ITEM-LEVEL INFORMATION VISIBILITY: AN APPLICATION OF RFID

By

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To my wife Peiqing and my son Ruoyang.

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Being able to reveal product information at the item-level in a way that is fully automatic, instantaneous, and touchless, radio frequency identification (RFID) is emerging as the hottest information tracing technology in supply chain management. While industry practitioners and academic literature argue that RFID brings value by reducing labor cost, increasing sales, decreasing inventory cost, accelerating physical flow, and improves quality control, they are mostly based on case studies, acknowledging the fact that everything works out well because information visibility eliminates uncertainty. This dissertation investigates the beneficial properties and business applications of item-level information visibility in three different perspective from extant literature review: (1) value of item-level information, (2) knowledge based item-level Manufacturing and (3) item-level information sharing in oligopoly. In the first part, we model the benefits of item-level visibility as the result of reduced randomness, and as a function of the scale of the information system, the distribution of the sample space(s), the control variables and the production functions. This static model is extended for multiple period, which is simulated to verify the generality and robustness of the model. In the second part, we introduce an innovative concept of item-level manufacturing that is backed up by a knowledge-based adaptive learning system. We quantify the potential benefit of such manufacturing scheme. In the third part, we consider a homogeneous product market and the incentive for oligopolists to reveal item-level product information with their customers, by modeling

it as a two-stage game. With a constant clearance discount rate, we derive pure strategy equilibria that are subgame perfect and demonstrate that complete information sharing is the unique Nash equilibrium of the game when the common demand is volatile and that no information revelation is the unique Nash equilibria when demand is not volatile. We show that the Nash equilibria is the same with a decreasing clearance discount rate and that neither complete information revelation nor zero information revelation is consistent with an equilibrium with an increasing discount rate. Results are similar in a duopoly non-homogeneous product market scenario.

CHAPTER 1
RFID AND ITEM-LEVEL INFORMATION VISIBILITY

1.1. Introduction

Being able to reveal product information at item-level in a way that is fully automatic, instantaneous, and touchless, radio frequency identification (RFID) is emerging as the hottest information tracing technology in supply chain management. It is a tracking system that uses tags (silicon chips implanted in a product or its packaging) to transmit information to a wireless receiver. It could be used to track any physical entity from candy bars to big screen TVs. The tag contains relevant item-level product information (Raza, Bradshaw, and Hague 1999; Shepard 2005). Unlike bar code that provides categorical-level information, RFID technology allows for distinguishing individual product by assigning to each of them a unique code, called electronic product code, that are embedded in RFID tags. Unlike bar codes, which need to be seen to be scanned, RFID tags do not require direct line-of-sight for data transmission purposes, making it possible to automatically read a large number of tags simultaneously.

In this chapter we will go through the technical background of RFID and some of its competing technologies in the area of automatic identification. We will discuss the business applications and benefits of these contemporary technologies and introduce some recent debates regarding RFID. We will finalize this chapter by raising the research question, followed by a comprehensive literature review.

1.1.1 Overview of Radio Frequency Identification

Radio frequency identification is a subset of a diverse family of different information tracing technologies, which is called AIDC (Automatic Identification and Data Capture). AIDC technologies share the common purpose of identifying, tracking, recording, storing and communicating essential business, personal, or product data. The process of information tracing includes methods for automatically identifying objects, collecting data about them, and entering that data directly into computer systems (i.e. without

human involvement). AIDC technologies include a broad range of solutions, including bar code, Radio Frequency Identification (RFID), biometrics, magnetic stripes, Optical Character Recognition (OCR), Optical Mark Recognition (OMR), smart cards, voice recognition, Radio Frequency Data Com (RFDC), Magnetic Ink Character Recognition (MICR), direct part marking, Electronic Article Surveillance (EAS), Machine Vision and Real-Time Locating Systems (RTLS), each with different data capacities, form factors, capabilities and "best practice" uses. AIDC is also commonly referred to as "Automatic Identification, "Auto-ID, and "Automatic Data Capture." Most AIDC technologies are classified and standardized by international and national technical standards.

A stream of AIDC technologies that includes bar code, RFID, magnetic stripes, smart cards and biometrics involves a process of recognizing objects, receiving information about the objects and transmitting the data into computer systems without any human involvement. Another stream of AIDC technologies that includes OCR, OMR, voice recognition and Machine Vision involves a process of obtaining external data, particularly through analysis of images, sounds or videos.

In order to better understand RFID and its value, which is the major issue in this thesis, we will briefly review some of the relevant AIDC technologies, their characteristics and their applications in the next section.

1.1.1.1 Review of AIDC technologies

1. Bar Code

Bar codes have promoted accurate data capture, rapid movement of goods, and many types of automation since their invention in the 1940s and have been widely used in retail stores, hospitals, and different manufacturing environments.

Bar codes provide a simple yet inexpensive method of encrypting text information, allowing data to be collected rapidly and with extreme accuracy. A bar code consists of a series of parallel, adjacent bars and spaces. Symbologies, which are predefined bar and space patterns, are used to encode small strings of character data into a printed symbol

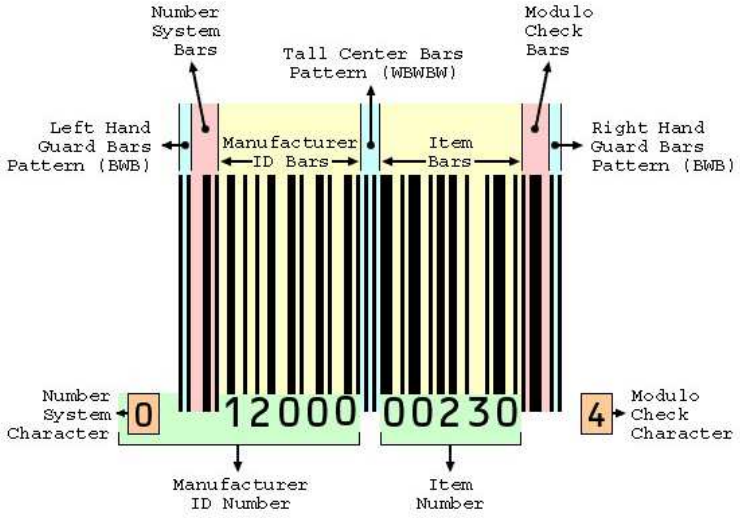

Figure 1-1. Basic bar code structure.

that can be thought of as a printed type of the Morse code with narrow bars representing dots, and wide bars representing dashes. There are many different bar code symbologies, or languages. Each symbology has its own rules for encoding characters, printing, decoding requirements, and error checking. International standards cover the common use of bar code, print quality measurements and equipment.

The basic structure of a bar code (Figure 1-1) consists of a leading and trailing quiet zone, a start pattern, one or more data characters, optionally one or two check characters and a stop pattern, which usually contains hierarchical information such as a manufacturer ID number and an item number.

2. Smart Cards

Smart card is a plastic card embedded with a computer chip that stores and transacts data that is associated with either value or information or both between users and is stored and processed within the card's chip that can hold either a memory or microprocessor, or both. The card data is read and processed via a reader that is linked to a computing system and can be either contact or contact-less.

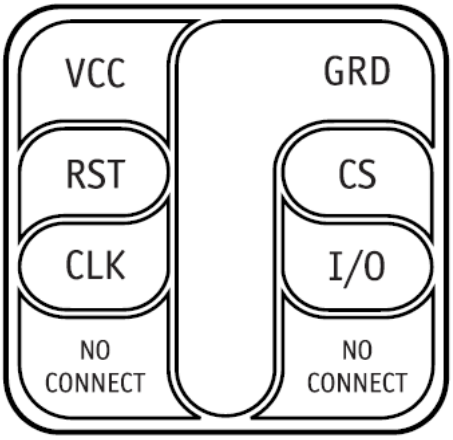

Figure 1-2. Typical module of microprocessor based contact smart card.

Figure 1-2 shows a typical module of a microprocessor based smart card that consists of a microprocessor, memory, and interfaces. The purpose of having a microprocessor on the smart card is for security reasons. The host computer and card reader actually "talk" to the microprocessor. Smart cards may have up to 8k of RAM, 346k of ROM, 256k of programmable ROM, and a 16bit microprocessor, according to international standards. [1]

3. Real Time Locating System RTLS

Using today's wireless technology, Real Time Locating Systems technology provides real-time visibility into exact locations of containers and cargo, thus providing critical visibility into supply chain activities. RTLS are fully automated systems that continually monitor the locations of assets or personnel. An RTLS solution typically utilizes battery-operated radio tags (active RFID) and a cellular locating system to detect the presence and location of the tags. [2]

The systems continually update the database with current tag locations as frequently as every several seconds or as infrequently as every few hours for items that seldom move.

[1] http://www.howstuffworks.com

[2] Startup launches low-cost trcking system, RFID Journal, http://www.rfidjournal.com, Aug. 9, 2005

The frequency of tag location updates may have implications for the number of tags that can be deployed and the battery life of the tag. In typical applications, systems can track thousands of tags simultaneously and the average tag battery life can be five or more years.

4. Radio Frequency Data Communication RFDC

Radio Frequency Data Communications (RFDC) provides wireless, real-time and duplex communications between AIDC devices and a host computer, using modern wireless communication technologies such as IEEE 802.11. RFDC is more and more used to link portable and mobile equipment to a remote wireless host, with two communication options: narrow band and spread spectrum with narrow band providing longer reception range and spread spectrum providing higher speed. The five frequently cited benefits to using Radio Frequency Data Communication are 1. increased database accuracy at all times; 2. reduced paperwork; 3. real-time operations; 4. higher productivity; 5. and shorter order response times.[3]

1.1.1.2 Tags, receiver, & information systems for RFID

RFID is a proven technology that has been in use since the 1970s in the area of automatic identification. In its simplest form, RFID is conceptually similar to bar code, yet being seen as a mean of enhancing data processes in terms of non-optical proximity communication, information density, and duplex communication ability. Operational RFID systems involve tags and readers, with tags that is usually marked on individual items containing transponders that emit messages readable by specialized RFID readers. A typical RFID system, Figure 1-3, consists of three major components: RFID tag, RFID reader with an antenna and transceiver, and a host system or connection to an information system.

[3] The mobile Internet is here, http://www.intel.com, white paper from Intel published on Nov.21, 2007.

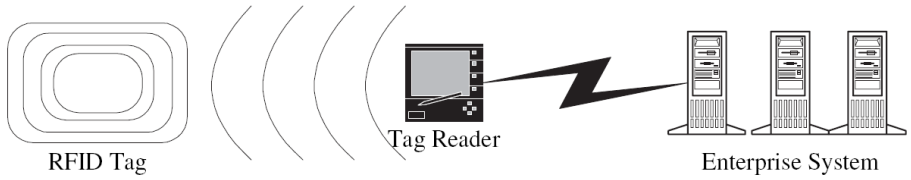

Figure 1-3. An RFID system.

RFID Tag

RFID tags fall into two broad varieties: those with a power supply (active tag) and those without (passive tag). Terminology-wise, a passive device is known as a "tag" while an active device is known as an "active tag" or "transponder"[4] . Being able to read and write comparing to passive tags' being read only, active tags are larger and more expensive than passive tags. Without internal power supply, passive RFID tags respond to the incoming radio frequency signal by the small electrical current induced in the antenna for the CMOS (Complementary Metal-Oxide Semiconductor) integrated circuit in the tag to power up, Figure 1-4. Passive tags have certain readable distances that ranges from about 10cm up to a few meters[5] and the corresponding information includes not only the ID numbers but stored data on the tag chips in writable EEPROM (Electrically Erasable Programmable Read-Only Memory).

There are also semi-passive tags where the battery powers the microchip but the device communicates by drawing power from the reader. Figure 1-5 shows the five classes of RFID tags. There is also a wide variety of shapes, sizes and protective housings for RFID tags. Some tags are wrapped in credit card sized packages and some can be injected beneath the animal skin. The smallest devices commercially available measure $0.4mm \times 0.4mm$ and are thinner than a sheet of paper, while the per chip cost can be as low as 1c currently.

[4] "TRANSPONDER" being the mixture of "TRANS"mitter and res"Ponder"

[5] Refer to ISO14443, ISO18000-6, and standard for electronic product code (EPC)

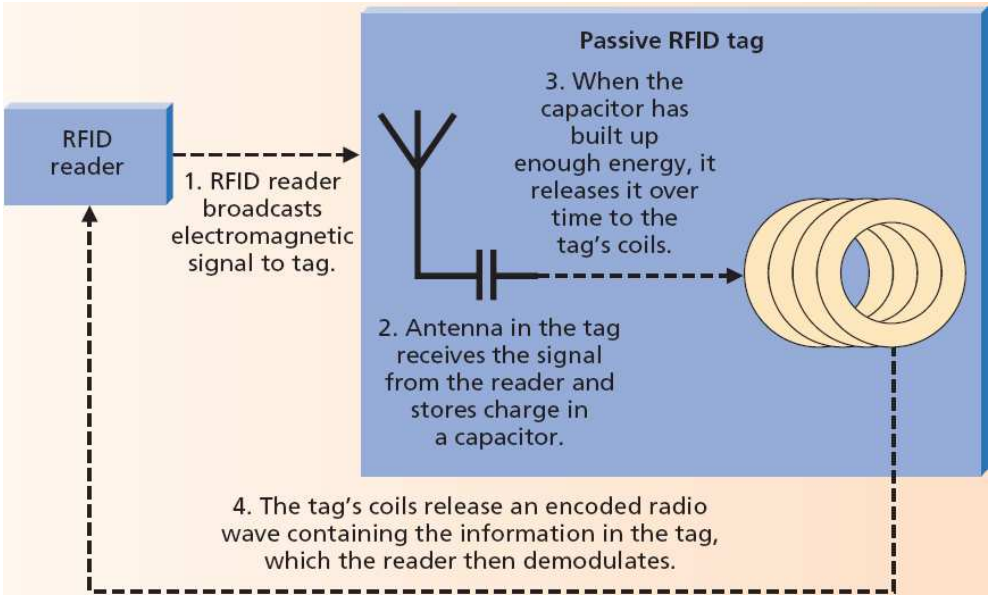

Figure 1-4. Simplified view of data transfer in low-frequency passive RFID tags.

RFID Receiver & Information System

Electro-magnetic response (data) from RFID tags are received by an RFID receiver, which usually contains a transmitting module, a control unit and an antenna. The receiver converts and transmits the data to a back-end information system for data analysis that includes collision control, data store, analysis and retrieval. A critical issue for the success of an RFID application is its computational data model and the query tools, which means that the RFID data read from a dynamic environment need to be coherent throughout the process of data collecting, cleaning, consistency checking, and persistency managing. Furthermore, RFID data warehousing is very different from the traditional data warehousing, Wang and Liu (2005).

Chawathe, Krishnamurthy, Ramachandran, and Sarma (2004), figure 1-6, suggested a layered architechture for managing RFID data. The lowest layer consists of RFID tags (located on objects such as cases and pallets). The next layer consists of tag readers. The interface between these two layers is the so-called RFID Air Interface and the RFID protocols for this interface specify the low-level details such as anti-collision techniques (similar to those used by other networking technologies). The third layer of the

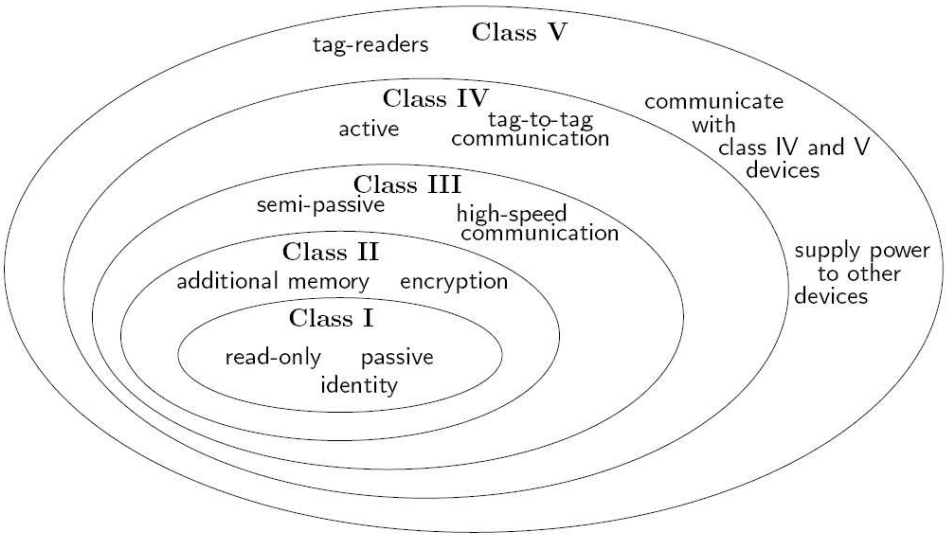

Figure 1-5. The RFID classes.

architecture is responsible for mapping the low-level data stream from readers to a more manageable form that is suitable for application-level interactions.

1.1.2 Business Applications

In the history of information tracing technologies in a commercial environment, OCR was initially selected as standards in some industries in 1970s. Bar code technology steadily grew to become more popular since then due to OCR's problematic high substitution error rate (SER) for it to be used in major industries. Compared to OCR, bar code technology has substantial advantages by having low printing cost and low error rate. The density of a bar code can be very high too, with the innovation of 2D symbologies and high density linear symbologies. Because of this reason, bar code is now the most popular technology in most of the industries for automating data input.

A smart card is a small card containing electronic circuits and memory chips that is able to store and encrypt information. Smart card-enhanced systems are in use today throughout several key applications, including health care, banking, entertainment and transportation. To various degrees, all applications can benefit from the added features and security that smart cards provide. It can also be made contact-less. One of the

constraints of smart card's business application is its cost which is relatively high, making it unusable in large scale.

Radio frequency identification (RFID) is a relatively old AIDC technology which was first commercially developed in 1940s. RFID has found its importance in a wide range of markets ranging from livestock identification to Automated Vehicle Identification (AVI) systems, because of its capability to track moving objects. RFID are effective in manufacturing environments where bar code labels could not survive. The many RFID business application includes: asset tracking, manufacturing, supply chain management, retailing, payment systems, security and access control. There are many other creative uses of RFID while more and more new RFID applications come into sight every year.

RTLS, being an application of RFID, is a system of finding the position of assets, using active RFID tages. Its major business application is in asset tracking with an expected global revenue exceeding US$1.6 billion by 2010 (RFIDupdate 2005). RFDC, providing similar functionalities as RFID, is normally used to speed data acquisition in receiving, pick/putaway, inventory, shipping (verification), sales area management, portable point-of-sale, and quality control. Despite the fully ranged functionalities of RFDC, it's impossible to maintain an RFDC system in a large scale because of its high cost.

1.1.3 Recent Debates

Despite its growing popularity and its technology advantage over the competing auto-id technologies, RFID has attracted some debates regarding to the issue of dada privacy, scalability, and innovative applications.

RFID Data Privacy Issue. The impending ubiquity of RFID tags poses a potentially widespread threat to consumer privacy. For an example, an RFID tag will broadcast its ID serial number (in other words, its EPC) to any nearby reader, which presents a clear potential for privacy violations. Who wants the medications and other contents of a purse to be scannable? Who wants his or her location to be tracked and

recorded based on the uique ID number in shoes or other clothing? Therefore, protecting privacy is ever becoming an objective and is getting much difficult when the RFID technology is becoming widely adopted. If an application can only read the RFID tags and the object that it owns, the privacy issues might be simplified. However, many applications do not in this category. So it's been debated that the legislation issues, the data privacy issues must be resolved before this technology can be widely applied in the business world.

Scalability Issues. Large-scale RFID data will exist everywhere. There may be noises and many duplicates read by the readers that continuously read RFID tags in their ranges. Data are collected in a large volumes such that in a containers or in pallets during the transportation. Also all RFID data are temporal and spatial. The tracing of their individual paths would become a problem when the number of tags becomes large. Therefore, the scalability issue has also been debated that the back end information system performance improvement should follow the pace of the increasing scale of the RFID system.

New Applications of RFID. Once the cost of RFID tags is pushed down to its low prices as a couple of cents per tag, almost every human-made product or any item that moves can be tagged. Explosive number of applications would be identified. From airplanes maintenance, Supermarket shopping activities, to the cyber fridge that records milk or the frozen food package to communicate the appropriate cooking instructions to microwave oven. Even PDA can have built-in readers for personal interactions when visiting the places of museums, hospitals, airports, and tourist attractions. It's been debated that weather an RFID tagged world is emerging, and if so, how fast.

1.2. Research Question

Knowing the fact that RFID is becoming more and more popular, we are naturally come to the question that to what extent will RFID benefit our life and what's the value of having RFID. The answer to this question can help business practitioners make sound

decisions when adopting an RFID system. The first step to answer this question is to know the qualitative benefits of RFID. We will further be able to quantify those benefits in various decision making models.

It's critical for companies to know the instantaneous status of items in a supply chain, processes items have gone through, and the history of movement of items during transactions. An item's instantaneous status includes its unique identity, precise location, physical status, and special key features. An effective and efficient information tracing system enables a company to rapidly intervene in targeted situations, consequently reducing operational cost and increasing productivity. Sahin, Dallery and Gershwin, (2002) gives a list of potential benefits of RFID technology on supply chain processes, which include: 1. reduction in labor costs; 2. increase in store selling area; 3. acceleration of physical flows; 4. reduction in profit losses; 5. more efficient control of the supply chain due to increased information accuracy; 6. better knowledge of customer behavior; 7. better knowledge of out-of-stock situations; 8. reduction of delivery disputes; 9. better management of perishable items; 10. better management of returns; 11. better tracking of quality problems; 12. better management of human consumed product recalls and customer safety; 13. improved total quality control.

The essence behind the passion of RFID in supply chain management is its capability to provide information visibility. Many of the benefits or potential benefits of using RFID can be explained by increased certainty (reduced uncertainty), directly resulting from information visibility. This increased certainty improves supply chain coordination, reduces inventory, increases product availability, improves total quality, provides better management of perishable item and returns, and so on. In this chapter, we use the factor of certainty as one of the key role to model the value of RFID information visibility.

A majority of literature on RFID discuss the value of RFID by using case study analysis (Dutta, Lee and Whang 2007; Delen, Hardgrave and Sharda 2007; Doeer, Gates and Mutty 2006; Karkkainen 2007; Lee, Peleg, Rajwat, Sarma and Subirana 2005).

However, there is paucity of model that analyze benefits using RFID. Among those questions, some are especially critical, such as 1. the statistical benefit of using RFID; 2. cost benefit analysis; 3. performance of a partially tagged system. While existing literature addressing some of these problems are more on a case by case basis, our aim is to try to fill the gap by modeling the potential benefit in general using descriptive statistics.

1.3. Literature Review

Although RFID shows numerous advantages compared to bar code (Raza, Bradshaw, and Hague 1999; Shepard 2005), the various benefits of RFID in supply chain management hasn't been very clear since it's invention during WWII. Most of the existing related literature are primarily case study Ngai, Cheng, Lai, Chai, Choi and Sin (2007) or simulations on a case-by-case basis, mostly in the fields of inventory management and replenishment, supply chain operations, and retailing.

1.3.1 Some General Discussions

Economist (2003) in its "The Best Thing since the Bar Code" states that smart tags will soon be made in their trillions and will replace the bar-code on the packaging of almost everything that consumer-goods giants such as Procter Gamble and Unilever make. They also state that smart tags can shrink inventories by 5-25% and that companies will start deploying smart tags in earnest in 2004, beginning with pricey, oft-stolen goods such as razors, cosmetics and pharmaceutical. In general, Dutta,Lee and Whang (2007) examines three dimensions of the value proposition of RFID and attempts to identify areas for further investigation. The first dimension consists of the generic architecture of RFID implementations and the drivers of value that can result from its components. The second consists of measurement issues associated with quantification of value. Since the complete benefits of RFID will only result when multiple independent organizations deploy the technology and coordinate the resulting information flows, the third dimension addresses incentives for achieving that diffusion.

Hardgrave and Miller(2006) state that the increased interest in RFID have spawned many articles and much speculation about its use, but much of what has been written and speculated is misleading or simply not true. They examine 10 common myths of RFID, including 1. Is RFID technology is mature and stable; 2. whether RFID can be used to continuously track people/objects wherever they go anywhere; 3. whether people can drive down the street and read RFID tags inside your home, thus knowing everything about you and your stuff; 4. whether RFID tags contain information about anything and everything, including sensitive personal information; 5. whether RFID is generating millions of terabytes of data; 6. whether you must have 100% reads at 100% of the read points for RFID to be useful; 7. whether major retailers have mandated that all suppliers tag all products for all stores; 8. whether RFID is costing the average Wal-Mart vendor $23 million annually; 9. whether RFID is the panacea for creating the perfect supply chain; 10. whether RFID is replacing the barcode.

Jogleker and Rosenthal (2005) examine the rationale behind the "crawl-before-run" (experimentation) strategy for RFID adoption and investigate the necessity to run experimentations. Lacy (2005) discusses Wal-Mart's pioneering adoption of RFID and the fact of other retailers' hesitation in RFID. O'Connor (2005) shows improved process efficiency as the biggest factor influencing the decision to deploy the RFID technology. Sahin, Dallery, and Gershwin (2002) provide a framework for identifying principles and functionalities of a traceability system in the context of a global supply chain. Using assessment criteria obtained by this analysis, they evaluate the performance of bar code and RFID systems. They conclude by describing benefits that RFID technology can provide to supply chain processes, which are measured as reduction in costs and improvement in the customer service level.

1.3.2 Area Targeted Discussions

1.3.2.1 Quality control

Ferrer and Ketzenberg (2004) develop four decision-making models to evaluate the impact of yield information and supplier lead time on manufacturing costs. They identify the operating conditions under which these capabilities are valuable, along with their relative impact on facility performance. Each model is formulated as an infinite horizon, stochastic dynamic program (Markov decision process). The results indicate that the yield information is generally quite valuable, while investments in supplier responsiveness provide trivial returns to products with few parts. However, as product complexity increases with large number of target parts, the value of short lead times increases.

1.3.2.2 Inventory management

Doer, Gates, and Mutty (2006) present an analysis of the costs and benefits of RFID technology for the management of ordnance inventory, using both qualitative and quantitative methods. Qualitative methods included a factorial structure for the non-cost related benefits of the implementation; quantitative methods include traditional ROI analysis to assess the value of implementing RFID. Dehorantius, Mersereau, and Schrage (2006) consider intelligent Inventory Management tools that account for record errors using a Bayesian inventory record. They further extend the paper to include practical replenishment and inventory audit policies, and illustrate how the needed parameters can be estimated using data from a large national retailer. Heese (2007) considers inventory record inaccuracy problem in a supply chain model by analyzing the impact of inventory record inaccuracy on optimal stocking decisions and profits. They find that inventory record inaccuracy exacerbates the inefficiencies resulting from double marginalization in decentralized supply chains and that such a supply chain benefits more from RFID technology.

1.3.2.3 Retailing

Alexander, Birkhofer, Gramling, Kleinberger, Leng, Moogimane, and Woods, (2002) use business case study of current leading practices for the adoption of the Auto-ID system to illustrate the impact of the Auto-ID system on specific pain points faced by companies in the consumer goods and retail value chain. Fleisch and Tellkamp (2005) examine the relationship between inventory inaccuracy and performance in a retail supply chain and show that an elimination of inventory inaccuracy can reduce supply chain costs as well as out-of-stock level. Karkkainen (2007) discusses the potential in utilizing RFID technology for increasing efficiency in the supply chain of short shelf life products.

1.3.2.4 Supply chain management

Dutta, Lee, and Whang (2007) examine three dimensions of the value proposition of RFID: generic architecture of RFID implementations and the drivers of value; measurement issues associated with quantification of value; incentives for achieving diffusion when multiple independent organizations deploy the technology and coordinate the resulting information flows. In McFarlane and Sheffi (2003), areas for short term deployment of Auto ID are identified and opportunities for longer term re-engineering of different sections of the supply chain are highlighted, using a simple categorization of supply chain operations.

Most existing literature in RFID tags mention / discuss them in detail. However, a comprehensive quantitative model of reduced uncertainty as a direct result of RFID information visibility is missing in extant literature. From an extensive survey of literature in this area, the lack of mention of this specific advantage leads to the natural conclusion that this either has not been attempted at the industry level or the literature has not caught up with recent industrial trends.

CHAPTER 2
VALUE OF ITEM-LEVEL INFORMATION VISIBILITY

In this chapter we quantify the benefit of item-level information visibility in a scenario where multiple factors determine an output. We first discuss two simple examples in the context and manufacturing and retailing respectively, followed by a general model. The results show that item-level information generates non-negative benefit, which agrees with Blackwell's Theorem (1951). We find the upper bound and other characteristics of the benefit function.

2.1. Two Examples

RFID has greatly increased the information visibility in a business stream line, from acquiring raw product, manufacturing, transportation, to retailing. Since the value of deploying RFID system hasn't been clear, let us consider the benefit of RFID information visibility, using a very simple example: the problem of manufacturing a motor engine.

Suppose that an engine builder needs to build an engine with a set of two engine bodies and a set of two engine tops. The two engine bodies have the same part number except that there's a little difference in the size of the hose that links the engine top. The two engine tops are of the same part number except the difference in the width of the connector to the body. A certain level of matching due to the size of the connectors on the engine body and top yields a certain length of usage life of the engine. Now let's assume that the hose size on the two engine bodies are $H_1 = 10$cm and $H_2 = 10.2$cm; the connector width on the two engine tops are $C_1 = 10.2$cm and $C_2 = 10.4$cm. We also know that the life of usage is $L(H_1, C_1) = L(H_2, C_2) = 10$ years, $L(H_1, C_2) = L(H_2, C_1) = 9$ years.

Without knowing detailed information of each component, the engine builder would have to randomly choose one component from each set, and the expected life of usage of the engine is $E[L] = E[E(H|C)] = 9.5$ years. If he knows the exact specs of all the

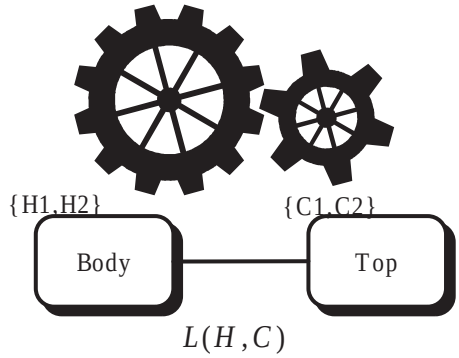

Figure 2-1. Building an engine from engine body and engine top, with different specs.

components, the life of usage of the engine is

$$L = \max\{L(H_1, C_1), L(H_2, C_2), L(H_1, C_2), L(H_2, C_1)\} = 10$$

years. If we further assume that the builder needs to build two engines, the total life of the two engines is 19 years without information visibility. The total life is 20 years with information visibility.

In this example we find that RFID can improve product quality from increased information visibility of major components. Now we will discuss another example in a retailing scenario. Suppose that a electronics store sells a new model mp3 player by placing a number of the players on its self-service shelf. We assume that the only one client in the store has 50% possibility of buying the mp3 player. The store restocks by placing 19 units of the mp3 players on the shelf every morning. The number of remaining units is uniformly distributed over the set $\{0, 1, 2, \cdots, 19\}$. If the shelf is empty, the client won't buy the mp3 player and the manager will restock the shelf if she knows it.

Without RFID tagging, the expected sales of the mp3 player is $50\% \cdot \frac{19}{20} = 0.475$ unit. With RFID information visibility, the expected sales is 0.5 unit. In other words, the store could sell 0.025 more unit of the mp3 player as a benefit of having RFID.

From the above two examples in this section, we find that the increased information visibility by deploying RFID is able to generate more value compared to the same case without information visibility. We find it a common factor in almost all the RFID case studies that without RFID decisions are made based on randomness; with RFID, decisions are made based on decision makers' ability to find the optimal strategy from revealed information. In the next section we will extend and generalize the discussion by setup a general model.

2.2. Single Item

The simplest scenario we can find in RFID application is to choose an item from a set of n possibilities $\{X|x_1, x_2, x_3, ..., x_n\}$. The production function $g(x_i)$ maps each possibility to an output, and we are interested in a specific output. Without loss of generality, we are interested in the maximizing production throughout the thesis. Without information visibility, choosing an item is purely random. The output is the expect value of all the possibilities $O : O = E[g(X)]$. With information visibility, we are able to find the maximum output $\tilde{O} : \tilde{O} = \max\{g(X)\}$. The difference (benefits) therefore is $\delta = \max\{g(X)\} - E[g(X)]$. In what follows, we are interested in quantifying δ and describing its characteristics.

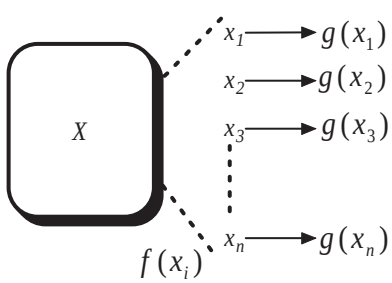

Figure 2-2. Simplest scenario: choose one item from a set of n possibilities.

Using descriptive statistics, we assume that in the set $\{X|x_1, x_2, x_3, x_n\}$, each variable x_i follows distribution $f_x(x)$. Function $y = g(x)$ denotes the production as a function of x. The distribution of Y is hence $f_y(y) = f_x(g^{-1}(y))g\prime(y)$. We assume that the decision maker

is interested in maximizing the production. Without information visibility, the decision maker randomly chooses an x_i and makes a production of $y = g(x_i)$. If we assume each x_i are equally possible to be chosen, the expected value of the production is

$$O = \frac{1}{n}\sum_{i=1}^{n} g(x_i)$$

. With information visibility, the decision make will maximize the production based on the information that he knows. Assume that the maximum can always be found, the distribution of the maximum production hence is:

$$f_n^y(y) = n \cdot f_x(g^{-1}(y))g\prime(y) \cdot \left(\int_{-\infty}^{y} f_x(g^{-1}(y))g\prime(y)dy\right)^{n-1} \tag{2–1}$$

Proof. The c.d.f. of the maximum production is:

$$\begin{aligned} F_n^y(y) &= Pr[y_1 \leq y, y_2 \leq y, \cdots, y_n \leq y] \\ &= F_y(y)^n \\ &= \left(\int_{-\infty}^{y} f_x(g^{-1}(y))g\prime(y)dy\right)^n \end{aligned}$$

Hence, its p.d.f. can be found by first order derivative, $f_n^y(y) = nf_y(y)F_y(y)^{n-1}$. □

Knowing the distribution of the maximum production, we are now able to quantify the benefits of having RFID information visibility δ as $\delta = \tilde{O} - O$, such that:

$$\delta = \int_y yu\prime(nu^{n-1} - 1)dy \tag{2–2}$$

where

$$u = \int_{-\infty}^{y} f_x(g^{-1}(y)g\prime(y)dy \tag{2–3}$$

In most business environments what is interesting is not only the best outcome, but also a set of the best outcomes. Then the problem simply becomes the sum of the best k productions in ranking statistics. Assuming that the underlying random variables $x_1, x_2, ...$

have a common density function, the c.d.f. of the kth best outcome is

$$f^{y}_{k:n}(y) = \frac{n!}{(k-1)!(n-k)!} u^{k-1}(1-u)^{n-k} f_y(y) \tag{2–4}$$

Hence, the sum of the best k is:

$$\begin{aligned}
\sum_{i=1}^{k} E[y_{i:n}] &= \sum_{i=1}^{k} \int_y y \cdot \frac{n!}{(i-1)!(n-i)!} u^{i-1}(1-u)^{n-i} f_y(y) dy \\
&= \int_y \sum_{i=1}^{k} \frac{n!}{(i-1)!(n-i)!} u^{i-1}(1-u)^{n-i} \cdot y f_y(y) dy \text{ (define } j = i-1) \\
&= \int_y n \sum_{j=0}^{k-1} \frac{(n-1)!}{j!(n-1-j)!} u^{j}(1-u)^{n-1-j} \cdot y f_y(y) dy \\
&= \int_y n F_{binomial(n-1,u)}(k) \cdot y f_y(y) dy
\end{aligned}$$

Hence the benefit of having information visibility, δ is:

$$\begin{aligned}
\delta &= \sum_{i=1}^{k} (E[y_{i:n}] - E[y]) \\
&= \int_y (n F_{binomial(n-1,u)}(k) - k) \cdot y f_y(y) dy
\end{aligned}$$

Theorem 1. $\delta \geq 0$.

Proof.

$$\begin{aligned}
\delta &= \int_y yu\prime(nu^{n-1}-1)dy \\
&= \int_y ydu^n - \int_y ydu \\
&= yu^n|_y - \int_y u^n dy - yu|_y + \int_y udy \\
&= \int_y (u-u^n)dy
\end{aligned}$$

Because $u \in [0,1]$, $u \geq u^n$. Hence we prove that δ is always greater than or equals to zero. Similarly, δ is greater than or equal to zero for the best k items. □

Theorem 2. *When $k \leq n$,*

$$\delta \leq \int_y (ne^{-2\frac{(n-k)^2}{n}} - k) \cdot yf_y(y)dy \leq \int_y (n-k) \cdot yf_y(y)dy$$

Proof. The upper bound for the lower tail of the binomial distribution function can be derived using Hoeffding's inequality as

$$F_{binomial}(k;n,u) \leq e^{-2\frac{(n-k)^2}{n}}$$

The same results can also be derived using Chernoff's inequality. Since the cumulative function is less than or equal to one, there exists a loose upper bound as

$$F_{binomial}(k;n,u) \leq 1$$

Therefore,

$$\begin{aligned}
\delta &= \int_y \left(n \sum_{j=0}^{k-1} \frac{(n-1)!}{j!(n-1-j)!} u^j (1-u)^{n-1-j} - k \right) \cdot yf_y(y)dy \\
&\leq \int_y (ne^{-2\frac{(n-k)^2}{n}} - k) \cdot yf_y(y)dy \\
&\leq \int_y (n-k) \cdot yf_y(y)dy
\end{aligned}$$

□

Theorem 3. *If $k = n$, $\delta = 0$*

Theorem 3 is easily provable by replacing k with n in the original equation. Theorem 3 means that if the experiment exhausts all the possibilities, the result with information visibility and the one without visibility are not different.

Theorem 4. *Larger the sample space variance, larger the benefit δ.*

Theorem 4 can be explained as that with larger sample space variance there's higher chance to see large samples on the right tail. It increases the density on the right tail of the order statistics also, thus increasing the expected value.

2.3. Multiple Cases

In reality, most decision making situations involve multiple cases, rather than one. We will generalize it by starting from a simplified two sets 2-2 example.

In a simplest case, $n = 2$ and $m = 2$. The two sets are $\{X|x_1, x_2\}$ and $\{Y|y_1, y_2\}$ respectively. There are four possible outputs $\{z_1 = g(x_1, y_1), z_2 = g(x_2, y_2), z_3 = g(x_1, y_2),$ and $z_4 = g(x_2, y_1)\}$. Without RFID information visibility, the expected output is the average of the outputs $E[Z]$. With visibility, we can identify each components and arrange the pair-matching to maximize the output $\max\{Z\}$.

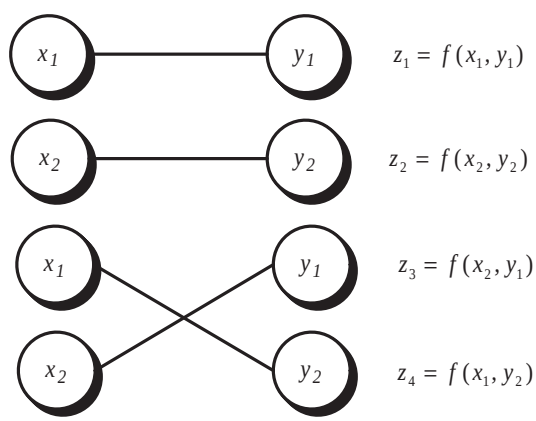

Figure 2-3. Simplified two sets 2-2 example.

To generalize the previous example, let's assume that we have a case of m multiple sets $\{X|X_1, X_2 \cdots X_n\}$. Each set X_i from $\{X_1|x_{11}, x_{12}, x_{13} \cdots x_{1n_1}\}$, $\{X_2|x_{21}, x_{22}, x_{23} \cdots x_{2n_2}\}$ $\cdots \{X_m|x_{m1}, x_{m2}, x_{m3} \cdots x_{mn_m}\}$ has n_i samples that have a same distribution. Variables

$X_1, X_2 \cdots X_m$ follow joint distribution $f_{X_1,X_2\cdots X_m}(X_1, X_2 \cdots X_m)$. Production function is defined as $Y = g(X_1, X_2 \cdots X_m,)$, with c.d.f. $F_y(y) = Pr[g(X_1, X_2 \cdots X_m) \leq y]$

$= \int \int \cdots \int_{g(X_1,X_2\cdots X_m)\leq y} f_{X_1,X_2\cdots X_m}(X_1, X_2 \cdots X_m) dX_1 dX_2 \cdots dX_m.$

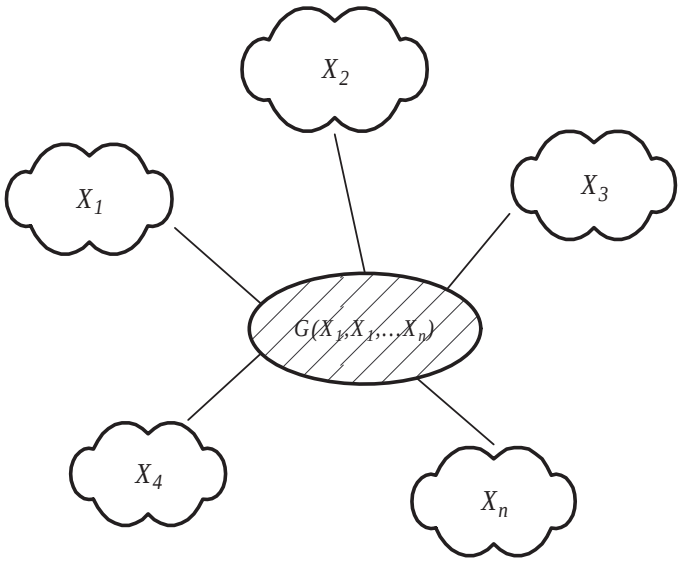

Figure 2-4. Multiple Cases

Without information visibility, one sample from each set is chosen randomly to produce the outcome. Hence the expected outcome is:

$$O = E[y] = \int_y y dF_y(y)$$

With information visibility, one sample from each set is chosen if such a collection produces the maximum possible outcome, $\tilde{O} = \max\{Y\}$. Because Y has $n_1 \cdot n_2 \cdots n_m$ different possible values in total, the distribution of $\tilde{O}$ is

$$f^y_{n_1 n_2 \cdots n_m}(y) = n_1 \cdot n_2 \cdots n_m \cdot f(y) \cdot F(y)^{n_1 \cdot n_2 \cdots n_m - 1}. \tag{2–5}$$

It's because

$$\begin{aligned} F(\max\{Y\}) &= Pr[y_1 \leq y, y_2 \leq y, \cdots, y_{n_1 \cdot n_2 \cdots n_m} \leq y,] \\ &= F_y(y)^{n_1 \cdot n_2 \cdots n_m} \end{aligned}$$

So,

$$\begin{aligned} f^{y}_{n_1 n_2 \cdots n_m}(y) &= F_y\prime(y)^{n_1 \cdot n_2 \cdots n_m} \\ &= n_1 \cdot n_2 \cdots n_m \cdot f(y) \cdot F(y)^{n_1 \cdot n_2 \cdots n_m - 1}. \end{aligned}$$

The difference between the production with information visibility and without thus is:

$$\delta = \int_y n_1 n_2 \cdots n_m \cdot u\prime(u^{n_1 n_2 \cdots n_m - 1} - 1) y dy \tag{2–6}$$

where

$$u = \int \int \cdots \int_{g(X_1, X_2 \cdots X_m) \leq y} f_{X_1, X_2 \cdots X_m}(X_1, X_2 \cdots X_m) dX_1 dX_2 \cdots dX_m \tag{2–7}$$

Let's define $N = n_1 n_2 \cdots n_m$. If the production includes the best k outcomes, δ becomes:

$$f^{y}_{k:N}(y) = \frac{N!}{(k-1)!(N-k)!} u^{k-1}(1-u)^{N-k} f_y(y) \tag{2–8}$$

Hence, the sum of the best k is:

$$\begin{aligned} \sum_{i=1}^{k} E[y_{i:N}] &= \sum_{i=1}^{k} \int_y y \cdot \frac{N!}{(i-1)!(N-i)!} u^{i-1}(1-u)^{N-i} f_y(y) dy \\ &= \int_y n F_{binomial(N-1,u)}(k) \cdot y f_y(y) dy \end{aligned}$$

Hence the benefit of having information visibility, δ is:

$$\begin{aligned} \delta &= \sum_{i=1}^{k} (E[y_{i:n}] - E[y]) \\ &= \int_y (N F_{binomial(N-1,u)}(k) - k) \cdot y f_y(y) dy \end{aligned}$$

Theorem 5. *If all the resources are used, the benefit of having information visibility is zero if there's only one case; the benefit is greater than zero if there are multiple cases.*

Proof. In a single case scenario, if all the n samples are used, the benefit of having information visibility is

$$\int_y (nF_{binomial(n-1,u)}(k) - k) \cdot y f_y(y) dy$$

It equals zero if $k = n$. In the scenario with multiple cases,this becomes

$$\int_y (NF_{binomial(N-1,u)}(k) - k) \cdot y f_y(y) dy$$

where $N = n_1 n_2 \cdots n_m$ and $k \in [0, \min\{n_1, n_2, \cdots, n_m\}]$. This is always greater than zero because of Theorem 1. □

2.4. Control Function

All we have discussed previously are based on the fact that sample X is static and non-changeable. Although in many cases it's true, in some others once X is observed, decision maker changes (improves) X in order to produce a better outcome. The second example of the electronic retailing store is such a case that X has only one sample that is equally likely to be $\{0, 1, \cdots, 19\}$. If x equals any number in $\{1, 2, \cdots, 19\}$, the decision maker takes no action. If x equals zero, the decision maker restocks, changing x back to 19. This process is like adding a function $\tilde{X} = \psi(X)$ to the original sample, making the sample non-static. In the previous example $\tilde{X}$ is $\psi(X) = \begin{cases} 19 & \text{if } X = 0 \\ X & \text{otherwise} \end{cases}$

The function $\psi(X)$ depends on the decision maker's business strategy and it may vary from case to case. The production function hence becomes $Y = g(\psi(X))$.

After all, we conclude that the benefit of introducing RFID information visibility is a function of the information scale, the distribution of the sample, the non-static function and the production function.

$$\delta = \Omega\left(k, X, \psi(X), g(X)\right) \tag{2–9}$$

Theorem 6. *if Y is positive, δ is a monotonic increasing function of n.*

Proof.

$$\begin{aligned}
\frac{\partial \delta}{\partial n} &= \frac{\partial \int_y yu\prime(nu^{n-1}-1)dy}{\partial n} \\
&= \int_y yu\prime(u^{n-1} + nu^{n-1}ln(n-1))dy \\
&\geq 0
\end{aligned}$$

□

2.5. Multiple Period: Dynamic Programming Approach

2.5.1 Finite Time

In a multiple period, the objective is to maximize the total utilities throughout the time period.

$$\max_{v_t} \left\{\delta(X_0, X_1, \cdots, X_T; v_0, v_1, \cdots, v_{T-1})\right\}$$

where v_t is a vector of control that can be chosen in every period by the decision maker, so that $v_{t-1} = \psi_{t-1}(X_{t-1})$.

In most cases in a business environment, such as SCM, retail, or quality control, the utility over a time period is the accumulated sum of utilities over separate time segments, $\{t_0, t_1, \cdots, t_{T-1}, t_T\}$. Now let's assume that the total utility is time-separable. That is:

$$\delta(X_0, X_1, \cdots, X_T; v_0, v_1, \cdots, v_{T-1}) = \delta_0(X_0, v_0) + \delta_1(X_1, v_1) + \cdots + \delta_{T-1}(X_{T-1}, v_{T-1}) + S(X_T)$$

where $S(X_T)$ is a "scrap" value function at the end of the program, where no further decisions are made. Let's define $\xi(\cdot)$ as an intertemporal function that connects the state and control variables such that $X_T = \xi_{T-1}(X_{T-1}, v_{T-1})$

Using Bellman's Method, the recursive function is:

$$V(X_{T-k}, k) = \max_{v_{T-k}} \{\delta_{T-k}(X_{T-k}, v_{T-k}) + V(X_{T-k+1}, k-1)\} \tag{2–10}$$

$$\equiv \delta_{T-k}(X_{T-k}, \psi_{T-k}(X_{T-k})) + V(\xi_{T-k}(X_{T-k}, \psi_{T-k}(X_{T-k}), k-1) \tag{2–11}$$

subject to:

1. $X_{T-k+1} = \xi_{T-k}(X_{T-k}, v_{T-k}, G(v_{T-k}))$ (2–12)
2. $X_0 = \tilde{X}_0$ (2–13)
3. $v_{T-k} = \psi_{T-k}(X_{T-k})$ (2–14)
4. $v_t \in \Theta$ for all $t = 0, 1, \cdots, T-1$ (2–15)

In constraint 4, Θ is the feasible set for the control variables that is assumed to be closed and bounded.

Now let's look at the above problem in more detail, first from the last time segment $t_{T-1} \sim t_T$ that is a simple 2 period problem, and then work backwards. The optimization problem of $t_0 = T-1$ is:

$$\max_{v_{T-1}} \{\delta_{T-1}(X_{T-1}, v_{T-1}) + S(X_T)\} \tag{2–16}$$

subject to:

1. $X_T = \xi_{T-1}(X_{T-1}, v_{T-1})$ (2–17)
2. $X_{T-1} = \tilde{X}_{T-1}$ (2–18)
3. $v_{T-1} = \psi_{T-1}(X_{T-1})$ (2–19)

Constraint 3 can be substituted into constraint 1 and further back into the objective function to characterize the solution as a value function:

$$V(X_{T-1}, 1) \equiv \delta_{T-1}(X_{T-1}, \psi_{T-1}(X_{T-1})) + S(\xi_{T-1}(X_{T-1}, \psi_{T-1}(X_{T-1}))$$

By similar derivations, we are able to find the value function when $t_0 = t_{T-2}$ as:

$$\begin{aligned} V(X_{T-2}, 2) &\equiv \max_{v_{T-2}} \{\delta_{T-2}(X_{T-2}, v_{T-2}) + V(X_{T-1}, 1)\} \\ &= \delta_{T-2}(X_{T-2}, \psi_{T-2}(X_{T-2})) + V(\xi_{T-2}(X_{T-2}, \psi_{T-2}(X_{T-2}), 1) \\ &\vdots \end{aligned}$$

The generalized value function when $t_0 = t_{T-k}$ is

$$V(X_{T-k}, k) \equiv \delta_{T-k}(X_{T-k}, \psi_{T-k}(X_{T-k})) + V(\xi_{T-k}(X_{T-k}, \psi_{T-k}(X_{T-k}), k-1) \tag{2–20}$$

After going through the successive rounds of single period maximization problems, eventually one reaches the problem in time zero:

$$V(X_0, T) \equiv \max_{v_0} \{\delta_0(X_0, v_0) + V(X_1, T-1)\} \tag{2–21}$$

subject to:

1. $X_1 = \xi_0(\tilde{X}_0, v_0)$ (2–22)
2. $X_0 = \tilde{X}_0$ (2–23)
3. $v_0 = \psi_0(\tilde{X}_0)$ (2–24)

Because X_0 is given a value at the outset of the overall dynamic problem, we have now solved for v_0 as a number that is independent of the Xs. It's easy to work out X_1, and hence v_1 from the control rule of that period, and then X_2, v_2 ... so on and so forth. This process can be repeated until all the X_i and v_i values are known. Then the overall problem is solved.

2.5.2 Infinite Time

With nondeterministic control rules in a finite time, we are able to find the optimization solution using recursive algorithm. Now let's further assume that the control function is deterministic and have the same form in every period. If we consider the future benefit in

time value, we are able to define the problem in infinite time as:

$$V_t(X_t) = \max_{v_t} \left\{ \beta\delta(X_t, v_t) + V_{t+1}(X_{t+1)} \right\} \tag{2–25}$$

subject to:

$$1. \quad X_{t+1} = \xi_0(X_t, v_t) \tag{2–26}$$

$$2. \quad X_0 = \tilde{X}_0 \tag{2–27}$$

$$3. \quad v_t = \psi(X_t) \tag{2–28}$$

where β is the discount factor and $0 \leq \beta \leq 1$. By defining

$$W_t(X_t) = \frac{V_t(X_t)}{\beta} \tag{2–29}$$

it's the same to write equation 3-25 in current value as:

$$W_t(X_t) = \max_{v_t} \left\{ \delta(X_t, v_t) + \beta W_{t+1}(X_{t+1)} \right\} \tag{2–30}$$

(Sargent 1987 and Stokey 1989) showed that the above iterations starting from any bounded continuous W_0 will cause W to converge as the number of iterations becomes large. Moreover,, the $W(\cdot)$ that comes out of this procedure is the unique optimal alue function for the infinite horizon maximization problem. Because $W(\cdot)$ is uniquely associated with the control function $\psi(\cdot)$, if we find the optimal control rule we find the maximum utility over the time.

CHAPTER 3
KNOWLEDGE BASED ITEM-LEVEL MANUFACTURING

Radio Frequency Identification (RFID) tags have gained wide-spread popularity in a wide variety of application domains. Their application in the manufacturing environment, however, still remains at a low level. Some of the impediments to RFID tag's inroad in this domain include its relative and associated cost, novelty, and simply the lack of awareness of its beneficial aspects. We consider the concept of item-level information in a mass manufacturing context by utilizing a knowledge-based learning system that supports such concept. We analyze some of the benefits of this manufacturing concept and compare it with those of traditional mass production scenario. Preliminary results indicate that manufacturing with item-level information is significantly advantageous when there is a large variance in the manufacturing process. We also show that this benefit is bounded. An example manufacturing scenario is simulated to verify results obtained through analysis.

3.1. Introduction

RFID (Radio Frequency IDentification) has been successfully used as a part of a mechanism for identifying and tracking objects using tags (silicon chips implanted in a product or its packaging) that communicate with a reader. RFID tags can be used to store and retrieve product information at an item-level in a way that is fully automatic, instantaneous, and touchless and could be used to track any object. Although RFID tags are becoming popular in disparate application areas, its application in manufacturing is still quite limited.

Although RFID tags have numerous advantages compared to bar codes (Raza, Bradshaw, and Hague 1999; Shepard 2005), the exact benefits of RFID in a manufacturing environment has not been clear since its introduction during WWII. A majority of existing literature on RFID applications are in the supply chain management area. A majority of these literature are case studies or simulations of domain-specific possible RFID

implementations, mostly in the fields of inventory management and replenishment, supply chain operations, and retailing. Atali, Lee and Ozer (2004) investigate the value of RFID under imperfect inventory information. Doer, Gates, and Mutty (2006) present an analysis of the costs and benefits of RFID technology for the management of ordnance inventory using both qualitative and quantitative methods. Gaukler, Seifert and Hausman (2007) study item-Level RFID in the Retail Supply Chain. Lee and Ozer (2005) investigate the value of RFID in a supply chain. Dutta, Lee, and Whang (2007) examine three dimensions of the value proposition of RFID: generic architecture of RFID implementations and the drivers of value; measurement issues associated with quantification of value; incentives for achieving diffusion when multiple independent organizations deploy the technology and coordinate the resulting information flows.

It is becoming increasingly critical for manufacturers to be knowledgable about an item's instantaneous status, the processes it has gone through, and its history of movements during transactions. An item's instantaneous status includes its unique identity, precise physical location, physical status, and special key features. Sahin, Dallery and Gershwin (2002) provide a list of potential benefits of RFID technology on supply chain processes including (1) reduction in labor costs, (2) increase in store selling area, (3) acceleration of physical flows, (4) reduction in profit losses, (5) more efficient control of the supply chain due to increased information accuracy, (6) better knowledge of customer behavior, (7) better knowledge of out-of-stock situations, (8) reduction of delivery disputes, (9) better management of perishable items, (10) better management of returns, (11) better tracking of quality problems, (12) better management of product recalls and customer safety, and (13) improved total quality control.

There have been a growing number of strategies that have been aimed at improving the general manufacturing process since the 1980s including Total Quality Management (Oakland 1995), Just-in-Time production (John 1989), Design for Manufacturability (Venkatachalam, Mellichamp and Miller 1993), lean manufacturing (Shah and Ward 2003),

reengineering, benchmarking and Mass Customization (Silveira, Borensteinb and Fogliatto 2001). The framework we propose for improving the manufacturing process is enabled by RFID tags and is different from existing process improvement strategies. Utilizing instantaneous item-level information of interstage products, it is possible to identify an optimal combination of resources as well as follow a customized item-level manufacturing setting. A knowledge-based learning support system is implemented to render item-level manufacturing highly intelligent and fully automatic.

We investigate an innovative concept of item-level manufacturing driven by a knowledge-based learning support system, enabled by advanced ID tracing technology such as RFID. Traditional mass manufacturing is based on certain standards that are generally established during the pre-manufacturing testing process. These standards are then applied to all production activities until there is a need to update them due to changes in working environment or system mass bias. It should be noted that in any manufacturing process, there is always a certain level of tolerance that is considered to be within an acceptable range. Clearly, there is variance even within a sample of objects passing the acceptable tolerance-level test. Acknowledging the presence of disparity in material quality and working environment across time, we argue that through utilization of item-level information during the manufacturing process, firms have the capability to produce higher quality products and thereby generate increased profit.

We consider a scenario where a product is manufactured from several RFID-tagged parts. Each of these tags contain information about the host part, including its unique identifier and other specifications of interest. Based on these specifications and some performance criterion, the most appropriate set of parts is selected to form the final product. The proposed knowledge-based framework aids this process by utilizing decision rules that select complementary parts based on their respective measured specifications.

The impetus behind RFID in supply chain management and manufacturing arises primarily from its inherent capability to provide item-level information visibility. Its

benefits can be explained by increased certainty (reduced uncertainty) that improves manufacturing coordination (Zhou and Piramuthu, 2008). We use the factor of certainty as a key element to model the value of RFID information visibility at the item-level in a manufacturing environment. Using descriptive statistical analysis, we illustrate some potential benefits of deploying item-level information in a manufacturing setting compared to a traditional mass production setting.

This chapter is organized as follows. A brief background introduction of manufacturing improvement strategies is discussed in section 2. We present the item-level production framework and compare it to a traditional mass manufacturing setting in Section 3. We model the benefit of item-level manufacturing in section 4. Section 4 also includes results from simulation to verify the model and to show the effectiveness of this new concept in manufacturing. Section 5 concludes this chapter with a brief discussion on the insights garnered and their implications.

3.2. Manufacturing Improvement Strategies

Over the past 10 years, the emphasis in strategic management thinking has shifted away from industry structure and competitive positioning, and toward internal, firm-specific, within strategic group factors (Cool and Schendel, 1988) such as culture (Barney, 1968a; Fiol, 1991), capabilities (Lawless, Bergh, and Wilsted, 1989; Stalk, Evans and Shulman, 1992), administrative skills (Powell, 1992), reputation (Weigelt and Camerer, 1988), know-how (Hall, 1992), learning (Senge, 1990; Garvin, 1993), process improvement (Stalk and Hout, 1990), and organizational climate (Hanson and Wernerfelt, 1989). The resource theory of the firm has accelerated this shift, asserting that economic rents may stem from any strategic factor-internal, external,economic, behavioral, tangible, or intangible that meets the tests of value, scarcity, and imperfect imitability (Wernerfelt, 1984; Barney,1986b; 1991; Peteraf, 1993). U.S. Manufacturing companies have rediscovered the power that comes from superior manufacturing and initiated a variety of activities to improve their competitiveness, including TQM (Total Quality Management), JIT

(Just-in-Time) production, and DFM (Design for Manufacturability), lean manufacturing, reengineering, benchmarking, and mass customization.

3.2.1 Total Quality Management

According to International Organization for Standardization, total quality management is a management approach for an organization centered on quality, and is based on the participation of all its members and aimed at long-term success through customer satisfaction that benefits all members of the organization and society. A major aim of TQM is to reduce variation from every process so that greater consistency of effort is obtained.

3.2.1.1 History of TQM

Total Quality Management's origins can be traced to 1949, when the Union of Japanese Scientists and Engineers formed a committee of scholars, engineers, and government officials devoted to improving Japanese productivity, and enhancing their postwar quality of life. Influenced by Deming and Juran, the committee developed a course on statistical quality control for Japanese engineers, followed by extensive statistical training and the widespread dissemination of the Deming philosophy among Japanese manufacturers.

In Japan, TQM resulted in such managerial innovations as quality circles, equity circles, supplier partnerships, cellular manufacturing, just-in-time production, and hoshin planning. American firms began to take serious notice of TQM around 1980, when some U.S. policy observers argued that Japanese manufacturing quality had equaled or exceeded U.S. standards, and warned that Japanese productivity would soon surpass that of American firms. Productivity trends supported these assertions, leading some opinion leaders to predict that-barring a radical change in American management practices-Japan and other Asian countries would soon dominate world trade and manufacturing, relegating the U.S. to second-tier economic status. Some high-profile American firms such as Ford, Xerox, and Motorola were easily convinced, having already lost market share to more

efficient, higher quality Japanese producers. These firms, under the guidance of Deming and other quality consultants, benchmarked Japanese practices and were among the first American TQM adopters. Based on their widely-publicized success, other large manufacturers soon jumped aboard, and by the end of the 1980s, a significant proportion of large U.S. manufacturers had adopted TQM . By that time, many large service firms had also expressed interest, and some-due in part to pressures from customers that employed TQM-had adopted full-fledged TQM initiatives.

3.2.1.2 TQM in manufacturing

Quality assurance through statistical methods is a key component in a manufacturing organization, where TQM generally starts by sampling a random selection of the product. The sample can then be tested for specifications that matter the most to end users. The causes of any failures are then isolated, followed by designing secondary measures of the production process, to address the causes of the failure. The statistical distributions of important measurements are tracked. When parts' measures drift into a defined "error band", the process is fixed. The error band usually has a tighter distribution than the "failure band", so that the production process is rectified before possible rejects are produced.

It is important to record not just the measurement ranges, but what failures caused them to be chosen. In that way, cheaper fixes can be substituted later (say, when the product is redesigned) with no loss of quality. Once TQM has been in use, it's very common for parts to be redesigned so that critical measurements either cease to exist, or become much wider.

It took people a while to develop tests to identify emergent problems. One popular test is a "life test" in which the sample product is operated until it fails. Another popular test is called "shake and bake" in which the product is mounted on a vibrator in an environmental oven, and operated at progressively more extreme vibration and

temperature until something fails. The failure is then isolated and engineers address this failure through necessary design improvement.

3.2.2 Just-in-Time Production

Just-in-time (JIT) is an inventory strategy implemented to improve the return on investment of a business by reducing in-process inventory and its associated carrying costs. In order to achieve JIT the process must have signals of what is going on elsewhere within the process. This means that the process is often driven by a series of signals, which can be Kanban, that tell production processes when to make the next part. Kanban are usually 'tickets' but can be simple visual signals such as the presence or absence of a part on a shelf. When implemented correctly, JIT can lead to dramatic improvements in a manufacturing organization's return on investment, quality, and efficiency. Some have suggested that "Just on Time" would be a more appropriate name since it emphasizes that production should create items that arrive exactly when needed and neither earlier nor later.

The philosophy of JIT is simple - inventory is defined to be waste. JIT inventory systems expose the hidden causes of maintaining inventory and are therefore not a simple solution a company can adopt; there is a radically new way in which the company must operate in order to manage its consequences. The ideas included in this way of thinking originate from many different disciplines including statistics, industrial engineering, production management and behavioral science. In the JIT inventory philosophy there are views with respect to how inventory is looked upon, what it says about the management within the company, and the main principle behind JIT.

Quick communication of the consumption of old stock which triggers new stock to be ordered is key to JIT and inventory reduction. This saves warehouse space and costs. However since stock levels are determined by historical demand, any sudden demand rises above the historical average demand will deplete inventory faster than usual and cause customer service issues. Some have suggested that recycling Kanban faster can also

help flex the system by as much as 10-30%. In recent years, manufacturers have touted a trailing 13 week average as a better predictor for JIT planning than most forecasters could provide.

3.2.3 Design for Manufacturability

The integration of design and manufacturing activities into one common engineering effort has been recognized as a key strategy for survival and growth. Design for manufacturability (DFM) is an approach to design that fosters the simultaneous involvement of product design and process design. The implementation of the DFM approach requires the collaboration of both the design and manufacturing functions within an organization. DFM is the process of proactively designing products to (1) optimize all manufacturing functions: fabrication, assembly, test, procurement, shipping, delivery, service, and repair, and (2) assure the best cost, quality, reliability, regulatory compliance, safety, time-to-market, and customer satisfaction.

3.2.4 Lean Manufacturing

Lean manufacturing is the optimal way of producing goods through the removal of waste and implementing flow, as opposed to batch and queue. Lean manufacturing is a generic process management philosophy and is renowned for its focus on reduction of the original Toyota seven wastes in order to improve overall customer value, but there are varying perspectives on how this is best achieved. The steady growth of Toyota, from a small company to the world's largest auto-maker has focused attention on how it has achieved this.

Lean production is a multi-dimensional approach that encompasses a wide variety of management practices, including just-in-time, quality systems, work teams, cellular manufacturing, supplier management, etc. in an integrated system. The core thrust of lean production is that these practices can work synergistically to create a streamlined, high quality system that produces finished products at the pace of customer demand with little or no waste.

3.2.5 Mass Customization

Mass Customization (MC) is the customization and personalization of products and services for individual customers at a mass production price. The concept has emerged in the late 1980s and may be viewed as a natural follow up to processes that have become increasingly flexible and optimized with respect to quality and costs. In addition, mass customization appears as an alternative to differentiate companies in a highly competitive and segmented market.

Mass customization can be defined either broadly or narrowly. The broad, visionary concept promotes MC as the ability to provide individually designed products and services to every customer through high process agility, flexibility and integration. MC systems may thus reach customers as in the mass market economy but treat them individually as in pre-industrial economies. MC systems are positioned below the main diagonal of Hayes and Wheelwright's product-process matrix, i.e. having medium to high-volume process types such as manufacturing cells or assembly lines that are able to deliver the high product varieties usually associated to functional or fixed-type operations.

They define MC as a system that uses information technology, flexible processes, and organizational structures to deliver a wide range of products and services that meet specific needs of individual customers (often defined by a series of options), at a cost near that of mass-produced items. In any case, MC is seen as a systemic idea involving all aspects of product sale, development, production, and delivery, forming a full-circle from the time of customer selecting or placing the order to receiving the finished product.

The justification for the development of MC systems is based on three main ideas. First, new flexible manufacturing and information technologies enable production systems to deliver higher variety at lower cost. Second, there is an increasing demand for product variety and customization (even segmented markets are now too broad as they no longer permit developing niche strategies). Finally, the shortening of product life cycles and

expanding industrial competition has led to the breakdown of many mass industries, increasing the need for production strategies focused on individual customers.

3.3. A Framework for Item-Level Manufacturing

3.3.1 Traditional Mass Manufacturing

Traditional mass manufacturing, which also goes by repetitive flow production, series production or flow production, is the production of a large quantity of standardized products usually on automated production lines. The manufacturing procedure strictly follows a set of pre-defined standards that are obtained from a test run of a small sample (Fig. 1). These standards include those related to parts, human labor, processes, machinery operations, and working environment. Once the standards are defined and generated, mass produced goods are generally manufactured strictly following these. Standards are kept unchanged unless large deviation in production occurs or a routinely scheduled test is arranged.

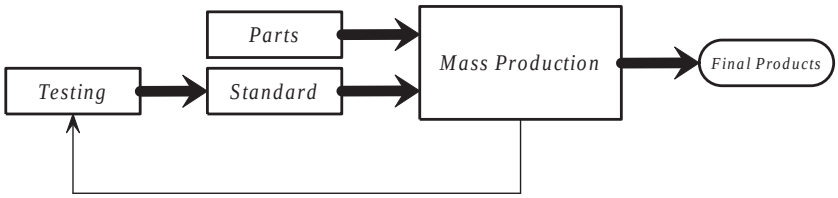

Figure 3-1. Classic mass production

Parts that form the final products follow standards obtained during the testing phase and are treated uniformly at the mass production stage. Acknowledging the quality or specification disparity in similar parts, we find that ignoring unique item-level specification information results in an inferior production process compared to the scenario where item-level information is considered in the manufacturing process. We analytically show this in section 3. Reduced uncertainty as a direct result of RFID item-level information visibility brings direct improvement in manufacturing as we discuss in the following section.

3.3.2 Manufacturing with Item-level Information

In this section we present the proposed framework for improving the manufacturing process through item-level information visibility: item-level manufacturing, enabled by RFID tracing technology and backed by a knowledge-based adaptive learning system. There are two major modules in this framework: Item-level Production module and the Adaptive Learning module (Fig. 2). Parts that are processed and assembled to form a final product are tagged with RFID, which are used to store and retrieve item-level information. This item-level information is gathered and analyzed by the problem solver to determine a good strategy that improves the quality of the final product. Once a final product is produced, its specifications are evaluated and are transmitted to the Adaptive Learning module for further analysis. In the Adaptive Learning module, quality information on the most recently manufactured item along with information from the input such as this item's item-level information, parameters of the working environment and Item-Level Production's decision are analyzed to update the knowledge-base that will be used to aid in manufacturing the next instance of the product.

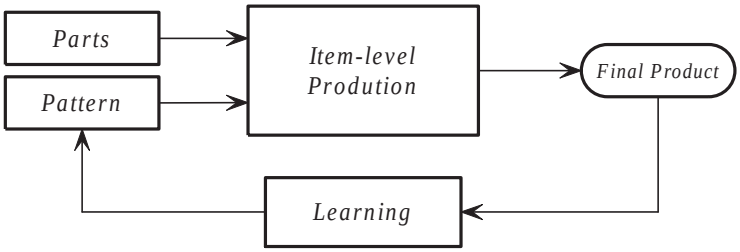

Figure 3-2. Item-level manufacturing

The considered adaptive knowledge-based framework supports adaptive decision-making to changes in the user preferences, the quality of the product and its components, and the environment. The dynamics of such a change may be such that some are amenable to a proactive stance or even a reactive stance from a decision-making perspective.

3.3.2.1 Item-level production component

Fig. 3 shows the expanded view of the Item-Level Production module comprising a problem solver and four operational submodules that include component matching, process adjustment, environment setting and machine adjustment. Both item-level part information and updated domain knowledge are input to this module to produce the final product. The Problem Solver analyzes item-level information with domain knowledge to make decisions related to matching parts and adjusting the manufacturing process which include the machines utilized as well as the environment.

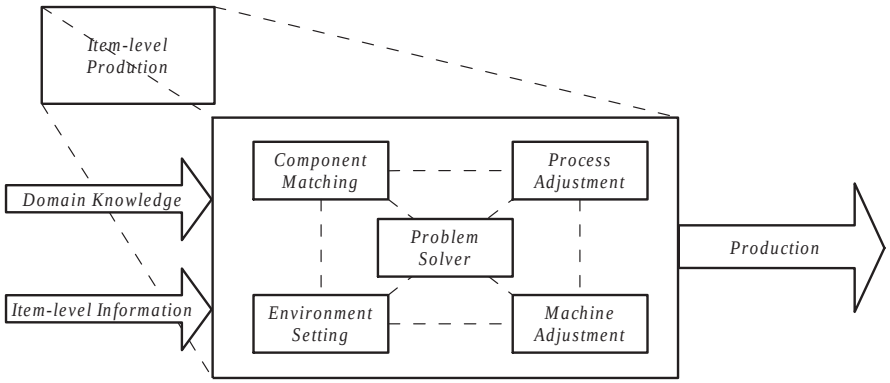

Figure 3-3. Item level production

The Problem Solver comprises a set of decision support tools that compute and deliver solutions to routine structured problems where all necessary inputs are deterministically known to fairly sophisticated 'intelligent' tools that pro-actively seek to provide appropriate support for making decisions in semi-structured or even unstructured environments. Dynamic environments that are essentially characterized by uncertainties in several dimensions necessitate a reasonably 'smart' decision support tool. These decision support tools are required to provide or assist in generating 'good' decisions in real-time.

Problem-solving capability is an essential characteristic of an adaptive knowledge-based system since it is a requirement for supporting decision-making situations. Compared to humans, the relative speed at which computers are able to solve problems are measured in multiple orders of magnitude. This is beneficially utilized in the considered adaptive

framework. The Problem Solver sub-component in this framework receives domain knowledge input indirectly from the Adaptive Learning component and item-level part information from supplier, and includes two sub-components: the knowledge-base and the Problem-solving component. The Adaptive Learning component provides the knowledge that is incorporated in the knowledge-base, which is a part of the problem-solving component. As knowledge in its knowledge-base becomes stale or when new knowledge or updates to existing knowledge become available, the Adaptive Learning component provides necessary knowledge input to bring the knowledge-base current. The other input to the Problem-solving component comes from the environment in terms of input data essential to solve the decision problem of interest.

Essential characteristics of the Problem-solving component include the ability to update its knowledge-base using input from the Adaptive Learning component, appropriately invoking necessary knowledge from its knowledge-base and using it to address the input decision making problem from the environment with the Problem-solver, and provide the most appropriate solution output for a given combination of existing knowledge and problem of interest.

The Problem Solver identifies and implements manufacturing decisions that include component matching, process adjustment, environment setting and machine adjustment which cover the four facets of 4M1E - Man, Machine, Method, Material and Environment. By considering the minor, albeit significant, variations from core specifications of instances of an item, the manufacturer is able to make accurate decisions to improve output performance with the exact specifications of individual item-level information.

3.3.2.2 Knowledge-based adaptive learning component

This component comprises of two main sub-components, namely the one for performance evaluation and the one for learning. These two sub-components work in concert to enable the system to iteratively learn through a feedback loop by evaluating itself based primarily on the quality of the resulting product.

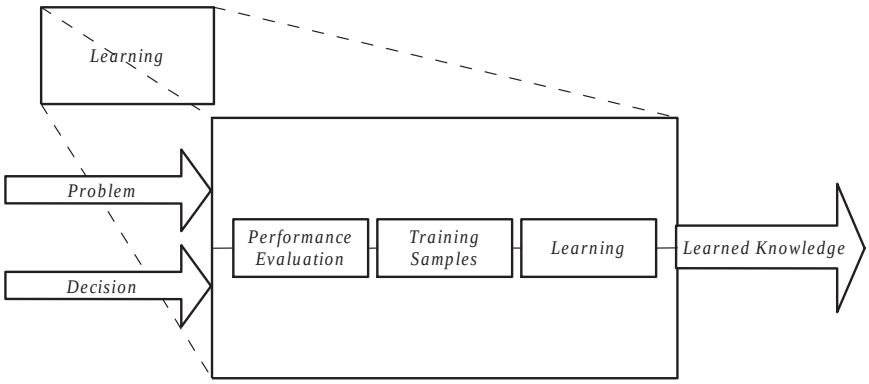

Figure 3-4. Adaptive knowledge-based Learning framework

Performance-evaluation

This sub-component is rather critical for maintaining the knowledge-base in the system current. The criticality of performance evaluation arises from the fact that almost all systems in a manufacturing environment can be considered dynamic. The dynamics in these systems necessitate the corresponding process of making decisions to be dynamic. The decision-making process cannot be truly dynamic when the source knowledge-base that it relies on remains static. Using input on product specifications and the quality of the most recently manufactured product which comprise the core essential data from recent performance of the system, the Performance Evaluation sub-component either assigns appropriate internal credit when the performance of the system was as expected or identifies deficits when the system performance is worse than expected. In the former case, the system identifies the parts of the knowledge-base that was used in the decision-making process and assigns (reinforcement) credit, which can then be used to efficiently fine-tune the knowledge-base for effective performance. In the latter case, it identifies the source of the deficits. Specifically, the best course of action for a given decision-making scenario is identified. This is then incrementally learned and incorporated in the knowledge-base for use in manufacturing the next instance of the item of interest.

This component is responsible for pro-actively keeping the knowledge-base from becoming stale. This is primarily done through indirectly monitoring the quality of the

knowledge-base through the performance of the system. A poor system performance indicates incomplete or stale knowledge in the knowledge-base. If the knowledge-base is incomplete, there is a need to identify and generate the 'missing pieces' of knowledge. If the knowledge-base is found to have necessary knowledge albeit stale, either a complete overhaul of that part of the knowledge-base can be done or additional knowledge can be added to refresh the knowledge-base. Given these requirements, the necessary characteristics of this sub-component include the ability to identify staleness and incompleteness in the knowledge-base using input from the finished product, and the ability to translate deficit identification to useable information that is incorporated in the updated knowledge-base.

The two sets of input that this sub-component receives include solution to the decision-making problem, which is essentially the quality of the manufactured product, and its specifications including any related tolerance factors. These inputs are mapped to determine any deviations that are addressable through modifications to the knowledge-base. The knowledge-base is then incrementally modified to reflect this additional knowledge. When the deviations are due to a freak circumstance (e.g., the machinery being interrupted due to some unforeseen reasons), a solution addressing this deviation may or may not be incorporated in the knowledge-base. The rationale behind this is simply the fact that the knowledge-base needs to be compact for it to respond instantaneously, and any irrelevant or unnecessary information does not warrant being incorporated in the knowledge-base.

Learning

Learning is an important characteristic of any intelligent system. Learning from experience has several advantages. It enables a system to incrementally build and improve its knowledge-base when and where deficits are identified through continual feedback from the environment. Although it is not possible to begin with a 'perfect' or 'complete' knowledge-base containing all possible knowledge of the domain of interest in most applications, the capacity to learn over time alleviates this burden on the system.

Without learning, a system is bound to repeat mistakes, which can prove to be expensive in monetary terms as well as in terms of resources including time, manpower, and materials. The knowledge-base of a system that does not have learning capability is bound to be static and hence become quickly stale in terms of knowledge in most dynamic environments that necessitate dynamically updating its knowledge-base to remain current. Static knowledge-bases are appropriate only in scenarios where the knowledge-base contains the complete domain knowledge that does not change with time and in static environments. Unless we are dealing with imaginary problems, it is hard to envision an application area where a static knowledge-base is appropriate. Learning is an important characteristic and the Learning component constitutes the core of the considered adaptive knowledge-based system framework since it is the primary source of knowledge. The manufacturing environment that depends on and is tailored toward incorporation and utilization of varying item-level information for its day-to-day operations is certainly not a static environment.

Although learning by itself can be accomplished through several means, we focus on machine learning as the mode of learning in the considered framework. The primary motivation behind this is the natural and seamless way in which such a learning can be incorporated with the rest of the framework to achieve improved performance results. Any of the several existing supervised machine learning algorithms such as decision trees, decision rules, feed-forward neural networks, genetic algorithms, etc. could be used in this component. Depending on the domain of interest, more specifically on the data characteristics including data types (e.g., numeric, alphanumeric, symbolic) and interactions among themselves in the domain of interest, an appropriate algorithm can be selected. For example, some algorithms such as those that are used in feed- forward neural network work better with real-valued data, while some others such as those used in inducing decision trees work better with symbolic data in general.

Given the implications of the No Free Lunch (NFL) theorems (e.g., Culberson, 1998; Igel and Toussaint, 2003; Schumacher et al., 2001;Wolpert and Macready's 1995), the criticality in selecting the most appropriate algorithm as well as the ability to incorporate domain knowledge (in the form of hints) in the learning algorithm to avoid some of the problems associated with the NFL theorems cannot be overstated. Other considerations include the time taken to learn a concept of interest since an application might prove to be time-critical that necessitates learning concepts quickly in real-time. For example, genetic algorithms and the back-propagation algorithm and its variants used in feed-forward neural network are iterative in nature and could possibly take longer to learn a concept. Others such as decision trees or decision rules are one-pass algorithms that generally are fast learners. The quality of learned concepts is, of course, of paramount importance. The choice of algorithm used in the Learning component should, therefore, depend on several factors including data characteristics, learning accuracy, quality of learned concepts including representational conciseness, learning speed, among others. Regardless, as long as learning is achieved somehow, the framework is able to function without much degradation in its resulting performance.

Being a part of the Adaptive Learning component, the Learning sub-component extensively interacts with the Performance Evaluation sub-component. The interaction between the Learning and Performance Evaluation sub-components is iterative as they are both synergistically related together. Output from the Performance Evaluation sub-component determines and triggers, to a great extent, the timing and extent of the Learning sub-component to accomplish its goals of learning the most appropriate knowledge in a timely manner. Essential characteristics of the Learning sub-component include the ability to (1) concisely, accurately, and quickly learn the concepts of interest, (2) accept necessary input data, and (3) generate learned concepts in a form that is required of the next component in the framework. The Performance Evaluation

sub-component is useless without the Learning sub-component since the latter identifies and takes necessary actions in response to the former's evaluation.

3.3.3 Tagged Items in Manufacturing

Given the enormous amount of information that these tagged items generate, a structured means to utilize this information for useable decision-making is necessary. An adaptive knowledge-based system framework is a natural fit for this application. Items in a manufacturing shop floor are always in a state of flux. Whereas 'similar' parts are indistinguishable in the absence of RFID tags, they broadcast every minute detail of their actual specifications when tagged. These specifications, when utilized, can lead to improved efficiency as well as overall quality of the final product. For example, although components that eventually end up in a final product need to satisfy some base-level specifications (e.g., minimum tolerance levels), minor variations among them can be amplified when several such components are put together to form a final product. There is, therefore, a need to select the most appropriate set of components even among those that have already passed the base quality check, etc., to improve the overall quality.

The following example illustrates this scenario in a manufacturing context. Consider the case of an LCD panel, which comprises at least three components including base, liquid crystal, and cover. Assume that a manufacturing plant has five assembly lines that produce the same type of LCD panels. Moreover, assume that all the individual components meet certain base-level quality criteria, which is given by the following list.

- base
    0. dates since manufacturing < 365 days
    0. percentage of surface flatness $> 90\%$
    0. material purity $> 94\%$
- liquid crystal
    0. date of manufacturing < 365 days
    0. material purity $> 97\%$

- cover
    0. date of manufacturing < 730 days
    0. percentage of surface flatness $> 97\%$
    0. material purity $> 90\%$

Without RFID tags, all the factory can do is to randomly pick an instance of each component and assemble an LCD panel on one of the five manufacturing lines. With RFID item-level information visibility, however, the factory has more information about every individual sample component such that a base sample carries information like $Base(life = 180days, S.F. = 97\%, M.P. = 95\%)$. The manufacturer is now able to distinguish among the individual mix of components that go into producing a final product. This item-level information and the means to utilize such information in the manufacturing process did not exist before the introduction of RFID tag technology. With RFID tagged components, a knowledge-based system can identify patterns that generally result in better quality, faster throughput, less wastage, etc. These patterns that result in a better product can be a combination of certain parameters, or exclusion of certain parameters, such as

$$Quality \sim \begin{cases} > 9.5/10, & \text{if } Base(L < 180days, S.F. > 97\%, M.P. > 95\%) \\ \\ < 6/10, & \text{if } Base(L > 270days, S.F. < 95\%, M.P. < 94.5\%) \\ & \&Cover(L > 540days, S.F. < 98\%, M.P. < 92\%) \\ \\ > 7/10\& < 9.5/10, & \text{if } Base(L > 180days, S.F. > 97\%, M.P. < 95\%) \end{cases}$$

Knowing these rules and the item-level information, the manufacturer thus is able to improve product quality by pro-actively pursuing decisions through appropriate decision aids such as an adaptive knowledge-based system.

We model the benefits of this self-learning item-level manufacturing scheme comparing to the classic mass production that is without such information and intelligence.

By defining a product function, we find a distribution of the maximum output and we assume that the adaptive learning system is able to perform reasonably close to the maximum. Thus we quantify the value of item-level manufacturing according to the manufacturing scale, statistic characteristics of parts and the production function. We use the results from chapter 2.

Let's consider m parts $\{X|X_1, X_2 \cdots X_m\}$ that jointly determine a production. Each part X_i consists of n_i samples that share the same distribution such as: $\{X_1|x_{11}, x_{12}, x_{13} \cdots x_{1n_1}\}$, $\{X_2|x_{21}, x_{22}, x_{23} \cdots x_{2n_2}\} \cdots \{X_m|x_{m1}, x_{m2}, x_{m3} \cdots x_{mn_m}\}$. Variables $X_1, X_2 \cdots X_m$ follow joint distribution $f_{X_1,X_2\cdots X_m}(X_1, X_2 \cdots X_m)$. Production function is defined as $Y = g(X_1, X_2 \cdots X_m,)$ with cdf:

$$F_y(y) = \int \int \cdots \int_{g(X_1,X_2\cdots X_m)\leq y} f_{X_1,X_2\cdots X_m}(X_1, X_2 \cdots X_m) dX_1 dX_2 \cdots dX_m \tag{3–1}$$

The sum of the best k production is:

$$\sum_{i=1}^{k} E[y_{i:N}] = \sum_{i=1}^{k} \int_y y \cdot \frac{N!}{(i-1)!(N-i)!} u^{i-1}(1-u)^{N-i} f_y(y) dy \tag{3–2}$$

$$= \int_y nF_{binomial(N-1,u)}(k) \cdot y f_y(y) dy \tag{3–3}$$

Hence the benefit of introducing item-level RFID information visibility is a function of the information scale, the distribution of the sample, and the production function, such that:

$$\delta = \Omega\left(k, X, g(X)\right) = \sum_{i=1}^{k} \left(E[y_{i:n}] - E[y]\right) \tag{3–4}$$

$$= \int_y (NF_{binomial(N-1,u)}(k) - k) \cdot y f_y(y) dy \tag{3–5}$$

Based on this study, we observe the following for this domain:

Result 1. The benefit of implementing item-level manufacturing is always positive

Result 2. The benefit of implementing item-level manufacturing is upper bounded loosely by $\int_y (n-k) \cdot y f_y(y) dy$ *and bounded tightly by* $\int_y (ne^{-2\frac{(n-k)^2}{n}} - k) \cdot y f_y(y) dy$

Result 1 and 2 prove that additional item-level information in this manufacturing setup always bring non-negative benefit to the RFID adopter. The result in Proposition 1 is consistent with Blackwell's Theorem (1951). We also prove that the benefit is bounded, which provides a guideline for decision making on future RFID item-level manufacturing adoption.

Result 3. The larger the variance in manufacturing parts, the larger the benefit of having item-level information during manufacturing.

Result 4. The benefit of implementing item-level manufacturing monotonically increases with manufacturing scale.

Result 5. If all the resources are used, the benefit of having item-level information visibility is zero if there's only one part; the benefit is positive if there are multiple parts.

The line of reasoning for Result 3 is as follows: with larger sample space variance the probability for a large number of samples to occur at the right tail is higher. Moreover, it increases the density at the right tail of the order statistics, thereby increasing the expected value. Result 5 proves that in a multiple-part manufacturing scenario, the learning system itself generates extra positive value.

3.3.4 Simulation Analysis

We investigate a quality control scenario using RFID to provide item-level information visibility in an engine manufacturing plant. Let's assume that the manufacturer makes engines by fitting a cap to an engine body. The dimensions of the cap and the body follow certain known distributions respectively. Because all caps (or, bodies) are manufactured in the same line, we assume that cap follows distribution $f(X_1)$ and that body follows distribution $f(X_2)$. The life of the engine is found to be an exponential (say) function of the difference in size (tolerance or fit) between the cap and the body $G(X_1, X_2) = e^{x_1 - x_2}$.

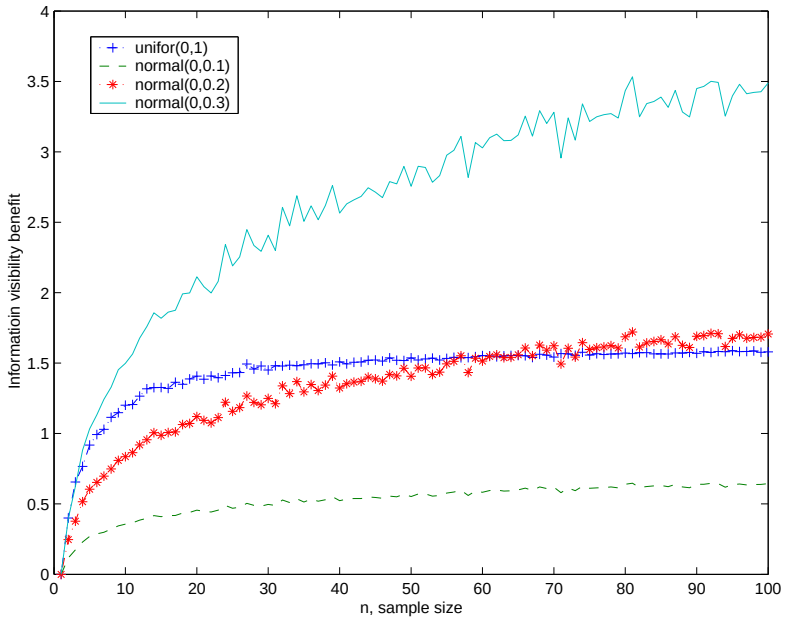

Figure 3-5. Benefit of having information visibility for fabrication quality control.

We assume that in the function $\delta = \Omega\left(k, X, G(X)\right)$, each factors being defined as:

$$\begin{aligned} X_1 &\sim \text{Uniform or Normal with variance } \sigma_1 \\ X_2 &\sim \text{Uniform or Normal with variance } \sigma_2 \\ G(x_1, x_2) &= e^{x_1 - x_2} \end{aligned}$$

The simulation result shows (Figure 8) that the benefit of information visibility increases with the scale of the manufacturing process which is consistent with the result in Proposition 4. The benefit function is concave and bounded, which agrees with Proposition 2. We experiment with four different sample spaces with different volatile levels (variance) and find that if the samples are more volatile, the more is the benefit of having RFID information visibility (Proposition 3). This can also be explained as when the sample spaces have large variance, there's more randomness. RFID as a means to reduce randomness benefits more as a consequence.

3.4. Conclusions

A manufacturing environment is dynamic where appropriate components are continually manufactured and assembled. Given the ever-changing nature of knowledge in such an environment, a static knowledge-base is prone to turning stale in a short period of time resulting in degradation of system performance. Stale knowledge is thus a major problem in any static knowledge-based system. The considered framework alleviates problems associated with stale knowledge through continually monitoring system performance as well as incorporation of updated and/or new knowledge. A major reason for RFID tag use is their exceptional ability to convey tracking information as well as information about the tagged object. Such information can be beneficially utilized to build better quality products.

We considered item-level information provided by incorporation of RFID tags in a manufacturing setting, and showed that it can be beneficially used to improve production quality. Whereas previously manufacturers were only able to utilize class-level information for manufacturing and assembly, RFID tags enable item-level manufacturing with more focus on the idiosyncrasies of each individual item as it relates to other items that are aggregated together to form a final product. Although the traditional manufacturing process resulted in finished products that satisfied tolerance constraints for each specification, item-level visibility enables improving their quality. Moreover, there are situations where two (or, more) parts that are well within acceptable specification tolerance levels could result in a finished product that is unacceptable due to mismatch among the individual parts. Such situations lead to unnecessary wastage of 'good' parts that could have been salvaged otherwise with the presence of item-level information. Due to its recent popularity, RFID tags and their applications in a manufacturing setting has not received much attention from researchers. Our study is a step in this direction of reducing such wastage as well as improving the overall quality of manufactured as well as assembled products.

CHAPTER 4
OTHER APPLICATIONS

In this Chapter, we extend the current discussion to potential research applications, such as the cost benefit analysis and the problem of incomplete information coverage.

4.1. Cost Benefit Analysis

The very first applicable problem that can be addressed using this model is to determine the scalability of an information system. Specifically in an RFID information system, marginal cost includes the per chip cost of an RFID tag and labor cost to attach the tags. By defining a cost function of an RFID application $c(n) = a \cdot n + b$, where b denotes the constant cost and a denotes the marginal cost, we are able to calculate the profit as

$$\Delta = \delta(n) - c(n) \tag{4–1}$$

$$= \int_y yu\prime(nu^{n-1} - 1)dy - cn - b \tag{4–2}$$

By taking the first order derivative on n, $\partial\Delta/\partial n$, we are able to find the optimal scale of the information system that would bring the maximum benefit of having item-level information visibility.

$$\begin{aligned}
\frac{\partial\Delta}{\partial n} &= \int_y yu\prime(u^{n-1} + nu^{n-1}ln(n-1))dy - c \\
&= \int_y yu\prime u^{n-1}(1 + nln(n-1))dy - \int_y c \cdot nu\prime u^{n-1}dy \\
&= \int_y yu\prime u^{n-1}(1 + nln(n-1) - c)dy \\
&= 0
\end{aligned}$$

If $nln(n-1) = c - 1$ or $n^{n-1} = e^{c-1}$, $\frac{\partial\Delta}{\partial n} = 0$. The result shows that the optimal scale of an information system is independent of the distribution of the samples as well as the the production function.

4.2. Incomplete Information

Although several leading retailers and their vendors have begun to adopt RFID technology, many others are still hesitant to do so mostly because the potential benefits and possible problems of implementing RFID traceability technology is not clear both from industrial and academic research. As a consequence, the business world will see a mixture of the nonvisible traditional supply chain and the RFID enabled information visible supply chain in the near term. It's natural to think that the RFID enabled information visibility is not always complete and therefore there is a need to consider such a problem of optimization when incomplete information is present.

The applications of incomplete information not only applies to manufacturing. In chapter 5, we show that in the context of congested market, there exists unique Nash equilibria for oligopolists to strategically reveal partial of the information for a homogeneous product (vertical incomplete) or for substitutable heterogeneous product (horizontal incomplete).

4.2.1 Vertical Incomplete Information

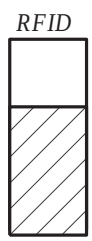

Figure 4-1. Vertical Incomplete Information .

Here we describe the incomplete information problem when not every component in the business chain is information traceable. The information incompleteness may be caused by the fact that not all upper-stream partners are equipped with RFID infrastructure so that only a portion of the products acquired have information visibility (Figure 4-1). Information incompleteness may also be caused by the fact that some of the components don't have information visibility horizontally in the system (Figure 4-2).

Information incompleteness arises both at vertical and horizontal levels. When information is not complete, it's natural that business practitioners are interested in knowing the optimal percentage of information coverage, the minimal required coverage, upstream & downstream relationship and the strategies for partial tagging. Using the results derived

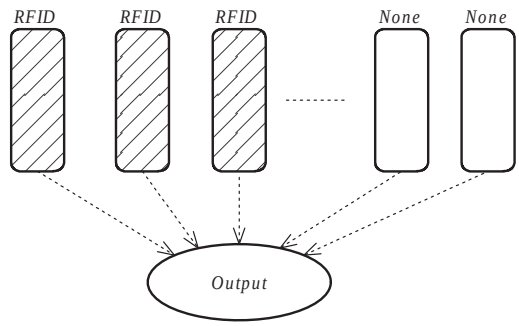

Figure 4-2. Horizontal Incomplete Information .

from Section 3, we find the absolute value of partial information in a horizontal one component example as

$$\delta(\tilde{n}, k, X, g(X)) = \int_y (\tilde{n} F_{binomial(\tilde{n}-1,u)}(k) - k) \cdot y f_y(y) dy$$

(4–3)

where $\tilde{n}$ denotes the magnitude of available information. Let's recall that n is the magnitude of original information, including both visible and invisible information. Then $n - \tilde{n}$ is the size of the invisible information. By assuming that the order statistics of the sample is symmetric we find that the value of information visibility comes from the first half of $\tilde{n}$. It implies the overall benefit of having information visibility is the same as equation (33) if $k \leq \frac{\tilde{n}}{2}$. Otherwise it becomes:

$$\delta = \int_y (\tilde{n} F_{binomial(\tilde{n}-1,u)}(\frac{\tilde{n}}{2}) - \frac{\tilde{n}}{2}) \cdot y f_y(y) dy$$

(4–4)

4.2.2 Horizontal Incomplete Information

To investigate the horizontal incomplete information, we consider an example of Linear Partial Information (L.P.I.) that has been widely used in decision making literature (Kofler, Kmietowicz and Pearman 1984). A standard approach of L.P.I. is to specify multiple evaluation measures $X_1, X_2, \cdots, X_n$ and assess an evaluation function $g(x_1, x_2, \cdots, x_n)$, where x_i is a specific sample (level) of X_i, that combines the measure into an index of the overall preferability of an alternative. One functional form that has been widely used is the weighted-additive decomposition

$$g(x_1, x_2, \cdots, x_n) = \sum_{i=1}^{n} k_i g_i(x_i)$$

where the g_i are single-dimensional functions, the k_i are positive weighting (scaling) constants, and larger values of g are more preferable.

With unknown information that we denote as $\tilde{x}$, the difference between full information revelation and the incomplete information is

$$Y - \tilde{Y} \quad = \quad \sum_{X_j \in \tilde{X}} \sum_{i=1}^{k} k_j E[g[X_{j,i:n}]]$$

where

$$\sum_{i=1}^{k} E[A_{i:n}] = \int_A n F_{binomial(n-1,u)}(k) \cdot A f_A(A) dA$$

We therefore find the ratio of the potential benefit of complete information revelation over horizontal incomplete information in L.P.I. as

$$\beta = \frac{\sum_{X_j \in \tilde{X}} \sum_{i=1}^{k} k_j E[g[X_{j,i:n}]]}{\sum_{X_j \in X} \sum_{i=1}^{k} k_j E[g[X_{j,i:n}]]} \tag{4–5}$$

CHAPTER 5
ITEM-LEVEL INFORMATION SHARING IN OLIGOPOLY

We consider a homogeneous product market and the incentive for oligopolists to share item-level product information with their customers. Enabled by RFID technology, each firm has the option to record and reveal item-level information of a proportion of its product. Each firm first decides its production plan and then decides its level of information revelation in a two-stage game. With a constant clearance discount rate, we derive pure strategy equilibria that are subgame perfect and demonstrate that complete information sharing is the unique Nash equilibrium of the game when the common demand is volatile and that no information revelation is the unique Nash equilibria when demand is not volatile. Furthermore, we show that the Nash equilibria is the same with a decreasing clearance discount rate and that neither complete information revelation nor zero information revelation is consistent with an equilibrium with an increasing discount rate. Results are similar in a duopoly non-homogeneous product market scenario.

5.1. Introduction

Thanks to modern ID trace, storage and retrieval technology such as RFID, business practitioners are able to obtain and record item level product information on any product. By acknowledging the individual quality disparity within a bin of homogeneous products, firms are facing a real problem on whether to share this item-level product information with their buyers. In a monopolist's market scenario, the clear choice for the firm is not to reveal this information. However, because revealing product information generates competitive advantage and possibly could increase sales, it may not necessarily be true in oligopolists' market.

In this chapter we investigate the incentives for item-level information sharing from firms to consumers in a market with duopolists selling homogeneous products. In contrast to earlier papers (Novshek and Sonnenschein 1982, vives 1984 and Gal-or 1985) where information sharing is about unknown common demand, or (Gal-or 1986) where

information is about unknown private costs, in the present research we consider the information transmission of item-level product information that is enabled by modern information tracing technologies such as RFID.

RFID (Radio Frequency IDentification) is a tracking system that uses tags (silicon chips implanted in a product or its packaging) to communicate with a reader. RFID tags can be used to store and retrieve product information at an item-level in a way that is fully automatic, instantaneous, and touchless and could be used to track any object from candy bars to big screen TVs. Despite its limited processing power and storage capacity, the item-level information it can store is dramatically higher than those using competing technologies such as bar code (Raza, Bradshaw, and Hague 1999; Shepard 2005). Unlike bar code that provides categorical-level information, RFID technology facilitates distinguishing individual instances of products by assigning a unique electronic product code (EPC) to each of them.

Retailers and manufacturers are now able to provide item-level information for almost any product. However, they are faced with realistic issues such as 1. whether they will benefit from sharing such information, 2. if so to what extent, and 3. what strategy should be followed to share this item-level information when various oligopolists compete with a homogeneous product.

A homogeneous product is defined as a product from an industry in which outputs from different firms are indistinguishable, however, no two homogeneous products are indeed the same. More precisely, the term "homogeneous" describes a group of products that follow a certain statistical criteria, which is pre-defined by an industry to convene marketing sales. Quality variance of different homogeneous products differs by a wide margin depending on the industry. If item-level product information is available, it brings additional value to the buyer by providing the opportunity to choose better products and making better control decisions (Zhou 2008). Other benefits include location

tracking, inventory monitoring, and so on, (Lee, Peleg, Rajwat, Sarma and Subirana 2005; Economist 2003; Gaukler, Selfert and Hausman 2007).

A firm might enjoy a better market position by virtue of processing the ability to reveal item-level product information by selling more of its above-average products than his competitors. This dynamic is especially salient when supply exceeds anticipated common demand. In this research we assume that firms don't manipulate or selectively reveal information although it's doable and beneficial to the firms under certain circumstances (Crawford and Sobel 1982; Greezy 2005). A buyer always benefits from additional information (Blackwell 1953) afforded by the choice to pick the best above average products.

This chapter is organized as follows. Section 2 presents a brief overview of relevant literature. Section 3 contains information about the model description, assumptions and setup. Derivation of equilibria appears in section 4, along with some analysis and discussion. Section 5 concludes the chapter with a brief discussion on the insights garnered and their implications.

5.2. Literature Review

The economic aspects of information sharing has long been studied and, moreover, it's generally believed that an increase in useful information results in generating positive value (Blackwell 1953). Eckwert and Zilcha (2001), however, show that under certain circumstances Blackwell theorem fails completely in exchange economies. They show that the Blackwell theorem holds in competitive equilibrium with risk averse consumers and risk neutral producers given that risk sharing markets are absent. When risk sharing markets are present, all agents may become worse off with better information.

Crawford and Sobel (1982) develop a model of strategic information transmission in which an informed agent transmits information (possibly noisy) to the principal who takes an action that determines the welfare of both. They show that the principal's equilibrium expected utility rises when the agent's preferences are more similar, assuming

that the principal bases his choice of action on rational expectations. Okuno-Fujiwara, Postlewaite and Suzumura (1990) analyze the problem of strategic information revelation, assuming agents may reveal some or all of their information to the principal prior to playing the game. They use the equilibria resulting from various revelation strategies to determine equilibrium revelation of information and to find sufficient conditions for complete revelation of all private information.

We consider strategic item-level product information transmission from the firm to the consumer, facilitated by modern tracing technology such as RFID. Most literature in oligopoly game theory with strategic information transmission deal with information associated with non-public information on common demand (Gal-or 1985) or unknown private costs (Gal-or 1986). We assume that the information sender doesn't manipulate the information nor does he selectively choose information within a certain range in favor of him. Krishna and Morgan (2001) study the model of expertise in which perfectly informed experts, who are biased, transmit information to a decision maker whose action decide the welfare of all and show that the expert withholds sizable information from the decision maker in a one-expert scenario. Greezy (2005), in his discussion of deception in information transmission, shows that the average person prefers not to lie and by doing so increases his payoff only by a little but greatly reduces the other's payoff. In this research we don't consider the moral games that have been studied before.

The research question in this chapter is enabled by RFID that as an emerging tracing and identification technology has numerous advantages compared to traditional bar codes (Raza, Bradshaw, and Hague 1999; Shepard 2005). However, the exact benefits of RFID in retailing and supply chain management hasn't been very clear since its introduction during WWII. Most existing literatures in the area of RFID applications are case studies or simulations of domain-specific possible RFID implementations, mostly in the fields of inventory management and replenishment, supply chain operations, and retailing. Lee and Ozer (2005) investigate the value of RFID in a supply chain. Dutta, Lee, and Whang

(2007) examine three dimensions of the value proposition of RFID. Gaukler, Seifert and Hausman (2007) study item-Level RFID in the Retail Supply Chain. Alexander, Birkhofer, Gramling, Kleinberger, Leng, Moogimane, and Woods (2002), based on business case study of current leading practices for the adoption of Auto-ID system, illustrate the impact of Auto-ID system on specific pain points faced by companies in the consumer goods and retail value chain.

5.3. The Model

A market consists of two firms each producing (or acquiring) a homogeneous product. The demand function facing this industry is stochastic and linear:

$$P = A - Q - e \tag{5–1}$$

The prior distribution of e, which is independent and with mean zero, is known to both firms. e may follow a different distribution according to the market characteristics of involved industry. $Q = Q_1 + Q_2$, where $Q_i, i = 1, 2$ denotes the quantity produced by firm i.

$$E(P) = A - Q \tag{5–2}$$

At the beginning of a time period, each firm decides the product acquisition/manufacturing plan on quantity: Q_i and the portion of the products with item-level information revealed: θ_i. The number of tagged units equals $\theta_i Q$ and the number of units without tags equals $(1 - \theta_i)Q$. Tags with item-level information can no longer be placed once the product is after manufacturing (acquisition). We assume that the cost of tagging negligible. It is a reasonable assumption given the unit cost of RFID to be 6c compared to a bottle of \$10 shampoo or a \$500 computer. We also assume that all the buyers are rational and buy the best product that is available.

At the end of the time period, the actual demand is realized and both firms may over-sell or under-sell. If a firm has unsold product, $h_i Q_i$ where h_i denotes the proportion

of unsold product to the total amount produced, it clears out the unsold with a discount rate ξ, $\xi \in (0, 1)$. In some industry the discount rate is constant and in others it may vary (increase or decrease) according to the amount of unsold, the capacity of the firm and the industry, $\xi = kh_i$, or $\xi = 1 - kh_i$.

The game in our model consists of two stage. At the first stage each firm makes its manufacturing or acquisition plan. At the second stage each firm decides how much item-level information should be revealed. The level of information revelation is chosen dependent upon the output plan and the distribution of the common demand. We derive pure strategy Nash equilibria that are subgame perfect and investigate the incentives to share item-level product information in possible scenarios such as non-constant discounting rate and nonsymmetric product quality distribution.

The incentive for revealing item-level information are investigated when the volatility of common demand ranges from extreme volatile to freezingly stable. We demonstrate that complete information revelation ($\theta_i^* = 1, i = 1, 2$) is a dominant strategy when demand is volatile and no information sharing ($\theta_i^* = 0, i = 1, 2$) is a dominant strategy when demand is not volatile.

Summary:

1. There are two players in the market - Duopoly;

2. Products are homogeneous and have the same statistical characteristics;

3. At the beginning of a time period, each player $i, i = 1, 2$ decides the product acquisition/manufacturing plan on quantity: Q_i and the portion of the products with item-level information revealed: θ_i, so the number of tagged units equals $\theta_i Q$ and the number of units without tags equals $(1 - \theta_i)Q$. Tags with item-level information can no longer be placed once the product is acquired/manufactured. Product per unit cost is denoted as C_i. Cost of tagging is assumed to be negligible.

4. The price is set as a function of expected accumulated demand $P = A - \sum_i Q_i$ with unsold product discount considered. Accumulated demand in a time period is statistically

known to both players. The actual accumulated demand by the end of a time period may be different from the expectation and follows certain distribution. To put it simple, we assume that with possibility p the demand will be $(1-\beta)(Q_1+Q_2)$ and $1-p$ the demand will be $(1+\beta)(Q_1+Q_2)$.

5. At the end of a time period, if there are unsold products, unsold products $q_i, i = 1, 2$ will be cleared out with a discount ξ;

6. Consumer behavior: Consumers buy the best above average product with known-item-level information first. If all the above average tagged products are sold out, consumers buy the untagged products until they are sold out. If both the above average tagged and the untagged products are sold out, consumers will buy the best of the below average tagged ones;

Assumptions:

- The cost of search is negligible. For instance, assume that the two firms are online retailers so consumers' search cost is minimal;
- Consumers have no prior preference on retailers;
- Tagging cost is negligible.

5.4. Derivation of The Equilibria

At the Nash equilibria the strategy of each firm consists of an output level and an amount of information to be revealed, namely the pair $\{Q_i, \theta_i\}$, where $\theta_i \in [0,1]$ and $Q_i \geq 0$. The payoff function of firm i is:

$$\pi_i(Q_i, \theta_i) = [Q_i - p(1-\xi)h_i(Q_i, \theta_i)Q_i]\,[A - (Q_i + Q_j^*)] - C_i Q_i \tag{5–3}$$

where $h_i(Q_i, \theta_i)$ denotes the proportion of player i's unsold product and ξ denotes the clearance discount rate. The unsold proportion of firm i's output is

$$h_i = \begin{cases} \frac{\theta_i \beta(Q_i+Q_j)}{(Q_i\theta_i+Q_j\theta_j)} & \text{I. } \beta(Q_1+Q_2) \leq \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \\ \frac{\theta_j Q_j - \theta_i Q_j + \theta_i \beta(Q_i+Q_j)}{\theta_i Q_i + \theta_j Q_j} & \text{III. } Q_1+Q_2 - \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \leq \beta(Q_1+Q_2) \\ \frac{(1-\theta_i)\beta(Q_i+Q_j)+\frac{1}{2}Q_j(\theta_i-\theta_j)}{(1-\theta_i)Q_i+(1-\theta_j)Q_j} & \text{II. otherwise} \end{cases} \tag{5–4}$$

The unsold portion of firm j's output is:

$$(\beta - h_i)\frac{Q_i}{Q_j} + \beta \tag{5–5}$$

Firm i chooses its decision rule $\theta_i(\cdot)$ and subsequently $Q_i(\cdot)$ to maximize (3), given decision rules chosen by the other firms. The quantity/information pair $\{(Q_1^*, \theta_1^*), (Q_2^*, \theta_2^*)\}$ is a Nash equilibrium if for each firm i, (Q_i^*, θ_i^*) solves

$$\max_{0 \le Q_i < \infty; 0 \le \theta_i \le 1} \pi_i[(Q_i, \theta_i), (Q_j^*, \theta_j^*)] \tag{5–6}$$

$$= \max_{0 \le Q_i < \infty; 0 \le \theta_i \le 1} [Q_i - p(1-\xi)h_i(Q_i, \theta_i)Q_i]\,[A - (Q_i + Q_j^*)] - C_i Q_i \tag{5–7}$$

5.4.1 Constant Clearance Discount Rate

Theorem 7. *If the clearance discount rate is constant and $\beta < \frac{1}{2}$, the unique Nash equilibrium of the two stage game is $\theta_i^* = 0$ and $Q_i^* = \frac{A}{3} + \frac{C_j - 2C_i}{3[1-p(1-\xi)\beta]}$.*

Proof. The first order condition on θ_i is

$$\frac{\partial \pi_i[(Q_i, \theta_i), (Q_j^*, \theta_j^*)]}{\partial \theta_i} = -p(1-\xi)Q_i[A - (Q_i + Q_j^*)]\partial h_i / \partial \theta_i \tag{5–8}$$

Under condition I:

$$\beta(Q_1 + Q_2) \le \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \tag{5–9}$$

Player i's unsold portion of his product is:

$$h_i = \frac{\theta_i \beta (Q_i + Q_j)}{(Q_i \theta_i + Q_j \theta_j)} \tag{5–10}$$

$$\partial h_i / \partial \theta_i = \frac{Q_j^* \theta_j^* \beta (Q_i + Q_j^*)}{(Q_i \theta_i + Q_j^* \theta_j^*)^2} > 0 \tag{5–11}$$

The payoff function is strictly decreasing function of θ_i. Hence under condition I, $\theta_i^* = 0$ is a dominant strategy for each firm.

Under condition II:

$$Q_1 + Q_2 - \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \ge \beta(Q_1 + Q_2) \ge \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \tag{5–12}$$

player i's unsold portion is:

$$h_i = \frac{(1-\theta_i)\beta(Q_i+Q_j)+\frac{1}{2}Q_j(\theta_i-\theta_j)}{(1-\theta_i)Q_i+(1-\theta_j)Q_j} \tag{5–13}$$

$$\partial h_i/\partial\theta_i = \frac{(1-\theta_j^*)Q_j[-\beta(Q_i+Q_j^*)+\frac{1}{2}Q_j^*+\frac{1}{2}Q_i]}{[(1-\theta_i)Q_i+(1-\theta_j^*)Q_j^*]^2} \tag{5–14}$$

The payoff function is strictly decreasing function of θ_i if $\beta < \frac{1}{2}$. Hence in condition II, $\theta_i^* = 0$ is also a dominant strategy for each firm.

The first order condition on Q_i is

$$\frac{\partial[[Q_i - p(1-\xi)\beta Q_i](A-Q_i-Q_j^*)-C_iQ_i]}{\partial Q_i} = 0$$

$$Q_i = \frac{A-Q_j^*}{2} - \frac{C_i}{2[1-p(1-\xi)\beta]} \tag{5–15}$$

Through a similarly procedure for firm j we have:

$$Q_j = \frac{A-Q_i^*}{2} - \frac{C_j}{2[1-p(1-\xi)\beta]} \tag{5–16}$$

Therefore,

$$Q_i* = \frac{A}{3} + \frac{C_j-2C_i}{3[1-p(1-\xi)\beta]} \tag{5–17}$$

$$Q_j* = \frac{A}{3} + \frac{C_i-2C_j}{3[1-p(1-\xi)\beta]} \tag{5–18}$$

□

According to the Theorem 7 no information revelation is a dominant strategy for each firm when the volatility of the common demand is low.

Theorem 8. *If the clearance discount rate is constant and $\beta > \frac{1}{2}$, the unique Nash equilibrium of the two stage game is $\theta_i^* = 1$ and $Q_i^* = \frac{A}{3} + \frac{C_j-2C_i}{3[1-p(1-\xi)\beta]}$.*

Proof. Under condition II:

When $\beta \geq \frac{1}{2}$, the first order condition on θ_i is strictly decreasing, according to (12). Hence $\theta_i^* = 1$ is a dominant strategy for each firm.

Under condition III:

$$Q_1 + Q_2 - \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \leq \beta(Q_1 + Q_2) \tag{5–19}$$

Player i's unsold portion is:

$$h_i = \frac{\theta_j Q_j - \theta_i Q_j + \theta_i \beta(Q_i + Q_j)}{\theta_i Q_i + \theta_j Q_j} \tag{5–20}$$

$$\partial h_i / \theta_i = \frac{\theta_j Q_j[(-1+\beta)(Q_i + Q_j)]}{(\theta_i Q_i + \theta_j Q_j)^2} \tag{5–21}$$

the first order condition on Q_i is

$$\frac{\partial[[Q_i - p(1-\xi)\beta Q_i](A - Q_i - Q_j^*) - C_i Q_i]}{\partial Q_i} = 0$$

$$Q_i = \frac{A - Q_j^*}{2} - \frac{C_i}{2[1 - p(1-\xi)\beta]} \tag{5–22}$$

Similarly for firm j

$$Q_j = \frac{A - Q_i^*}{2} - \frac{C_j}{2[1 - p(1-\xi)\beta]} \tag{5–23}$$

Therefore,

$$Q_i* = \frac{A}{3} + \frac{C_j - 2C_i}{3[1 - p(1-\xi)\beta]} \tag{5–24}$$

$$Q_j* = \frac{A}{3} + \frac{C_i - 2C_j}{3[1 - p(1-\xi)\beta]} \tag{5–25}$$

□

Theorem 8 shows that complete information revelation is a dominant strategy for each firm when the volatility of the common demand is high.

5.4.2 Variable Clearance Discount Rate

Theorem 9. *When $\beta < \frac{1}{2}$, if $\frac{\partial \xi}{\partial h} \leq 0$, the unique Nash equilibrium of the game is $\theta_1^* = \theta_2^* = 0$; if $\frac{\partial \xi}{\partial h} > 0$, there exists no equilibrium where $\theta_1^* = \theta_2^* = \theta \in [0, 1]$.*

Proof. When the clearance discount rate decreases with the quantity of unsold product, we model it as a linear function with h_i such as $\{\xi = 1 - kh_i : \xi \in (0, 1)\}$ where k is a constant

$kh_i \in (0,1)$. The first order condition on θ_i becomes:

$$\frac{\partial \pi_i[(Q_i,\theta_i),(Q_j^*,\theta_j^*)]}{\partial \theta_i} = -p[A-(Q_i+Q_j^*)]2kQ_ih_ih_i' \tag{5–26}$$

where $p \geq 0$, $A-(Q_i+Q_j^*) \geq 0$ and $h_i \geq 0$. When $\beta < \frac{1}{2}$, we have $h_i' > 0$ and $h_i \geq 0$. So the equilibria on information sharing is $\theta_i^* = \theta_j^* = 0$.

If the clearance discount rate increases with the quantity of unsold product, $\{\xi = kh_i : \xi \in (0,1)\}$. The first order condition on θ_i is

$$\frac{\partial \pi_i[(Q_i,\theta_i),(Q_j^*,\theta_j^*)]}{\partial \theta_i} = -p[A-(Q_i+Q_j^*)]h_i'(1-2kh_i) \tag{5–27}$$

And the second order condition is

$$\frac{\partial^2 \pi_i[(Q_i,\theta_i),(Q_j^*,\theta_j^*)]}{\partial \theta_i^2} = -p[A-(Q_i+Q_j^*)][h_i''-2k(h_i''h_i+h_i'^2)] < 0 \tag{5–28}$$

$$\partial h_i/\theta_i = \frac{Q_j^*\theta_j^*\beta(Q_i+Q_j^*)}{(Q_i\theta_i+Q_j^*\theta_j^*)^2} > 0$$

$$\frac{\partial^2 h_i}{\theta_i^2} = \frac{-Q_iQ_j^*\theta_j^*\beta(Q_i+Q_j^*)(Q_i\theta_i+Q_j^*\theta_j^*)}{(Q_i\theta_i+Q_j^*\theta_j^*)^4} < 0$$

Thus, $h_i = \frac{1}{2k}$ maximizes firm's payoff function. Now let's assume there exists an equilibrium and $h_i \neq \beta$, then $h_i = \frac{1}{2k}$ is the necessary condition for a unique equilibrium for firm i. Following the same procedure we can obtain the necessary condition for firm j. Then we have $h_iQ_i + h_jQ_j = \frac{1}{2k}(Q_i+Q_j) = \beta(Q_i+Q_j)$, which signifies $\frac{1}{2k} = \beta$ or $h_i = \beta$, which contradicts the assumption. □

In contrast to the case when the clearance discount rate is decreasing, completely reveal product information or reveal nothing is not necessarily a dominant strategy when clearance discount rate is an increasing function of the proportion of unsold product.

Theorem 10. *When $\beta > \frac{1}{2}$, if $\frac{\partial \xi}{\partial h} \leq 0$, the unique Nash equilibrium of the game is $\theta_1^* = \theta_2^* = 1$; if $\frac{\partial \xi}{\partial h} > 0$, there exists no equilibrium where $\theta_1^* = \theta_2^* = \theta \in [0,1]$.*

Proof. When $\beta > \frac{1}{2}$, $h_i' < 0$, so the first order derivative on the payoff function is positive if $\frac{\partial \xi}{\partial h} \leq 0$, according to (24). Therefore, the unique equilibria is $\theta_i^* = \theta_j^* = 1$.

When $\beta > \frac{1}{2}$, we find that $\partial \pi_i[(Q_i, \theta_i), (Q_j^*, \theta_j^*)]/\partial \theta_i = 0$ if

$$h_i = \frac{1}{2k} \tag{5–29}$$

$$\Rightarrow \quad \frac{\theta_j^* Q_j^* - \theta_i Q_j^* + \theta_i \beta(Q_i + Q_j^*)}{\theta_i Q_i + \theta_j^* Q_j^*} = \frac{1}{2k}$$

$$\Rightarrow \quad \theta_i = \frac{(1-2k)\theta_j^* Q_j^*}{2k\beta(Q_i + Q_j^*) - 2kQ_j^* - Q_i}$$

Similarly,

$$\theta_j = \frac{(1-2k)\theta_i^* Q_i^*}{2k\beta(Q_j + Q_i^*) - 2kQ_i^* - Q_j}$$

Following a similar proof procedure as in Theorem 9, we can prove that $h_i = h_j = \frac{1}{2k}$ contradicts the existence of a unique Nash equilibrium. □

Proposition 1. When $\frac{\partial \xi}{\partial h} > 0$, neither complete nor zero information revelation is consistent with an equilibrium.

This proposition is naturally concluded from the results in Theorem 9 and Theorem 10.

Theorem 11. *Theorems 7 to 10 are true if quality information is not symmetrically distributed.*

Proof. If the quality of both firms' product are asymmetric distributed, we denote the σ_i as the portion of firm i's below average product. The unsold portion can be found as:

$$\tilde{h}_i = \begin{cases} \frac{\sigma_i \theta_i \beta(Q_i+Q_j)}{(Q_i\theta_i\sigma_i + Q_j\theta_j\sigma_j)} & \text{I. } \beta(Q_1+Q_2) \leq \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \\ \frac{\sigma_j\theta_j Q_j - \sigma_i\theta_i Q_j + \sigma_i\theta_i\beta(Q_i+Q_j)}{\theta_i Q_i\sigma_i + \theta_j Q_j \sigma_j} & \text{III. } Q_1 + Q_2 - \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \leq \beta(Q_1+Q_2) \\ \frac{(1-\theta_i\sigma_i)\beta(Q_i+Q_j) + \frac{1}{2}Q_j(\theta_i\sigma_i - \theta_j\sigma_j)}{(1-\theta_i\sigma_i)Q_i + (1-\theta_j\sigma_j)Q_j} & \text{II. otherwise} \end{cases} \tag{5–30}$$

By replacing θ_i as $\tilde{\theta}_i = \theta_i \sigma_i$, we find that it's indeed the same formula as in the symmetric case. $\square$

5.5. Non-homogeneous Product

In this section, we examine the game between two competing firms selling non-homogeneous products that are substitutable. We model this as a Bertrand game using price instead of quantity as decision variable. The strategy of each firm consists of its price and the proportion of information to reveal, namely the pair $\{P_i, \theta_i\}$. The output plan is determined by the estimated common demand as:

$$Q_i(P_i, P_j) = A - P_i + bP_j \tag{5–31}$$

The payoff function of firm i is:

$$\pi_i(P_i, \theta_i) \quad = \quad [Q_i - p(1-\xi)h_i(P_i, \theta_i)]P_i - C_i Q_i \tag{5–32}$$

Firm i chooses its decision rule $P_i(\cdot)$ and subsequently $\theta_i(\cdot)$ to maximize (29), given decision rules chosen by the other firms. The price/information pair $\{(P_1^*, \theta_1^*), (P_2^*, \theta_2^*)\}$ is a Nash equilibrium if for each firm i, (P_i^*, θ_i^*) solves

$$\max_{0 \le P_i < \infty; 0 \le \theta_i \le 1} \pi_i[(P_i, \theta_i), (P_j^*, \theta_j^*)] \tag{5–33}$$

$$= \max_{0 \le Q_i < \infty; 0 \le \theta_i \le 1} [Q_i - p(1-\xi)h_i(P_i, \theta_i)]P_i - C_i Q_i \tag{5–34}$$

Theorem 12. *Theorems 7 to 11 are true for duopoly in a non-homogeneous product market.*

Proof.

$$\begin{aligned} \pi_i(P_i, \theta_i) &= [Q_i - p(1-\xi)h_i(P_i, \theta_i)]P_i - C_i Q_i \\ &= [A - P_i + bP_j - p(1-\xi)h_i(P_i, \theta_i)]P_i - C_i(A - P_i + bP_j) \end{aligned}$$

The first order derivative on θ_i is:

$$\frac{\partial \pi_i}{\partial \theta_i} = -p(1-\xi)P_i \frac{\partial h_i}{\theta_i} \tag{5–35}$$

Since $h_i(\theta_i)$ follows the same formula that we found in previous section, we can prove the same theorems with non-homogeneous product in a similar procedure described before.

□

5.6. Concluding Remarks

Modern tracing technology such as RFID has made it possible to reveal item-level information of almost any product in any industry. We investigate the incentives to reveal such information in a competing market dealing with a homogeneous product. We find that firms are paid to completely reveal information if the common demand is volatile. If the demand is stable, however, it's worse off if competing firms reveal any of their product information. This result applies if the unsold product clearance discount rate is constant or decreasing. If the discount rate increases with the number of unsold, neither complete nor zero information revelation is consistent with an equilibrium for both firms. We also find that the above findings apply even if the item-level information is not symmetrically distributed.

The analysis presented here leaves unanswered many interesting questions in the field of item-level information revelation and sharing. One interesting problem in signalling is a firm's best information transmission strategy if it can selectively reveal information to maximize its own utility.

As an immediate extension to this chapter, we are working on the games of information revelation in a horizontally and vertically differentiated market. This research also has wide applications in supply chain management when unsold merchandize are usually stored in inventory for use in the next period rather than simply being cleared out at a discount.

APPENDIX A
MATLAB CODES

```
---------------------------------------------
-                                           -
-Simulation 1: Quality Control               -
-                                           -
---------------------------------------------




clear all;
for j=1:100 \% n=j ~ number of random cases
    n1=j;n2=j;

    for i=1:100 \% i ~ take average of 100 repeated experiments

        \%UNIFORM distribution ---------------------------------------
        \%Xs are uniformly distributed
        x1=rand(n1,1)-0.5;
        x2=rand(n2,1)-0.5;



        %y=G(x1,x2), y is a function of both x1 and x2
        y=exp(x1-x2);
        z(i)=mean(y);
```

```
yy=zeros(n1,n2);
x_1=x1*ones(1,n1);
x_2=ones(n2,1)*x2';
yy=exp(x_1-x_2);

zz(i)=max(max(yy));

%GAUSSIAN Distribution N(0,0.1)--------------------------------------
tmp=randn(500);

x1g=tmp(300:299+n1)'/10;
x2g=tmp(400:399+n2)'/10;

%y=G(x1,x2), y is a function of both x1 and x2
yg=exp(x1g-x2g);
zg(i)=mean(yg);



yyg=zeros(n1,n2);
x_1g=x1g*ones(1,n1);
x_2g=ones(n2,1)*x2g';
yyg=exp(x_1g-x_2g);

zzg(i)=max(max(yyg));

%N(0,0.3) ---------------------------------------------------
x1g3=tmp(300:299+n1)'*0.3;
```

```
x2g3=tmp(400:399+n2)'*0.3;

%y=G(x1,x2), y is a function of both x1 and x2
yg3=exp(x1g3-x2g3);
zg3(i)=mean(yg3);



yyg3=zeros(n1,n2);
x_1g3=x1g3*ones(1,n1);
x_2g3=ones(n2,1)*x2g3';
yyg3=exp(x_1g3-x_2g3);

zzg3(i)=max(max(yyg3));

%N(0,0.2) ---------------------------------------------------
x1g2=tmp(300:299+n1)'*0.2;
x2g2=tmp(400:399+n2)'*0.2;

%y=G(x1,x2), y is a function of both x1 and x2
yg2=exp(x1g2-x2g2);
zg2(i)=mean(yg2);



yyg2=zeros(n1,n2);
x_1g2=x1g2*ones(1,n1);
x_2g2=ones(n2,1)*x2g2';
yyg2=exp(x_1g2-x_2g2);
```

```
        zzg2(i)=max(max(yyg2));



    end
    % delta(j) ~ sample space following uniform distribution
    delta(j)=mean(zz-z);
    % delta(j) ~ sample space following normal distribution distribution (0.0.1)
    deltag(j)=mean(zzg-zg);
    % delta(j) ~ benefit of having normal distribution (0.0.2)
    deltag2(j)=mean(zzg2-zg2);
    % delta(j) ~ benefit of having normal distribution (0.0.3)
    deltag3(j)=mean(zzg3-zg3);



end

%Plots start here
plot(1:100, delta,'-.+',1:100, deltag, '--', 1:100, deltag2, '-.*', 1:100, deltag3, '-')
legend('unifor(0,1)','normal(0,0.1)','normal(0,0.2)','normal(0,0.3)')
xlabel('n, sample size');
ylabel('Informatioin visibility benefit');
```

APPENDIX B
CONSUMER BEHAVIOR IN ITEM-LEVEL REVEAL MARKET

B.1. Symmetric Distribution

I. $\beta(Q_1 + Q_2) \leq \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2)$

Player i's unsold portion of the his product is:

$$h_i = \frac{\theta_i \beta(Q_i + Q_j)}{(Q_i\theta_i + Q_j\theta_j)} \tag{B–1}$$

$$\begin{aligned}
\partial h_i/\theta_i &= \frac{(Q_i\theta_i + Q_j^*\theta_j^*)\beta(Q_i + Q_j^*) - Q_i\theta_i\beta(Q_i + Q_j^*)}{(Q_i\theta_i + Q_j^*\theta_j^*)^2} \\
&= \frac{Q_j^*\theta_j^*\beta(Q_i + Q_j^*)}{(Q_i\theta_i + Q_j^*\theta_j^*)^2} \\
&> 0
\end{aligned}$$

$$\begin{aligned}
\partial h_i/Q_i &= \frac{(Q_i\theta_i + Q_j^*\theta_j^*)\theta_i\beta - \theta_i^2\beta(Q_i + Q_j^*)}{(Q_i\theta_i + Q_j^*\theta_j^*)^2} \\
&= \frac{\theta_i\beta Q_j(\theta_j - \theta_i)}{(Q_i\theta_i + Q_j^*\theta_j^*)^2}
\end{aligned}$$

II.$Q_1 + Q_2 - \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \geq \beta(Q_1 + Q_2) \geq \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2)$

player i's unsold portion can be described as:

$$\begin{aligned}
h_i &= \left[\frac{(1-\theta_i)Q_i\left[\beta(Q_i + Q_j) - \frac{1}{2}(\theta_i Q_i + \theta_j Q_j)\right]}{(1-\theta_i)Q_i + (1-\theta_j)Q_j} + \frac{1}{2}\theta_i Q_i\right]/Q_i \\
&= \frac{(1-\theta_i)\beta(Q_i + Q_j) - \frac{1}{2}(1-\theta_i)\theta_j Q_j + \frac{1}{2}\theta_i(1-\theta_j)Q_j}{(1-\theta_i)Q_i + (1-\theta_j)Q_j} \\
&= \frac{(1-\theta_i)\beta(Q_i + Q_j) + \frac{1}{2}Q_j(\theta_i - \theta_j)}{(1-\theta_i)Q_i + (1-\theta_j)Q_j}
\end{aligned}$$

$$
\begin{aligned}
\partial h_i/\theta_i &= \frac{[(1-\theta_i)Q_i + (1-\theta_j^*)Q_j^*]\cdot(-\beta(Q_i+Q_j^*)+\frac{1}{2}Q_j^*)}{[(1-\theta_i)Q_i + (1-\theta_j^*)Q_j^*]^2} + \\
&\quad \frac{(1-\theta_i)Q_i\beta(Q_i+Q_j^*)+\frac{1}{2}Q_iQ_j(\theta_i-\theta_j)}{[(1-\theta_i)Q_i + (1-\theta_j^*)Q_j^*]^2} \\
&= \frac{-(1-\theta_j^*)Q_j^*\beta(Q_i+Q_j^*)+(1-\theta_j^*)Q_j^*\frac{1}{2}Q_j^*+\frac{1}{2}Q_iQ_j(1-\theta_j)}{[(1-\theta_i)Q_i + (1-\theta_j^*)Q_j^*]^2} \\
&= \frac{(1-\theta_j^*)Q_j[-\beta(Q_i+Q_j^*)+\frac{1}{2}Q_j^*+\frac{1}{2}Q_i]}{[(1-\theta_i)Q_i + (1-\theta_j^*)Q_j^*]^2} \\
&> 0, \text{ if } \beta < \tfrac{1}{2} \\
&< 0, \text{ if } \beta > \tfrac{1}{2} \\
&= 0, \text{ if } \beta = \tfrac{1}{2}
\end{aligned}
$$

III.$Q_1 + Q_2 - \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \leq \beta(Q_1 + Q_2)$ Player i's unsold portion can be described as:

$$
\begin{aligned}
h_i &= \left[Q_i - \frac{\theta_i Q_i(1-\beta)(Q_i+Q_j)}{\theta_i Q_i + \theta_j Q_j}\right]/Q_i \\
&= \frac{(\theta_i Q_i + \theta_j Q_j) - \theta_i(Q_i+Q_j) + \theta_i\beta(Q_i+Q_j)}{\theta_i Q_i + \theta_j Q_j} \\
&= \frac{\theta_j Q_j - \theta_i Q_j + \theta_i\beta(Q_i+Q_j)}{\theta_i Q_i + \theta_j Q_j}
\end{aligned}
$$

$$
\begin{aligned}
\partial h_i/\theta_i &= \frac{(\theta_i Q_i + \theta_j Q_j)(-Q_j + \beta(Q_i+Q_j)) - \theta_j Q_i Q_j + \theta_i Q_i Q_j - \theta_i Q_i \beta(Q_i+Q_j)}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&= \frac{\theta_j Q_j[-Q_j + \beta(Q_i+Q_j) - Q_i]}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&= \frac{\theta_j Q_j[(-1+\beta)(Q_i+Q_j)]}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&< 0
\end{aligned}
$$

$$
\begin{aligned}
\partial h_i/Q_i &= \frac{(\theta_i Q_i + \theta_j Q_j)\theta_i\beta - \theta_i(\theta_j Q_j - \theta_i Q_j + \theta_i\beta(Q_i + Q_j))}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&= \frac{\theta_i(\theta_j Q_j\beta - (\theta_j Q_j - \theta_i Q_j + \theta_i\beta Q_j)}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&= \frac{\theta_i Q_j(-1+\beta)(\theta_i + \theta_j)}{(\theta_i Q_i + \theta_j Q_j)^2}
\end{aligned}
$$

B.2. Skewed Distribution

I. $\beta(Q_1 + Q_2) \leq \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2)$

Player i's unsold portion of the his product is:

$$
h_i = \frac{(\theta_i + \sigma_i/Q_i)\beta(Q_i + Q_j)}{(Q_i\theta_i + Q_j\theta_j + \sigma_i + \sigma_j)} \tag{B–2}
$$

$$
\begin{aligned}
\partial h_i/\theta_i &= \frac{(Q_i\theta_i + Q_j^*\theta_j^*)\beta(Q_i + Q_j^*) - Q_i(\theta_i + \sigma_i)\beta(Q_i + Q_j^*)}{(Q_i\theta_i + Q_j^*\theta_j^*)^2} \\
&= \frac{(Q_j^*\theta_j^* - Q_i\sigma_i)\beta(Q_i + Q_j^*)}{(Q_i\theta_i + Q_j^*\theta_j^*)^2} \\
&> 0
\end{aligned}
$$

$$
\begin{aligned}
\partial h_i/Q_i &= \frac{(Q_i\theta_i + Q_j^*\theta_j^*)\theta_i\beta - \theta_i^2\beta(Q_i + Q_j^*)}{(Q_i\theta_i + Q_j^*\theta_j^*)^2} \\
&= \frac{\theta_i\beta Q_j(\theta_j - \theta_i)}{(Q_i\theta_i + Q_j^*\theta_j^*)^2}
\end{aligned}
$$

II.$Q_1 + Q_2 - \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2) \geq \beta(Q_1 + Q_2) \geq \frac{1}{2}(\theta_1 Q_1 + \theta_2 Q_2)$

player i's unsold portion can be described as:

$$\begin{aligned}
h_i &= \left[\frac{(1-\theta_i)Q_i\left[\beta(Q_i+Q_j)-\frac{1}{2}(\theta_iQ_i+\theta_jQ_j)\right]}{(1-\theta_i)Q_i+(1-\theta_j)Q_j}+\frac{1}{2}\theta_iQ_i\right]/Q_i \\
&= \frac{(1-\theta_i)\beta(Q_i+Q_j)-\frac{1}{2}(1-\theta_i)\theta_jQ_j+\frac{1}{2}\theta_i(1-\theta_j)Q_j}{(1-\theta_i)Q_i+(1-\theta_j)Q_j} \\
&= \frac{(1-\theta_i)\beta(Q_i+Q_j)+\frac{1}{2}Q_j(\theta_i-\theta_j)}{(1-\theta_i)Q_i+(1-\theta_j)Q_j}
\end{aligned}$$

$$\begin{aligned}
\partial h_i/\theta_i &= \frac{[(1-\theta_i)Q_i+(1-\theta_j^*)Q_j^*]\cdot(-\beta(Q_i+Q_j^*)+\frac{1}{2}Q_j^*)}{[(1-\theta_i)Q_i+(1-\theta_j^*)Q_j^*]^2}+ \\
&\quad \frac{(1-\theta_i)Q_i\beta(Q_i+Q_j^*)+\frac{1}{2}Q_iQ_j(\theta_i-\theta_j)}{[(1-\theta_i)Q_i+(1-\theta_j^*)Q_j^*]^2} \\
&= \frac{-(1-\theta_j^*)Q_j^*\beta(Q_i+Q_j^*)+(1-\theta_j^*)Q_j^*\frac{1}{2}Q_j^*+\frac{1}{2}Q_iQ_j(1-\theta_j)}{[(1-\theta_i)Q_i+(1-\theta_j^*)Q_j^*]^2} \\
&= \frac{(1-\theta_j^*)Q_j[-\beta(Q_i+Q_j^*)+\frac{1}{2}Q_j^*+\frac{1}{2}Q_i]}{[(1-\theta_i)Q_i+(1-\theta_j^*)Q_j^*]^2} \\
&> 0, \text{ if } \beta<\tfrac{1}{2} \\
&< 0, \text{ if } \beta>\tfrac{1}{2} \\
&= 0, \text{ if } \beta=\tfrac{1}{2}
\end{aligned}$$

III.$Q_1+Q_2-\frac{1}{2}(\theta_1Q_1+\theta_2Q_2)\leq\beta(Q_1+Q_2)$ Player i's unsold portion can be described as:

$$\begin{aligned}
h_i &= \left[Q_i-\frac{\theta_iQ_i(1-\beta)(Q_i+Q_j)}{\theta_iQ_i+\theta_jQ_j}\right]/Q_i \\
&= \frac{(\theta_iQ_i+\theta_jQ_j)-\theta_i(Q_i+Q_j)+\theta_i\beta(Q_i+Q_j)}{\theta_iQ_i+\theta_jQ_j} \\
&= \frac{\theta_jQ_j-\theta_iQ_j+\theta_i\beta(Q_i+Q_j)}{\theta_iQ_i+\theta_jQ_j}
\end{aligned}$$

$$
\begin{aligned}
\partial h_i/\theta_i &= \frac{(\theta_i Q_i + \theta_j Q_j)(-Q_j + \beta(Q_i + Q_j)) - \theta_j Q_i Q_j + \theta_i Q_i Q_j - \theta_i Q_i \beta(Q_i + Q_j)}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&= \frac{\theta_j Q_j[-Q_j + \beta(Q_i + Q_j) - Q_i]}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&= \frac{\theta_j Q_j[(-1 + \beta)(Q_i + Q_j)]}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&< 0
\end{aligned}
$$

$$
\begin{aligned}
\partial h_i/Q_i &= \frac{(\theta_i Q_i + \theta_j Q_j)\theta_i \beta - \theta_i(\theta_j Q_j - \theta_i Q_j + \theta_i \beta(Q_i + Q_j))}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&= \frac{\theta_i(\theta_j Q_j \beta - (\theta_j Q_j - \theta_i Q_j + \theta_i \beta Q_j)}{(\theta_i Q_i + \theta_j Q_j)^2} \\
&= \frac{\theta_i Q_j(-1 + \beta)(\theta_i + \theta_j)}{(\theta_i Q_i + \theta_j Q_j)^2}
\end{aligned}
$$

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