions that need to be made. We would expect such a Geo to have higher labor requirements to manage customer allocations and ensure customers are satisfied. In other business environments, the supply assurance requirements are more relaxed, and buyers are comfortable trusting vendors to meet their orders without explicit guarantees. Part of this can be attributed to the type of products in demand in a particular market. Certain markets may be more competitive and require access to the latest and greatest constrained products, while others may favor access to lower cost, highly available products that have more stable supply. The balance of products needed may require one Geo to favor more complex allocations schemes, while another may prefer a simpler and more automated process.

5.2.4. Headcount Estimates

Given the numerous differences in organizational structure between Geos, we solicited best guess estimates of the number of heads necessary to accomplish allocations related tasks as designed for each geographic region. Judgments were made to define the percentage of time a particular person was spending on allocations related tasks, to account for the different organizational structures in which a single person might devote time to other tasks. The weighted average of the numbers of heads of each role and the percent time each head spends on allocations gives a total number of heads required to manage allocations.

Estimates of Total Heads Needed to Manage Allocations							
	Total Heads Role 1	% Time on Allocations	Total Heads Role 2	% Time on Allocations	Total Heads Role 3	% Time on Allocations	Total Heads Allocations
Geo 1	25	90%	2	90%	1	90%	25.20
Geo 2	16	95%	4	80%	2	80%	20.00
Geo 3	30	25%	20	80%	4	100%	27.50
Geo 4	35	50%	1	100%	5	50%	21.00
Geo 5	17	80%	4	80%	0	0%	16.80

Table 8 – Estimated Total Heads to Manage Allocations (Data disguised at the request of Intel Corp.)

5.3. Sample Model

A robust model to predict an accurate number of heads needed to manage allocations will require more detailed data than was collected in this study. However, a preliminary multivariate regression was performed to demonstrate the techniques that could be used in future studies. The goal is to produce a picture similar to Figure 13, showing the trend in labor as the total number of allocation groups is adjusted.

To model the number of heads accurately, we must account for the differences in complexity of managing allocations across each site. We assume that the total number of heads needed is influenced by the SKU complexity, SKU Volume, and total number of allocation groups being managed. Since we only have one data point in time per Geo, we cannot perform a time variant analysis and fit a curve for each Geo. Instead we fit a linear model across all Geos, and then graph the predicted number of heads as we vary the number of allocation groups. Each point on a curve represents the number of heads required to manage allocations tasks given the number of allocations groups that are being used. Though simplistic, the model results in a figure that complements the inventory story well. It assumes a linear relationship between allocation buckets and headcount, when in reality each individual Geo may have a unique trend line and may or may not necessarily be linear. Additional data would be needed to understand how each individual Geography performs at different levels of complexity, which could be an interesting follow on study to this analysis.

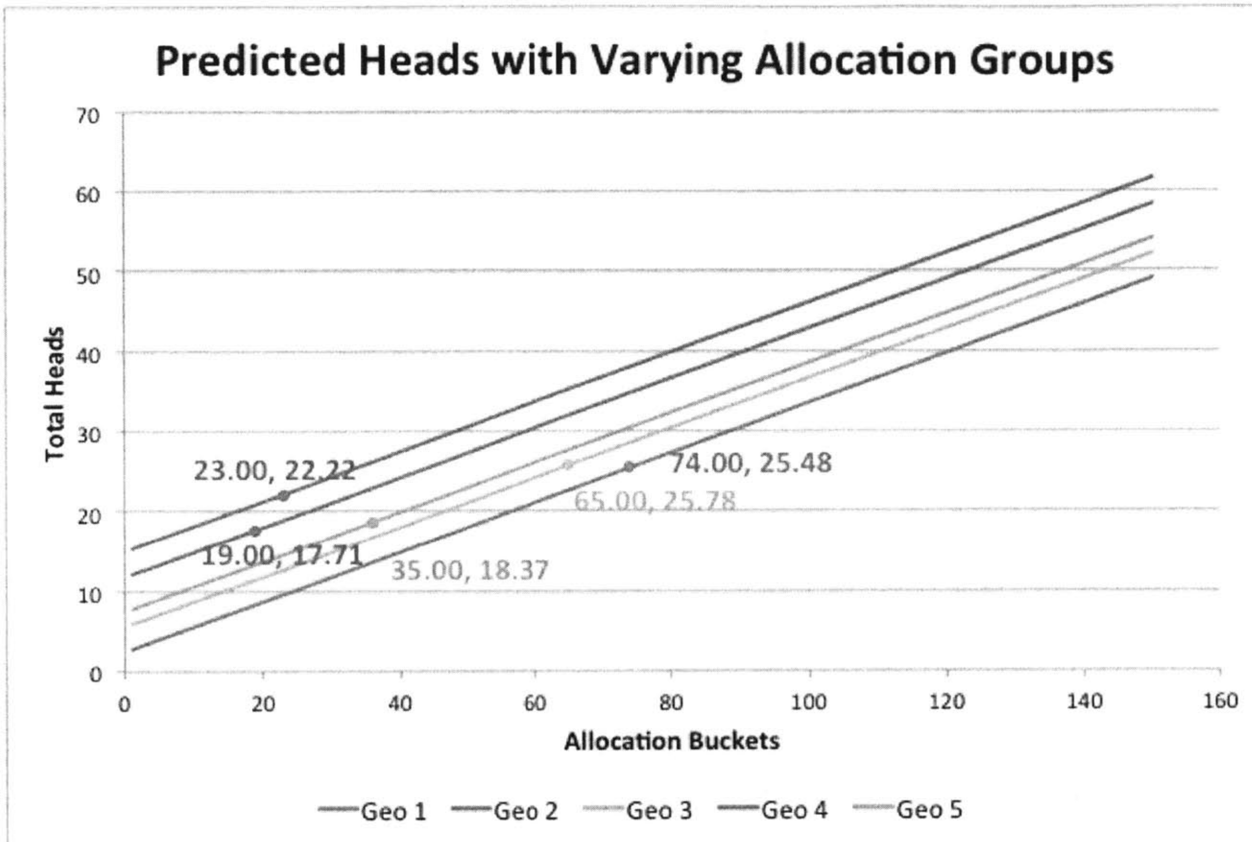

Figure 13 – Sample Regression Plotting Number of Heads vs. Allocation Groups (Data disguised at the request of Intel Corp.)

This page intentionally left blank

6. Key Takeaways and Summary

Throughout this project it became clear that allocations served an important role in the organization, and that modifications to the process could not be made without understanding the total impact to the organization and customers. In addition, it was clear that the process has a direct impact on important supply chain characteristics, including the design of order fulfillment processes and tools, the organizational structure of customer facing divisions, and the strategic use of inventory. Continued support and refinement of these processes can help ensure a manufacturer such as Intel continues to meet expectations of customers in volatile markets.

6.1. Inventory

6.1.1. Excess Inventory due to Allocations

Some excess inventory is carried due to the fact that customers are incentivized to inflate forecasts, since there is no penalty for over-estimating. Though there is some flexibility in the allocations process that allows supply analysts to remix the supply base, in aggregate our analysis suggests that customer order inflations drive up the total amount of supply that Intel prepares during each planning window. As noted in Section 4.1.3, we see a moderate number of allocations that do not end up being shipped after Intel had already commitment to incurring the cost of producing and storing the product in inventory.

But when comparing excess allocation to EOH Inventory, a supplier may determine that the total amount of excess inventory is acceptable. In Intel's case, significant inventory is being held to deal with the overall level of demand volatility that is apparent in the semiconductor industry. The portion of inventory that we determined to be attributable to the allocations process may not be considered a significant cost, but for other suppliers this amount of inventory may be considered too much. Many organizations may not realize to what extent excess allocations may be impacting inventory levels, and an important first step is adding the appropriate pieces to the supply chain toolset to track such data. Using an analysis methodology as show in the study, or by directly adding links between allocations and shipments and tracking them over time, an organization can gain insight into how much its customers inflate orders and whether the cost of providing supply assurance is worth the investment.

6.1.2. Fewer Allocation Groups can Reduce Inventory on Hand

Given that the allocations process resulted in inflated customer orders and higher inventories, we also found that reducing the reliance on allocation groupings can help reduce total inventories. The model we present in Section 4.2 suggests pooling inventory across groups of customers, rather than creating individual allocation buckets for every customer, is both feasible and could result in moderate inventory savings. These results arise from a simplistic customer segmentation method using the predefined allocation hierarchy already in use at Intel. There is further potential in designing more strategic customer groupings that pool customers together based on their demand volatilities and other factors, to further optimize the effect of pooling.

Though the benefits of simplifying allocations may look appealing, any organization considering this must decide whether the impact to customer service is worth a change to the ordering process. Pooling customers together may require a policy change in terms of giving customers explicit supply assurance. If two customers are pooled together in a single allocation group, the supplier may not always be able to guarantee that orders from both customers can always be filled. The supplier could decide to continue giving explicit supply assurance, recognizing that under constrained supply there is a chance of missing an order. Alternatively, the supplier could refuse to give direct assurance of supply, though this could alienate the customer base already reliant on the ordering process. Other options would require working with customers to come to an agreement about supply assurance guarantees and what is expected when supply is constrained. Though the specific strategy will depend on the organization, it is clear that making such changes must take into account the impact to the customer.

6.2. Labor

6.2.1. Geographic Differences

The headcount analysis in Chapter 5 was an initial step in better understanding how the allocations process drives labor costs. It became clear that each geographic region must localize their strategy for managing allocations, as each market will have different requirements and customers with different expectations. In addition, complexity factors will impact the allocation strategy for a region differently, since each market will have different characteristics and require a labor strategy tailored to the market in order to be effective. These geographic differences become important factors in devising a local or global allocations strategy, as well as understanding how to compare performance between different sales organizations. Future studies as discussed in Chapter 7 can continue to research how the allocations process can impact labor, and create a method to determine a labor strategy for different allocations processes.

6.2.2. Tacit Knowledge

Significant portions of the allocations process at Intel relies on the expertise and judgment of supply analysts. Under heavy supply constraints, an organization may become overwhelmed by the allocation decisions that need to be made. In addition, tacit knowledge is difficult to codify, making it harder to create standard process to replicate across a business unit, as well as share with other portions of a firm to replicate best practices. Simpler allocation policies rely less on tacit knowledge, but for firms as large as Intel the process becomes complex very quickly. There is potential to study decision support tools to help supply analysts make better decisions as discussed in Chapter 7, and help create standard process in an attempt to create a global allocations strategy (see Section 6.3.5).

6.3. Allocations Strategy

6.3.1. Cost vs. Service Tradeoffs

The allocations process fills a need for managing supply constraints that for some customers is a prerequisite for doing business with Intel. Given that the semiconductor market moves rapidly, some Intel customers have come to rely on the supply assurance that allocations provides in order for them to stay competitive and keep their products up to date. At the same time, we have deduced that due to the gradual increase in allocation groups under management, inventory and labor costs have increased in order to provide this service. This natural tension between cost and service is at the center of any efforts of optimizing an allocations process. Care must be taken to determine the most important service characteristics of a particular customer base, and then a tailored allocations process can be put in place to support it. In addition, geographic differences in customer expectations must be considered before attempting to alter allocations processes across entire product lines.

6.3.2. Flexibility

Allocations processes tend to reduce supply flexibility due to the commitment of supply to a particular customer or group of customers. We noted that over time, allocation buckets tend to proliferate as new product lines are introduced and as new customers begin purchasing from Intel.

This results in fewer opportunities to remix the supply base during each planning window, since an allocation for each group reserves a portion of the supply base for that customer. Conversely, in Section 4.2.5 we discussed the potential for improved supply flexibility through the use of fewer customer allocation groups, to take advantage of pooling. The potential to improve supply flexibility is therefore a key decision factor for a manufacturer designing an allocations process.

In addition, it was found that allocations processes were typically not flexible enough to handle specialized process deviations for particular customers or SKUs. This was noted in business units that chose to run their entire product line either on or off allocations, when in reality some products could have benefitted from a process could be flexibly switch between the two. The result of this inflexibility is that large divisions of an organization may run order fulfillment process either with or without allocations, when a more optimal configuration is to run certain constrained products on allocations to ration supply while the rest can run off allocations with a simpler, quicker process. This highlights an area for future improvements, in that a more flexible allocations process could reduce the total amount of inventory carried, the total amount of labor required, and the average response time to an order.

6.3.3. Managing Complexity

A key factor in managing a cost effective allocations process is in determining the appropriate amount of complexity to adequately meet customer needs. A number of factors tend to increase the complexity of managing allocations, which in turn can negatively affect key performance metrics. For example, the total number of SKUs and number of customers being served increase the number of allocation buckets that require sizing each week, potentially increasing the time needed to respond to orders. Over time, the overall number of allocation buckets tends to increase, resulting in a fragmented and less flexible supply base as well as the need for additional labor to help make allocation decisions. Allocations processes are further complicated by differences in the process between business units and geographies in a large company, since the process is tailored to the unique customers being served by each division.

Any organization attempting to create or manage an allocations process needs to understand the impact it will have on the complexity of order fulfillment. An effective allocations process requires skilled analysts, a reliable IT system, and well-defined processes. In addition to these resources, the response time to incoming orders will typically need to be longer, so service may be enhanced by giving customers supply assurance it can also be considered less attractive to some customers who prefer a very quick turnaround for their orders.

6.3.4. Demand Distortions

Forecast accuracy is a concern for any supplier using a build-to-stock strategy, but when using allocations a supplier may have to accept lower forecast accuracy in order to provide supply assurance during constraints. When customers are not penalized for changing order sizes at the last minute, they are incentivized to inflate forecasts to 'reserve' allocations to ensure they have adequate supply, and then adjust the order to true demand quantities when an order has to be confirmed. This results in the supplier taking on some added costs to prepare and store additional supply (See Section 6.1.1.1). In addition to additional demand volatility, there is also the potential for introducing the bullwhip effect, since the supplier may be insulated from true demand and overcompensates for inflated orders, which can ripple up the supply chain.

However, an organization may determine that such added costs are worth the cost due to the ability to garner larger or long-term contracts with customers who would not do business without assurance during supply constraints. Krishnan et al. suggest a few potential methods to dealing with this situation, including instituting Collaborative Planning, Forecast, and Replenishment (CPFR) techniques, using options-based contracts, or by altering the supplier's allocation policy to more systematically pool customers together to offset demand volatility (Krishnan, Kleindorfer, & Heching, 2007).

6.3.5. Centralized vs. Localized Allocation Strategies

The balance of local flexibility with global optimization is a common tradeoff in supply chain management, and it is another key decision area in the development of an allocations strategy. At Intel, allocations strategies are largely tailored to individual business units and geographical regions. Since the particular aspects of a business unit's products will influence customer expectations, and the geographic market in which a product is sold will also yield different business expectations (see Section 6.4.1), it makes sense that localized allocations strategies were developed and managed independently. However, in many cases there is still a need for a competent global allocations strategy that ensures the firm does not run into issues with excess inventory or labor, and allows dissemination of best practices across divisions, such as new tools or methods of judging demand. The creation of more flexible allocations processes could help large organizations run standard processes that can adapt to different situations, and becomes a focal point for potential future studies surrounding allocations as discussed in Chapter 7.

6.3.6. Running Leaner

Inventory savings can also be considered beneficial because they enable a supplier to successfully meet customer demand with fewer physical products. Recall in Section 6.1.1.2 that we discussed the importance of considering flexibility when designing and modifying an allocations process. For firms with products that are severely constrained, being able to operate with less inventory on hand implies that a larger percentage of customer orders could be shipped, as opposed to being carried at the supplier due to supply/demand mismatches. Instead of looking purely at costs savings in reducing inventory, a stronger value proposition may result from meeting customer demand with fewer total units of product.

As a result, strategically increasing the amount of pooling could help ease inventory requirements during times of supply constraints. A firm that can dynamically alter the amount of pooling they use based upon market conditions, customer demand, and supply availability could be in a position to more optimally match supply to demand. We discuss future studies in Chapter 7 that could help achieve more flexible order fulfillment process to operate with leaner inventory levels, including studying allocations criteria to determine when to shift allocation policies and developing new tools to help supply analysts make more informed allocation decisions.

7. Future Work

Several opportunities exist to further explore the topics of allocations and its impact on the supply chain. Some of them directly follow the analysis presented here, while others are potentially interesting tangents within the realm of optimizing allocations processes.

7.1. Pilot Studies

Pilot studies are a natural extension of the modeled predictions of this study. This requires determining the required steps to modify the allocation process, potentially requiring database and tool modifications, and then allowing live customer orders to be filled using the simplified process. Pilots would confirm the inventory savings on live orders, and test the revised ordering process to see if it can be managed with fewer allocation buckets.

Selecting the appropriate Business Unit, Customer Groups, and SKUs to run the pilot with would be a first key milestone. High profile customers and product lines will not be good first choices until the modified ordering process has proven to work. Instead, lower demand products, or those with predictable demand may make a better initial pilot study. Higher volume customers or more volatile SKUs can be gradually added and tested after initial pilots are successful and the process is hardened. Second, mapping and altering the order fulfillment process to manage allocations with fewer customer groups will be necessary. Supply Analysts will be key participants who execute and help shape the new process. Third, tools modification will be necessary to both run the process and help to better track the impact that allocations has on inventory. In particular, database modifications that allow traceability from a shipment to an allocation would allow much deeper analysis on the inventory effects of allocations. The methods used in the analysis provide an approximation to this link since none currently exists, and if changes are already being made to tools it is suggested that these additions also be made.

7.2. Allocations Criteria

Current allocations processes are rigid in that an entire customer base must typically be either on or off allocations. This inflexibility contributes to the numerous inventory and labor problems addressed in this study. Additional study can be done to research flexible allocation methods that enable a manufacturer to identify and select specific products and customers to be 'on-allocations' or 'off-allocations'. A significant portion of this would be to deeply understand the current process and the modifications needed to tools to determine if the costs of changes are worth any potential benefits.

Another important component of a flexible allocations process is determining a robust procedure for when a specific product SKU or family should be put on or taken off allocations. This could involve a number of general factors as well as some that are specific to a particular industry or company. But the intent is to better understand the signals that indicate when a product should transition to one process or the other. Some examples of potential allocations criteria include:

- New Product Introductions – New products are typically constrained due to manufacturing delays in building up supply and high demand. New products are typically constrained and could be candidates for allocations.
- Supply Constraints – Supply side production issues or market driven demand spikes can both cause spurious periods of constrained or unconstrained supply.
- Product Transitions – Products follow roadmaps in which certain products families are phased out in favor of new products. These planned product lifecycles will typically have a predictable effect on supply constraints.

Investigation into these and other allocation triggers could help analysts make better decisions on how to manage specific product families. Simulations or pilots could be run to test any hypothetical allocations criteria, and eventually a new process could be established that can flexible move product between on-allocation and off-allocation states.

7.3. Labor Study

The labor analysis performed in this study help gain some initial insights into labor strategies of managing allocations. A more complete study could give more detailed quantitative results, and could also investigate alternate organization designs and roles to manage allocations. Data for labor ought to be collected in a more standardized way, and this formal survey would form the basis of data collection to more accurately determine the labor implications of allocations. Key areas of interest would include:

- Role Definitions – Though analysts across geographies share role titles, their actual jobs may differ greatly. A more in depth breakdown of the various roles necessary to manage allocations, and how they map to one another across different divisions would help refine the total headcount numbers used in this study.

- Factors Affecting Labor – Given that a significant portion of the allocations process is driven by tacit knowledge of the workforce, it would be interesting to study how process automation can reduce the need for analysts to manage portions of the allocations process.
- Geographic Specific Labor Strategies – It is clear that each geography has unique customers with unique needs. Specialized allocation strategies tailored to the business needs of each geography could be investigated and help reduce labor expenses and improve customer satisfaction.

7.4. Tools Development

The toolset used in allocations management at Intel is comprehensive, yet a significant portion of the process still requires manual decision making by supply analysts. New tools could be investigated, designed, and deployed to help streamline the process.

7.4.1. Optimal Allocation Schemes

We reviewed a number of high-level classes of allocation strategies in Chapter 2. It would be interesting to research an optimal algorithm for determining allocation bucket sizes. Currently, the process is heavily reliant on the judgments of human analysts, but there is potential to both codify this knowledge and further refine it for improved inventory performance. Simulations could be performed using historical demand data to determine inventory levels if different bucket sizes were used. Using these simulations, optimal allocation strategies could be derived for specific groups of customers, SKUs, time periods in the product lifecycle, or one of many other characteristics. Such an initiative could help minimize excess inventory, streamline processes to require less labor and tacit knowledge, and standardize an allocations methodology that could be adopted across a large organization.

7.4.2. Visualization Tools

Many analysts primarily use the data provided to them in spreadsheet or tabular forms. There is a need for improved visualization tools to help analysts quickly interpret the overall allocations situation, make decisions during the weekly planning process, and understand the implications of such decisions as supply is moved around the customer base. For instance, in a constrained supply situation, an analyst could have a tool that visualizes the total amount of supply being requested by all customers, and historical volatility estimates. Such a tool would make the fragmentation of supply much more visible, and help determined how to redistribute supply across the customer base. Furthermore, the toolset could build in simulation capabilities to visualize the impact of making changes in the current ordering period. The intent with tools development is to help ease some of the burden of analysts, who are currently required to make many of these decisions on their best judgment. A stronger set of tools will not only result in better decisions being made, but help make the process more standardized across a large enterprise.

8. Bibliography

1. Adelman, D., & Mersereau, A. J. (2010). *Dynamic Capacity Allocation to Customers Who Remember Past Service.*
2. Cachon, G. P., & Lariviere, M. A. (1999). *Capacity Choice and Allocation: Strategic Behavior and Supply Chain Performance.* Duke University, The Fuqua School of Business, Durham.
3. Cachon, G. P., & Lariviere, M. (1999, May). Capacity Allocation Using Past Sales: When to Turn-and-Earn. *Management Science , 45* (5), pp. 685-703.
4. Chow, J. (2004). *Analysis of New Approaches to Improve the Customer Responsiveness of Intel's Microprocessor Supply Chain* . Massachusetts Institute of Technology. MIT.
5. Fine, C. H. (1996). *Industry Clockspeed and Competency Chain Design: An Introductory Essay.* Sloan School of Management, The InternationalCenterforResearchon the Management of Technology . Massachusetts Institute ofTechnology.
6. Gartner. (2011). *Key Issues for Semiconductor and Electronics Manufacturing, 2011* . Stamford, CT: Gartner.
7. Gartner. (2011, 6 1). *The Gartner Supply Chain Top 25 for 2011.* Retrieved from http://www.gartner.com/resources/213700/213740/the_gartner_supply_chain_top_213740.pdf
8. Gonçalves, P. (2003). *Why Do Shortages Inflate To Huge Bubbles?* Sloan School of Management, Operations Management / System Dynamics Group, Cambridge, MA.
9. Grimes, D. (2012). *Semiconductor & Circuit Manufacturing in the US* . IBISWorld. IBISWorld.
10. Intel Corporation. (2011). *Annual Report.* Santa Clara.
11. Intel Corporation. (2012). *General Company Information.* Retrieved 03 02, 2012, from Intel.com: http://www.intel.com/intel/company/corp1.htm
12. Kilger, C., & Meyr, H. (2008). Demand Fulfillment and ATP. In H. Stadtler, & C. Kilger, *Supply Chain Management and Advanced Planning* (pp. 181-198). Berlin, Germany: Springer.
13. Kilger, C., & Wagner, M. (2008). Demand Planning. In H. Stadtler, & C. Kilger, *Supply chain management and advanced planning : concepts, models, software, and case studies* (pp. 133-160). Berlin: Springer.
14. Krishnan, J., Kleindorfer, P., & Heching, A. (2007). *Demand Distortions and Capacity Allocation Policies.* INSEAD-Wharton, Alliance Center for Global Research and Development. INSEAD.
15. Meyr, H. (2009). Customer segmentation, allocation planning and order promising in make-to-stock production. *OR Spectrum , 31*, pp. 229-256.
16. New York Times. (2011, 12 13). *Intel Corporation.* Retrieved 1 8, 2012, from http://topics.nytimes.com/top/news/business/companies/intel_corporation/index.html
17. Ng, T., Sun, Y., & Fowler, J. (2010). Semiconductor Lot Allocation Using Robust Optimization. *European Journal of Operational Research* , 557-570.
18. Quante, R., Meyr, H., & Fleischmann, M. (2009). Revenue management and demand fulfillment: matching applications, models, and software. *OR Spectrum , 31*, pp. 31-62.
19. Silver, E. A., Pyke, D. F., & Petersen, R. (1998). *Inventory Management and Production Planning.* New York: John Wiley & Sons.
20. Simchi-Levi, D., Kaminsky, P., & Simchi-Levi, E. (2008). *Designing and Managing the Supply Chain.* New York: Mcgraw-Hill/Irwin.

21. Sun, Y., Feller, A., Shunk, D., Fowler, J., Callarman, T., & Duarte, B. (2007). Decision Paradigms in the Semiconductor Supply Chain: A Survey and Analysis. *Proceedings of the 3rd Annual IEEE Conference on Automation Science and Engineering*. Scottsdale, AZ.
22. Sun, Y., Fowler, J. W., & Shunk, D. L. (2007). *Policies for Allocating Product Lots to Customer Orders in Semiconductor Manufacturing Supply Chains.* Arizona State University , Department of Industrial Engineering, Tempe.
23. Talluri, K. T., & Van Ryzin, G. (2005). *The Theory and Practice of Revenue Management.* Springer.