

Essays on Modelling and Analysis of Purchasing Process for Producers

by

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Essays on Modelling and Analysis of Purchasing Process for Producers

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*To my dear parents, my great brother,
and my beloved spouse...*

ABSTRACT

This thesis consists of three essays that address various practices and phenomena in the procurement processes of the producers. In the first two essays, we examine the group purchasing and e-auction practices by considering an industrial case. Specifically, in the first essay, we study a supply chain in which a group purchasing organization works with a set of buyers and suppliers under demand and price uncertainty. For the studied supply chain setting, we develop a two-period stochastic model and analytically derive the optimal decisions for all parties in the market. The results indicate that a group purchasing organization helps buyers and suppliers to mitigate demand and price risks effectively while collecting a premium by serving as an intermediary between them. In the second essay, we empirically examine a unique dataset collected from a third-party firm offering e-auction solutions for its corporate customers. With this effort, we provide an understanding of how the product category, the 2008 global financial crisis, the auction format, the number of bidders, the group purchasing, the contract type, and the auction platform ownership affect the buyer surplus achieved in the reverse auctions. Additionally, in the third essay, we study the purchasing, production, and sales policies for a continuous-review discrete material flow production/inventory system with fluctuating and correlated purchasing and sales prices, exponentially distributed raw material and demand inter-arrival times, and processing times. We model the system as a Markov decision process and analytically prove that the optimal purchasing, production, and sales strategies are state-dependent threshold policies. Additionally, the structural properties of the switching curves are established.

ÖZETÇE

Bu tez, üreticilerin tedarik süreçlerindeki farklı uygulamaları ve olguları ele alan üç ayrı çalışmadan oluşmaktadır. İlk iki çalışmada, grup satın alma ve e-ihale uygulamalarının kullanıldığı bir durum göz önünde bulundurulmuş ve bu iki uygulama incelenmiştir. Bu bağlamda, ilk çalışmada, bir grup satın alma organizasyonun, talep ve fiyat belirsizliği altında bir dizi alıcı ve tedarikçi ile çalıştığı tedarik zinciri ele alınmıştır. Ele alınan bu tedarik zinciri için iki periyotlu stokastik model geliştirilmiştir. Geliştirilen model kullanılarak, sistemdeki taraflara ait en iyi kararlar analitik olarak elde edilmiştir. Elde edilen sonuçlar bir grup satın alma organizasyonun alıcılar ve tedarikçiler arasında aracı bir kurum olarak faaliyet gösterirken kâr edebileceğini ve bu iki tarafın, talep ve fiyat risklerini etkin bir şekilde yönetmelerine yardım edebileceğini göstermiştir. İkinci çalışmada, kurumsal müşterileri için e-ihale çözümleri sunan aracı bir firmadan toplanan bir veri kümesi incelenmiştir. Bu incelemeyle, ürün kategorisinin, 2008 küresel finansal krizinin, ihale formatının, teklif veren tedarikçi sayısının, grup satın almanın, sözleşme türünün ve çevrimiçi ihale platformu mülkiyetinin ters ihalelerden elde edilen alıcı fazlasını nasıl etkiledikleri ortaya konulmuştur. Ayrıca, üçüncü çalışmada, sürekli gözden geçirilebilen kesik materyal akışına sahip bir üretim/envanter sistemi satış ve alış fiyatlarının ilintili olduğu ve dalgalandığı bir çevre göz bulunduru- larak incelenmiştir. Bu incelemede, sistemdeki hammadde ve talep gelişleri arasındaki sürelerin ve üretim zamanlarının üstel dağılıma uydukları kabul edilmiştir. İncelenen sistem bir Markov karar süreci olarak modellenmiş ve sisteme ait en iyi satın alma, üretim ve satış stratejilerinin duruma bağlı eşik politikaları olduğu analitik olarak ispat edilmiştir. Çalışmada değişim eğrilerine ilişkin yapısal özellikler de tartışılmıştır.

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nesnenin içinde en çok sevdiğim yürek, üstüne en çok titrediğim insan kalbi senin göğsündekidir.”

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Chapter 1

INTRODUCTION

In today's global market, many factors force producers to have a competitive advantage by focusing attention on their entire supply chain. Procurement is one of the most strategic activities involved in supply chain management as it ensures identification, sourcing, access, and management of the external resources that a producer requires for fulfilling its long- and short-term objectives. The procurement function encompasses a number of initiatives from spending the producer's funds in sourcing goods and services to establishing and managing relationships with the qualified suppliers. Therefore, it has a significant effect on the producer's overall performance, not only in terms of cost but also in terms of quality, innovation, responsiveness, and revenue generation.

With the recognition of the importance of the procurement function in overall performance, the majority of producers have started paying close attention to their procurement functions and adopting innovations in procurement processes. These efforts together with the rapid advent of the Internet technologies have led to the emergence of the e-auction and group purchasing implementations. In the recent years, the interest in the e-auction and group purchasing practices has been growing at a phenomenal rate since they are easy to use, cost-effective, and highly accessible.

Despite the growing adoption and popularity of the e-auction and group purchasing practices among the producers, we spotted that the existing literature has not addressed some of the points regarding these practices. To fill these gaps in the literature, we dedicate the first two essays of this dissertation to the examination of the e-auction

and group purchasing practices. In the following paragraphs, we give a brief summary of what kind of research models are developed in the first two essays to examine these two practices. Additionally, we discuss the contributions of both essays to the literature and the main findings derived from them.

In the first essay, we study a group purchasing practice. To do so, we present a stochastic model of a supply chain consisting of a set of buyers and suppliers and a group purchasing organization (GPO). The GPO combines orders from buyers in a two-period model. Demand and price in the second period are random. An advance selling opportunity is available to all suppliers and buyers in the first-period market. Buyers decide how much to buy through the GPO in the first period and how much to procure from the market at a lower or higher price in the second period. Suppliers determine the amount of capacity to sell through the GPO in the first period and to hold in reserve in order to meet demand in the second period. The GPO conducts a uniform-price reverse auction to select suppliers and decides on the price that will be offered to buyers to maximize its profit.

By determining the optimal decisions of buyers, suppliers, and the GPO, we answer the following questions: Do suppliers and buyers benefit from working with a GPO? How do the uncertainty in demand, the share of GPO orders in the advance sales market, and the uncertainty in price influence the players' decisions and profits? What are the characteristics of an environment that would encourage suppliers and buyers to work with a GPO? We conclude that a group purchasing organization helps buyers and suppliers to mitigate demand and price risks in an effective way and benefits all parties subject to certain conditions. Based on the numerical results, we observe that an increase in the share of GPO orders in the advance sales market encourages the suppliers to participate in the GPO and it yields an increase in the GPO's profit. When the demand variation increases the GPO's marginal benefit has a decreasing effect on the supplier's expected profit. In addition, an increase in demand variation leads to a decrease in the premium that the GPO collects from the other parties

by serving them as an intermediary. We find that high variation in the suppliers' production costs yields an increase in the GPO's and retailers' profits but adversely affects the supplier's profit.

The main contributions of the first essay are to develop a detailed analytical model of a supply chain with a GPO and a group of suppliers and to derive the conditions that lead to a beneficial cooperation for all parties in the market. In this context, it helps the understanding of the dynamics of the group purchasing organizations and provides researchers a better understanding of the impacts of the market dynamics -such as the purchasing price, demand variability, power of cooperation in terms of the partners' market shares, and so on- to this collaboration practice. We also believe that the insights into the operation of the group purchasing organization will be of value to the producers planning to participate in a group purchasing organization as the buyer or supplier.

In the second essay, we study an e-auction practice. More specifically, we empirically examine the impacts of the product category, the auction format, the 2008 global financial crisis, the group purchasing, the contract type, the platform ownership, and the number of participating suppliers on the buyer surplus obtained from e-auctions. To this end, we collect a unique dataset from a purchasing firm that offers e-auction solutions to its corporate customers. The dataset includes the transaction details of 15458 e-auction events which are performed in 14 different product categories by using three auctioning formats between years 2006 and 2016. Additionally, it covers two customer types, the group purchasing organization that is authorized to act as a purchasing agent for a group of individual firms and the individual buyers that make purchases on their own.

By using a standard Tobit model, we show that the product categories, the auction type, and the number of participating suppliers have significant effects on the decrease in the procurement prices with respect to the minimum of the initial submitted bids. On the basis of the results obtained from the Tobit model, we also ascertain that

the positive impact of having one more bidder in the auction on the buyer surplus decreases as the number of bidders is getting larger. The results indicate that the 2008 global financial crisis led to an increase in the buyer surplus. By employing the Welch's ANOVA and Games-Howell Pairwise Comparisons tests, we classify the product categories into three major groups based on their impacts on the average of the decrease in the procurement prices. The results reveal that there is an opportunity of achieving a large decrease in the procurement prices for the complex products such as ad, service, and high-tech manufacturing system. Additionally, we employ the student's t-test with unequal variances assumption to examine the impacts of the group purchasing, the contract type, and the platform ownership on the buyer surplus. With this analysis, we established the result that the average decrease in procurement prices is higher for the group purchasing option than for the individual buying option. It is also concluded that the types of contract between buyers and auctioneer and the platform ownership have no statistically significant effects on the average decrease in procurement prices.

The main contribution of the second essay is analyzing the buyer surplus, attempting a number of factors that have not been addressed in the literature. The insights derived in the essay could be of value to the producers planning to incorporate e-auctions and group purchasing programs into the procurement processes, since they provide a guideline on how to achieve a higher surplus by specifying the product category, auction format, and number of participating suppliers and identify the effect of being a member of the group purchasing on the buyer surplus. Additionally, as the majority of the factors that we deal with have not been addressed in the literature, we strongly regard that this essay provides researchers to the new understanding of how and what factors affect the buyer surplus within the reverse auction context.

Pursuing competitive advantage in the procurement process by adopting the new practices would not be sufficient to strengthen producers' procurement processes. Producers also need to consider a number of basic issues such as fluctuating and

correlated purchasing and sales prices, supplier selection, changing consumer patterns, and so on. Raw materials purchased from suppliers and finished goods sold to consumers usually represent the main components of the revenue and cost structures. Therefore, the operational hedging strategies handling the fluctuating purchasing and sales prices have a vital importance for the producers. Although there exists a need in practice for the operational hedging strategies handling the fluctuating market prices, the current literature does not give the necessary attention to this issue. The most of production/inventory models in the existing literature adopt the constant price assumption.

To address this need in the literature, in the third essay, we study fluctuating and correlated purchasing and sales prices in a continuous-review discrete material flow production/inventory system with exponentially distributed raw material and demand inter-arrival times. The sales and purchasing prices are driven by the random environmental changes that evolve according to a discrete state space continuous-time Markov process. In the system, there are raw materials and finished goods inventories. If an arriving raw material is purchased it is kept in the raw materials inventory. When a unit of raw material released into the system, it is processed there and then placed into the finished goods inventory. The system has a limited production capacity because a single server processes raw material individually with exponential processing times. With this setting, the system is controlled by purchasing, production, and sales decisions.

We model the system as an infinite-horizon Markov decision process under the average reward criterion and prove that the optimal purchasing, production, and sales strategies are state-dependent threshold policies. Additionally, we establish the monotonicity properties of the optimal policies and propose a linear programming formulation to numerically compute the policy parameters. Through a range of numerical experiments, we study the effects of the sales price variation, purchasing price variation, correlation between sales and purchasing prices, and customer arrival

rate on the system performance measures. It is observed that the negative correlation between the sales and purchasing prices, high sales price variation, high purchasing price variation, and high customer arrival rate yield an increase in the system profit. Additionally, we study how to allocate the limited capacity to the inventories when there is a limited capacity for assigning both raw materials and finished goods inventories. The numerical results show that increasing the capacity of the raw materials inventory leads to a higher profit for the system when the raw material arrival rate is the smallest one compared to the demand arrival and production rates. It is also observed that increasing the capacity of the finished goods inventory yields a higher profit for the system when the demand arrival rate is the smallest one compared to the raw material arrival and production rates. In addition, we examine under which circumstances the use of the optimal policy notably improves the system profit compared to the use of the *buy low and sell high* naive policy. It is found that the positive impact of using the optimal policy on the profit decreases with an increase in sales price variation, an increase in the purchasing price variation, and a negative correlation between the sales and purchasing prices.

The main contributions of the third essay are establishing the optimal purchasing, production, and sales policies for a production system operating with randomly fluctuating and correlated purchasing and sales prices and revealing the effects of the sales price variation, purchasing price variation, correlation between sales and purchasing prices, limited raw materials and finished goods inventories, and limited production capacity on the system performance measures. Hence, it extends the state of the art in the analysis of the continuous-review discrete material flow production/inventory system and helps us to understand how the fluctuations in the market prices affect the system performance. Additionally, we believe that the insights derived from the third essay would be beneficial for the producers managing their operations in an international basis and operating in the sectors depend on the commodity markets as these producers have to deal with the price fluctuations in the market.

The rest of this dissertation is organized as follows: Chapter 2, 3, and 4 address the first, second, and third essays, respectively. An overall conclusion of the dissertation and future works are provided in Chapter 5. Additionally, all the necessary proofs and supplementary materials for each chapter are given in the appendix devoted to the corresponding chapter.



Chapter 2

ANALYSIS OF A GROUP PURCHASING ORGANIZATION UNDER DEMAND AND PRICE UNCERTAINTY

Increasing intensity of competition has led companies to search for new business models that improve their competitiveness and profitability. In situations where companies are not able to achieve these goals on their own, they seek ways to partner with other entities in the market in order to benefit from possible cost reductions, demand pooling effects, higher capacity utilization, and improved flexibility to respond to uncertainty in the business environment (Tan and Akçay, 2014). The emergence of group purchasing organizations (GPOs) offers a practical framework to benefit from cooperation in purchasing. Briefly, the term GPO refers to an organization established to capitalize on the purchasing power of a group of businesses. The mechanism is also referred to as *joint procurement*, *purchasing consortium*, and *cooperative purchasing* (Nollet and Beaulieu, 2003).

Industry-specific GPOs are observed in many industries such as health care, manufacturing, food service, and pharmaceuticals (Nagarajan et al., 2010; Hu et al., 2012; Jin and Yu, 2015). Non-industry-specific GPOs operate across different sectors for procuring common products and fulfill aggregate non-strategic demand for indirect supplies and services. The purchasing volume obtained by a GPO through its members

and the possibility of mitigating demand and price risks during the selling season are the key factors that enable vendors to offer discounts. GPOs also offer many services in addition to collective procurement, such as supplier discovery, spend management, sourcing and contracting, data management, and price benchmarking.

This study is based on a project implemented in a company that mainly manages collective procurement of indirect materials and services for its customers. Tan (2014) describes the project in detail as a case study. The company benefits from the economies of scale generated by the collective purchasing power of its customers, from its abilities to support customers' procurement divisions with the expertise of working in different business segments, and from managing supplier relations to ensure the quality of services and products. Accordingly, the business model used in this company is very similar to a group purchasing organization.

Suppliers used in a specific procurement project are selected according to the result of an auction. For example, the logistics services managed and executed by this company cover 810 destinations originating from 81 cities, exports to 65 countries, and imports from 17 countries. This company purchases thousands of containers in a single procurement project. Similarly, for the procurement of marketing materials such as promotional products and on-line portal services, more than 3000 different products and services are offered by organizing approximately 5000 auctions in a year.

Several questions need to be answered to facilitate the successful operation of a GPO: Do all parties in such a supply chain, namely, buyers, suppliers and GPO, always benefit from cooperation on purchasing? Otherwise, how and under what conditions does cooperation lead to non-beneficial outcomes for at least one of the parties? How do factors such as demand variation, wholesale price, supplier capacity, number of suppliers in the GPO, and number of buyers in the GPO influence the decision to participate? To address these research questions, we develop a detailed two-period stochastic model with demand and price uncertainty. As opposed to using a stylistic model that may not consider the details of operations in this industrial

setting, we fully characterize the optimal decisions of all parties in the detailed model described in this study and determine their expected profits, both with and without a purchasing organization. This analytic model allows us to analyze the effects of system parameters on these decisions and determine the conditions for successful GPO operations.

The main contributions of this study is developing a detailed analytic model of a supply chain with several suppliers and buyers as well as a GPO, and determining the conditions that lead to a beneficial cooperation for all parties in the market, based on an industrial project. To the best of our knowledge, this is the first analytic model in the literature that captures the dynamics of GPO operations and their effects on suppliers and buyers under price and demand uncertainty.

2.1 Literature Review

Numerous studies have examined cooperation among firms on production, distribution, and sales in supply chains (e.g., Gerchak and Diwakar (1991); Benjaafar et al. (2005); Tan and Akçay (2014); Yu et al. (2015)). In this section, we focus only on papers dealing with cooperation on procurement. Table 2.1 compares our work with the existing literature discussed in this section.

The notion of purchasing group organizations and the motives behind using GPOs are empirically discussed in Nollet and Beaulieu (2003), Tella and Virolainen (2005), and Erhun (2009). Only a limited number of studies have analyzed group purchasing organizations analytically. The papers that adopt the buyer's and/or GPO's perspective to analyze the group purchasing mechanisms are listed as follows. Saha et al. (2011) explore the decisions of large-demand buyers who join a GPO but later decide to directly procure from the supplier by renegotiation in an uncertain product price setting. They show that under high price uncertainty, a GPO acts as a demand aggregator for small buyers and as an information provider for large buyers. Chen and Roma (2011) show that group buying is always preferable for

Model	Demand	Supplier Capacity	Supplier Selection	GPO Problem	GPO	Supplier Problem	Buyer Problem		Supplier		Study																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																																												
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Two-Period	Single-Period	Random	Constant	Unapacitated	Capacitated	Contract Based	Virtual Option	Max Revenue	Min Cost	Not Considered	Single	Multiple	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 2.1: A summary table for the reviewed studies

homogeneous buyers in a supply chain consisting of a single manufacturer and two buyers who compete for end customers. However, for heterogeneous buyers, group purchasing is beneficial for the smaller buyer whereas it can be detrimental for a larger one. Li (2012) examines the implications of buyer heterogeneity in the context of group buying. The author finds that buyers can benefit from group buying when the sellers' bargaining power relative to that of the buyer group is low and/or buyers' preferences toward sellers are sufficiently differentiated. Zhou and Xie (2014) extend the work of Chen and Roma (2011) by considering the supplier as an active member who determines the discount schedule based on whether retailers choose individual or group buying. They find that group buying may hurt the efficiency of the supply chain, and a mixed discount schedule can be used to prevent these negative effects. In the work of Zhou et al. (2017), the potential role of group purchasing organizations in facilitating information sharing and coordinating horizontal competition is discussed from the buyer's perspective. The authors reveal that a GPO has the opportunity to gain significant advantages by addressing the system inefficiencies due to double marginalization and information asymmetry.

The number of papers that focus on the suppliers perspective in the group buying models is limited. Anand and Aron (2003) analyze the market and product characteristics that incentivize a supplier to use the group buying mechanism and compare the posted-pricing mechanism with the price-quantity schedule offered to the group buying customers in different scenarios involving demand uncertainty and economies of scale. Hu and Schwarz (2011) analytically address the effects of contract administration fees that GPOs charge to suppliers and whether GPOs can reduce procurement prices or total purchasing costs for their members. The authors show that eliminating contract administration fees and having buyers pay for GPOs' contracting services instead of suppliers would have no effect on the profit or cost function of any party in the market. Hu et al. (2012) examine the impact of a group purchasing organization on a health-care product supply chain by using a game-theoretic model that consists of

a profit-maximizing supplier with a quantity-discount schedule, a profit-maximizing GPO, and fixed-demand single-product. Yang et al. (2017) study the group buying process from the suppliers perspective and reveal that the number of GPO members strongly influences the suppliers decision either to contract or not with the GPO.

In addition, several studies consider group buying as a virtual sales channel for suppliers, and compare it with the option of selling only to individuals (e.g., Luo and Wang (2015); Tran and Desiraju (2017); Zhang and Liu (2017); Zhang et al. (2016)).

Table 2.1 shows that most of the existing literature considers the GPO as a virtual sales channel and does not explore the effect of group buying mechanism on the revenues of all parties in the supply chain. In addition, none of these studies explore the conditions that lead to a beneficial cooperation for all parties in the market when the suppliers have limited capacity. Our model mainly differs in the detailed operational modeling of a whole supply chain consisting of suppliers with limited capacity, buyers with random demand and price, and a GPO that works with a subset of profit-maximizing suppliers and buyers. The GPO is considered a risk-neutral expected-profit maximizer, whose procurement process is modeled as a uniform-price reverse auction mechanism. Price competition between buyers is not considered since they act as a price taker in the market where there are a large number of competitors. However, we allow buyers/suppliers who work with the GPO to negotiate directly with others in the market in the first and second periods before they decide to purchase/sell their commodities through the GPO. To the best of our knowledge, this is the first paper in the literature on GPOs to use detailed stochastic modeling of capacity setting, an auction mechanism, and advance order commitments in a two period setting in which demand and price are random.

2.2 Model

The supply chain we examine consists of h symmetrical suppliers, n identical buyers with stochastic demand for a single homogeneous product, and a GPO that operates

as an intermediary. Each party in the market is rational, risk-neutral, and seeks to maximize its expected profit.

The system is analyzed in two periods. The first period is referred to as *the advance selling period*, and the second period as *the selling season*. Advance selling is possible for all parties in the supply chain, and the market price for the advance sales is w_{fp} . As an alternative procurement channel, the GPO announces a price for the first period, w_r , to the potential buyers for the organization. The list of notations used in our model is given Table 2.2.

2.2.1 Time Sequence

The time sequence of the model is depicted in Figure 2.1. In the first period, each potential buyer i , $i \in \{1, 2, \dots, n\}$ decides on whether or not to use a GPO. When the option of working with a GPO results in a higher profit than the market option, the buyer procures all its advance orders at a unit price of w_r and submits the advance order quantity q_G to the GPO. Since buyers are identical, the GPO consolidates $Q_G = nq_G$ units under this setting. When the buyers use the GPO option in the first period, the structure of advance sales market will be as shown in Figure 2.2(b). Buyer i prefers to procure q_{NG} units from the advance selling market at a unit price of w_{fp} when the market option is more profitable. If the buyers prefer the market option, that is, when $q_G = 0$ for each buyer, the GPO cannot function. In the case where there is no functional GPO in the market, the advance sales market structure will be as shown in Figure 2.2(a).

If $q_G > 0$, the GPO will organize a uniform-price reverse auction among the potential suppliers in order to procure Q_G units. Each potential supplier j , where $j \in \{1, 2, \dots, h\}$, is invited to participate in the auction. When the option of working with the GPO is more profitable compared to the market option, supplier j informs the GPO that it will participate in the auction with an allocated capacity of Δ_G . Otherwise, supplier j will use the market option for both periods.

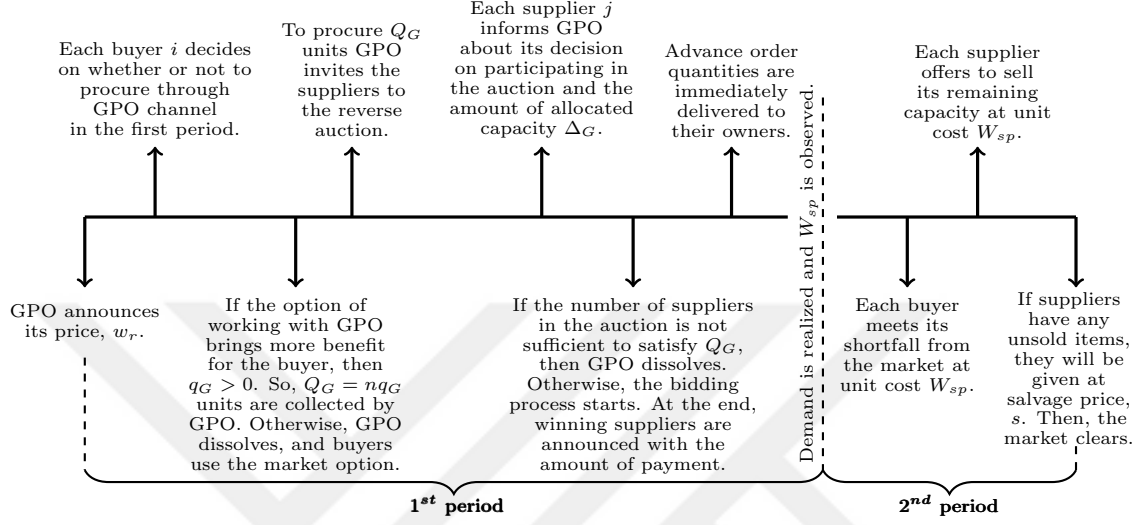


Figure 2.1: Time sequence for the model

The GPO is able to operate only when the total capacity allocated by the suppliers who participate in the auction is sufficient to provide Q_G units. When a sufficient number of suppliers do not participate in the auction, no clearing price can be determined. If the GPO cannot function, because buyers prefer the market option or are unable to induce suppliers to allocate the required capacity, the suppliers and the buyers use the market option for the first period.

When the conditions for conducting an auction are met, the participating suppliers submit their price bids to the GPO. The GPO sorts all the submitted bids in an ascending order and announces the winning bidders at the end of the first period. Since a uniform-price reverse auction is used to determine the price, each winning supplier receives a unit price equal to the lowest losing bid. The advance order quantities are delivered to the buyers immediately after the auction.

Since all deals between the potential buyers and suppliers are completed at the GPO auction in the first period, the losing suppliers cannot sell their capacities in the first period. The losing suppliers, as well as winning suppliers with remaining capacity, can sell their products in the second market, along with the suppliers who did not

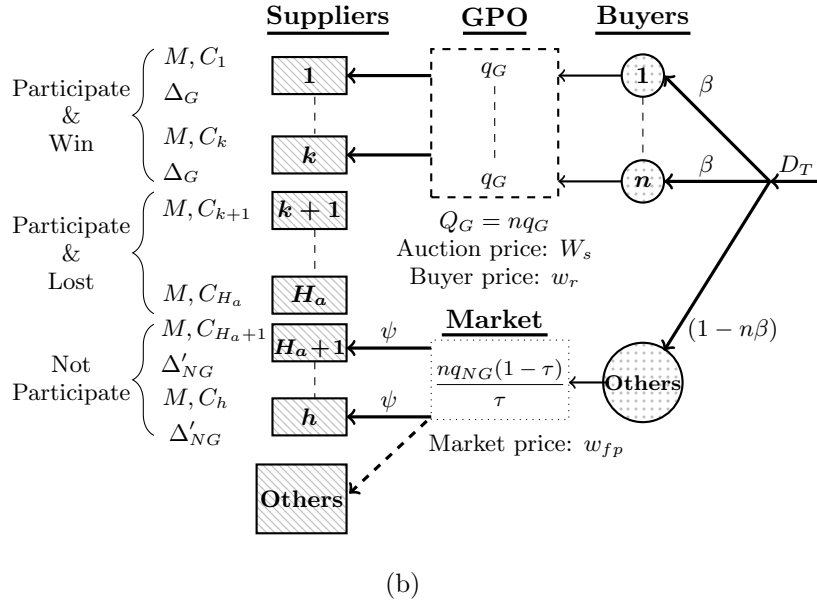
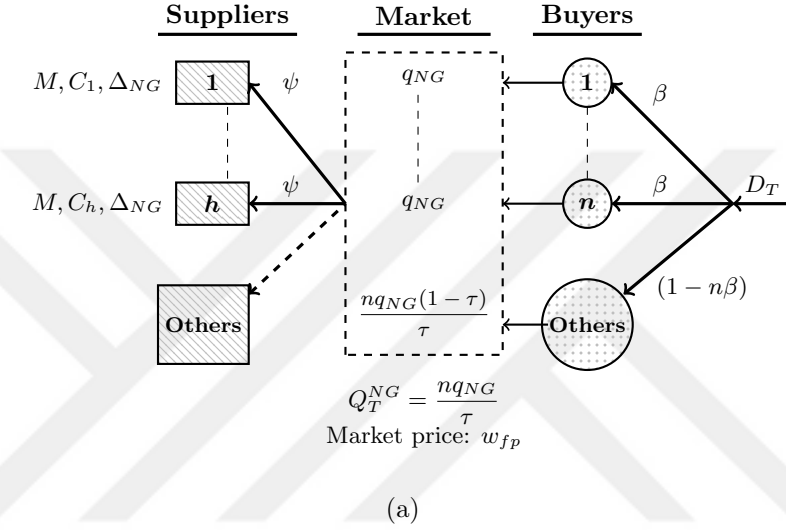


Figure 2.2: Illustrations of the models for the first period (a) when there is no GPO (b) when there is a functional GPO in the market

participate in the auction.

In the second period, the wholesale price at which buyers can absorb the additional supply and the demand are observed. Each buyer's demand is fully met with the additional supply from the suppliers in the market at the second period wholesale price. The buyers charge a retail price for each unit demanded. At the end of the second period, each supplier receives a salvage value for each unit left unsold. Finally, all the transactions are completed and the market clears.

2.2.2 Price Model

Since a competitive advance sales market consists of a large number of suppliers and buyers, each individual party in the market acts as a price taker. The market price for advance sales, w_{fp} , is considered exogenous and is perfectly known at the time suppliers and buyers decide to participate in the GPO before the selling season starts.

The price that the GPO charges to the buyers, w_r , is perfectly known to all buyers before they decide whether or not to participate in the GPO. The GPO determines w_r so as to maximize its expected profit. The price the GPO pays to the suppliers, W_s , is determined by an auction mechanism. Therefore, it is a random variable with the expectation $E[W_s] = w_s$.

The wholesale price in the second period, W_{sp} , is also a random variable with the expectation $E[W_{sp}] = w_{sp}$. All parties in the market perfectly know w_{sp} before the selling season starts. Since w_{fp} and w_r are constant prices known before the selling season starts, the wholesale price in the second period is considered as an independent variable from them. In addition, the wholesale price in the second period does not depend the total demand in the market. This consideration can be justified when the market is so competitive that the parties in the market are essentially price takers (Zhao et al., 2016).

The price charged by the buyers for customer sales in the second period, p , is constant and given exogenously. We assume that $p > w_{sp} > \max\{w_r, w_{fp}\}$ because

operating as a buyer in the market is clearly not profitable when $\max \{w_{sp}, w_r, w_{fp}\} \geq p$ and $w_{sp} > p > \max \{w_r, w_{fp}\}$. In addition, procuring in the first period either through the GPO or through the market does not create added value for the buyer when $\max \{p, w_r, w_{fp}\} \geq w_{sp}$. A case in which advance procurement is possible only through the GPO in this price setting can also be analyzed with w_{fp} set sufficiently high, that is, $w_{fp} > w_{sp}$. The salvage value is denoted by s .

2.2.3 Demand Model

Total demand in the market, D_T , includes the demand in the first and second periods. D_T is a random variable with the probability density function $f_{D_T}(x)$ and the cumulative density function $F_{D_T}(x)$. $F_{D_T}(x)$ is a continuous and twice-differentiable function where $F_{D_T}(x) = 0$ for all $x \leq 0$ and $f_{D_T}(x) > 0$ for all $x > 0$.

Buyer i , $i \in \{1, 2, \dots, n\}$, can get only a portion of the demand, depending on its market share β , $0 < \beta < 1/n$. The demand for buyer i is βD_T , which has a cumulative distribution function $F_B(y)$ and density function $f_B(y)$. The other buyers in the market who do not participate in the GPO manage their procurement activities on their own by using the market option for both periods. Their potential demand is the remaining portion of the total demand, that is, $(1 - n\beta) D_T$.

For both periods, all buyers in the market prioritize the suppliers who are invited to participate in the auction as preferred business partners. Accordingly, the other suppliers are used as a spot market when all potential suppliers for the GPO are unable to satisfy the demand in one of the periods.

When there is no functional GPO in the market, as shown in Figure 2.2(a), the buyers procure nq_{NG} units of advance orders in total at a unit price of w_{fp} . nq_{NG} captures τ percent of the whole advance sales market and this information is known to all market participants. In this setting, the total amount of advance orders procured in the whole supply chain, Q_T^{NG} , is described as $Q_T^{NG} = \frac{nq_{NG}}{\tau}$. Since q_{NG} is a decreasing function of w_{fp} and τ is a constant, the total amount of advance orders procured in

the whole supply decreases as the market price for advance sales increases.

The market share of a supplier in the first and second periods is denoted by ψ where $0 < \psi < \frac{1}{h}$. With no functional GPO in the market, as shown in Figure 2.2(a), supplier j can get a maximum of ψQ_T^{NG} units in the first period. Since the total demand decreases by Q_T^{NG} units at the end of the first period due to advance sales in the market, the potential suppliers share the remaining demand in the second period according to their market shares. The buyers procure additional supply if their demand in the second period is positive. Accordingly, where there is no functional GPO in the market, the second-period demand for supplier j , D_s^{NG} , follows a conditional distribution given that it is positive. The conditional cumulative distribution function is denoted with $F_{D_s^{NG}}(z)$, where $D_s^{NG} = \max\{0, \psi (D_T - Q_T^{NG})\}$ given that $\psi (D_T - Q_T^{NG}) > 0$.

When there is a functional GPO in the market, as depicted in Figure 2.2(b), the buyers who are members of the GPO procure $Q_G = nq_G$ units. Since the other buyers in the market still trade at the market price w_{fp} , their total advance order quantity remains the same, equal to $\frac{(1 - \tau) nq_{NG}}{\tau}$. In this setting, the total amount of advance orders procured in the whole supply chain is $Q_T^G = Q_G + \frac{(1 - \tau) nq_{NG}}{\tau}$ and the buyers who are members of the GPO capture $\frac{Q_G}{Q_T^G}$ percent of the whole advance sales market. Suppliers who participate in the auction compete for a portion of Q_G units in the first period, and the non-participating suppliers appropriate the remaining advance orders according to their market shares. After the first period, the total demand in the market decreases by Q_T^G units. As a result, the supplier's demand in the second period follows a conditional distribution, with the cumulative distribution function being $F_{D_s^G}(u)$, where $D_s^G = \max\{0, \psi (D_T - Q_T^G)\}$ given that $\psi (D_T - Q_T^G) > 0$.

2.2.4 Model of the Buyer

We consider buyers who enter the market to procure a homogeneous non-direct material, such as stationery, a service, or container space for transportation. Therefore, competition between buyers is not considered here.

Buyers always meet their demand either using the GPO in the first period and the market in the second period or using only the market in both periods; that is, there are no lost sales on the buyers' side.

Buyers pay an extra unit of transaction cost, e_r , for each item procured through their own efforts. This cost covers the expenses for supplier selection, transportation, and administrative services.

2.2.5 Model of the Supplier

For all suppliers, an opportunity to install capacity occurs well before the selling season. Therefore, we consider a case where supplier j , decides the capacity, M , before the selling season starts. In our setting, the production capacity can also be thought of as on-hand inventory before the selling season starts. For instance, the truck fleet or container space that a logistics company owns can also be considered as capacity in our setting.

Each of the potential suppliers for the GPO decides to allocate a portion of its capacity either to the GPO, which will pay a unit price W_s in the first period, or to the advance sales market, which will provide a unit price w_{fp} . The supplier chooses one of these two possible options according to its expected profit. When supplier j evaluates the option of working with the GPO as more profitable, it decides on the allocated capacity for the GPO, Δ_G , and the bid to be submitted in the auction. Δ_G cannot be partitioned by the GPO, and it cannot exceed the amount of advance orders consolidated in the GPO, that is, $0 \leq \Delta_G \leq Q_G$.

The production cost per unit, C_j , of supplier j , is assumed to be private information. Without any information, each party in the market believes that C_j is distributed uniformly over the interval $[\underline{c}, \bar{c}]$. To avoid trivial cases, we assume $\underline{c} > s$. Suppliers pay an extra unit transaction cost, e_s , for each item sold by their own efforts. This cost covers the expenses for transportation and administrative services.

The number of suppliers in the purchasing organization is treated as private infor-

mation by the GPO in order to avoid collusion. Otherwise, the suppliers may collude to manipulate the auction price, and the GPO will never become functional. Lacking information on the number of suppliers, supplier j uses a single-point estimation of the expected W_s to derive its profit function (for a similar assumption, see, e.g., Hao (2000)).

The single-point estimation of the expected auction price, $\hat{w}_s$, is based on historical data and is common for all suppliers. In the numerical experiments for our setting, we only consider cases where the point estimation of the expected auction price, $\hat{w}_s$, does not significantly deviate from the realized value, varying at most by $\pm 5\%$ of the realized value.

2.2.6 Model of the Group Purchasing Organization

The GPO invites h suppliers to work in the auction. However, the number of suppliers it will work with will depend on the capacities that the suppliers allocate to the GPO. Since each supplier submits an allocated capacity of Δ_G as a batch in the auction, the GPO will work with $k = \left\lceil \frac{Q_G}{\Delta_G} \right\rceil$ suppliers to fulfill the total advance order quantity coming from its customers. This implies that the amount of $k\Delta_G$ is going to be procured at the end of auction, and a portion of the purchased items, $(k\Delta_G - Q_G)$, remains in the hands of the GPO. The excess amount of the purchased products is assumed to be sold at the salvage price s .

If the GPO attempts to compete with suppliers by selling the remaining amount of supply in the second period, the market will collapse for the suppliers, and the GPO will be the monopolist. Accordingly, no suppliers may be willing to work with the GPO. The competition boards in practice make regulations on these issues to preserve the fair market competition and to prevent market manipulations. In this setting, making the GPO sell the extra amount of supply at the salvage value forces the GPO to match supply and demand as closely as possible.

The GPO also pays an extra unit transaction cost, e_g , for each procured item in

h : The number of the suppliers who are members of the GPO	n : The number of the buyers who are members of the GPO
j : The index for the suppliers who are members of the GPO	i : The index for the buyers who are members of the GPO
w_{fp} : The market price for the advance sales	w_r : The purchasing price offered by the GPO to the buyers in the first period
W_s : The price the GPO pays to the suppliers at the end of auction	w_s : The expectation of W_s , $E[W_s] = w_s$
e_g : The extra transaction cost that the GPO pays for each procured item in the auction	$\hat{w}_s$: The estimation of the expected auction price in which it is used by the supplier
e_r : The extra transaction cost that the buyer pays when the market option is used in the first period	e_s : The extra transaction cost that the supplier pays when the market option is used in the first period
W_{sp} : The wholesale price in the second period	w_{sp} : The expectation of W_{sp} , $E[W_{sp}] = w_{sp}$
p : The price charged by the buyers for the sales in the second period	s : The salvage price
q_G : The advance order quantity when a buyer chooses to work with the GPO option	Q_G : Total advance order quantity consolidated by the GPO
q_{NG} : The advance order quantity when a buyer chooses to work with the market option	Q_T^{NG} : Total amount of advance orders procured in the whole supply chain when there is no functional GPO
τ : The portion of the first period market captured by the buyers who are members of the GPO, $\tau = nq_{NG}/Q_T^{NG}$	Q_T^G : Total amount of advance orders procured in the whole supply chain when there is a functional GPO
γ : The minimum premium guaranteed to the buyers by the GPO	k : The order of the last winning supplier in the auction, $k = \lceil Q_G/\Delta_G \rceil$
C_j : The production cost of supplier j in which it is uniformly distributed over the interval $[\underline{c}, \bar{c}]$	H_a : The number of suppliers that participate in the auction
M : The total amount capacity a supplier has before the selling season starts	Δ_G : The capacity that is allocated by a participating supplier for the GPO in the first period

Table 2.2: A list of notations

Δ_{NG} : The capacity allocated by a participating supplier or non-participating supplier for the advance order market when there is no GPO β : The market share of a buyer on the total demand D_T : Total demand in the market including the first and second periods $F_{D_T}(x)$: The cumulative distribution function of the total demand, D_T $f_{D_T}(x)$: The probability density function of the total demand, D_T D_s^{NG} : The second-period demand for a supplier when there is no functional GPO in the market, $D_s^{NG} = \max\{0, \psi(D_T - Q_T^{NG})\}$ $F_{D_s^{NG}}(z)$: The conditional cumulative distribution function of D_s^{NG} θ : The lower bound for the probability of obtaining a functional GPO in the market	Δ'_{NG} : The capacity allocated by a non-participating supplier for the the advance order market when there is a functional GPO ψ : The market share of a supplier in the first and second periods βD_T : The demand for a buyer $F_B(y)$: The cumulative distribution function of the buyer's demand, βD_T $f_B(y)$: The probability density function of the buyer's demand, βD_T D_s^G : The second-period demand for a supplier when there is a functional GPO, $D_s^G = \max\{0, \psi(D_T - Q_T^G)\}$ $F_{D_s^G}(u)$: The conditional cumulative distribution function of D_s^G
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Table 2.2: (cont'd) A list of notations

the auction. This cost covers the expenses for transportation, supplier selection, and administrative services. The effect of economies of scale on the transaction cost is imposed considering that $\max\{e_s, e_r\} \geq e_g$.

Since the number of suppliers in the GPO is not public information in the market, the suppliers and buyers are not able to estimate the probability of existence of a functional purchasing organization. The GPO therefore specifies a lower bound for the probability of obtaining a functional GPO in the market, represented by θ . θ can be considered as a service level that is offered by the GPO to its partners. In practice, it is estimated from the historical data set and justified based on the experts' opinions. Specifically, the parties in the market use θ to decide whether to participate in the

auction. This information is shared truthfully with the other parties in the market (for a similar analysis, see, e.g., Moinzadeh (2002); Cachon and Marshall (2000)).

2.3 Analysis of the Model

In this section, we analyze the described model and present the analysis results. For clarity, we normalize all financial parameters to the salvage value s by setting $s = 0$ without loss of generality.

Before analyzing the model, we introduce a particular setting as an example to clarify the operation of a GPO and the modeling assumptions. In the model, we consider a particular setting where the buyers are identical in terms of the unit production cost, retailing price, and demand for analytical tractability of the model. This particular setting can be used to model firms that work with powerful buyers. For example, in textile-apparel industry, a large buyer works with many small-to-medium size firms and sets a price for its products considering the market conditions. A small firm cannot influence the market price dynamics and only compete to get an order. Although different styles of apparel products may vary greatly in their characters such as color and appearance, there is typically no significant difference in the production costs (Zhou et al., 2015). In such a setting, to decrease the production or procurement costs, the firms typically either join or form a group purchasing organization and collectively manage the procurement of indirect materials and services.

With the market structure mentioned above, let us consider collaborative procurement of containers used by a group of firms to ship products to a particular location. The market price for container shipments directly depends on the fuel cost used to transfer the items from one destination to another. As a result, the market price for the current market (the advance selling period) is typically known by all parties in the market. However, since the fuel price fluctuates according to the commodity market and since the global demand for containers changes with time, the market price for container shipments for the next period (the selling season) is uncertain. Therefore,

the suppliers and buyers generally use the advance sales option to mitigate the price risks effectively. Under this setting, the only difference among the suppliers is the fixed cost related to installed capacity, i.e., truck fleet and containers. Due to this fact, the suppliers differ from each other in terms of the production cost or service cost.

Before an auction takes place, the GPO performs a comprehensive cost analysis to determine the reasonable price and success probability for the project. Given the price offered by the GPO, the market price in the advance sales period, and the market price in the selling season, each firm first decides how many containers it will buy from the GPO. If the buyers are interested, the GPO consolidates these orders and invites suppliers to an auction for, say, a total of 2000 containers for its members. A supplier who has 100 containers available may decide to allocate 80 of them to the GPO, which organizes an auction for the procurement. We assume that if this supplier firm is deemed to be one of the winners of the auction, it supplies 80 containers, but does not accept requests for the supply of, say, 73 containers. The supplier solves an optimization problem to determine the number of containers that will be offered to the GPO in the advance sales period and the number of containers that will be kept for the market in the sales season. In this optimization, the suppliers know that if the total demand for containers is 10000 on average, the GPO, which procures 2000 containers in the advance selling period, decreases the available demand for them in the selling season. From this information, the GPO can determine how the buyers and suppliers will decide to optimize their expected profits. The GPO consolidates the information to determine the price that will be offered to the buyers to maximize its expected profit.

2.3.1 Analysis of Buyers

For a buyer who considers working directly with the suppliers in the first period, without joining the GPO, the expected profit, $E[\Pi_r^{NG}(q_{NG})]$, is

$$E[\Pi_r^{NG}(q_{NG})] = pE[\beta D_T] - (w_{fp} + e_r)q_{NG} - (w_{sp} + e_r)E[(\beta D_T - q_{NG})^+]. \quad (2.1)$$

The first term is the total revenue, the second term is the cost of advance purchasing, and the last term is the cost of purchasing in the second period.

For a buyer who considers the option of working with the GPO in the first period, the estimated profit function is given as

$$E[\hat{\Pi}_r^G(q_G)] = \theta (pE[\beta D_T] - w_r q_G - (w_{sp} + e_r) E[(\beta D_T - q_G)^+]) + (1 - \theta) E[\Pi_r^{NG}(q_{NG})]. \quad (2.2)$$

The first term represents the buyer's profit when there is a functional GPO in the market, and the second term denotes the buyer's profit when the GPO cannot operate due to an insufficient number of suppliers in the auction.

Note that the buyer analysis is based on the lower bound of the probability that a functional GPO operates in the market, θ . Using the probability that a functional GPO operates in the market instead of the lower bound, we can obtain the expected profit for the buyer, $E[\Pi_r^G(q_G)]$. Since θ is the lower bound, the buyer's expected profit is always more than or equal to the expected profit obtained by using the estimated probability.

The optimal advance order quantities for the market and GPO options are derived by maximization of the expected profit functions in Equations (2.1) and (2.2), respectively. The optimal order quantities for both the options are stated in the following proposition. The proofs are provided in Appendix A.1.

Proposition 1. *For a given w_r quoted by the GPO, the buyer will work with the GPO in the first period when $E[\hat{\Pi}_r^G(q_G^*)] - E[\Pi_r^{NG}(q_{NG}^*)] \geq 0$. In this case, the optimal advance order quantity is defined as*

$$q_G^* = \begin{cases} F_B^{-1} \left(1 - \frac{w_r}{w_{sp} + e_r} \right) & \text{if } w_{sp} + e_r \geq w_r \geq 0 \\ 0 & \text{otherwise} \end{cases}. \quad (2.3)$$

In addition, the total advance order quantity consolidated in the GPO is $Q_G^* = nq_G^*$.

On the other hand, when $E[\hat{\Pi}_r^G(q_G^*)] - E[\Pi_r^{NG}(q_{NG}^*)] < 0$, the buyer will use the market option in the first period and

$$q_{NG}^* = \begin{cases} F_B^{-1} \left(1 - \frac{w_{fp} + e_r}{w_{sp} + e_r} \right) & \text{if } w_{sp} + e_r \geq w_{fp} + e_r \geq 0 \\ 0 & \text{otherwise} \end{cases}. \quad (2.4)$$

Comparing $E[\hat{\Pi}_r^G(q_G^*)]$ with $E[\Pi_r^{NG}(q_{NG}^*)]$ gives the condition that induces the buyer to work with the GPO, as stated in the following proposition.

Proposition 2. *For the given parameters $w_{sp} + e_r \geq \max\{w_r, w_{fp} + e_r\}$, the buyer will work with GPO in first period when $w_r \leq w_{fp} + e_r$.*

2.3.2 Analysis of Suppliers

Each supplier decides whether to participate in the auction with no information on the number of suppliers in the GPO. Therefore, a supplier's profit function is derived from the estimated auction price and the lower bound of the probability that a functional GPO operates in the market. Supplier j does not expect to be one of the winners in the auction if its production cost, $C_j = c$, is greater than or equal to the estimated auction price, that is, $c \geq \hat{w}_s$. If the supplier prefers to participate in the auction rather than use the market option where $c \geq \hat{w}_s$, the supplier will have no chance of selling its capacity to the GPO, and will lose the opportunity to join the advance selling market. Therefore, where a supplier loses the auction with a GPO operating in the market, the supplier's expected profit function is defined as in the first component of the following equation; the rest represents a case with no functional GPO in the market:

$$\begin{aligned} E[\hat{\Pi}_{sj}^G(\Delta_{NG}) | c \geq \hat{w}_s] &= \theta((w_{sp} - e_s)E[\min\{M, D_s^G\}] - cM) \\ &\quad + (1 - \theta)((w_{fp} - e_s)\Delta_{NG}) \\ &\quad + (1 - \theta)((w_{sp} - e_s)E[\min(M - \Delta_{NG}, D_s^{NG})] - cM). \end{aligned} \quad (2.5)$$

On the other hand, a supplier whose production cost is less than $\hat{w}_s$ expects to be one of the winners in the auction. However, the probability of winning in the auction

cannot be determined by the supplier. The supplier derives its expected profit function with the expectation that it would definitely win at the end of the auction. Thus, the expected profit function of the supplier is defined as

$$\begin{aligned} E\left[\hat{\Pi}_{s_j}^G(\Delta_G, \Delta_{NG}) | c < \hat{w}_s\right] &= \theta(\hat{w}_s \Delta_G + (w_{sp} - e_s) E[\min\{M - \Delta_G, D_s^G\}]) \quad (2.6) \\ &+ (1 - \theta)((w_{fp} - e_s) \Delta_{NG}) . \\ &+ (1 - \theta)((w_{sp} - e_s) E[\min(M - \Delta_{NG}, D_s^{NG})]) - cM \end{aligned}$$

The first term is the expected profit of the supplier given that a GPO is operational and the supplier is one of the winners at the end of the auction. The rest represents a case in which no GPO can operate in the market.

Once a supplier decides to trade with the market in the first period, its expected profit does not change based on whether its production cost is greater than or equal to $\hat{w}_s$. Accordingly, the expected profit of the supplier selling to the market in the first period is the same for suppliers with $c < \hat{w}_s$ and $c \geq \hat{w}_s$, and is given as

$$\begin{aligned} E\left[\Pi_{s_j}^{NG}(\Delta'_{NG}, \Delta_{NG}) | c\right] &= \theta((w_{fp} - e_s) \Delta'_{NG} + (w_{sp} - e_s) E[\min(M - \Delta'_{NG}, D_s^G)]) \quad (2.7) \\ &+ (1 - \theta)((w_{fp} - e_s) \Delta_{NG}) \\ &+ (1 - \theta)((w_{sp} - e_s) E[\min(M - \Delta_{NG}, D_s^{NG})]) - cM. \end{aligned}$$

The first component expresses the profit function for a case where a GPO operates but the supplier does not participate in the auction. The last two terms represent a case where there is no functional GPO in the market. Essentially, for both of the components, the total revenue for the supplier can be expressed as the sum of revenues obtained from sales to individual buyers in the first and second periods. However, since the second-period demand for supplier j directly depends on whether or not a functional GPO operates in the market, the allocated capacity for the advance order market changes. When no GPO can operate due to an insufficient number of suppliers in the auction, a non-participating supplier allocates Δ_{NG} units of its capacity for the advance order market. On the other hand, if an operational GPO exists in the market, the allocated capacity for the first period will be Δ'_{NG} .

The optimal allocated capacities for all the options are expressed in Proposition 3.

Proposition 3. *If the GPO yields more benefits for supplier j , with production cost less than the estimated auction price, the supplier will be eager to trade with the GPO. In this case, it allocates*

$$\Delta_G^* = \begin{cases} \text{If } w_{sp} - e_s \geq \hat{w}_s \geq 0, \\ \min \left\{ \max \left\{ 0, M - F_{D_s^G}^{-1} \left(1 - \frac{\hat{w}_s}{w_{sp} - e_s} \right) \right\}, Q_G^* \right\} \\ \text{Otherwise,} \\ 0 \end{cases} . \quad (2.8)$$

Supplier j never assigns a portion of its capacity to the GPO if its production cost c is greater than or equal to the estimated auction price, that is, $c \geq \hat{w}_s$.

When a supplier evaluates the market option as more beneficial, the portion of its capacity that it will allocate to the buyers in the market when the GPO is operational is given as

$$\Delta_{NG}'^* = \begin{cases} \text{If } w_{sp} - e_s \geq w_{sp} - w_{fp} \geq 0, \\ \min \left\{ \max \left\{ 0, M - F_{D_s^G}^{-1} \left(\frac{w_{sp} - w_{fp}}{w_{sp} - e_s} \right) \right\}, \psi \frac{nq_{NG}(1 - \tau)}{\tau} \right\} \\ \text{Otherwise,} \\ 0 \end{cases} \quad (2.9)$$

The portion allocated to the buyers when no GPO is operational in the market is given as

$$\Delta_{NG}^* = \begin{cases} \text{If } w_{sp} - e_s \geq w_{sp} - w_{fp} \geq 0, \\ \min \left\{ \max \left\{ 0, M - F_{D_s^{NG}}^{-1} \left(\frac{w_{sp} - w_{fp}}{w_{sp} - e_s} \right) \right\}, \psi Q_T^{NG} \right\} \\ \text{Otherwise,} \\ 0 \end{cases} . \quad (2.10)$$

The condition that induces a supplier to favorably evaluate the option of working with the GPO, in terms of the expressions of allocated capacities for the different cases above, is stated in the following proposition.

Proposition 4. *When a supplier's production cost is less than the estimated auction price, the supplier considers the GPO beneficial to it if and only if the following inequality holds.*

$$\Delta_{NG}^* \left(1 - \frac{w_{fp} - e_s}{w_{sp} - e_s}\right) - \Delta_G^* \left(1 - \frac{\hat{w}_s}{w_{sp} - e_s}\right) + \int_0^{M - \Delta_{NG}^*} F_{D_s^G}(u) du - \int_0^{M - \Delta_G^*} F_{D_s^G}(u) du \geq 0 \quad (2.11)$$

When $\hat{w}_s \geq w_{fp} - e_s$ and $w_r \leq w_{fp} + e_r$, the above inequality definitely holds. With $c < \hat{w}_s$, therefore, supplier j believes that the GPO will be beneficial.

On the other hand, suppliers whose production costs are greater than or equal to the estimated auction price would never believe that the GPO is beneficial for them. Therefore, they would never participate in the auction.

Proposition 4 implies that given $c < \hat{w}_s$, supplier j definitely chooses the GPO option in the market when it believes the auction price will be higher than the market price in the first period and the GPO plays a market maker role for the suppliers.

Since a supplier uses the estimated auction price to make its capacity allocation decision, its expected profit will be different than the estimated one. With the chosen optimal capacity allocations, the expected profit function for any supplier j is

$$\begin{aligned} E \left[\Pi_{s_j}^G (\Delta_G^*, \Delta_{NG}^*) | c \right] &= P \{ H_a \geq k + 1 \} P \{ c < W_s \} w_s \Delta_G^* \\ &\quad + P \{ H_a \geq k + 1 \} P \{ c < W_s \} (w_{sp} - e_s) E \left[\min \{ M - \Delta_G^*, D_s^G \} \right] \\ &\quad + P \{ H_a \geq k + 1 \} P \{ c \geq W_s \} ((w_{sp} - e_s) E \left[\min \{ M, D_s^G \} \right]) \\ &\quad + P \{ H_a < k + 1 \} (w_{fp} - e_s) \Delta_{NG}^* - cM \\ &\quad + P \{ H_a < k + 1 \} (w_{sp} - e_s) E \left[\min (M - \Delta_{NG}^*, D_s^{NG}) \right] \end{aligned} \quad (2.12)$$

where w_s is the expected auction price, H_a is the number of bidders in the auction, and $P \{ H_a \geq k + 1 \}$ is the probability of obtaining an operational GPO in the market. These terms are detailed in the next section.

Since the auction price is the lowest losing bid, the probability of being one of the winners in the auction is equivalent to $P\{C_j = c < W_s\} = P\{C_j = c < C_{(k+1)}\}$. Considering the fact that for any selected supplier j , c can be assigned to k empty places before the $(k+1)^{th}$ order and it can be selected from h suppliers, this probability is defined as $P\{C_j = c < C_{(k+1)}\} = \frac{k}{h}$.

2.3.3 Analysis of Auction

With incomplete information on the suppliers' production costs, the GPO uses a uniform-price reverse auction to select the suppliers and determine the purchasing price. The uniform-price reverse auction is a multi-unit auction in which a fixed number of identical units of a homogeneous commodity are purchased for the same price (Krishna, 2002). In our model, the assumptions on the auction and suppliers guarantee that the discriminatory auction, in which identical units of a single item are sold at different prices, and the uniform-price auction yield the same expected revenue for the GPO. We next investigate the bidding behavior of the suppliers when they participate in such a purchasing organization with a uniform-price reverse auction in a two-period stochastic model. Proposition 5 states that bidding a value other than the supplier's actual production cost does not improve the supplier's payoff in this structure.

Proposition 5. *When every bidder demands just a single batch, and can indeed bid for only one batch, a Bayesian-Nash equilibrium results such that all bidders reveal their true condition; that is, the suppliers bid at their actual production costs.*

The above proposition shows that the dominant strategy for a supplier is to reveal the truth and bid at its actual cost. The main rationale behind this result is that the supplier cannot set Δ_G strategically to manipulate the auction price due to lack of information on the number of suppliers in the GPO.

If the conditions required for a GPO to operate in the market are met, only suppliers whose production cost is less than $\hat{w}_s$ might participate in the auction. Since

the unit production cost is a supplier's private information, and the other parties in the market only know the distribution that it follows, the number of suppliers that participate in the auction, H_a , is a random variable. It is expressed as

$$H_a = \sum_{j=1}^h I_{\{C_j < \hat{w}_s\}} \quad (2.13)$$

where I is an indicator function that takes 0 or 1 depending on the condition $C_j < \hat{w}_s$. Therefore, H_a has a binomial distribution with the following probability mass function:

$$P\{H_a = m\} = \binom{h}{m} p_a^m (1 - p_a)^{h-m} \text{ where } p_a = P\{C_j < \hat{w}_s\} = \frac{\hat{w}_s - \underline{c}}{\bar{c} - \underline{c}}. \quad (2.14)$$

To be able to perform a uniform-price reverse auction, the number of suppliers in the auction must be greater than or equal to $(k + 1)$. Otherwise, the clearing price cannot be determined and no purchasing organization would be functional. Therefore, the probability of obtaining a functional GPO in the market is defined as

$$P\{H_a \geq k + 1\} = \sum_{m=k+1}^h \binom{h}{m} p_a^m (1 - p_a)^{h-m} \text{ where } k = \left\lceil \frac{Q_G}{\Delta_G} \right\rceil. \quad (2.15)$$

When there is a functional GPO in the market, the $(k + 1)^{st}$ minimum of H_a uniformly distributed numbers is paid to all winners. The expectation regarding this payment is given in the following proposition.

Proposition 6. *When the production cost of each supplier who participates in the auction is uniformly distributed between $\underline{c}$ and $\hat{w}_s$ and when the number of bidders H_a follows a binomial distribution, the expected auction price, w_s , is defined as in the following expression:*

$$\begin{aligned} w_s &= E[W_s] = E[C_{(k+1)} | H_a \geq k + 1] \\ &= \underline{c} + (\hat{w}_s - \underline{c}) \left(\frac{k + 1}{(h + 1)p_a} - \frac{\binom{h-1}{k} h p_a^k (1 - p_a)^{h-k}}{(h + 1)P\{H_a \geq k + 1\}} \right) \end{aligned} \quad (2.16)$$

2.3.4 Analysis of the Group Purchasing Organization

The risk-neutral GPO sets the value of w_r by solving the following optimization problem:

$$\max_{w_r \in [0, (1-\gamma)(w_{fp} + e_r)]} E[\Pi_{GPO}] = P\{H_a \geq k + 1\} (Q_G^* w_r - k \Delta_G^* (w_s + e_g)) \quad (2.17)$$

$$\text{s.to } E[\Pi_r^G(q_G^*)] - E[\Pi_r^{NG}(q_{NG}^*)] \geq \mathcal{E} \quad (2.18)$$

$$P\{H_a \geq k + 1\} \geq \theta \quad (2.19)$$

$$E[\Pi_{GPO}] \geq 0 \quad (2.20)$$

Equation (2.17) gives the GPO's expected profit, that is, the difference between the total amount of money received from the buyers and the total amount of money paid to suppliers plus transaction expenses.

The individual rationality constraint for a single buyer is defined as in Equation (2.18). The GPO knows that buyers would not join the organization without an incentive—the increased profit that the GPO option provides. To encourage buyer participation, the GPO provides a minimum premium to each buyer, setting its offered price at the maximum of $(1 - \gamma)(w_{fp} + e_r)$, where $\gamma \in [0, 1]$. Hence, it guarantees that buyers obtain premiums from the GPO. Thus, the incentive rationality constraint for the buyers would always be greater than a positive $\mathcal{E}$ value. Since potential buyers are identical, it is sufficient that a single buyer meet this constraint.

Since the GPO shares the lower bound of the probability that a GPO operates in the market with its partners, Equation (2.19) ensures that the probability of a functional GPO operating in the market is greater than or equal to this value. Finally, Equation (2.20) ensures that operating in the market is beneficial for the GPO.

Since k is defined as the rounded-up value of a fraction involving Q_G^* in Equation (2.15), the objective function has a discontinuous form, which means it contains one or more breaks on $[0, (1 - \gamma)(w_{fp} + e_r)]$. In addition, Q_G^* and Δ_G^* , defined in Equations (2.3) and (2.8), are the partial functions of w_r . From these results, the above problem has a non-linear objective function that does not yield a closed-form solution when

optimized with respect to w_r for the general case. In order to determine the optimal value of w_r numerically, we use a uniform line search algorithm over the closed interval $[0, (1 - \gamma)(w_{fp} + e_r)]$. w_r , which has the largest value for Equation (2.17) and satisfies all the constraints, is picked as the solution of the problem. If there is no solution such that all constraints are satisfied, then it is concluded that the GPO would not be functional for that set of system parameters.

2.4 Numerical Results

In this section, we investigate the effects of system parameters by using an analytic model that describes the optimal decisions of suppliers, buyers, and the GPO through numerical experiments. All the analytic results are validated by a simulation of the system. Since the results depend on the optimal decisions of the buyers, suppliers, and the GPO, the analytic results derived in this study allow evaluation of the system much more efficiently compared to a similar performance evaluation study based on simulation.

For all instances, the system parameters are set as follows: The retail price p , which is charged from the end customer for each of the demanded units, is assigned as $p=45$. Since it would not affect any decisions that parties in the market take, only a single value for this parameter is considered in the numerical analysis. The minimum premium guaranteed to the buyers by the GPO set to $\gamma=10\%$ for all instances, as stated in the work of Tan (2014). The lower bound of the probability of obtaining a functional GPO should be chosen as high as possible, therefore it is set to $\theta=90\%$. The extra transaction costs for the buyers, suppliers, and the GPO are selected as $e_r=5$, $e_s=3$, and $e_g=1$, respectively. In all instances, the total demand distribution, D_T , is assumed to be uniform. Under the uniform demand assumption, Proposition 1, Proposition 3, and Proposition 4 can be stated in a closed form. The closed-form expressions for the uniformly distributed demand case are given in Appendix A.2. In addition, we only consider cases where the point estimation for the expected auction

price $\hat{w}_s$ varies at most by $\pm 5\%$ of its realized value, that is, $|w_s - \hat{w}_s| \leq 0.05w_s$, in order to limit the effects of wrong estimations on the results.

We use a wide range of test problems in order to assess the effects of buyers' and suppliers' market shares, the variability of production cost, the variability of total demand, the market price for advance sales, and the share of GPO orders in the advance sales market on the profits of the parties in the supply chain. For this purpose, we consider variations around the base scenario introduced in above. At the beginning of each subsection where we address the effect of considered parameters, we present the details related to how these variations are configured. For the range of parameters analyzed in the numerical experiments, the GPO's optimization problem defined in Section 2.3.4 gives the optimal price offered by the GPO to its customers as $w_r^* = (1 - \gamma)(w + e_r)$. That means that the buyers enjoy higher profits compared to the market option, since w_r^* is always less than the sum of transaction expenses for the buyer and market price for the first period, when GPO is functional. With these arguments, the premium that the buyer gains from the GPO can be directly determined for a given set of parameters. Therefore, the numerical analysis related to the buyer's profit is not presented in this section. In addition, to see whether a GPO is indeed beneficial for supplier j , we define $\nabla \Pi_{s_j} = E[\Pi_{s_j}^G(\Delta_G^*, \Delta_{NG}^* | c)] - E[\Pi_{s_j}^{NG}(\Delta_{NG}^{*'}, \Delta_{NG}^* | c)]$ and use it in the numerical analysis of the supplier's expected profit.

2.4.1 Effects of Buyer's and Supplier's Market Shares

For the analysis of the impacts of buyer's and supplier's market shares on the profits of the parties in the supply chain, we define a basic scenario where $w_{sp}=30$, $w_{fp}=20$, $p=45$, $n=10$, $\tau=70\%$, $\underline{d}_T=50000$, $\bar{d}_T=80000$, $\underline{c}=10$, $\bar{c}=12$, $e_r=5$, $e_s=3$, $e_g=1$, $M=10000$, $\theta=90\%$, and $\gamma=10\%$. We create three different variations of the scenario considering the following values for the buyer's market share: $n\beta=0.33$ ($n=10$, $\beta=0.033$), $n\beta=0.50$ ($n=10$, $\beta=0.05$), and $n\beta=0.67$ ($n=10$, $\beta=0.067$). In each variation, the suppliers' total market share, $h\psi$, is changed from 0.02 to 0.98 with an incremental value of 0.02.

For the given values of buyer's market share and suppliers' total market share, we generate a set of problem instances by ranging the number of suppliers from 30 to 80, i.e., $h \in \{30, 31, 32, \dots, 80\}$. With this configuration setting, 2499 problem instances are generated for every variation of the basic scenario.

In each set of problem configured for the given values of buyer's market share and suppliers' total market share, the average, maximum, and minimum of the profits that the GPO and supplier obtain are determined. They are depicted for the GPO and supplier in Figure 2.3 and Figure 2.4, respectively.

Having partners with a strong market position in terms of market share in the supply and demand markets affects the expected profit functions of the GPO and the suppliers. Figure 2.3 shows that an increase in the buyer's market share has a positive impact on the expected profit of the GPO. Because, the GPO sells more advance orders to its customers with an increase in β , the revenue from advance sales increases. Figure 2.3 also indicates that the average profit level of the GPO increases as the market share of a supplier increases for a given $n\beta$. The main rationale behind this pattern is that the amount of excess inventory potentially due to batch selling in the auction, $(Q_G - k\Delta_G)$, decreases as the supplier's market share increases.

Figure 2.4 shows that the GPO is highly beneficial for the supplier when the total market share of the suppliers in the GPO is less than $h\psi = 0.2$. As the market share of a supplier increases for a given $n\beta$, the marginal benefit of the GPO decreases for the supplier and converges to almost zero after $h\psi = 0.9$.

Figure 2.4 also indicates that an upward change in the buyer's market share increases the benefit that a supplier derives from the GPO. However, with an increase in the supplier's market share, the positive impact of the high β in the expected profit function of supplier also disappears. These observations imply that the GPO serves as a market maker for the supplier in case of a small market share for a single supplier, ψ , and a high market share for a single buyer in the GPO, β , so that the supplier benefits more from the GPO.

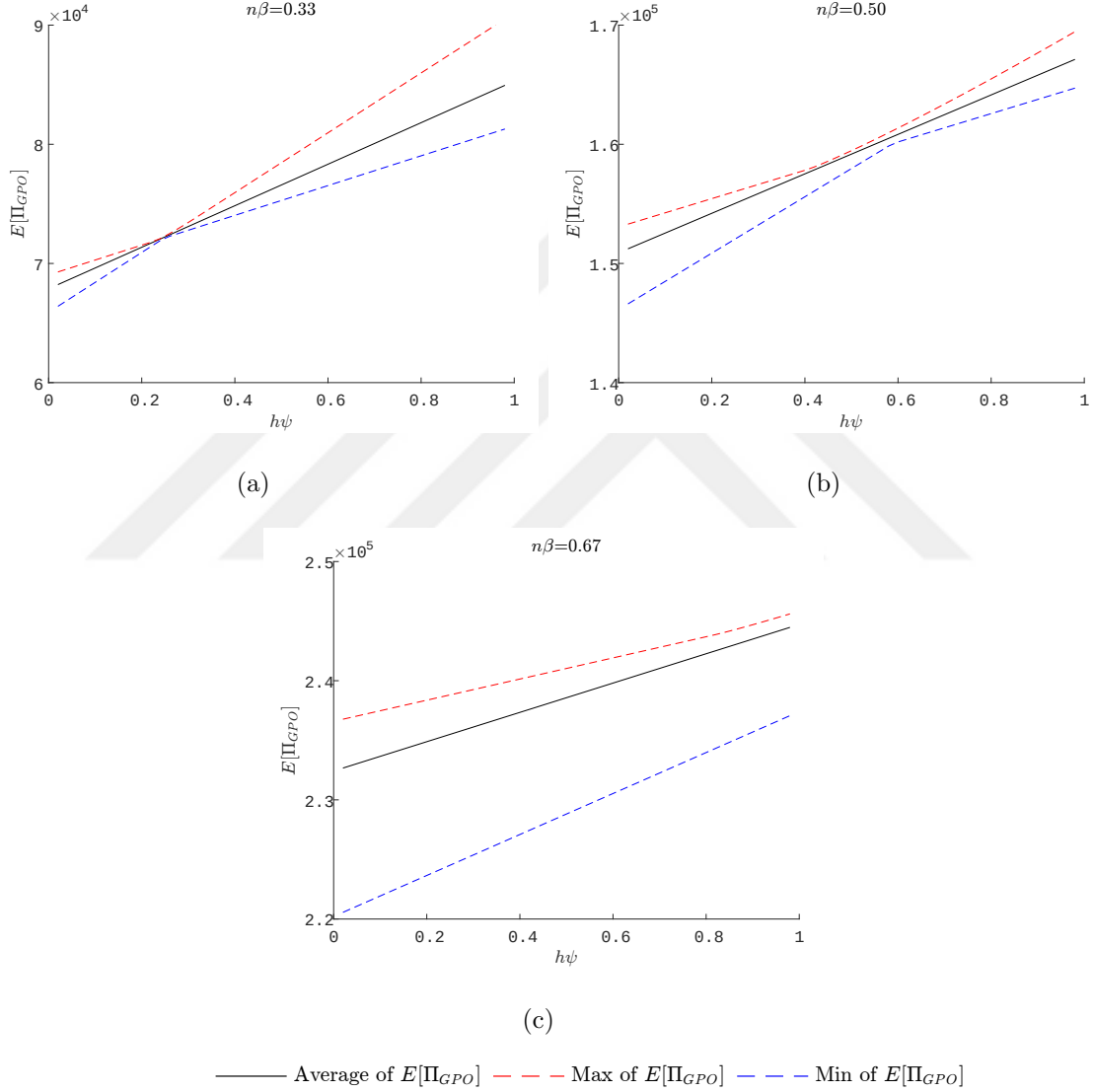


Figure 2.3: Impact of suppliers' total market shares on the GPO's expected profit function when $w_{sp} = 30$, $w_{fp} = 20$, $p = 45$, $n = 10$, $h \in \{30, 31, \dots, 80\}$, $\tau = 70\%$, $\underline{d}_T = 50000$, $\bar{d}_T = 80000$, $\underline{c} = 10$, $\bar{c} = 12$, $e_r = 5$, $e_s = 3$, $e_g = 1$, $M = 10000$, $\theta = 90\%$, $\gamma = 10\%$ (a) buyers' total market share $n\beta = 0.33$ ($n = 10$, $\beta = 0.033$) (b) buyers' total market share $n\beta = 0.50$ ($n = 10$, $\beta = 0.05$) (c) buyers' total market share $n\beta = 0.67$ ($n = 10$, $\beta = 0.067$)

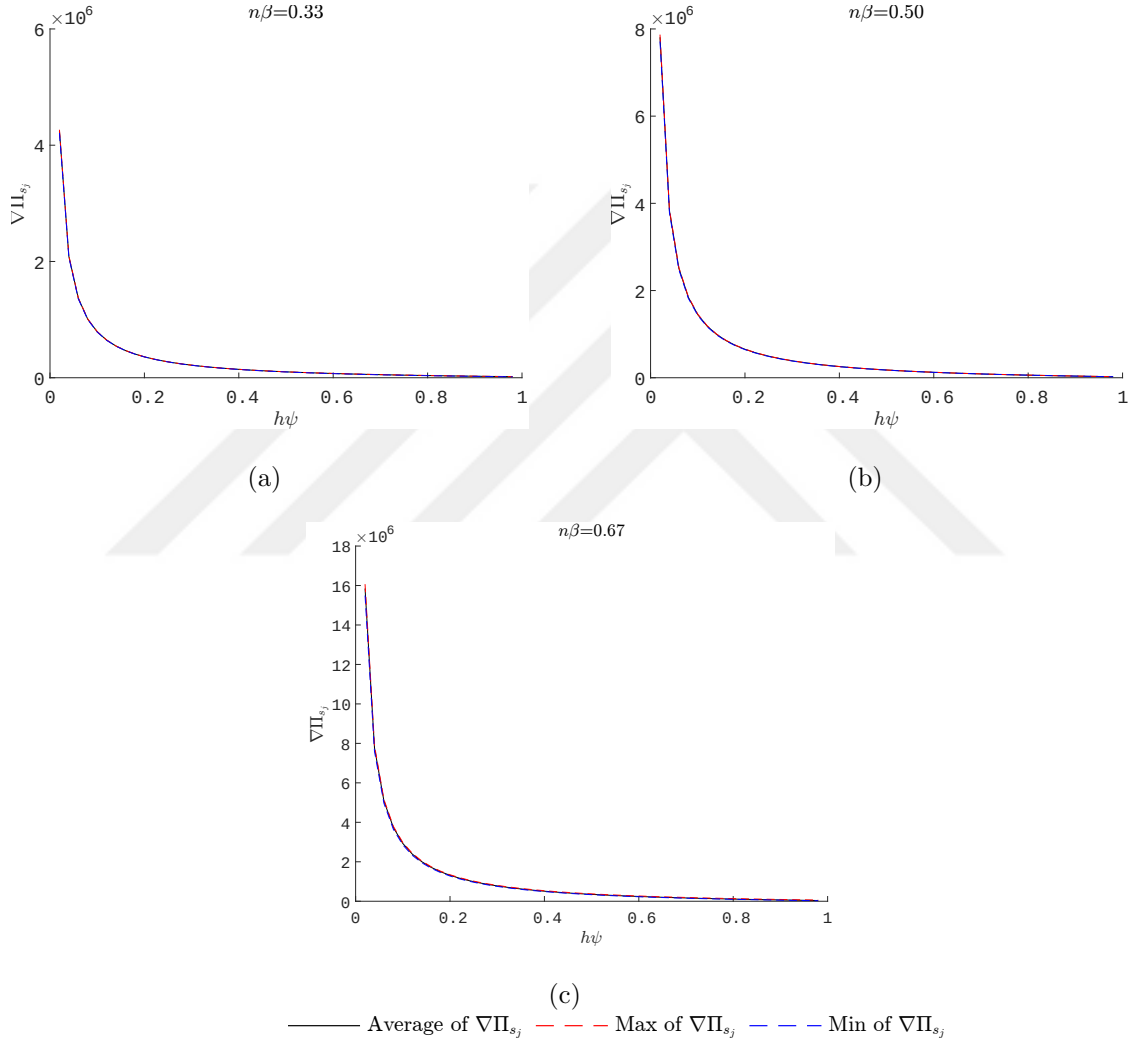


Figure 2.4: Impact of suppliers' total market shares on the supplier's benefit from participating in the GPO when $w_{sp} = 30$, $w_{fp} = 20$, $p = 45$, $h \in \{30, 31, 32, \dots, 80\}$, $\tau = 70\%$, $\underline{d}_T = 50000$, $\bar{d}_T = 80000$, $\underline{c} = 10$, $\bar{c} = 12$, $e_r = 5$, $e_s = 3$, $e_g = 1$, $M = 10000$, $\theta = 90\%$, $\gamma = 10\%$ (a) buyers' total market share $n\beta = 0.33$ ($n = 10$, $\beta = 0.033$) (b) buyers' total market share $n\beta = 0.50$ ($n = 10$, $\beta = 0.05$) (c) buyers' total market share $n\beta = 0.67$ ($n = 10$, $\beta = 0.067$)

2.4.2 Effects of Market Price for Advance Sales and Share of GPO Order in the Advance Sales Market

In order to analyze the impacts of market price for advance sales and share of GPO order in the advance sales market on the profits of the parties in the supply chain, we describe a basic scenario in which $w_{sp}=30$, $p=45$, $h=50$, $\beta=0.05$, $\psi=0.015$, $\underline{d}_T=50000$, $\bar{d}_T=80000$, $\underline{c}=10$, $\bar{c}=12$, $e_r=5$, $e_s=3$, $e_g=1$, $M=10000$, $\theta=90\%$, and $\gamma=10\%$. Three different variations of the scenario are constructed with the following values of the advance sales market price: $w_{fp}=18$, $w_{fp}=21$, and $w_{fp}=24$. In each variation, the share of GPO order in the advance sales market, τ , is changed from 0.65 to 1 with an incremental value of 0.007. For the given values of market price for advance sales and share of GPO order in the advance sales market, we generate a set of problem instances by ranging the number of buyers from 1 to 50, i.e., $n \in \{1, 2, 3, \dots, 50\}$. With this configuration setting, 2500 problem instances are generated for every variation of the basic scenario.

In each set of problem configured for the given values of market price for advance sales and share of GPO order in the advance sales market, the average, maximum, and minimum of the profits that the GPO and supplier obtain are determined. Figure 2.5 and 2.6 respectively show how changes in the price of the advance sales market, w_{fp} , and the share of the GPO order in the advance sales market, τ , affect the average profit levels of the GPO and suppliers, as well as the maximum and minimum profit levels of the GPO and suppliers.

In Figure 2.5, for a given τ value, the average profit level of the GPO rises significantly when the wholesale price increases in the first period. With an increase in w_{fp} , the GPO will have an opportunity to set its price at a higher level so that its marginal benefit per product is higher. Figure 2.5 also shows that for a given w_{fp} , the average profit level of the GPO usually slightly rises with an increase in the share of GPO orders in the advance sales market.

Figure 2.6 indicates that the GPO's positive impact on the supplier's expected

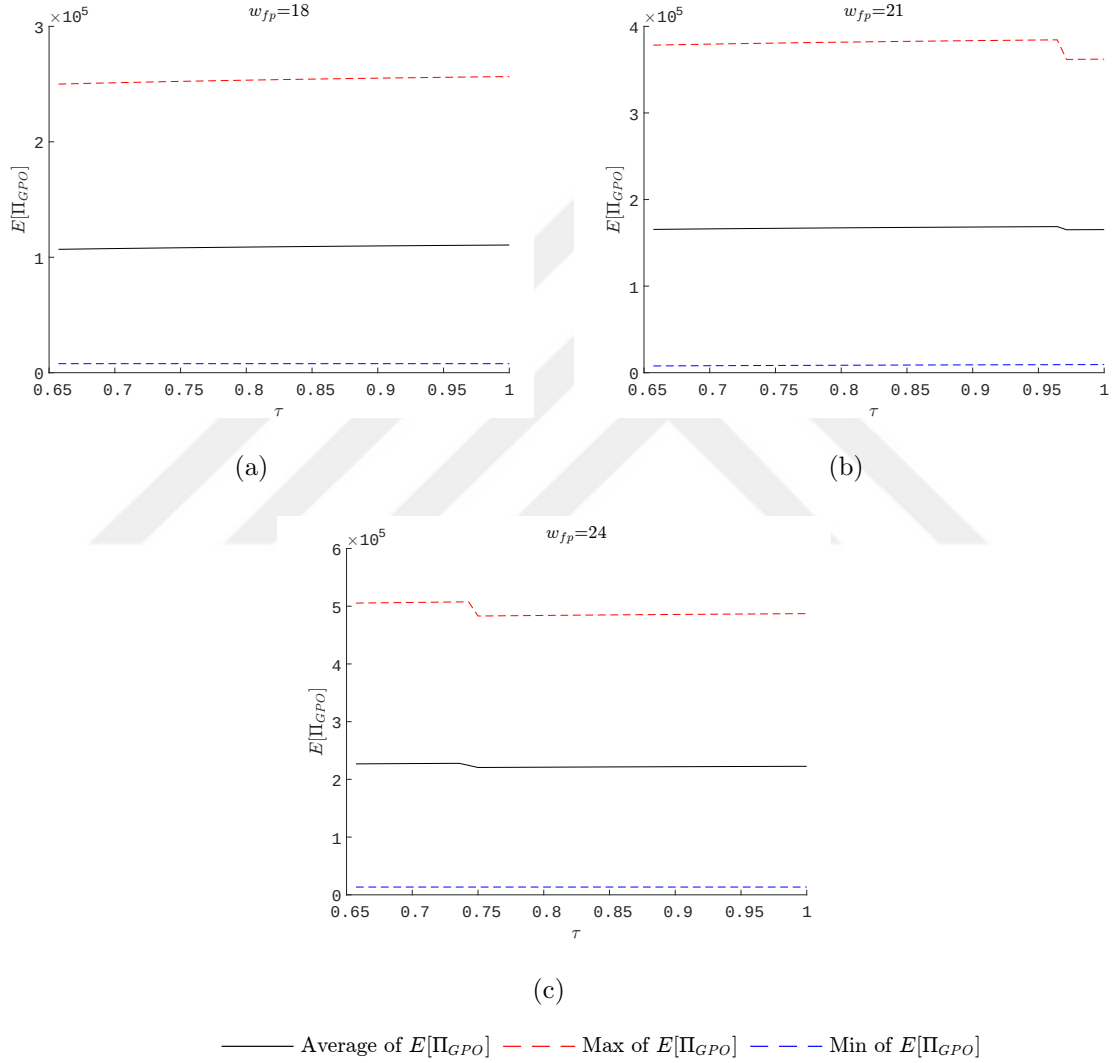


Figure 2.5: Impact of share of GPO orders in the first period market on the GPO's expected profit function when $w_{sp} = 30$, $p = 45$, $n \in \{1, 2, 3, \dots, 50\}$, $h = 50$, $\beta = 0.05$, $\psi = 0.015$, $\underline{d}_T = 50000$, $\bar{d}_T = 80000$, $\underline{c} = 10$, $\bar{c} = 12$, $e_r = 5$, $e_s = 3$, $e_g = 1$, $M = 10000$, $\theta = 90\%$, $\gamma = 10\%$ (a) the market price in the first period $w_{fp} = 18$ (b) the market price in the first period $w_{fp} = 21$ (c) the market price in the first period $w_{fp} = 24$

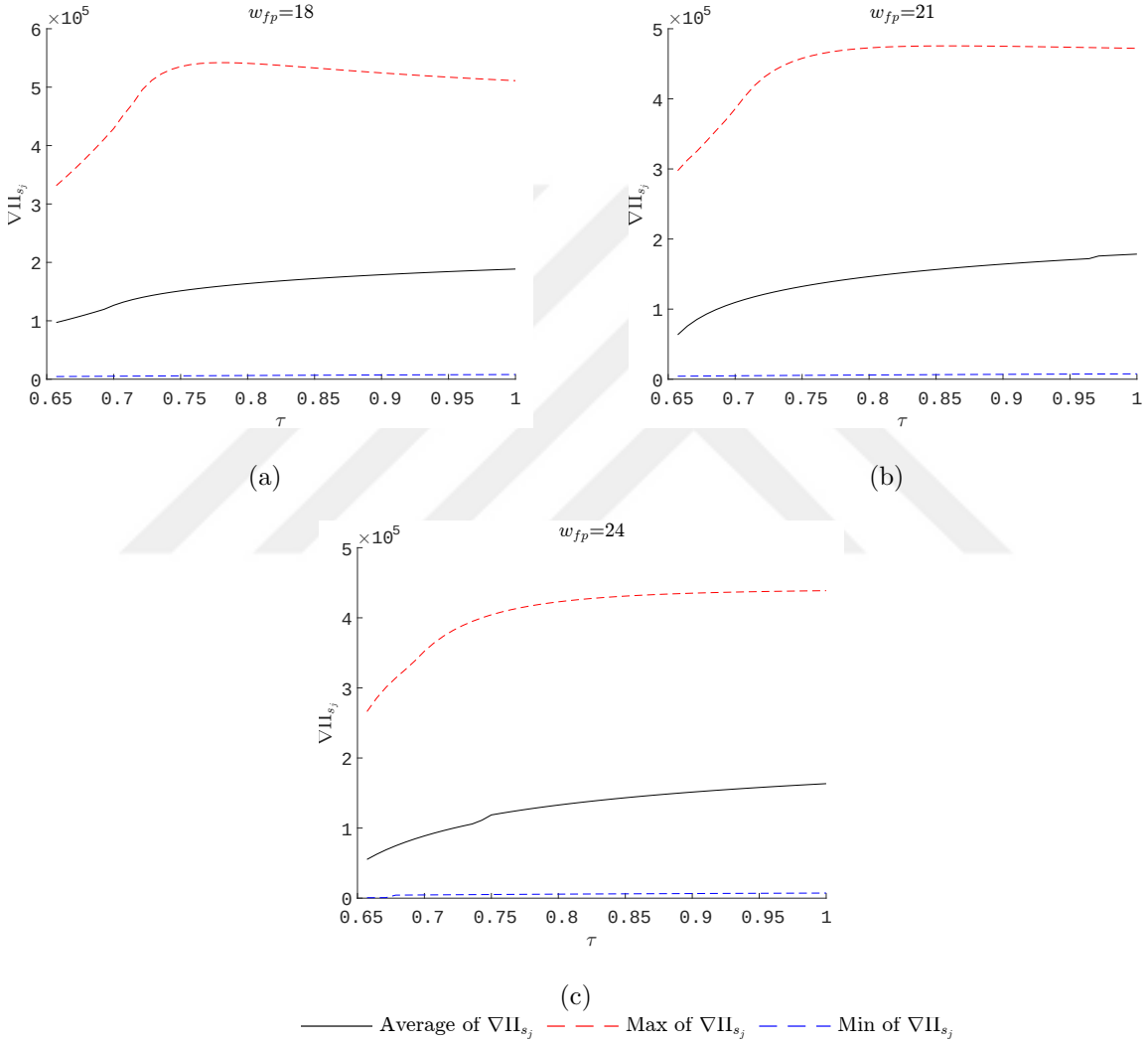


Figure 2.6: Impact of share of GPO orders in the first period market on the supplier's benefit from participating in the GPO when $w_{sp} = 30$, $p = 45$, $n \in \{1, 2, 3, \dots, 50\}$, $h = 50$, $\beta = 0.05$, $\psi = 0.015$, $\underline{d}_T = 50000$, $\bar{d}_T = 80000$, $\underline{c} = 10$, $\bar{c} = 12$, $e_r = 5$, $e_s = 3$, $e_g = 1$, $M = 10000$, $\theta = 90\%$, $\gamma = 10\%$ **(a)** the market price in the first period $w_{fp} = 18$ **(b)** the market price in the first period $w_{fp} = 21$ **(c)** the market price in the first period $w_{fp} = 24$

profit rises with an increase in the value of τ for a given w_{fp} . With a high τ , the GPO serves as a market maker for the suppliers, because only a small group of non-participating buyers can trade in the advance sales market. Accordingly, participation in GPO gives the suppliers a chance to sell their idle capacities in the first period. For the advance sales market, Figure 2.6 shows that the GPO benefit in the supplier's expected profit declines with an increase in the market price. Consequently, when the market price for advance sales, that is, w_{fp} , is low and when GPO buyers represent a high portion of total advance orders, namely, τ is high, the marginal benefit of the GPO has an increasing effect on the suppliers' profit.

2.4.3 Effects of Variabilities of Production Cost and Total Demand

Figure 2.7 and 2.8 depict the effects of variation in total demand and production costs, represented by the coefficients of variation of demand (cv_{D_T}) and production cost (cv_{C_j}), on the average profit levels of the GPO and supplier, respectively.

For the analysis, we define a basic scenario where $w_{sp}=30$, $w_{fp}=20$, $p=45$, $n=10$, $h=50$, $\beta=0.05$, $\psi=0.015$, $\tau=70\%$, $e_r=5$, $e_s=3$, $e_g=1$, $\theta=90\%$, and $\gamma=10\%$. We create three different variations of the scenario considering the following values for the coefficient of variation of the total demand in the market: $cv_{D_T}=0.13$, $cv_{D_T}=0.31$, and $cv_{D_T}=0.49$. In each variation, the coefficient of variation of production cost, cv_{C_j} , is changed from 0.05 to 0.30 with an incremental value of 0.005. For the given values of the coefficients of variation of demand and production cost, we generate a set of problem instances by ranging the supplier's total capacity from 3000 to 10000 with an incremental step of 250, i.e., $M \in \{3000, 3250, 3500, \dots, 15000\}$. With this configuration setting, 2500 problem instances are generated for every variation of the basic scenario.

Figure 2.7 shows that the average profit level of the GPO increases with production cost variability. When production cost variability increases, the lower bound of the distribution of production cost and, in turn, the expected auction price decrease. As

the expected auction price decreases the GPO's expected profit increases while the supplier's expected profit decreases. As a result, Figure 2.8 shows that the GPO benefit in the supplier's expected profit slightly declines with an increase in the production cost variability.

For the same average demand, $\underline{d}_T$ decreases with an increase in cv_{D_T} . This leads to a decrease in the GPO's total revenue from advance sales. Therefore, as Figure 2.7 shows, the average profit level of the GPO declines as the coefficient of variation of total demand increases. When cv_{D_T} increases, the GPO's marginal benefit also has a decreasing effect on the supplier's expected profit as a result of the GPO-driven market downsizing in the first period (see Figure 2.8).

2.5 Managerial Insights

Based on the numerical results, we summarize our main findings, which provide managerial insights into the operation of the group purchasing organization and its effects on suppliers and buyers, as follows:

1. Where the market share of a supplier is small, the supplier's profit significantly increases through GPO participation. This result can be attributed to the fact that participating in the GPO provides the supplier an opportunity to reach a sizable advance sales market in the first period, which cannot be done on its own. In addition, the profit of the GPO increases as the expected auction price and the excessive amount of supply from the auction decline with a decrease in the supplier's market share.
2. Participating in the GPO benefits the supplier in case the buyer's market share is high. However, the positive impact of a high buyer's market share on the expected profit of the supplier disappears when the supplier's market share goes up. Under this setting, the GPO loses its role as a market maker for the suppliers. An increase in the buyer's market share leads to more buying power and advance

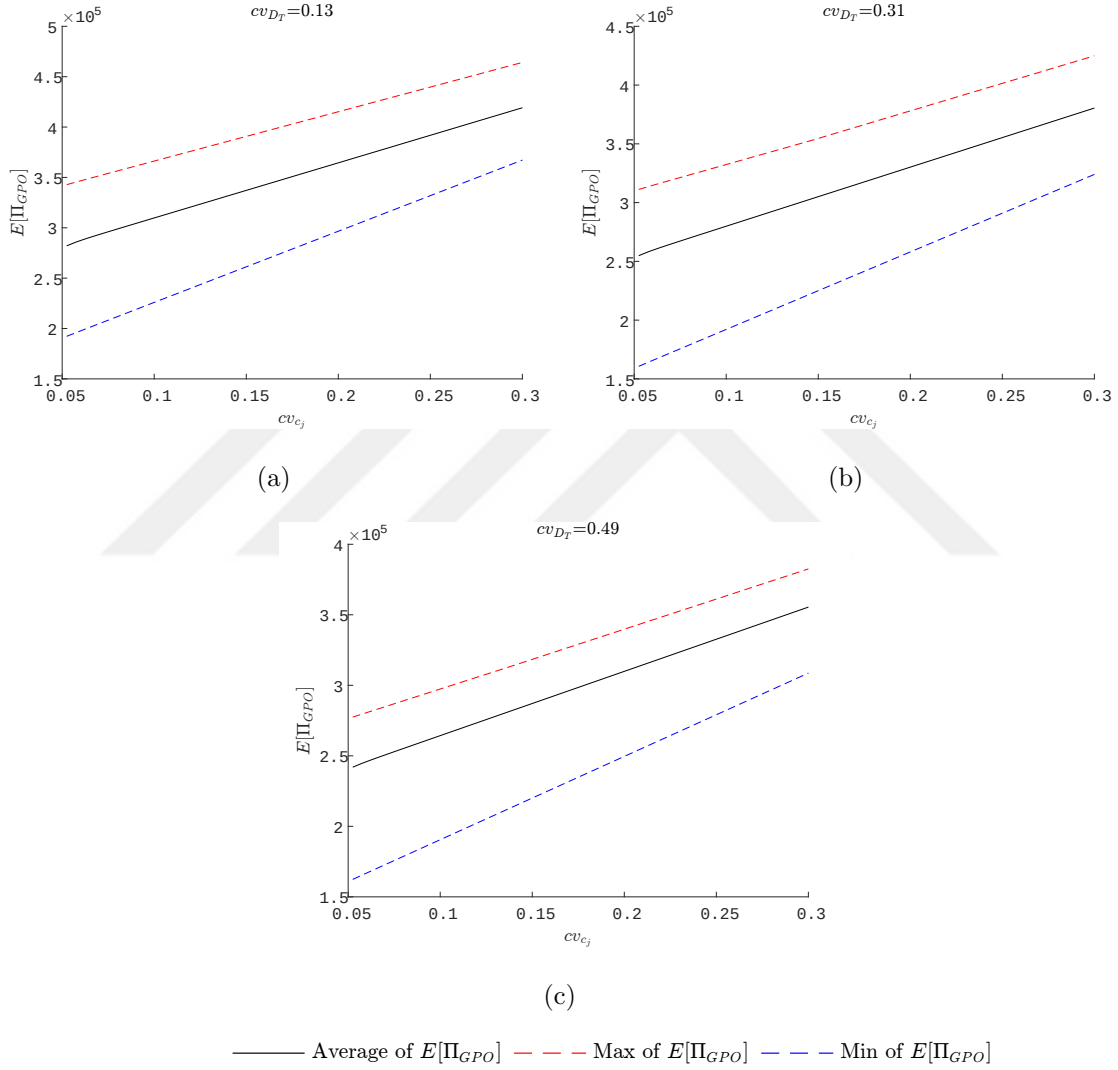


Figure 2.7: Impact of variability in production cost on the GPO's expected profit function when $w_{sp} = 30$, $w_{fp} = 20$, $p = 45$, $n = 10$, $h = 50$, $\beta = 0.05$, $\psi = 0.015$, $\tau = 70\%$, $e_r = 5$, $e_s = 3$, $e_g = 1$, $\theta = 90\%$, $\gamma = 10\%$, $M \in \{3000, 3250, 3500, \dots, 15000\}$ (a) the coefficient of variation of total demand, $cv_{D_T} = 0.13$ (b) the coefficient of variation of total demand, $cv_{D_T} = 0.31$ (c) the coefficient of variation of total demand, $cv_{D_T} = 0.49$

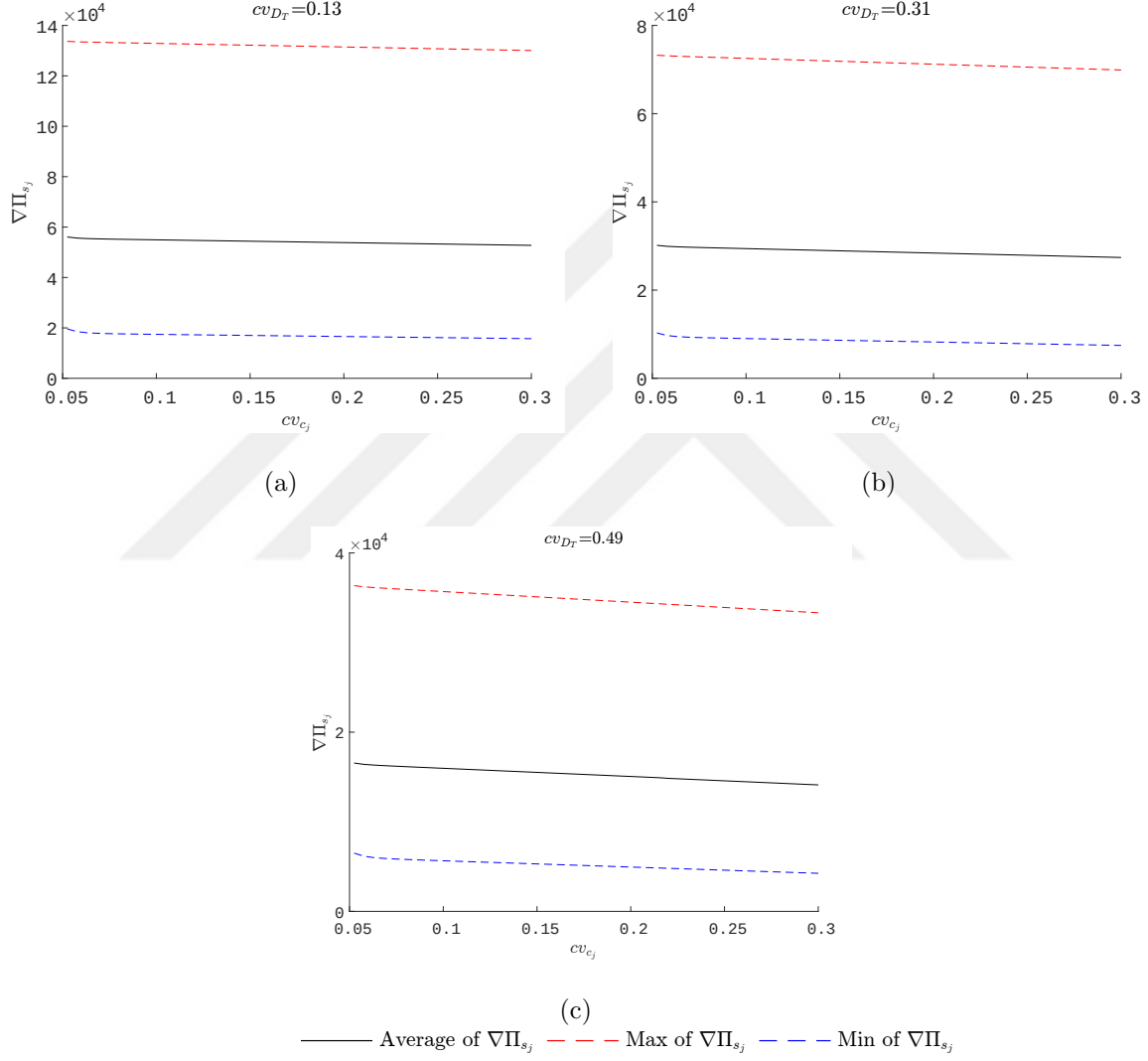


Figure 2.8: Impact of variability in production cost on the supplier's benefit from participating in the GPO when $w_{sp} = 30$, $w_{fp} = 20$, $p = 45$, $n = 10$, $h = 50$, $\beta = 0.05$, $\psi = 0.015$, $e_r = 5$, $e_s = 3$, $e_g = 1$, $\theta = 90\%$, $\gamma = 10\%$, $M \in \{3000, 3250, 3500, \dots, 15000\}$ (a) the coefficient of variation of total demand, $cv_{D_T} = 0.13$ (b) the coefficient of variation of total demand, $cv_{D_T} = 0.31$ (c) the coefficient of variation of total demand, $cv_{D_T} = 0.49$

sales orders for the GPO. By using this advantage, the GPO sells more products to its customers, lowering the auction price in their favor. Accordingly, a higher buyer's market share implies a higher premium for the GPO.

3. High variation in production cost improves the GPO's profit but adversely affects the supplier's profit. The lower bound of the supplier's production cost declines under this setting, leading to a decrease in the expected auction price.
4. For the GPO, the total revenue obtained from advance sales decreases with an increase in the variation in total demand. For the suppliers, the increase in variation also leads to a market loss in the first period. Therefore, the GPO benefit declines for both parties as the variation in demand increases.
5. When the share of GPO orders in the advance sales market increases, the GPO provides added value to suppliers by offering them a chance to sell their idle capacities in the first period. In other words, the GPO plays a market maker role for the suppliers under this setting. On the other hand, since the expected auction price tends to decrease with an increase in the share of GPO orders in the advance sales market, the profit function of the GPO goes up.
6. As the market price for advance sales rises, the GPO can set its price at a higher level. Hence, for the GPO, the marginal profit per item procured through its channel increases. In addition, since the market price for the first period increases, the positive impact of the GPO on the supplier's expected profit decreases.

2.6 A Summary of Findings

We present a detailed two-period stochastic model in which there is a group purchasing organization working with a set of buyers and suppliers under demand and price uncertainty. In this model, advance sales opportunities are available in the first period

to all parties in the market. The buyers and suppliers decide whether to cooperate with the GPO in the first period. If they do, the GPO employs a uniform-price reverse auction to determine the procurement price and to select the suppliers to be used for procuring advance orders of its customers. This model captures the main dynamics observed in the industrial case accurately described in Tan (2014).

Under this setting, we first characterize how buyers optimally decide whether to use the option of working with the GPO and how much to buy through advance order opportunities to maximize their profits. We then analyze the suppliers' decisions on participation in the GPO and capacity they would sell in the first period. Furthermore, the analysis for the auction mechanism is derived.

Our model captures the effects of demand uncertainty, share of GPO orders in the advance sales market, demand and price uncertainty, and variation in production cost. We investigate the effects of system parameters on the operation of the supply chain, analytically and through a range of numerical experiments. Based on these numerical results, we provide managerial insights into the operation of the group purchasing organization and its effects on suppliers and buyers. In the cases where the buyer's market share is high or the supplier's market share is low, participating in the GPO significantly benefits the supplier. Because, in these two cases, the supplier can reach a sizable advance sales market in the first period by participating in the GPO. An increase in the buyer's market share or a decrease in the supplier's market share implies a higher premium for the GPO and buyers. In addition, we observe that for the GPO and suppliers, the group buying benefit decreases as the variation in demand increases. However, high variation in production cost leads to an increase in the GPO's profit but adversely affects the supplier's profit.

We conclude that a group purchasing organization helps buyers and/or suppliers to mitigate demand and price risks in an effective way and benefits all parties subject to certain conditions.

Chapter 3

AN EMPIRICAL ANALYSIS OF THE MAIN DRIVERS AFFECTING THE BUYER SURPLUS IN E-AUCTIONS

Procurement is one of the important business functions to ensure identification, sourcing, access, and management of the external resources that a firm requires for fulfilling its long and short term objectives. The procurement function is responsible for a number of initiatives from spending the firm's funds in sourcing goods and services to establishing and managing relationships with qualified suppliers. Ultimately, procurement has a significant effect on the firm's performance, not only in terms of cost but also in terms of quality, innovation, responsiveness, and revenue generation (Nair et al., 2015).

With the recognition of importance of the procurement in overall corporate performance, the majority of firms have started paying close attention to their procurement functions (Lawson et al., 2009). As a result of these efforts, online procurement tools that the firms employ to strengthen the management of their supplier networks and the procurement processes have emerged in practice. Among these tools, electronic reverse auction, which is also known as procurement auction, e-procurement, business-to-business auction, has become a commonly used online procurement tool. In its basic form, an electronic reverse auction is an online, real-time dynamic auction between a buyer and a group of pre-qualified suppliers who compete against each other to win the business to supply goods or services that have clearly defined specifications

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for design, quantity, quality, delivery, and related terms and conditions (Beall et al., 2003).

The term *reverse* emphasizes the fact that buyers and sellers roles switch from that of a traditional auction. In the traditional auctions, also referred to as forward auctions, a seller offers a product that is demanded by several buyers who compete and bid up the price (Manoochehri and Lindsay, 2008). At the end of the auction, the bidder who submits the highest bid is awarded the product. However, in a reverse auction, the buyer takes on the role of the seller and controls the auction process. The buyer announces its intent to purchase a specific quantity of a product or service. Suppliers of these items or of services compete with each other and lower their price to win the auction. As a result, the price of the object being auctioned decreases in the reverse auction, rather than increases as it would in the forward auction. Reverse auctions can be conducted in various formats, but the most popular ones are *English*, *Dutch*, *first-price*, and *second-price* auctions. Within the reverse auction context, the *English* auction is an iterative auction where the bidders submit subsequently decreasing bids. This iterative process continues until a price is reached where there is just a single bidder who is willing to supply the auctioning item. The *Dutch* auction is the reverse of the English auction where the price is monotonically increased by the buyer until there is a bidder who is willing to supply the auctioning item at the currently announced price (Chandrashekar et al., 2007). In the *first-price* auction, each bidder has the opportunity to submit a single bid by a particular deadline. Once the deadline expires the bids are examined and the lowest bidder supplies the good or service at the price she offered. In the *second-price* auction, the bidding rules are similar the ones employed in the *first-price* auction. However, when the *second-price* auction is employed the winning bidder does not charge the amount of her own bid, but the amount of the second-lowest bid.

In practice, most of the buyers prefer working with a specialized third-party service provider which is also referred as the market maker to conduct the reverse auctions,

rather than building and employing their private infrastructures. Basically, the market maker is an intermediary firm, independent of the buyer and sellers that provides the facilities, processes, know-how and infrastructure to create an electronic market for conducting competitive bidding (Hsiao and Teo, 2005). Their business models mostly depend on a fee that may be fixed, or proportional, or both to the value of the auctioned products and/or services (Mabert and Skeels, 2002). For instance, Ariba, one of the leading market makers, charges an extra fee that is 1%-3% of the transaction value on top of a participation fee. Covisint, another well-known market maker, only uses a fixed subscription fee to charge its corporate customers. In practice, the market makers not only offer the infrastructure and know-how that facilitates to conduct the reverse auctions, but also provide a practical framework to benefit from cooperation in purchasing. For this purpose, they operate group purchasing programs in which the buyers across different sectors can participate in for procuring common products through the online reverse auctions (Karabağ and Tan, 2017). Within this context, the market maker acts as an intermediary firm that is authorized to conduct the auction on behalf of a group of buyers. In this case, the main function of the market maker is to get more price discount for the buyers by using their joint buying power with its own e-auction platform. In the literature, this mechanism is also referred to as joint procurement, purchasing consortium, and cooperative purchasing (Nollet and Beaulieu, 2005). For a more detailed discussion on the group purchasing programs, we refer the reader to the works of Chen et al. (2009), Hu et al. (2012), and Karabağ and Tan (2017).

The choice of using, or not, the reverse auction is a typical tactical decision within the context of strategic sourcing (Standing, 2009). Essentially, for the buyers, the reverse auction is a supportive procurement tool to response the strategic initiatives such as cost savings, demonstrate the transparency of purchasing decisions, reduce the cycle times of the procurement projects, access to a larger supplier base, and increase process efficiencies (Tai et al., 2010; Schoenherr and Mabert, 2011). With the high

level of competition in the bidding process and the visibility of competing bids, the supplier bids would be more fierce and hence the buyer would obtain lower purchase prices. Requests for information and bidding processes are prepared and completed electronically, instead of paper-based processes which are rather time-consuming. Hence, the cycle time and the administrative costs associated with the purchasing processes reduce whereas the efficiency of the sourcing process increases. The reverse auctions have the ability to bring buyers and sellers from all over the world together in an open environment as they are conducted through the Internet. As a result, the true value of the auctioning item is clearly observed. The ease of access to the procurement event conducted with online reverse auction would also lead to a broader supplier base for the buyers. From the suppliers' perspective, most important motivations that drive the decision to participate in are the chances of reaching new buyers and having an outlet to sell the excess capacity (Karabağ and Tan, 2017). The reverse auctions also help the suppliers to gain valuable information about the existing market, providing a better understanding of competitors' cost structures. Another important motivation for the sellers to engage in the auctions is a possible improvement in the negotiation time. The fact that less time is required for e-auctions compared to traditional competitive bidding reduces the supplier's reliance on forecasting for planning purposes, as well as the administrative costs (Hartley et al., 2004). Detailed reviews regarding the motivations in which the e-auction implementations provide for the buyers and suppliers are found in the works of Elmaghraby (2007), Rothkopf and Whinston (2007), and Gupta et al. (2009).

The cost-saving is the key driver that incentives the buyers to adopt the reverse auctions into their procurement process. The reverse auctions have been shown to achieve a saving up to 40% on purchases of industrial goods and services (Jap, 2002). Based on the case study of five larger firms in diverse industries, Hur et al. (2006) revealed that the use of reverse auctions led to initial price reductions of 13% to 20%. Additionally, Emiliani and Stec (2004) showed that by using the reverse auctions, a

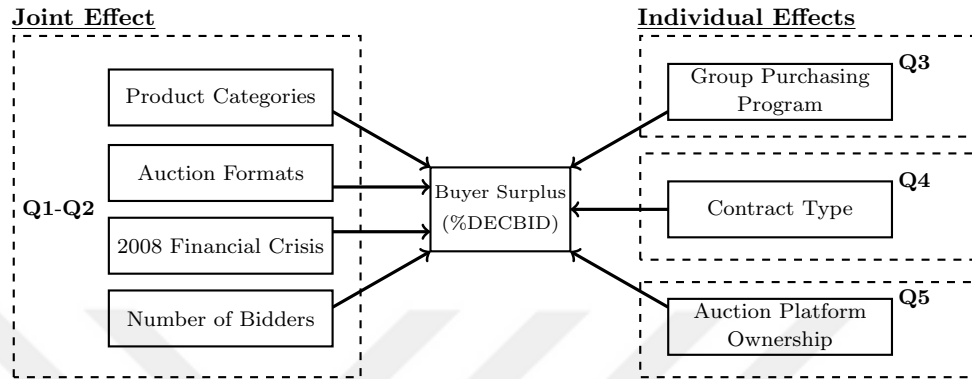


Figure 3.1: Research model

buyer in the aerospace industry was able to achieve a saving between 20% to 30% on purchases of indirect goods and a saving between 0.5% and 2% on purchases of direct materials. In practice, the cost-saving achieved with the use of e-auction implementations is typically measured by the difference between the historic price and the lowest bid. The *historic* price, also referred to as the *current* price, can be considered as the most recent price in which the buyer paid for the product before using the auction or as the minimum price in which the buyer received in the RFQ process that is conducted just before the auction (Amelinckx et al., 2008). In addition, the *lowest* bid refers to the final bid achieved at the end of the auction. With this definition, the cost saving basically measures the difference between the price a buyer is willing to pay for goods/services and the price a buyer actually pays. So, it can be called as the buyer surplus (Mithas and Jones, 2007).

The economic significance of the reverse auctions has managed to attract the attention of the researchers in the operations management and economics fields. As a result, in the literature, the number of studies focused on the factors that have notable effects on the buyer surplus has increased significantly. In this research stream, typically, the impacts of *the number of bidders* (Millet et al., 2004; Mithas and Jones, 2007; Park et al., 2012; Onur et al., 2012; Gurakar and Taş, 2015; Raventós and Zolezzi, 2015), *the number of submitted bids* (Millet et al., 2004; Mithas and Jones, 2007; Pavel

et al., 2013; Raventós and Zolezzi, 2015), *the amount of auctioning item* (Bapna et al., 2003; Koppius et al., 2004; Percy and Giunipero, 2006; Park et al., 2012), *the auction duration* (Mithas and Jones, 2007; Raventós and Zolezzi, 2015), *the reservation price* (Bapna et al., 2003; Kauffman and Wood, 2006; Mithas and Jones, 2007; Onur et al., 2012; Pavel et al., 2013), *the ranking information during the auction* (Millet et al., 2004; Mithas and Jones, 2007; Elmaghraby et al., 2012; Tunca et al., 2014; Setia and Speier-Pero, 2015), *the information about the auctioning item* - description, photo, etc.- (Koppius et al., 2004; Kauffman and Wood, 2006; Stoll and Zöttl, 2017), *the non-price attributes of the auctioning item* (Koppius et al., 2004; Engelbrecht et al., 2007; Haruvy and Katok, 2013; Tunca et al., 2014; Stoll and Zöttl, 2017; Moretti and Valbonesi, 2015), and *the supplier incumbency* (Kauffman and Wood, 2006; Mithas and Jones, 2007; Tunca et al., 2014) have been addressed. However, we are not aware of any studies that examine the joint impacts of the product category, the auction format, the number of bidders, and the 2008 financial crisis on the decrease in the auction prices. Additionally, to the best of our knowledge, none of the existing studies attempt to classify the product categories based on their impacts on the average decrease in procurement prices and analyze the impacts of the group buying, the e-auction platform ownership, and the type of contract between buyers and auctioneer on the average decrease on the procurement prices. To fill these gaps in the literature, we consider the following research questions:

- Q1: What are the effects of the product category, the auction type, the number of bidders, and the economic crisis on the decrease in the procurement prices with respect to the minimum of the initial submitted bids?
- Q2: How can the product categories be classified according to their impact on the decrease observed in procurement prices?
- Q3: Does the group purchasing programs yield a greater decrease in the procurement prices achieved at the end of an auction compared to buying individually?

- *Q4*: Are there differences among the decreases achieved when different contract types are used?
- *Q5*: Does having own e-auction platform yield more reduction in the procurement prices?

To address these research questions, we use a unique dataset from a third-party e-auction platform provider. The research model we employed in this study is summarized in Figure 3.1. We address the first research question by employing the Tobit model. With this approach, we study the joint effects of the product category, the auction type, the number of bidders, and the 2008 global financial crisis on the buyer surplus. For dealing with the second research question, we employ the Welch's ANOVA and Games-Howell Pairwise Comparisons tests and classify the product categories into three major groups. Lastly, the third, fourth, and fifth research questions are examined by using the student's t-test with unequal variances assumption. Hence, we investigate the individual effects of the auction platform ownership, the contract type, and the use of the group purchasing on the buyer surplus, namely without considering the other treatments effect.

3.1 Literature Review

In the literature, there are a limited number of empirical studies devoted to determining what factors could affect the buyer surplus. The datasets that analyzed in these studies typically include the transaction details of the e-auctions conducted either in the private or public sector. Based on this particular specification, we categorize the existing studies into two groups: (1) the studies that deal with the dataset from the private sector and (2) the studies that deal with the dataset from the public sector. With this effort, in the following paragraphs, we discuss the ones most related to our work. The studies that examine the e-auction implementations from the supplier's and third-party's perspectives are not included in the review as the corresponding literature

stream is beyond the scope of this study.

In recent years, there has been an increasing reliance on e-auctions for buying activities conducted in the private sector. E-auctions are being used for everything from purchasing agricultural commodities to acquiring high-tech manufacturing systems. Although there are numerous e-auction implementations in the private sector, the datasets regarding these auctions are typically not publicly available. As a result of this fact, the number of studies that deal with the datasets from the private sector is scarce in the literature. The need to develop theories and practices concerning the adoption, implementation, and utilization of e-auctions in the private sector has also been highlighted in several studies (Standing et al., 2010; Schoenherr et al., 2012; Pham et al., 2015).

Bapna et al. (2003) provide both analytical and empirical evidence regarding the importance of bid increment and lot size in the revenue generation. Koppius et al. (2004) investigate the effect of online product representation on the auction price by analyzing a dataset on flower auctions. The authors show that the deficient informational quality of the on-screen flower pictures in comparison to the real flowers leads to a decrease in the final price. Millet et al. (2004) study a dataset collected from a multinational firm and find that different auction types lead to different participation dynamics. They also find that the highest price reduction results are obtained by inviting at least five or six, up to a maximum of 13. Kauffman and Wood (2006) explore the factors that can be manipulated by the auctioneer to increase the bidder's utility, using the data gathered from eBay. The authors conclude that scheduling an e-auction in the weekend and the existence of a picture increase the price a bidder is willing to pay. By utilizing a dataset on the procurement auctions of a firm in the automotive sector, Mithas and Jones (2007) study the effects of certain auction parameters on the buyer surplus. They claim that bidding competition and information asymmetry affect the buyer surplus whereas bid decrement and auction duration have no effects on the surplus. Park et al. (2012) study a dataset collected from an outsourcing company

in Korea. The authors find that as the purchasing amount and number of bidders increases the winning bid price in the auction decreases. In the work of Tunca et al. (2014), the impacts of incumbency and supplier service quality on the buyer surplus are examined by using a dataset including the transaction details of the open-ended scoring auctions. They demonstrate that the open-ended award structure can improve the buyer surplus when the buyer's preference for non-price attributes is strong and the cost differences among the suppliers are low. By using a dataset collected from a third-party auction platform provider, Stoll and Zöttl (2017) establish a framework for the auctions where both price and non-price characteristics of the auctioning items matter for determining the winner. They find that concealing non-price information in the auctions leads to an increase in the buyer surplus up to 15% when the non-price characteristics of an auctioning item are of high importance for the buyers.

A number of governments have initiated e-auction implementations to increase the transparency in their administrative works and to achieve better economic outcomes. As a result of this effort, a growing body of literature deals with the adoption of e-auction implementations in the public procurement and examines its effects on the auction prices. In this context, Onur et al. (2012) examine the effectiveness of the auctions that are organized by the public procurement authority in Turkey. They conclude that allowing foreign participants to participate in the auction and the threshold value for conducting an auction have notable effects on the number of bidders and the auction price. Based on the auction data from Slovak municipalities, Pavel et al. (2013) investigate the factors that may affect the auction prices and the efficiency of e-auctions. Their work shows that each additional bid submitted in the auction leads to a decrease in the auction price. Raventós and Zolezzi (2015) explore the impact of electronic auctions on the price paid by the public sector for pharmaceuticals and medical devices in Chile. They found that the price of drugs and medical devices falls with an increase in the number of bidders and/or the amount of auctioned items. Gurakar and Taş (2015) find that after e-auction adoption in Turkey, the number of

firms submitting bids in the procurement auctions significantly decreases whereas the procurement costs rise. Based on these results, they conclude that e-auction adoption has adverse effects on the efficiency of government procurement auctions. The effects of subcontracting options on the auction prices are examined by Moretti and Valbonesi (2015). The authors observe that the bidders in a position to choose whether or not to subcontract mostly submit lower prices than the partially qualified firms which are mandated to engage in the subcontracting.

In the literature, there exist a number of studies investigating the factors that drive the buyer surplus by employing laboratory experiments or surveys. Based on a survey of 142 purchasing professionals employed in diverse industries in the U.S., Percy and Giunipero (2006) reveal that an increase in the amount of the auctioning item leads to a decrease in the unit purchasing price. Engelbrecht et al. (2007) compare the buyer-determined auction mechanisms where the buyer is free to select the bid that maximizes her surplus and the price-based auction mechanisms where the buyer commits to awarding the contract to the low price bidder. The comparison result emphasizes that the buyer-determined auction mechanisms increase the buyer surplus only as long as enough suppliers participated in the auction. With a laboratory experiment, Elmaghraby et al. (2012) explore how giving information to the suppliers about the bids that are submitted throughout the duration of the auction affect the buyer surplus. They find that giving the rank information to the bidders yields a higher decrease in the procurement prices, compared to giving the full information to the bidders. Setia and Speier-Pero (2015) investigate the impacts of full and partial price visibilities on the auction prices. Unlike the work of Elmaghraby et al. (2012), they reveal that the full price visibility provides a higher reduction in the procurement prices, compared to the partial price visibility. As the main reason for this result, the authors claim that the full price visibility helps overcome suppliers' cognitive barriers that inhibit determination of appropriate bids in real time. Haruvy and Katok (2013) examine the effects of bidders' quality transparency, price visibility, and the interaction

between these two parameters on the auction prices. Their findings indicate that when each bidder exactly knows the owner of each bid submitted during the auction and the information about bidder quality is public, the buyer achieves a low surplus.

Table 3.1 compares our study with the existing literature in terms of the factors whose impacts on the buyer surplus have been studied. Our study differs from the existing studies since it is the first attempt, to the best of our knowledge, to empirically examine the joint impacts of the product category, the auction format, the 2008 financial crisis, and the number of bidders on the buyer surplus. For this examination, we collected a dataset from one of the leading e-auction providers in Turkey. The dataset covers the transaction details of 15458 auction events that were conducted with 16728 suppliers between March 2006 and March 2016. In the dataset, we classified the procurement projects into 14 different product categories by employing a keyword search algorithm. They are listed as follows: construction, chemical, indirect material, direct material, electrical works, service, logistics, health-care, metal, plastics, advertisement, manufacturing systems, technological equipments, and textile. Three different auction types, *Lot*, *Split*, and *Dutch*, were employed for organizing the procurement projects.

Based on the results obtained from the empirical analysis, we observe that the product category, the auction format, and the 2008 financial crisis have a notable effect on the buyer surplus. Additionally, we find the positive marginal impact of the number of bidders to the buyer surplus is not constant and the positive impact decreases as the number of bidders increases. The review reveals that such a result regarding the number of bidders has not ever been emphasized in the literature. Accordingly, we believe that our work contributes to the literature by establishing the result that a positive impact of having one more supplier in the auction to the buyer surplus decreases when the number of bidders is getting larger.

Additionally, we are not aware of any studies in the current literature that empirically examine how the group buying programs, the contract types, and the auction

	Studied Factors											Data Specifications				
Study	Number of Bidders	Number of Bids	Amount of Item	Auction Duration	Reservation Price	Value of Information	Non-price Attributes	Supplier Incumbency	Product Category	Auction Format	Financial Crisis	Origin of The Data	Auctioning Item(s)	Time Frame	Buyer Type	Auction Type
Bapna et al. (2003)		✓		✓							Financial Crisis	E-auction Provider	Not Given	Not Given	1	1
Koppius et al. (2004)		✓			✓	✓	✓					Auction House	Flowers	1995-1997	1	2
Kauffman and Wood (2006)				✓	✓	✓		✓				E-bay	U.S. Rare Coins	1999-2001	1	1
Pearcy and Giunipero (2006)		✓										Survey	-	-	-	-
Engelbrecht et al. (2007)							✓					Laboratory Experiment	-	-	-	-
Mithas and Jones (2007)	✓	✓		✓	✓	✓		✓				U.S. Auto Industry	Manufacturing Parts	2001-2003	1	1
Park et al. (2012)	✓		✓									E-auction Provider	Manufacturing and Maintenance Parts	2001-2007	1	1
Onur et al. (2012)							✓	✓				P.P.A. in Turkey	Construction, Service and Goods	2004-2006	1	1
Elmaghraby et al. (2012)					✓							Laboratory Experiment	-	-	-	-

Table 3.1: Summary table for the studies covered in literature review

	Studied Factors											Data Specifications				
Study	Number of Bidders	Number of Bids	Amount of Item	Auction Duration	Reservation Price	Value of Information	Non-price Attributes	Supplier Incumbency	Product Category	Auction Format	Financial Crisis	Origin of The Data	Auctioning Item(s)	Time Frame	Buyer Type	Auction Type
Haruvy and Katok (2013)								✓				Laboratory Experiment	-	-	-	-
Pavel et al. (2013)	✓			✓								P.P.A. in Slovenia	Construction and IT	2007-2009	1	2
Tunca et al. (2014)						✓	✓	✓				General Electric	Legal Services Contracts	2003	1	2
Gurakar and Taş (2015)	✓											P.P.A. in Turkey	Construction, Service and Goods	2004-2012	1	1
Moretti and Valbonesi (2015)							✓					P.P.A. in Italy	Construction	2000-2008	1	1
Raventós and Zolezzi (2015)	✓	✓	✓									P.P.A. in Chile	Pharmaceuticals and Medical Devices	2001-2006	1	1
Setia and Speier-Pero (2015)						✓						Laboratory Experiment	-	-	-	-
Stoll and Zöttl (2017)						✓	✓					E-auction Provider	Service	2007-2008	1	2
This Work	✓								✓	✓	✓	E-auction Provider	14 Product Categories	2006-2016	2	3

Table 3.1: (cont'd) Summary table for the studies covered in literature review

platform ownership affect the average decrease in the procurement prices. Another contribution of this study is helping the understanding of the impacts of these factors on the surplus derived from auctions. For this purpose, we use the particular structure of our dataset. In the dataset, the auctions were conducted for two types of customers: (1) the group purchasing organization that is authorized to act as a purchasing agent for a group of individual firms and (2) the individual buyers that make purchases on their own. For managing the transactions between the buyer and auctioneer, three different contract types, *Percentage*, *Fixed*, and *Mixed*, have been used. Within the time covered by the dataset, the e-auction platform provider was acquired by one of its corporate customers. Based on the results we obtained from the analysis of the dataset, it is established that the group purchasing has a notable effect on the average decrease in the procurement prices. However, it is concluded that there is no difference between the contract types in terms of their effects on the average decrease in the procurement prices. We also find that the platform ownership has no significant effects on the average decrease in the procurement prices.

3.2 Hypothesis Development

In this section, we develop nine hypotheses by utilizing the findings and conclusions of the existing studies and considering the opinions of the experts.

3.2.1 The impact of the product categories on the buyer surplus:

With growing attention on the use of the reverse auctions for the purchase of various products and services, firms become concerned whether this tool is equally effective in providing price reductions across the different product categories. In the literature, several studies also emphasize this emerging concern in practice and state the importance of an additional investigation regarding the effects of the product categories on the buyer surplus (Van den Poel and Leunis, 1999; Lee, 2009; Rao, 2009).

However, despite the fact that the need for this research stream is highlighted,

the number of studies that deal with the impacts of the product category on the buyer surplus has been quite scarce. Jap (2002) conducts an exploratory study on purchasing practitioners to ascertain what kind of products are appropriate for the reverse auctions. The author examines only a limited number of the maintenance and repair supplies. Based on this examination, the author claims that the online auctions perform well for the commodity products. Similarly, Manoochehri and Lindsay (2008), Tassabehji (2010), and Schoenherr and Mabert (2011) propose that the use of the reverse auction is advantageous in the purchase of commodity items, especially where the price is the primary consideration. The main intuition behind this result is that the number of suppliers willing and able to bid on the business is likely to be higher when the auctioned item is standard. Another reason that makes commodities ideal candidates for e-auctions is that the quality requirements are very easily fulfilled by the suppliers (Schoenherr and Mabert, 2011).

Contrary to common belief, Carter et al. (2004) reveal that a complex item or service can be auctioned, as long as its attributes can be translated into unambiguous specifications. Percy and Giunipero (2006) also support this idea and report that the e-auctions are not only suitable for commodities or standardized items, it is also possible to use them for the purchase of the products with more complex attributes. However, both studies do not precisely specify which of the products in the other categories excluding the commodity category are suitable for the auctions.

To address this need in the literature, we study the effects of the different product categories on the buyer surplus and classify them based on their impacts on the average buyer surplus achieved through the e-auctions. The cost structure of a product is often different in each product category, resulting in different amounts of buyer surplus. More specifically, the cost structures of the products in the categories of chemical and logistics directly depend on commodity prices such as oil, natural gas, and bulk chemicals. Therefore, the marginal profits for the suppliers that operate in the chemical and logistics categories are typically smaller than those for the suppliers

in the other categories. For these categories, we expect that decreases in procurement prices achieved at the end of the auctions will be limited. The products in the categories of advertisement and manufacturing systems are mostly experience goods such as the design of a manufacturing system, the automation of a current system, and the creation of an ad campaign. Therefore, the suppliers that operate in the categories of advertisement and manufacturing systems tend to increase their marginal profits on the business to be auctioned. When the competition among the suppliers is increased by an e-auction the suppliers can exceedingly reduce their marginal profits to be successful at the end of the auction. As a result, we expect that the average decrease in the procurement prices is higher for the advertisement and manufacturing systems auctions than for the other product categories. Consequently, we posit that the product categories have a notable impact on the buyer surplus.

Hypothesis 1. *The product categories have a notable influence on the buyer surplus.*

If the product categories have an influence on the buyer surplus then they can be categorized based on their impact on the average decrease in procurement prices. Therefore, we propose the following hypothesis.

Hypothesis 2. *The product categories can be grouped based on their impacts on the average decrease in procurement prices.*

3.2.2 The impact of the auction type on the buyer surplus:

There is a significant literature that deals with the effects of the auction type on the auctioneer surplus within the traditional auction setting. Of the seminal analytical studies in this research stream, Vickrey (1961), Myerson (1981), and Bulow and Roberts (1989) reveal that the *English* and *Dutch* auction formats yield the same expected revenue to the auctioneer. This result, which also referred to as the revenue equivalence theorem in the literature, is obtained with the assumptions in which the bidders are risk-neutral and have independent valuations about the price. Additionally,

Milgrom and Weber (1982) analytically compare the *English* and *Dutch* auction types in a setting where the winning bidder's pay-off may depend upon her personal preferences and the quality of the object being sold. The authors find that the *English* auction type yields a higher expected revenue for the auctioneer than the *Dutch* auction type under the assumptions that the bidders are risk-neutral and the price valuations are independent. Böheim and Zulehner (1996) also show that when bidders' valuations are affiliated, the *English* auction yields a higher expected revenue than the first-price, the second-price, or the *Dutch* auction types. For a problem setting where the private valuations are correlated and the bidders are risk-neutral, Wang (1998) derive that the *English* auction type outperforms the *Dutch* auction type in terms of generating revenue for the auctioneer. It is important to note that the assumptions considered in these studies typically do not provide robust results. Accordingly, even if there is a slight deviation from one of the restrictive assumptions the given results could considerably vary (Leong, 2008).

As formal theoretical predictions concerning the effects of the auction types on the auctioneer surplus strictly depend on model assumptions and often fail to capture the complexities in real-life auctions, research efforts have been devoted to establishing their empirical validity mostly using lab experiments and field observations (Hong et al., 2015). Soudry (2004) review the empirical and analytical studies that deal with the relative comparisons between the *English*, *Dutch*, first-price, and second-price auctions. The author highlights that within the forward auction context, the *English* auction is superior to the *Dutch* and first-price auctions. Bapna et al. (2009) study a dataset collected from one of the auction platform providers that offer forward auction service for its individual customers. They claim that the *English* auctions, on average, extract more revenue per unit than the *Dutch* auctions. With the empirical analysis of a dataset that covers the fish auctions in Denmark, Brendstrup and Paarsch (2006) derive that the *English* auction garners the auctioneer a higher expected revenue than the *Dutch* auction. Shachat and Wei (2012) use laboratory experiments to examine

the relative performance of the *English* and first-price auctions. With this effort, they show that the average and variances of the prices achieved with the use of the first-price auction are lower than the ones achieved with the use of the *English* auction. By considering an experimental auction market selling a single risky object, Hong and Nishimura (2003) find that the *English* auction yields a higher seller revenue compared to the second-price auction.

With the review given above, we conclude that none of the studies in the literature focus on the comparison of the effects of the *English* and *Dutch* auctions on the buyer surplus by considering the reverse auction setting. To address this need in the literature and to extend the findings in the forward auctions to the context of the reverse auctions, we address the effects of *English* and *Dutch* auctions on the buyer surplus. Consistent with the previous findings in the forward auction literature, we expect a greater buyer surplus in the *English* auctions compared with the *Dutch* auctions. Thus:

Hypothesis 3. *English auctions yield more buyer surplus compared to Dutch auctions.*

Auction types can also be classified on the basis of the number of suppliers to be used for purchasing the item at the end of the auction. At a basic level, this involves a choice between competition on a winner-take-all basis or competition that allows for split awards among a number of bidders (Anton et al., 2010). In practice, the auctions in which a winner supplies all the auctioned items are referred to as *Lot* auctions whereas the auctions in which multiple suppliers provide the auctioned items are called as *Split* auctions.

There exists a vast literature focusing on the effect of the *Lot* auctions on the buyers within the reverse auction setting. The studies in this research stream claim that the transaction and administrative costs were reduced due to the lot-award structure (Jap, 2002). Additionally, with the lot-award structure, production economies of scale are obtained in the auctions. Based on these facts, Jap (2007) and Aloini et al. (2012) reveal that in industrial procurement, the auctions with the lot-award

structure yield more price reductions than the auctions with the split-award structure. The results derived from these studies depend on the expert ideas or surveys rather than an econometric analysis. Accordingly, we believe that an econometric analysis addresses the effects of the award structure on the buyer surplus would contribute to the literature by showing whether the intuition in practitioners' minds is coherent with the results that have been obtained in practice.

For this purpose, in this work, we focus on the effects of the award structure on the buyer surplus. From the discussion and drawing on the results in above studies, a higher buyer surplus is expected to be obtained in the *Lot* auctions compared with the *Split* auctions.

Hypothesis 4. *Lot auctions yield more buyer surplus compared to Split auctions.*

3.2.3 The impact of the 2008 global financial crisis on the buyer surplus:

Global crises typically generate impetuous changes in the market demand, because, during the downturn periods, many companies dramatically reduce purchases and cut inventories while others temporarily close or go out of business. For instance, the economic downturn that began during the fall of 2008 has notably affected many firms' revenues, with some of them reporting decreases in sales of 30% and more (Krause and Ellram, 2014). Dooley et al. (2010) also report that the crisis in 2008 results in a 3.2% sales decrease across the entire manufacturing sector in the U.S. compared with the previous year. These dramatic effects of the economic downturns provide significant challenges to all the parties in the supply chain, especially the suppliers.

During the economic recession periods, the suppliers often bear the costs of a downturn in demand through an ability to use accumulated resources and/or to absorb fixed costs (Morris and Imrie, 1992). More specifically, the economic recession periods would likely force the suppliers to push down their prices in order to sell the excess capacities resulted due to crimping demand from deteriorating economic conditions. In such a case, the revenues that could be obtained through the e-auctions would

be more important for the suppliers, because, the reverse auctions provide to the suppliers a chance of reaching new buyers and an outlet to sell the excess capacity (Schoenherr et al., 2012).

This fact naturally increases the competition among the suppliers participating in the auctions when there exists an economic downturn in the market. So, the suppliers struggling to find a market for their product due to an economic recession would lower the price as much as they can do in order to be the winner at the end of auction. In fact, during the economic recession periods, many buyers use the reverse auctions as a tactical weapon to drive supplier prices down and they expect to gain more benefit than the time when there is no economic recession (Hutt and Speh, 2005).

From this discussion and drawing on the results regarding the effects of economic downturn periods on the suppliers, we posit the following hypothesis:

Hypothesis 5. *The 2008 global financial crisis led to an increase in the buyer surplus.*

3.2.4 *The impact of the number of bidders on the buyer surplus:*

In the case of procurement auctions and contract bidding, several empirical studies report that higher number of bidders lowers purchasing price. For instance, Percy and Giunipero (2006) and Park et al. (2012) state that an increase in the number of bidders participating in the auction leads to an increase in the buyer surplus as it intensifies the competition among the bidders in the online market. Smeltzer and Carr (2003) and Wyld (2011) propose that a minimum of five viable bidders is needed to lower purchasing prices by creating a competitive bid environment. Along similar lines, Millet et al. (2004) empirically show that the highest price reduction results are obtained by inviting at least five or six, up to a maximum of 13.

There are also a number of analytical works that are devoted to the analysis of the impact of the number of bidders on the buyer surplus. Ağralı et al. (2008) study a logistics spot market in which a number of firms asking for transportation and two types of carriers are matched through the reverse auctions. They show that a reduction

in the auction prices is positively associated with an increase in the number of bidders. Chen (2012) examines the coordination mechanism for supply chain with multiple competing suppliers in the electronic market. The author denotes that the auctions where the number of bidders is high result in a lower purchasing price. Karabağ and Tan (2017) develop an analytical model to analyze the impact of the existence of an e-auction provider in the market on the buyers and suppliers. Consistent with the previous results, their numerical analysis indicate that as the number of bidders increases in the auctions the purchasing price reduces.

All the studies discussed in above assert that the impact of the number of bidders on the buyer surplus is constant and this effect does not alter as the number of bidders changes. However, we believe that the positive impact of having an extra supplier in the auction on the buyer surplus decreases as the number of bidders is getting larger. So, we hypothesize the following:

Hypothesis 6. *The positive impact of having one more bidder in the auction on the buyer surplus decreases as the number of bidders is getting larger.*

3.2.5 The impact of the group purchasing on the average decrease in procurement prices:

Group purchasing is the practice of several buyers forming a consortium by gathering through a third-party in order to negotiate with the suppliers at a more favorable price. For the buyers, it typically provides larger volume discounting and cost-saving opportunities through economies of scale. The third-party typically charges the buyers based on a fee that is determined according to the value of the item being purchased and it generally offers the group purchasing services to its corporate customers through the e-auctions.

The notion of group purchasing and the motives that drive the buyers and suppliers to use the group purchasing programs are well-established in the works of Schotanus et al. (2010) and Wei et al. (2011). Nollet and Beaulieu (2003) perform over 70

interviews with the purchasing experts who work in the health-care sector and identify the critical factors impacting on the development of purchasing groups. Ghaderi et al. (2012) empirically study the effects of a successful group purchasing program on the logistics activities operated by a group of small- and medium-sized food enterprises. Their results show that a reduction of 10% to 30% in the logistics cost can be achieved when the group purchasing option is used instead of using the individual buying option. Similarly, the benefits of group purchasing programs to the corporate customers are well discussed in the work of Tan (2014) by introducing an industrial case study.

Additionally, in the operations management literature, there exist several analytical studies that deal with the notion of group purchasing. Keskinocak and Savaşaneril (2008) study the underlying economics behind the collaborative procurement programs and the effects of collaboration on the buyer and supplier profitability. The authors ascertain that the buyers are always willing to collaborate if they have no limitations on procurement quantities, such as uncapacitated storage limit. Chen et al. (2009) and Hu et al. (2012) analytically show that a group purchasing programs can have positive and significant impacts to the buyer surplus when the certain conditions satisfied. Similarly, Karabağ and Tan (2017) analytically show that under the certain conditions, a group purchasing organization helps buyers and/or suppliers to mitigate demand and price risks and so it could be beneficial for all parties in the market.

To the best of our knowledge, we are not aware of any empirical studies that focus on whether the findings derived from the analytical models and surveys are coherent with the practice. With the analysis conducted in our work, we aim to fill this gap in the literature. Consistent with the previous findings, we expect that the purchases conducted with the group purchasing options, on the average, results in a lower price than the ones conducted with the individual buying options. Thus:

Hypothesis 7. *The average purchasing prices achieved with the group purchasing options is lower than the one achieved with the individual buying option.*

3.2.6 The impact of the contract type on the average decrease in procurement prices:

In practice, the market maker typically charges its corporate customers based on three contract types, *Fixed*, *Percentage*, and *Mixed* in exchange of the use of the e-auction platform. In the *Fixed* contract type, the market maker asks the buyers to pay a fixed fee as a member of its network and/or a user of the platform. The market maker generally receives the payment from the buyers in advance as the payment amount is independent of the number of transactions being processed in the online marketplace. The fixed fee contracts are typically used for encouraging the buyers to use the online marketplace and for reducing the possible extra costs associated with the tax issues (Hartmann, 2002). In the *Percentage* contract, the market maker generally charges the buyers based on a per-transaction commission as a non-decreasing function of the order quantity being transacted in the auction or a per-transaction commission as a non-decreasing function of the wholesale price and order quantity (Jin and Wu, 2001). In practice, the former is referred as a scheme based on the commission charged by the order quantity whereas the latter is called as a scheme based on the commission charged by the transaction volume. It is common to pay between 0.25 and 5% of either the transaction volume or the order quantity. The pricing schemes that depend on the transactions in the auction introduce an additional financial risk for the buyers, as the margin for the exchange is dependent on the product pricing above costs instead of fixed transaction fees (Hartmann, 2002). In the *Mixed* contracts, the buyers pay a fixed service fee as well as a commission based on the transactions in the auction. Essentially, it combines features from the *Fixed* and *Percentage* contracts.

Even though the buyers use the e-auction platform provided by the third-party, they generally manage the RFQ processes on their own. In the RFQ process, the buyers ask the participating suppliers to submit their best initial offers for the auctioning item. With the minimum of the bids received in the RFQ process, the buyer or the auctioneer typically measure the auction efficiency. In fact, in some cases, this efficiency measure is used to determine the payment fee for the buyers who use the

e-auction platform with the *Percentage* contracts. In such a case, the buyer has a strong incentive to encourage the suppliers to lower their initial bids. Because, the efficiency appeared at the end of the auction can relatively be decreased with this effort and the buyer pays less service fee to the auctioneer. Additionally, as the buyer put an extra effort to further reduce the suppliers' initial bids submitted in the RFQ process, she would not lose her buyer surplus to be obtained at the end of auction. From this discussion, we expect that the auctions conducted with the *Percentage* contracts have a lower average decrease in procurement prices compared with the ones conducted with the *Fixed* contracts. Thus, we consider the following hypothesis:

Hypothesis 8. *Percentage contract type yields a lower average decrease in procurement prices compared to Fixed contract type.*

3.2.7 The impact of the ownership of the e-auction platform on the average decrease in procurement prices:

The buyers can employ either a third-party e-auction provider or its own infrastructure to conduct the reverse auctions. In most of the time, establishing a private auction infrastructure does not only require a high investment in the information technology but also require an experience and a large supplier base to manage and operate the online marketplaces. Additionally, using a private auction platform may lead a deteriorating buyer and supplier relationships. Because, once a buyer runs its own auction platform, the suppliers could become skeptical as to the legitimacy of bids or come to believe that the auction platform is being manipulated by the owner (Wyld, 2011). The discontent among suppliers for the auctions conducted with the private platforms starts adversely affecting suppliers' bidding behaviors. In the literature, this issue is referred to as the buyer's opportunism. To avoid these possible risks, the buyers mostly prefer to use the specialized third-party providers, rather than establishing and employing their private infrastructures.

In the literature, the opportunism issue has received increasing attention in recent

years. Tangpong et al. (2010), and Handley and Benton Jr (2012) provide a detailed overview regarding the opportunism issue addressed within the supply chain management and reverse auction literature. Based on a survey study, Jap (2002) ascertains that the suppliers' suspicions of opportunism increase after the open-bid auction, because, the suppliers consider this auction type as an exploitative and unfair tool. Manoochehri and Lindsay (2008), Tassabehji (2010), and Spann et al. (2018) report that suppliers typically view e-auctions as a tool that increases buyer opportunism and that damages their relationships with the buyers. The authors also emphasize that the buyer surplus achieved with the use of auctions tend to decrease due to the suppliers' perceptions of opportunism. With a lab experiment, Gattiker et al. (2007) find that the e-auctions lead to a lower level of trust among the suppliers compared to the face-to-face negotiations. Jap (2007) conducts a survey analysis and reveals that as the number of suppliers and the amount of auctioning item increase the opportunism suspicions among the suppliers decreases. By conducting a laboratory experiment, Carter and Stevens (2007) observe that when the suppliers' perceptions of opportunism increase the buyer profit tend to decrease. Wyld (2011) suggests to the use of the third-party e-auction providers to avoid these issues. The author reveals that the involvement of the third-party provides a neutrality and legitimacy to the reverse auctions, and thus, the trust factor among the parties in the market is enhanced. The author also claims that the buyer can improve its surplus by using the platform provided by a third-party firm rather than using its own platform.

To the best of found knowledge, we are not aware of any empirical studies that focus on whether the findings derived from the surveys are coherent with the practice. By filling this gap, we aim to contribute to the understanding of the effect of the auction platform ownership on the buyer surplus. Consistent with the findings in the previous studies, we posit that the average decrease in procurement prices is higher for the auctions conducted through the third-party auction provider than for the auctions conducted through the private auction platform.

Hypothesis 9. *The average decrease in procurement prices is higher for the auctions conducted through the third-party auction provider than for the auctions conducted through the private auction platform.*

3.3 Data Description

This study is based on a third party auction provider that offers online marketplace services to its corporate customers. The company has 131 corporate customers from different sectors and provides them to auction solutions for over 1500 different products and services. Its supplier network encompasses approximately 17000 providers from the different parts of the world. The platform provider was established in 2001 and operated as an independent company until June 2013 when it was acquired by one of its corporate customers. After this acquisition, the platform provider has begun to offer not only services related to e-auction solutions but also collective procurement events.

3.3.1 Auction data

The dataset analyzed in this work is gathered from the online auction platform. Table 3.2 presents the data structure. The raw dataset includes all the variables presented in Table 3.2, except for the product category, the buyer type, and the crisis variables.

Our dataset consists of 130 different individual buyers and a group purchasing organization. All the procurement events are mapped into two classes depending on the buyer type in the dataset. We observe that 89% of the 15458 auction events were conducted for the individual buyers and 11% of the auction events were executed for the GPO. With this structure of the dataset, we are able to investigate the effects of the group purchasing programs on the average decrease in procurement prices achieved due to the auctions.

The dataset contains more than 1500 different products ranging from a hand tool that was bought at a price of 150 USD to a logistics project that was given to a bidder

Collected Data	Description
Auction Number	: A unique identity number given for each auction.
Starting Date and Hour	: Starting date and hour of the auction.
Finishing Date and Hour	: Finishing date and hour of the auction.
Auction Duration (DURATION)	: Duration of the auction in minutes.
Buyer Name	: Name of the firm that will buy the product from the bidders at the end of auction.
Product Name	: Name of the product that will be bought at end of auction. Technical specifications for the product are also given here.
Number of Bids (BIDS)	: The number of bids submitted during the auction.
Number of Invited Suppliers (INVITED)	: The number of suppliers which are invited to the auction.
Number of Participated Suppliers (BIDDERS)	: The number of suppliers which participated in the auction among the invited ones.
Auction Type	: There are three auction types that are administered by the auctioneer: <i>Lot</i> , <i>Split</i> and <i>Dutch</i> .
Contract Type	: There are three contract types that are used by the auctioneer: <i>Fixed</i> , <i>Percentage</i> and <i>Mixed</i> .
RFQBID	: The minimum of bids in the RFQ process. Unit of this variable is 10000 USD.
Resulting Bid	: Winning bid at the end of auction. It is kept in USD.
Decrease in RFQBID	: The difference between RFQBID and Resulting Bid. It is kept in USD.
%DECBID	: Relative difference between RFQBID and Resulting Bid, $((\text{RFQBID} - \text{Resulting Bid}) / \text{RFQBID})100$.

Table 3.2: Main structure of the dataset

that offered a price of 33 million USD. Although the name of the product and its technical specifications are covered by the raw dataset, there is no information about the product categories. To address this issue, the 15458 auction events are classified into 14 product categories by using a keyword matching algorithm. The keywords of medicine, hospital, medical, prosthesis, surgery, and patient are some of the examples

Added Data	Description
Product Category	: The auctions comprise of 14 different categories: construction, chemical, indirect material, direct material, electrical works, service, logistics, health-care, metal, plastics, advertisement, manufacturing systems, technological equipments, and textile.
Buyer Type	: Indicator variable shows the type of buyer. There are two different buyer types such as the GPO that acts as a purchasing agent for a group of individual firms and the individual buyers that make purchases on their own. In the buyer type variable, the individual buyers are coded as 1 whereas the GPO is represented by 0.
Crisis	: The global financial crisis of 2008 and its effects are controlled by this variable. The variable is equal to 1 for the years 2008 and 2009. Otherwise, it is zero.

Table 3.2: (cont'd) Main structure of the dataset

used for determining the products in the health-care category. Transportation, cargo, shipping, road, airline, maritime, and partial freight are employed to determine the products in the logistic category. As a result of this effort, each product in the dataset is mapped into one of 14 different categories. We also match the product categories considered in our work with the ones proposed as the United Nations Standard Products and Services Code. The details can be found in Table B.1, which is given in Appendix B. The structure of the dataset allows us to examine the impact of the product categories on the buyer surplus obtained with the use of e-auctions.

Following the global financial crisis of 2008, the effects of the economic crisis were felt deeply in all the countries of the world and the majority of firms witnessed major declines in output, profitability, and trade (Alfaro and Chen, 2012). To observe how this phenomenon affected the surplus of the buyers that used e-auctions, we investigate the effects of the years 2008 and 2009 separately. To do so, we create the Crisis variable in such a way that it is equal to 1 for the years 2008 and 2009 whereas it is 0 for the other years.

Table 3.3 shows the distributions of the number of auctions organized in the different product categories and the number of auction formats used in the procurement events.

Product Category	Auction Type			Total	% Percentage
	<i>Lot</i>	<i>Split</i>	<i>Dutch</i>		
Direct Material	3285	253	812	4350	28.1%
Construction	3053	69	335	3457	22.3%
In-Direct Material	2181	159	109	2449	15.8%
Health-Care	61	1677	2	1740	11.3%
Service	563	30	106	699	4.5%
Electrical Works	483	21	80	584	3.8%
Metal	368	18	35	421	2.7%
Technological Equipments	316	25	59	400	2.6%
Textile	321	47	20	388	2.5%
Logistics	204	124	11	339	2.2%
Advertisement	244	11	26	281	1.8%
Chemical	109	12	41	162	1.1%
Manufacturing Systems	80	13	23	116	0.8%
Plastics	57	12	3	72	0.5%
Total	11325 (72.9%)	2471 (16.4%)	1662 (10.7%)	15458	100%

Table 3.3: Frequency table for the number of auctions organized in different the product categories and the number of auction formats used in the procurement events

Direct material auctions take the majority with 28% of all auctions, followed by auctions for construction with 22% and indirect material auctions comprising 16%. In the dataset, three different auction formats are used by the auctioneer: *Dutch*, *Lot*, and *Split*. As Table 3.3 indicates, *Lot* is the most frequently used auction method, accounting for 73% of all auctions. *Split* and *Dutch* constitute 16% and 11% of all auctions, respectively. Since the dataset includes *Dutch*, *Lot*, and *Split* auction types it allows us to address the Hypotheses 3 and 4.

In the dataset, there are also three contract types employed to manage the relationship between the buyers and the auctioneer. These are *Percentage*, *Fixed*, and *Mixed*. The numbers of *Percentage* and *Fixed* contract types that are used in the e-auction events are 12004 and 359, respectively. In addition, the *Mixed* contract type

was used in 3095 auctions. Due to this structure of the dataset, we are able to address the Hypothesis 8.

3.3.2 Auction Procedure

In the purchasing organization, the procedure for an e-auction starts with the preparation of the request for quotes (RFQ) process. RFQ is a typical process that includes the determination of the list of potential suppliers to be invited to participate in the auction event, the submission of the detailed specification of the item to be auctioned, and the declaration of the auction details. The specifications of the product and the list of suppliers are determined by the buyer. When the buyer does not define the list, the participants are proposed by the auctioneer considering the buyer requirements and the characterization of the product. Under this setting, the buyer reviews the auctioneer's list of the proposed suppliers and prunes the list as required.

Once the approval from the buyer for the product specifications and the list of the suppliers are received, the auctioneer provides a recommendation on what type of the auction should be used for the item to be auctioned. With this recommendation, the auctioneer fully describes the auction parameters, such as the bid decrement and the starting time. The last decisions on each auction parameter and whether to implement the proposed auction format are given by the buyer.

After the buyer's decisions on the auction format and its parameters, the required settings in the e-auction platform are specified by the auctioneer. Next, the auctioneer invites all of the suppliers in the pre-specified list to participate in the e-auction. Each invited supplier gets the details of the e-auction and informs the auctioneer whether he is willing to participate in the auction. Before the e-auction starts, the buyer requests the participating suppliers to submit their best initial offers for the auctioning item. Each participating supplier is obliged to participate in these negotiations and to respond to the request of submitting an initial offer.

The initial bids are received from all of the participating suppliers before starting

the e-auction and the smallest of the initial bids, referred to as RFQBID, is obtained. Since the online system is used while conducting this process, the auctioneer also has the information on the initial offers and RFQBID. With this effort, the buyer and the auctioneer determine the price of the item before executing the e-auction. In the dataset, the difference between the prices before and after the e-auction refers to the efficiency of the e-auction. In this study, we focus on how this difference is affected by the 2008 global financial crises, the product category, the auction type, and the number of bidders.

In *Percentage* contracts, the buyer may put an extra effort to reduce the initial offers because he will pay the service fee to the auctioneer according to the decrease in the minimum of the initial submitted bids. On the other hand, the suppliers may submit their best initial bids since they expect that there will be a high level of competition in the auction when the number of bidders is high. These phenomena may lead the fact that the decrease in the procurement price with respect to RFQBID will be quite small or even zero. That is, since the initial submitted bids are in fact good offers, there is a little room for the decrease that may be achieved at the end of the auction.

Once the RFQBID is determined, the buyer starts the e-auction. During the auction time frame, all of the participants submit their bids electronically. Each submitted bid has a time stamp and only the bids that conform to the auction rules are considered as valid. The auctioneer is responsible for operating all of the steps without any technical or synchronization problems. After following the pre-specified rules for the chosen auction format, the auction terminates. The summary results of the auction and the winning bidder are submitted to the buyer as a single report.

3.3.3 Auction Formats

The dataset consists of three auction types, *Dutch*, *Lot*, and *Split*. In a *Dutch* auction, the auctioneer begins by calling out an initial price low enough so that presumably no

bidder is interested in selling the item at that price. In our dataset, the initial price in *Dutch* auctions is generally set to lower than 25% of RFQBID. The initial price is gradually increased at the fixed time intervals until one of the bidders agrees to sell the item at the stated price.

Lot and *Split* auctions are the reverse auction mechanisms where more than one items can be auctioned at a time. In a *Lot* auction, all of the auctioning items are considered as a single one. Therefore, each submitted bid should include a single price for all items. However, in *Split*, the bidder can submit a different price for each auctioning item so that a different auction for each item is executed simultaneously. Accordingly, there is only one winning bidder in a *Lot* auction whereas there may be more than one winner in a *Split* auction.

For *Lot* and *Split* auctions, except the difference in the rules for determining the structure of award, the auction rules are the same as the rules of the *English* auction. Therefore, one can consider the *Split* auction as a special case of the *Lot* auction. In an *English* auction, an auctioneer starts requesting bids from all of the participants. During the auction, each participant can only bid by meeting the rule proposed by the auctioneer. More specifically, in our dataset, the auctioneer only accepts bids that are smaller than the current lowest one. By considering this rule, the bidders dynamically submit successively lower bids for the item. The auction stops when no bidder is willing to decrease its bid below the lowest standing bid.

3.3.4 Descriptive Statistics

The descriptive statistics for the minimum of bids submitted in the RFQ process (RFQBID), the relative difference between RFQBID and the resulting bid (%DECBID), the auction duration (DURATION), and the number of bids submitted during the auction (BIDS) are given in Table 3.4.

The overall average and standard deviation of %DECBID are 8.4% and 9%, respectively. That is, on the average, the e-auction platform yielded a 8.4% decrease in

Product Category	RFQBID (10000\$)		%DECBID (percentage)		DURATION (minutes)		BIDS (number)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Advertisement	16.1	28.8	13.3	11.7	49.2	30.3	58.8	70.7
Plastics	14.3	45.2	12.9	11.3	44.7	23.8	29.1	33.3
Manufacturing Sys.	20.5	50.9	11.5	9.3	48.7	30.8	36.6	42.4
Service	31.7	75.9	10.5	11.8	53.1	36.6	45.5	56.1
Textile	12.4	26.2	9.6	8.6	54.5	27.5	45.4	40.1
Direct Material	12.0	33.2	9.4	10.2	46.7	153.0	26.4	35.9
In-Direct Material	21.5	132.2	8.9	8.6	48.0	43.8	40.3	52.3
Construction	28.3	91.1	8.9	8.0	50.1	38.1	39.8	35.8
Metal	21.6	43.8	8.6	9.9	44.8	23.8	27.4	26.0
Technological Eq.	34.5	207.3	8.6	8.7	48.4	79.5	29.3	30.4
Electrical Works	26.8	111.5	7.5	6.9	49.0	29.9	33.9	32.9
Logistics	108.2	202.4	4.9	5.2	80.7	58.7	81.3	101.0
Chemical	84.6	258.1	4.2	4.5	41.6	29.0	24.1	38.2
Health-Care	2.8	9.0	3.3	2.9	53.0	29.4	64.6	52.4
Total	21.4	93.7	8.4	9.0	48.6	41.5	39.5	46.7

Table 3.4: Descriptive statistics for the lowest bid submitted in the RFQ process, the percentage decrease in RFQBID, the auction duration, and the number of bids

procurement prices with respect to the minimum of the initial submitted bids. Table 3.4 indicates that the average %DECBID is relatively higher for the advertisement, plastics, and manufacturing systems categories than for the others. Table 3.3 shows that although there is an opportunity of achieving a large decrease in procurement prices by using e-auctions, buyers do not frequently use e-auctions for the products in the advertisement, plastics, and manufacturing systems categories. On the other hand, for the categories of chemical, health-care, and logistics, the average %DECBID is relatively small compared to that in the other product categories. With these arguments, one can conclude that the product category may have an effect on %DECBID and that the product categories may be classified based on the level of %DECBID.

In all product categories, %DECBID has a positively skewed distribution and the

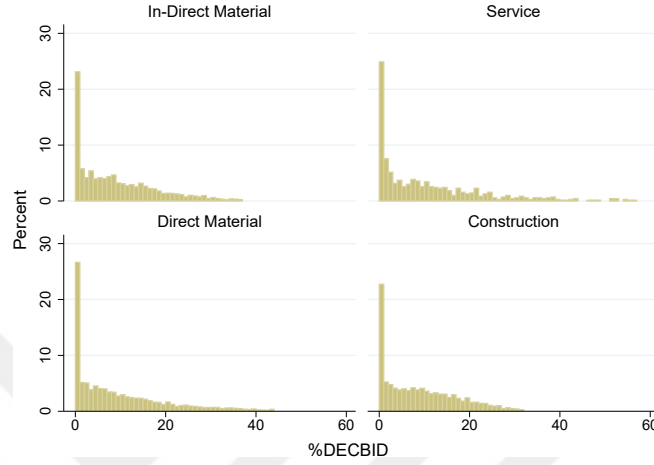


Figure 3.2: For the categories of indirect material, service, direct material, and construction, histograms of the percentage decrease in RFQ BID



Figure 3.3: For the categories of indirect material, service, direct material, and construction, histograms of the numbers of bidders

number of observations at zero is considerably higher than that at other values. In 2428 auctions, RFQ BID is the auction price and the owner of this bid is the winner of the auction. Therefore, %DECBID equals zero in these auctions. Figure 3.2 depicts the histograms for indirect material, service, direct material, and construction categories. It shows that 23% of indirect material auctions yield no decrease in RFQ BID whereas

%DECBID is zero in around 25% of auctions executed for products in the service category. In 27% of direct material auctions and 22% of construction auctions, a decrease in RFQ BID is not observed.

Figure 3.3 shows that in the indirect material, service, direct material, and construction categories, the number of bidders follows a slightly right-skewed distribution and the average number of bidders are between 3 and 4. We observe that the distributions of the number of bidders in the other categories are also right-skewed as the ones depicted in Figure 3.3, however, the average number of bidders participating in the auctions are mostly greater than 4. For the sake of brevity, they are not presented in here.

3.4 Methodology

In this section, we specify the statistical methods employed in the analysis of the hypotheses and provide the reasons why we choose these tools for the analysis.

With Figure 3.2, we have spotted that our dataset contains a significant proportion of observations in which there is no decrease in RFQ BID, i.e., %DECBID=0. These observations comprise around 16% of our dataset. The classical methods such as linear regression model probably do not account for the piling up of zeros and could result in biased estimates for the effects of the product category, the auction type, the 2008 global financial crisis, and the number of bidders on the buyer surplus. To avoid this issue that may arise in the analysis of the Hypotheses 1, 3, 4, 5 and 6, we utilize the standard Tobit model (Tobin, 1958). The results related to the model are discussed in Section 3.5.1.

In the standard Tobit framework, the dependent variable can take on the value of zero with positive probability but is a continuous random variable over strictly positive values. This special distribution characteristic of the dependent variable is referred as the corner solution response. To develop a model that accommodates the corner solutions, Tobin (1958) introduces a latent variable, y_i^* , that satisfies the classical

linear model assumptions for a given sample. By making use of the latent variable, the standard Tobit model is expressed as

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases} \quad \text{where} \quad y_i^* = \mathbf{X}_i \boldsymbol{\beta} + \epsilon_i, \quad \epsilon_i | \mathbf{X}_i \sim \text{Normal}(0, \sigma^2). \quad (3.1)$$

y_i is the dependent variable and $\mathbf{X}_i$ is the vector of the independent variables. In addition, $\boldsymbol{\beta}$ is the vector of the coefficients and ϵ_i is the error term for the i^{th} observation. The Tobit model proceeds by applying maximum likelihood estimation to all data points including the zeros.

In the Tobit model, the estimated coefficients are the partial effects of the explanatory variables on the latent variable, y_i^* . The partial effect of the k^{th} explanatory variable, x_k , on the dependent variable, y_i , depends on $\mathbf{X}_i$ throughout calculated probability distribution associated with the explanatory variables, but always has the same sign as the corresponding Tobit coefficient. In other words, since the derivative calculations performed to obtain the partial effects result in the different value for each $\mathbf{X}_i$, the Tobit coefficients do not represent partial effects of the explanatory variables on the dependent variable. Additionally, the Tobit coefficients imply the direction of the relationship between the corresponding explanatory variable and the dependent variable due to the fact that the partial effects of explanatory variables have the same sign as the corresponding Tobit coefficient. For more detailed discussion on the issue in the estimation of the partial effect of x_k on y_i , we refer the reader to Wooldridge (2002).

To overcome the issue in the estimation of the partial effect of x_k on y_i , the method of Average Partial Effects (APE) is used following the work of Wooldridge (2002). For the case in which x_k is a discrete variable, the partial effect of increasing x_k from a given value, say h to $h + 1$, is stated as follows:

$$APE = \frac{1}{N} \sum_{i=1}^N \left(\Phi \left(\frac{\mathbf{X}_i' \hat{\boldsymbol{\beta}}}{\hat{\sigma}} \right) \mathbf{X}_i' \hat{\boldsymbol{\beta}} + \hat{\sigma} \phi \left(\frac{\mathbf{X}_i' \hat{\boldsymbol{\beta}}}{\hat{\sigma}} \right) - \Phi \left(\frac{\mathbf{X}_i \hat{\boldsymbol{\beta}}}{\hat{\sigma}} \right) \mathbf{X}_i \hat{\boldsymbol{\beta}} - \hat{\sigma} \phi \left(\frac{\mathbf{X}_i \hat{\boldsymbol{\beta}}}{\hat{\sigma}} \right) \right). \quad (3.2)$$

In the above equation, the terms with hat are the estimates obtained from the data and N is the number of observations. $\Phi(\cdot)$ and $\phi(\cdot)$ are the cumulative distribution and the probability density functions of the standard normal distribution, respectively. $\mathbf{X}'_i$ is the vector at which x_k equals $h + 1$ whereas $\mathbf{X}_i$ is the vector at which x_k is equal to h . For both vectors, the remaining explanatory variables equal their own values as observed at the i^{th} data point.

Since the product categories are coded as categorical variables in the Tobit model the coefficients regarding these variables are estimated according to a base category. So, the coefficients report the relative difference that could be obtained when the auction is conducted in another product category instead of the base one. Due to this fact, the Tobit coefficients only give a rough idea which of the product categories can be considered in the same group. To classify the product categories in a correct manner, each category should be compared with each other and the groups should be formed according to these results. Since the product categories do not satisfy the assumptions of equal variances and of equal sample sizes the tests to be used in the classification analysis should be robust against these issues. Therefore, for the pairwise comparisons conducted across the product categories, we use Games-Howell test (Games and Howell, 1976) that is rather similar to Tukey's test in its formulation, but, does not assume equal variances and sample sizes. Additionally, before conducting pairwise comparisons tests, we should assure that the average percentage decrease in at least one product category is different than the ones in the others. To perform this analysis, we utilize Welch's ANOVA test (Welch, 1951) that is a modification of one-way ANOVA allowing for non-homogeneous variances across the groups. With the Games-Howell and Welch's ANOVA tests, we evaluate the Hypothesis 2 and present the corresponding results in Section 3.5.2.

When the buyer type, contract type, and the ownership of the e-auction platform are treated as an exogenous variable in the standard Tobit model, the number of observations would not be sufficient to get unbiased and consistent estimates of the

coefficients. Specifically, the number of observations would be zero for some of the combinations of the categorical variables. Therefore, we use two sample student t-test with unequal variances assumption while assessing the Hypotheses 7, 8, and 9, which respectively consider the possible impacts of the buyer type, contract type, and the ownership of the e-auction platform on average decrease in procurement prices. The results related to the tests are discussed in Sections 3.5.3, 3.5.4, and 3.5.5.

3.5 Empirical Analysis

In this section, the results of the statistical analyses conducted to address the hypotheses stated in Section 3.2 are presented.

3.5.1 Analysis of the effects of the product category, the auction type, the 2008 global financial crisis, and the number of bidders on the buyer surplus

For the analysis of the effects of the product category, the auction type, the 2008 global financial crisis, and the number of bidders on the buyer surplus, we employ the standard Tobit model and present results in Table 3.5. The inflation rate, days when the auction conducted, and currencies used in the auction have been considered as the control variables in the Tobit model. However, as the coefficients corresponding to the inflation rate, days when the auction conducted, and currencies used in the auction have not been statistically significant we have ignored these control variables and presented the results obtained without them. To address a potential violation of the assumption of homoscedastic error terms, the robust standard errors are estimated for the coefficients. They are presented in parentheses next to the Tobit coefficients. Electrical works in the product categories, *Dutch* in the auction types, and the years in which there is no global financial crisis are treated as the base level for the Tobit model.

Because the coefficient of determination obtained for the Ordinary Least Squares estimators is misleading when the dependent variable is a corner solution response

Variables/Method	Standard Tobit Model with MLE	
	Dependent variable: %DEC BID	Average Partial Effects (APE)
Auction Type		
<i>Lot</i>	4.09*** (0.26)	3.42*** (0.64)
<i>Split</i>	1.32*** (0.40)	1.01*** (0.33)
Product Category		
Plastics	4.98*** (1.39)	4.10*** (1.23)
Manufacturing Sys.	4.81*** (1.02)	3.95*** (0.82)
Advertisement	4.20*** (0.78)	3.42*** (0.65)
Service	2.66*** (0.61)	2.11*** (0.53)
Direct Material	1.86*** (0.39)	1.46*** (0.32)
Technological Eq.	1.28* (0.67)	0.98* (0.50)
Textile	1.09* (0.61)	0.86* (0.47)
Construction	0.59 (0.38)	0.45 (0.30)
Metal	0.25 (0.63)	0.19 (0.47)
In-Direct Material	-0.17 (0.41)	-0.13 (0.29)
Chemical	-3.15*** (0.65)	-2.23*** (0.43)
Logistics	-5.52*** (0.58)	-3.68*** (0.32)
Health-Care	-5.97*** (0.49)	-4.06*** (0.32)
Crisis	0.81*** (0.22)	0.63*** (0.17)
BIDDERS	0.65*** (0.04)	-
Constant	0.81*** (0.40)	-
Number of observation	15458	-
$\hat{\sigma}$	9.69	-
Pseudo R^2	32%	-
Likelihood Ratio (LR) χ^2 Test	139.48***	-

Note: The limit for the corner solution is 0 and the number of observations at zero is 2428. Significance at the 10%, 5% and 1% levels are denoted respectively by *, **, ***.

Table 3.5: Tobit model for the average percentage decrease in procurement prices

(Wooldridge, 2002), we define the Pseudo R^2 which states the square of the correlation between the dependent variable and its estimate obtained by the Tobit model. Based on this pseudo R^2 , that is 32% in the model, one can say that the Tobit conditional mean function fits the data moderately well. In addition, the p-value of the Likelihood Ratio test indicates that at least one of the Tobit coefficients is not equal to zero.

The partial effects of the auction types, the product categories, and the global financial crisis on %DECBID are estimated by *APE*. The estimated *APE* values are also given in Table 3.5. The standard deviations of these estimations are obtained by using the bootstrapping method with 200 repetitions and they are presented in parentheses next to the corresponding *APE* values.

The *APE* values for the chemical, indirect material, and logistics product categories are negative and statistically significant at the 1% level. That is, e-auctions in these categories tend to yield a lower decrease in RFQ BID compared to the ones in the electrical works category. In Table 3.5, the *APE* values also show that %DECBID significantly rises when e-auctions are implemented in the advertisement, manufacturing systems, and plastics product categories. According to the results, Hypothesis 1 is supported, that is, the product categories have an influence on the buyer surplus.

In Table 3.5, the Tobit coefficients indicate that the *Lot* and *Split* auctions exert positive and significant effects on %DECBID. This implies that the *Lot* and *Split* auctions led to a higher buyer surplus than the *Dutch* auctions. In the dataset, the auctioneer essentially implements the *English* auction rules while operating the *Lot* and *Split* auctions. The only difference between these two auction types stems from the award structure implemented at the end of auction. Since both *Lot* and *Split* auctions are superior to the *Dutch* auctions in terms of increasing the buyer surplus one can also conclude that the *English* auctions outperform the *Dutch* auctions. In addition, the *APE* value regarding the *Lot* auction means that %DECBID increases by 3% on average when the *Lot* auction is used. The *APE* value of the *Split* auction indicates that %DECBID increases on average by 1% with the use of the *Split* auction.

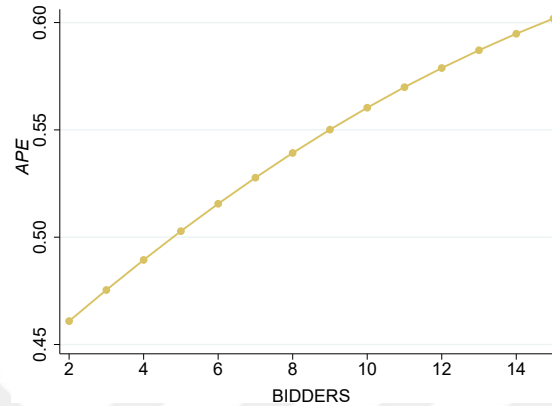


Figure 3.4: Average Partial Effects (APE) for the number of bidders

Thus, one can conclude that the *Lot* auctions outperforms than the *Split* auctions in terms of decrease in procurement prices. On the basis of these results, we can conclude that Hypothesis 3 and Hypothesis 4 are supported. That is, the *Lot* auctions yield more buyer surplus compared to the *Split* auctions and the *English* auctions yield more buyer surplus compared to the *Dutch* auctions.

The Tobit coefficient regarding the crisis variable indicates that there is a positive association between %DECBID and the years in which the global financial crisis was observed. This association is also statistically significant at the 1% level. The corresponding *APE* value implies that %DECBID increased by 0.6% on average in the years that the effect of global financial crisis was observed. As a result, we can conclude that Hypothesis 5 is supported, that is, the 2008 global financial crisis led to an increase in the buyer surplus. This effect is also investigated for the years 2010 and beyond by adding the dummy variables. However, the analysis shows that the effect of the economic crisis is not statistically significant after 2010.

The partial effects of the different numbers of bidders on %DECBID are estimated by *APE* and presented in Figure 3.4. The *APE* values for the different numbers of bidders are statistically significant at the 1% level. Figure 3.4 indicates that increasing the number of bidders leads to an increase in %DECBID. However, it is also observed

that the positive marginal impact of the number of bidders on %DECBID is not constant and it gradually declines as the number of bidders increases. Specifically, an increase in the number of bidders from m to $m + 1$ leads to a higher marginal benefit to buyer surplus, compared to an increase in the number of bidders from $m + 1$ to $m + 2$. As a result, Hypothesis 6 is supported, that is, the positive impact of having one more bidder in the auction on the buyer surplus decreases as the number of bidders is getting larger.

3.5.2 Classification of the product categories based on their impacts on the average decrease in procurement prices

In this section, we classify the product categories based on their impacts on the average decrease in procurement prices. Additionally, we determine the %DECBID levels that roughly separate each group from the others.

Source	DF Num	DF Den	F-Value	p-value
Prdouct Category	13	1409.5	247.2	0.00

Table 3.6: Welch's ANOVA Test

We primarily investigate whether the average percentage decrease in at least one product category is different than the ones in the others. For this investigation, we use Welch's ANOVA test and present the corresponding results in Table 3.6. The p-value regarding the test is smaller than 0.05 which implies that at least one product category has a different average percentage decrease in the procurement prices compared to the others.

For the Welch's ANOVA test, the results indicate that not all product category means are equal. However, these results do not tell us precisely which product category means are different and which of the product categories can be considered in the same group. To identify statistically significant differences between specific product

Product Category	N	Average %DECBIID	Grouping
Advertisement	281	13.3	A
Plastics	72	12.9	A
Manufacturing Sys.	116	11.5	A B
Service	699	10.5	A B
Textile	388	9.6	B
Direct Material	4350	9.4	B
In-Direct Material	2449	8.9	B
Construction	3457	8.9	B C
Technological Eq.	400	8.6	B C
Metal	421	8.6	B C
Electrical Works	584	7.5	C
Logistics	339	4.9	D
Chemical	162	4.2	D E
Health-Care	1740	3.3	E

Note: Product categories that do not share a letter are significantly different.

Table 3.7: Games-Howell Pairwise Comparisons Test Results

categories and to group the product categories in a correct manner, we need to perform a pairwise comparisons post-hoc test. To address this issue, we employed the Games-Howell Pairwise Comparisons tests. The results regarding the classification of the product categories are given in Table 3.7. For the sake of brevity, the results regarding the pairwise mean comparisons across product categories are given in Appendix B.

The results regarding the Games-Howell tests indicate that for the advertisement, plastics, manufacturing systems, and service categories, there is no statistical difference on the average decrease in procurement prices. That is, these product categories can be considered in the same group. As the advertisement, plastics, manufacturing systems, and service categories have higher averages compared to others we name the group containing these categories as *High*. The Games-Howell tests results imply

that textile, direct material, indirect material, construction, technological equipments, metal, and electrical works categories can constitute a group. The group including these categories is called as *Medium*. From the Games-Howell tests results, it is also observed that the logistics, chemical, and health-care categories can form a group. Since the averages percentage decreases in the procurement prices are smaller for logistics, chemical, and health-care categories than for the others, the group covering these categories is named as *Low*. The results of the classification of the product categories are summarized in Table 3.8.

With these efforts, we also confirm that Hypothesis 2 is supported, that is, the product categories can be grouped based on their impacts on the average decrease in procurement prices.

<i>High</i>	<i>Medium</i>		<i>Low</i>
- Advertisement	- Construction	- Metal	- Chemical
- Manufacturing Sys.	- Direct Material	- Textile	- Health-Care
- Plastics	- Electrical Works	- Technological Eq.	- Logistics
- Service	- In-Direct Material		

Table 3.8: Classification of the product categories based on the average decrease in procurement prices

Additionally, we specify the %DECBID levels that roughly separate each group from the others. For specifying the separation levels, we use the highest average %DECBID and the lowest average %DECBID in the *Medium* group, which are 9.6% and 7%, respectively. To observe whether the levels are appropriate for classifying the product categories, we construct a 95% lower one-sided confidence interval on the mean of %DECBID for each product category and present them in Figure 3.5.

Figure 3.5 indicates that the separation levels, 9.6% and 7%, moderately well work for classifying the product categories into three major groups. With these levels, we can provide an additional information on the groups. For the product categories in the

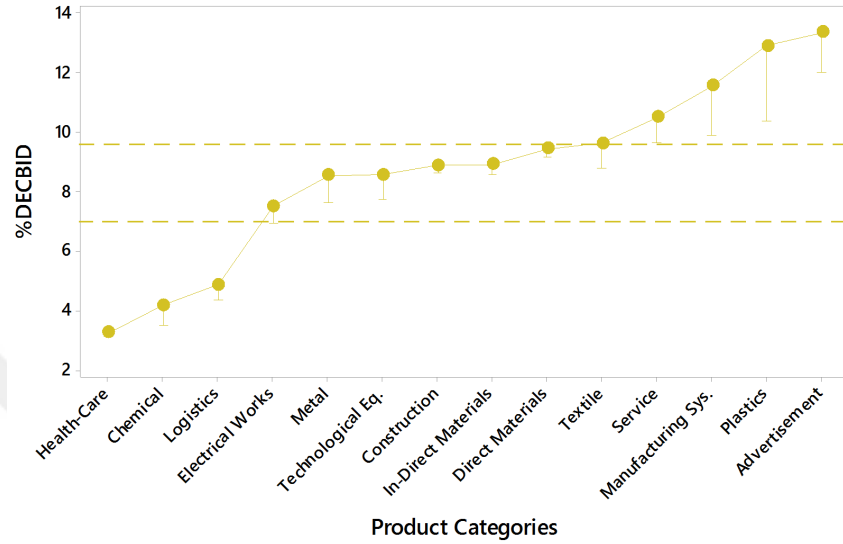


Figure 3.5: 95% lower one-sided confidence intervals on the averages of %DECBID by the product categories

Low group, the average percentage decrease in procurement prices is lower than 7%. Additionally, the average percentage decrease in procurement prices is between 7% and 9.6% for the product categories in the *Low* group whereas the average percentage decrease in procurement prices is higher than 9.6% for the product categories in the *High* group.

To statistically confirm the observations acquired from the figure, we also perform the student's t-test at the significance level of 0.05. We test the hypotheses that for the chemical, health-care, and logistics categories, the average %DECBID is smaller than 7%. As all of the obtained p-values are lower than 5%, we reject the null hypotheses. That is, there is sufficient evidence at the 0.05 level of significance to conclude the average %DECBID is smaller than 7% for the chemical, health-care, and logistics categories. We investigate the hypotheses that the %DECBID means in the construction, direct material, electrical works, indirect material, metal, technological equipments, and textile categories are smaller than 9.6%, but higher than 7%. The p-values obtained from student's t-tests imply that the considered hypotheses are

supported. As a result, we can conclude that for the *Medium* group, the average %DECBID is between 9.6% and 7%. We also assess the hypotheses that for the advertisement, manufacturing systems, service, and plastics categories, the average %DECBID is greater than 9.6%. The obtained p-values support the hypotheses at the significance level of 0.05. So, we conclude that the average %DECBID is greater than 9.6% for the product categories in the *High* group. With these efforts, we give an idea about the %DECBID levels that roughly separate each group and identify the product categories that can provide high benefits for the buyers when the e-auction implementations are used.

3.5.3 Analysis of the effect of the group buying on the average decrease in procurement prices

In the dataset, we observe two buyer types: (1) the individual buyers that make purchases on their own and (2) the GPO that is an entity authorized to act as a purchasing agent for a group of individual buyers. In this section, it is investigated whether there is a difference between these two buyer types with respect to the average percentage decrease in RFQ BID. The result of this investigation allows us to understand the effect of group purchasing programs on the average percentage decrease in procurement prices.

Variable	GPO			Individual Buyers			Differences in Means
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	
%DECBID	1662	9.24	8.97	13796	8.32	8.95	$\mu_{GPO}^{\%DECBID} > \mu_{Individual}^{\%DECBID***}$
BIDDERS		6.63	4.12		4.81	2.93	$\mu_{GPO}^{BIDDERS} > \mu_{Individual}^{BIDDERS***}$

Significance at the 10%, 5% and 1% levels are denoted respectively by *, **, ***.

Table 3.9: Comparisons of the buyer types with respect to the average percentage decrease in the procurement prices and the average number of bidders

The hypothesis that the average percentage decrease in RFQBID is higher for the GPO than for the individual buyers, $\mu_{GPO}^{\%DECBID} - \mu_{Individual}^{\%DECBID} > 0$, is considered while conducting the statistical test. The results are presented in Table 3.9. As a result of the test, the null hypothesis is rejected at the 1% significance level. Thus, we conclude that the average purchasing prices achieved with the group purchasing options is lower than the one achieved with the individual buying option. This implies that Hypothesis 7 is supported.

By considering the hypothesis that the average number of bidders that participate in the auctions executed for the GPO is higher than the average number of bidders that participate in the auctions executed for the individual buyers, $\mu_{GPO}^{BIDDERS} - \mu_{Individual}^{BIDDERS} > 0$, we also compare the GPO and the individual buyers with respect to the average number of bidders. Two sample student t-test with unequal variances assumption is employed for the statistical comparison. The results are presented in Table 3.9. At the 1% significance level, the null hypothesis is rejected. Thus, we draw the conclusion that the average number of bidders that participate in auctions executed for the GPO is higher than that for the individual buyers. With this effort, we conclude that the group purchasing programs achieve more decrease in the procurement prices compared to the individual buyers. One of the possible reasons behind this result is the fact that more suppliers participate in the auctions executed for the group purchasing option compared to the ones for the individual buying option. Additionally, since the GPO combines the demands of a group of individual buyers in the auctions, there could be a positive impact of the economies of scale on the findings related to %DECBID and BIDDERS.

3.5.4 Analysis of the effect of the contract types on the average decrease in procurement prices

In this section, we examine the effects of *Percentage* and *Fixed* contract types on the average decrease in procurement prices by using two sample student t-test with

unequal variances assumption. The hypothesis that the *Fixed* contract type yields a higher average decrease in procurement prices compared to the *Percentage* contract type, $\mu_{Fixed}^{\%DECBID} - \mu_{Percentage}^{\%DECBID} > 0$, is considered while conducting the statistical test. The results are presented in Table 3.10.

Variable	<i>Percentage Contract</i>			<i>Fixed Contract</i>			Differences in Means
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	
$\%DECBID$	12004	8.58	8.98	359	8.86	8.95	$\mu_{Fixed}^{\%DECBID} = \mu_{Percentage}^{\%DECBID}$

Significance at the 10%, 5% and 1% levels are denoted respectively by *, **, ***.

Table 3.10: Comparisons of Percentage and Fixed contract types with respect to the average percentage decrease in the procurement prices

As a result of the test, at the 1% significance level, the null hypothesis cannot be rejected. So, there is no statistical evidence to conclude that the *Fixed* contract type yields a higher average decrease in procurement prices compared to the *Percentage* contract type. One of the possible reasons behind this result is that the auctioneer reasonably determines the values of the contract parameters in the *Fixed* and *Percentage* contract types. Thus, both of the contract types yield the same efficiency in terms of the decrease in procurement prices. In addition, the buyers generally attach importance to the offers submitted in the RFQ process and attempt to decrease it as much as they can without considering the contract type. As a result, there is no difference between the *Fixed* and *Percentage* contract types with respect to the average decrease in procurement prices. Consequently, we cannot support Hypothesis 8 that the *Fixed* contract type yields a higher average decrease in procurement prices compared to the *Percentage* contract type.

A comparison between the *Mixed* and the other contract types is not considered in this section. Since the customer specific contract parameters in the *Mixed* are not observed in the dataset, we cannot compare the *Mixed* contracts and the other two

contract types, accurately. Because, in the *Mixed*, the contract parameters can be specified in a way that the fixed fee is significantly higher than the amount of share. In such a case, the effect of *Mixed* on the decrease in procurement prices would be similar to that of the *Fixed* contract. On the other hand, in the *Mixed*, the amount of share can be set to a higher level compared to the fixed fee. Under this setting, the effects of the *Mixed* on the decrease in procurement prices would be similar to that of the *Percentage* contract. This fact leads to the higher variance in the decrease in procurement prices achieved with the use of the *Mixed* contract type. Hence, the comparison between the *Mixed* and the other contract types would not be consistent and unbiased.

3.5.5 *The effect of the ownership of the e-auction platform on the average decrease in procurement prices*

In June 2013, the e-auction platform was acquired by one of the platform's corporate users. The new owner of the platform is a member of a large industrial group that has 113 companies located across 22 countries with 26 billion USD total consolidated revenue. The new owner represents and makes use of a notable buying power on behalf of its group. By using the economies of scale that the group has, it began to offer the group purchasing events for the members of its own group and the other customers.

In the dataset, all the procurement events conducted for the new owner of the platform, including before and after the acquisition, were managed with the *Percentage* contracts. Additionally, most of the procurement events were run by implementing the *Lot* auction rules. In the analysis, to avoid the effects of the other factors except for the ownership change, we eliminate the data points that include the *Split* and *Dutch* auctions. As a result of this effort, we obtain a dataset that covers the online purchasing events organized for the new owner of the platform and that does not include any additional policy, structural or contract changes. So, the dataset we prepared for this analysis includes a natural experiment that allows investigating the

effect of the ownership of the e-auction platform on the buyer surplus.

Variable	After the Acquisition			Before the Acquisition			Differences in Means
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	
%DECBID	962	10.45	9.78	700	7.58	7.41	$\mu_{Before}^{\%DECBID} = \mu_{After}^{\%DECBID}$

Significance at the 10%, 5% and 1% levels are denoted respectively by *, **, ***.

Table 3.11: Comparisons of the averages of percentage decrease in procurement prices obtained before and after the date the e-auction platform is acquired by the purchasing organization

To exploit this natural experiment, we test the hypothesis that the average decrease in procurement prices obtained before the acquisition of the e-auction platform is higher than the average decrease in procurement prices obtained after the acquisition, $\mu_{Before}^{\%DECBID} - \mu_{After}^{\%DECBID} > 0$. Two sample student t-test with unequal variances assumption is employed for conducting the hypothesis test and the results are presented in Table 3.11. As a result of the test, at the 1% significance level, the null hypothesis cannot be rejected. So, there is no statistical evidence to conclude that the average decrease in procurement prices achieved before the acquisition is higher than the average decrease in procurement prices achieved after the acquisition. This result implies that the Hypothesis 9 is not supported.

One of the possible reasons behind this result is that the suppliers' perceptions of opportunism could decrease after the acquisition as the new owner of the platform possibly conduct high volume auctions due to its operations scope. This result is coherent with the findings in the work of Jap (2007). Another reason underlying behind this result could be the fact that the new owner of the auction platform still continues to provide auction solutions to the ones out of its group. This fact may not change the suppliers' perceptions to the owner of the auction platform and the suppliers can perceive the owner as the one operating the platform independently rather than the one operating the platform for its group and the other corporate

customers. On the other hand, this reason also is coherent with the findings in the work of Wyld (2011).

3.6 A Summary of Findings

In this section, we summarize the main findings derived from the empirical analysis and the possible factors that drive these findings. Table 3.12 indicates the summary of the hypotheses test results.

Hypothesis 1. The product categories have a notable influence on the buyer surplus.	Supported
Hypothesis 2. The product categories can be grouped based on their impacts on the average decrease in procurement prices.	Supported
Hypothesis 3. <i>English</i> auctions yield more buyer surplus compared to <i>Dutch</i> auctions.	Supported
Hypothesis 4. <i>Lot</i> auctions yield more buyer surplus compared to <i>Split</i> auctions.	Supported
Hypothesis 5. The 2008 global financial crisis led to an increase in the buyer surplus.	Supported
Hypothesis 6. The positive impact of having one more bidder in the auction on the buyer surplus decreases as the number of bidders is getting larger.	Supported
Hypothesis 7. The average purchasing prices achieved with group purchasing options is lower than the one achieved with the individual buying option.	Supported
Hypothesis 8. <i>Percentage</i> contract type yields a lower average decrease in procurement prices compared to <i>Fixed</i> contract type.	Not Supported
Hypothesis 9. The average decrease in procurement prices is higher for the auctions conducted through the third-party auction provider than for the auctions conducted through the private auction platform.	Not Supported

Table 3.12: Results of statistical tests

The empirical results indicate that product categories have a notable effect on the buyer surplus. The decrease in procurement prices significantly increases when the e-auction is executed in one of the categories of advertisement, manufacturing systems, service, and plastics. We attribute this result to the fact that the products in the categories of advertisement, service, and manufacturing systems are experience goods, thus bidders mostly intend to increase the initial offers submitted before the

e-auction starts. However, it is observed that the buyer surplus decreases when the e-auction is conducted in the chemical, logistics, and health-care categories. The cost structures of products in the chemical and logistics categories directly depend on the commodity markets, thus, the decrease in procurement prices that can be achieved at the end of the auction is limited. The buyers in the health-care category use e-auctions to easily document their transactions rather than to increase their surpluses. This particular use of e-auctions explains why the e-auctions conducted in this category yield a lower decrease in procurement prices compared to the other categories. The majority of the existing literature has proposed that the use of the reverse auction is advantageous in the purchase of commodity items, especially where the price is the primary consideration. However, in this study, we ascertain that this online procurement tool is not only a valuable tool for the purchase of commodity items, but also could be of value for purchasing more complex items. The results we obtain here imply that there is an opportunity of achieving a large decrease in the procurement prices for the complex products which are in the advertisement, service, and manufacturing systems categories by using e-auctions.

We show that *English* auctions yield more buyer surplus compared to *Dutch* auctions whereas *Lot* auctions yield a greater increase in the buyer surplus compared to *Split* auctions. The superiority of the *English* auction over the *Dutch* auction can be related to the auction dynamics. In the *English* auctions, the bidders compete with each other by submitting consecutively bids. This structure creates an iterative process that continues until a price is reached where there is just a single bidder who is willing to supply the auctioning item. However, in *Dutch* auctions, the price is monotonically increased by the auctioneer until there is a single bidder who is willing to supply at the currently announced price. The bidding rules difference causes the fact that the competition among the suppliers is less in the *Dutch* auctions compared to the *English* auctions. As a natural result of this fact, we observe that *Dutch* auction's efficiency is worse than *English* auction's efficiency. The results regarding

the comparison of the *English* and *Dutch* auctions efficiencies' seem coherent with the forward auction literature. However, we are not aware of any studies that deal with the comparison of the impacts of *English* and *Dutch* auction types on the buyer surplus by considering the reverse auction setting. Therefore, we believe that with this analysis, our work contributes to the literature by extending the corresponding result to the context of reverse auctions. Additionally, the superiority of the *Lot* auction over the *Split* auction can be attributed to the economies of scale. Because in the *Lot* auction type, the winner supplies all the auctioning items whereas in the *Split* auction type, the auctioning items can be supplied by multiple suppliers. Since the *Lot* auctions generally offer the high-volume transactions due to its award-structure the bidders participating in the *Lot* auction type could be more willing to be a winner compared to the ones participating in the *Dutch* auction type. This fact intensifies the competition in the *Lot* auctions thereby increasing its efficiency. The results that we derived for the comparison of the impacts of the *Lot* and *Split* auction types are in the same line with the literature. The existing studies focus on this subject by conducting surveys and/or laboratory experiments. By conducting an econometric analysis on a real dataset, we reveal that the practitioners' intuitions that have been observed in the surveys are coherent with the results that have been obtained in practice. So, this can be considered as another contribution of the study to the literature.

We conclude that the 2008 global financial crisis led to an increase in the buyer surplus. The economic downturn periods typically leads a reduction in the market demand, because, most of the companies dramatically cut their spendings to bear the possible financial and/or operational risks. This effect could force the suppliers to lower their prices in order to sell off the excess capacities emerged due to crimping demand. As a result of a downturn in the market, the competition among the suppliers participating in the auctions would intensify so that the auction prices would go down. To the best of our knowledge, this is the first attempt to focus on the analysis of the financial crisis on the buyer surplus obtained with the use of the e-auctions. So,

another contribution of this study is the understanding of how this factor affects the buyer surplus. Unlike the existing studies, we observe that the positive impact of having one more bidder in the auction on the buyer surplus decreases as the number of bidders is getting larger. This result can be attributed to the fact that the competition in the auction does not further increase after a certain number of suppliers participates in the event. The results regarding this factor also indicate that most of the positive effect of this factor can be achieved by inviting 5 to 10 suppliers to the auction.

As a result of the analysis on the effect of the product categories on the buyer surplus, we classified the product categories into three groups according to the average percentage decrease in the procurement prices and determine the %DECBID levels that roughly separate each group from the others. The chemical, health-care, and logistics categories are grouped as the group that yields *Low* decrease in procurement prices. The average decrease in procurement prices for the auctions in this group is smaller than 7%. The construction, direct material, electrical works, indirect material, metal, technological equipments, and textile categories are grouped as the group that yields *Medium* decrease in procurement prices. The average decrease in procurement prices for the auctions in this group is between 7% and 9.6%. The advertisement, manufacturing systems, service, and plastics categories are grouped as the group that yields *High* decrease in procurement prices. The average decrease in procurement prices for the auctions in this group is greater than 9.6%. With this effort, we give an idea about the %DECBID levels that roughly separate each group and specify the product categories that can provide high benefits for the buyers when the e-auction implementations are used.

The statistical analyses imply that the average purchasing prices achieved with the group purchasing options is lower than the one achieved with the individual buying option. One of the possible reasons behind this result is that the number of bidders participating in the auctions conducted for the group purchasing programs is higher than the number of bidders participating in the auctions conducted for the individual

buyers. The economies of scale that are created with the group purchasing events could also be effective on the results obtained for the average decrease in procurement prices and the number of bidders. Additionally, we conclude that there is no statistical difference between the contract types of *Fixed*, in which a fixed fee is charged for executing the e-auction, and *Percentage*, in which a share is charged from the generated value due to the e-auction. This result may be attributed to the fact that the auctioneer reasonably determines the values of the contract parameters in *Fixed* and *Percentage* contract types. Another reason can be the fact that, without considering the contract type, the buyers give importance to the process in which the offers are submitted before the e-auction starts. We also find that there is no statistical evidence to conclude that the average decrease in auctions prices are higher for those who use the third-party's platform than for those who use their own platform. This result implies that the suppliers' perceptions to the auctioneer have not changed after one of the platform's corporate users acquired the auction platform. That is, the suppliers have continued to believe in the new service provider's neutrality and legitimacy. This can be ascribed to the fact that the suppliers' concerns about opportunism decrease since the service provider likely manages the auctions being large transaction volumes because of its operations scope. Another reason could be the fact that the new provider has still continued to provide auction solutions to the other corporate buyers rather than using the platform for only its own purchasing events. Another contribution of this study is to incorporate the analysis regarding the effects of the group purchasing, contract type, and auction platform ownership on the buyer surplus into the reverse auction literature.

Chapter 4

PURCHASING, PRODUCTION, AND SALES STRATEGIES FOR A PRODUCTION SYSTEM WITH LIMITED CAPACITY AND FLUCTUATING SALES AND PURCHASING PRICES

In many industries, manufacturers of standard products purchase raw materials from commodity markets and sell their products at market prices that are determined by the external market conditions. As a result, their revenue and cost structures are directly affected by the volatility of purchasing and sales prices in the markets.

In particular, manufacturers whose products are related to the agricultural, mineral, oil, and energy sectors make transactions based on the commodity markets and must deal with the price fluctuations in both sales and purchasing operations. For instance, Figure 4.1(a) shows how tomato and tomato paste prices change between the years 1965 and 2015. Figure 4.1(b) also depicts the monthly rate of changes in the price of crude oil and in the price of gasoline between the years 2013 and 2017.

This dependence on market price fluctuations also occurs for industrial goods, such as D-RAM or white goods (Berling and Martínez-de Albéniz, 2011). In addition, manufacturers that execute their purchasing, production, and sales operations in an international setting with different currencies have a similar issue because of the fluctuations in the spot rate of different currencies. Due to the high competition in the markets for standard products, manufacturers cannot individually exert an

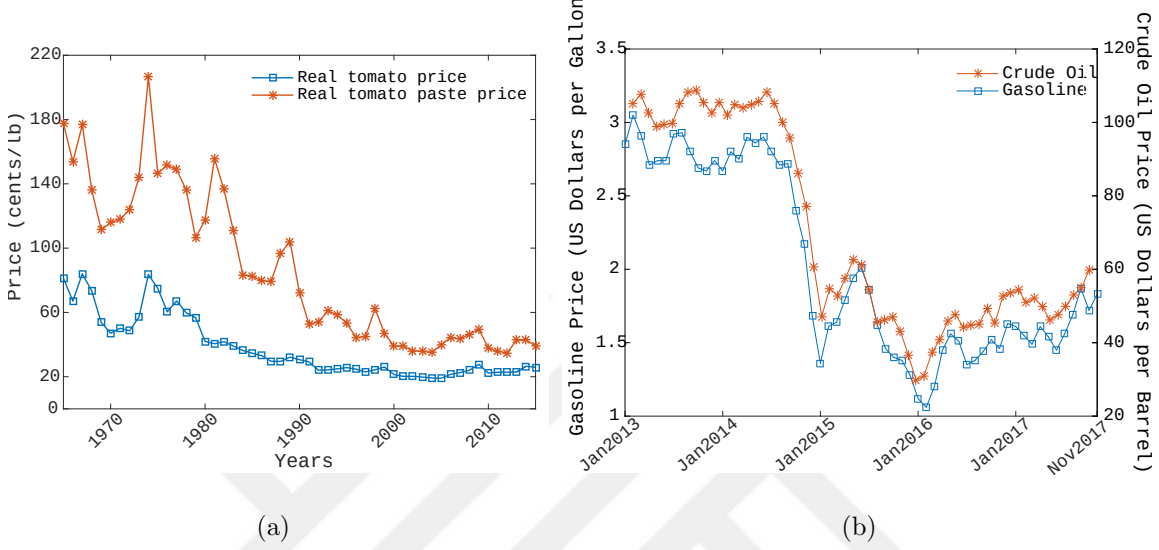


Figure 4.1: (a) Yearly price for tomato paste and tomatoes in California U.S. Figure, from <http://morningstarco.com/statdocs/2016%20Exhibits.pdf>. (b) Monthly rate of changes in the price of crude oil and in the price of gasoline, from <https://data.worldbank.org/data-catalog/commodity-price-data>.

influence over the selling and purchasing prices. In this environment, reflecting the fluctuations in the purchasing prices directly on the sales price will not be accepted by the customers since the prices for the standard products are determined by the market conditions (Berling and Xie, 2014).

To cope with the volatility in the market prices, manufacturers can utilize an operational hedging strategy in terms of purchasing, production, and sales decisions. However, in the literature, the most of the production and inventory control models do not consider a need for the operational hedging strategies that handle the fluctuating market prices. Furthermore, to the best of our knowledge, none of the existing studies focus on the impacts of the correlation between sales and purchasing prices on a production/inventory system where the sales and purchasing prices together fluctuate in a random fashion.

Our aim in this article is developing an analytical model that can be used to

determine the optimal purchasing, production, and sales strategies for a manufacturer with a finite capacity and explaining how the sales price variation, purchasing price variation, correlation between sales and purchasing prices, limited raw materials and finished goods inventories, and limited production capacity affect the performance of a production/inventory system. In this context, we focus on the following research questions:

- What are the optimal purchasing, production, and sales policies for a production/inventory system in which the sales and purchasing prices evolve according to the random environment changes?
- What are the impacts of sales price variation, purchasing price variation, correlation between sales and purchasing prices, limited raw materials and finished goods inventories, and limited production capacity on the system performance measures?
- Under which circumstances does the use of the optimal policy significantly improve the profit compared to the use of the *buy low and sell high* naive policy where the manufacturer buys only when the purchasing price is low and sells only when the sales price is high?

In order to answer these questions, we study a continuous-review discrete-material flow production/inventory system with raw materials and finished goods inventories and consider that the sales and purchasing prices are driven by a randomly fluctuating environment. In our study, the price fluctuations are modeled by a discrete state space, continuous time Markov process. The demand and raw material arrival processes are characterized as Poisson processes and the production system with a limited capacity is modeled as a single server with exponential processing times. Under this problem setting, we model the system as an infinite-horizon Markov decision process under the average reward criterion.

To address the first research question, we employ the *event-based dynamic programming* approach. With this effort, we analytically prove that the optimal purchasing,

production, and sales strategies are state-dependent threshold policies. We also propose a solution procedure based on a linear programming formulation to numerically identify the optimal threshold levels for purchasing, production and sales strategies.

We answer the second question by conducting a range of numerical experiments. As a result, we observe that the negative correlation between sales and purchasing prices yields a higher average reward for the manufacturer. The positive correlation between sales and purchasing prices lowers the average reward for the manufacturer while increases the average inventory and customer service levels. We notice that a higher variation in either the sales price or purchasing price yields a higher profit for the manufacturer. Additionally, we conclude that limited raw materials and finished goods inventories and limited production capacity have considerable effects on the system performance measures.

Finally, in order to address the last question, we first modify the linear programming formulation to model the operation of a producer that uses the *buy low and sell high* naive purchasing and sales policy but determines the production policy optimally. Then by using numerical experiments, we show that the high sales price variation, high purchasing price variation, and negative correlation yield a decrease in the difference between the profits achieved by using the optimal and naive policies.

We consider deriving the optimal purchasing, production, and sales policies for a production system operating with randomly fluctuating and correlated purchasing and sales prices and using the derived policies to show the impacts of sales price variation, purchasing price variation, correlation between sales and purchasing prices, limited raw materials and finished goods inventories, and limited production capacity on the system performance measures as the main contributions of this study.

4.1 Literature Review

In the literature, a number of studies typically examine either the impact of fluctuating sales price or of fluctuating purchasing price on the optimal purchasing, production or

sales policies. In most of these studies, the optimal control models with the different time and state space representations are employed. Based on these representations, the current literature is categorized into several groups and each group is discussed in this review.

The discrete-time discrete-state space models in the literature primarily focus on inventory systems. As one of the early studies in this literature, Özekici and Parlar (1999) develop an infinite-horizon inventory model with unreliable suppliers, where the demand, supply, and cost parameters are affected by a randomly changing environment. In their model, the random changes in the environment states are modulated by a time-homogeneous Markov process. The authors show that an environment-dependent base-stock policy is optimal when the order cost is linear in order quantity. Additionally, an (s, S) policy is found to be optimal when a fixed cost of ordering is in place. In the work of Özekici and Parlar (1999), the supplier is either fully available or unavailable based on the state of the environment. Erdem and Özekici (2002) extend this assumption by considering a case in which the supplier is always available, but its capacity is random and dependent on the state of the environment. Papachristos and Katsaros (2008) further the work of Erdem and Özekici (2002) by introducing a constant lead time and by considering the effect of stochastic ordering of the random variables that represent the supplier's capacity levels on the optimal policy parameters. Gavirneni (2004) considers an uncapacitated production/inventory system in which the purchasing cost fluctuates over the time due to the changes in the exchange rate. The purchasing cost fluctuations are modeled with a time-homogeneous Markov chain. The author proves the optimality of an order up to policy and proposes a simple myopic heuristic for finding the policy parameters. De Cuyper et al. (2013) study the optimal inventory control policy when the lead time of purchased parts follows a phase-type distribution and the purchasing price is a random variable that follows a Markovian process. Liu and Yang (2015) focus on a problem in which a make-to-stock firm periodically controls both the purchasing activity and sales price.

Study	Control Decisions			Objective Function	Purchasing Price		Sales Price		Production Process			Demand Process		Raw Material Process	
	Purchasing	Production	Sales Pricing		Random	Deterministic	Random	Deterministic	Uncapacitated	Capacitated	Random	Deterministic	Random	Random	Deterministic
Özekici and Parlar (1999)	✓			Min TDOC	✓				✓	✓	✓	✓			
Erdem and Özekici (2002)	✓			Min TDOC	✓				✓	✓	✓	✓			
Gallego and Hu (2004)	✓			Min TDOC	✓				✓	✓	✓	✓			
Gavirneni (2004)	✓			Max LRAR	✓			✓	✓		✓				
Mohebbi (2006)											✓				
Papachristos and Katsaros (2008)	✓			Min TDOC	✓				✓	✓	✓	✓		✓	
Gayon et al. (2009)	✓	✓	✓	Max LRAR		✓			✓	✓	✓	✓			
Arnold et al. (2009)	✓			Min TDOC		✓							✓	✓	
Cao et al. (2009)	✓	✓		Min TDOC		✓			✓	✓	✓	✓		✓	
Wu and Chen (2010)	✓	✓	✓	Max TDR	✓		✓		✓	✓	✓	✓		✓	

TDOC: Time Discounted Operating Cost, LRAR: Long-Run Average Reward, TDR: Time Discounted Reward

Table 4.1: A summary table for the reviewed studies

Study	Control Decisions		Objective Function	Purchasing Price		Sales Price	Production Process			Demand Process	Raw Material Process
	Purchasing	Production	Sales Pricing		Random	Random	Uncapacitated	Capacitated	Random	Random	Deterministic
Arnold et al. (2011)	✓			Min TDOC	✓		✓		✓	✓	✓
Berling and Martínez-de Albéniz (2011)	✓			Min TDOC	✓		✓		✓	✓	✓
De Cuyper et al. (2013)	✓			Min TDOC	✓		✓		✓	✓	✓
Berling and Xie (2014)	✓			Min TDOC	✓		✓		✓	✓	✓
Liu and Yang (2015)	✓		✓	Max LRAR	✓		✓		✓	✓	
This Work	✓	✓	✓	Max LRAR	✓	✓	✓	✓	✓	✓	✓

TDOC: Time Discounted Operating Cost, LRAR: Long-Run Average Reward, TDR: Time Discounted Reward

Table 4.1: (cont'd) A summary table for the reviewed studies

The authors consider that the purchasing price randomly fluctuates according to a Markovian fashion and the demand is a random variable depending on the sales price. For the considered problem setting, they show that the optimal purchasing policy is a base-stock type.

In the literature, the continuous-time continuous-state space models are also employed to describe the fluctuations in sales and/or purchasing prices as Markov diffusion processes. Wu and Chen (2010) consider a problem setting where an individual firm controls production and two stages of inventory specifying the deterministic purchasing, production, and sales rates. The sales and purchasing prices are modeled as standard Brownian motion processes. Under this problem setting, the authors study the relation between the inventory and short-term price variation. They also characterize the rational expectations equilibrium for the market in which there are competitive production firms. Berling and Martínez-de Albéniz (2011) examine the optimality of a price-dependent base-stock policy when the demand is a Poisson process and the purchasing price evolves either as a geometric Brownian motion or an Ornstein-Uhlenbeck process. Berling and Xie (2014) propose a heuristic to handle the computational intractability issue raised while obtaining the parameters for the optimal policy suggested in the work of Berling and Martínez-de Albéniz (2011). In some of the studies that consider continuous-time continuous-state space framework, the fluctuations in purchasing or operating costs are defined as a deterministic function of time. Arnold et al. (2009) study the optimal purchasing and inventory policies for a firm that operates in an environment where the ordering cost is zero and the purchasing price, demand, and inventory holding costs vary over time. Arnold et al. (2011) extend the analysis of Arnold et al. (2009) to a production model with finite production rate. Cao et al. (2009) consider a production/inventory system whose operations are subject to the time-dependent deterministic fluctuations in the demand, production cost, and purchasing cost over time.

A number of studies have also employed the random environment framework to

model the randomness in the supply and/or demand processes. In the context of this literature, Gallego and Hu (2004) study the optimal policies for production/inventory systems with finite capacity and Markov-Modulated demand and supply processes. Mohebbi (2006) focuses on a capacitated production/inventory system with compound Poisson demand, where both production and demand processes are subject to independently and randomly changing environmental conditions. The author derives the limiting distribution of the inventory level and provides a number of numerical results concerning the system performance measures. Gayon et al. (2009) consider a make-to-stock production/inventory system in which the customer demand is price-sensitive and its distribution depends on the state of the random environment. The authors study the effects of different pricing strategies on the system profit and derive the optimal replenishment policies for each considered pricing strategy.

Table 4.1 compares the studies discussed above and our work in different aspects. From this comparison, we note that the existing studies typically focus on either the downstream or upstream side of a production or inventory system. Since a production/inventory system with raw materials and finished goods inventories is considered in our work, we study downstream and upstream sides of the system together. In particular, most of the existing studies ignore the process of purchasing raw materials to facilitate the analysis. They typically assume that a raw material is always ready whenever it is required for the production. This assumption generally does not hold in practice because of the randomness in the delivery times in the supply process, the structure of the market, and the suppliers' limited capacities. Unlike most of the existing studies, we include the purchasing process in the system as a stochastic process.

With this effort, we believe that the model provides a better representation for a manufacturer operating in agricultural sector. In the agricultural sector, the raw material arrivals are random because of the harvest times, the geographic location of the suppliers, and weather conditions. In such a setting, the manufacturer generally

decides on whether to buy the harvested raw materials or not. If the manufacturer decides not to buy she loses the current purchasing opportunity. When the raw material is required for the manufacturer she has to wait until the next harvest time. Additionally, when the raw material arrivals rate is set to a sufficiently higher value than the other rates in the system the model allows us to analyze a setting where the raw material is almost always available for the manufacturer. Because, with this particular setting, the frequency of raw material arrivals increases thereby increasing the number of raw material purchase opportunities for the manufacturer. As a natural result of this fact, the system would resemble the one in which the manufacturer is able to buy a raw material whenever she needs it. Hence, the obtained results can be employed to derive inferences regarding the system where the raw materials are always available.

Table 4.1 also shows that the existing studies typically consider a random fluctuation in either sales or purchasing price. However, in our work, both sales and purchasing prices are subject to the random environment changes that evolve based on a continuous-time Markov chain. With this problem setting, we study the impacts of sales and purchasing price variations on the system performance measures. Additionally, unlike the existing studies, we address the effects of correlation between sales and purchasing prices on the system. In our work, the demand and raw material arrivals are considered as two independent Poisson processes. The production capacity is limited because a single server processes raw materials individually with exponential processing times.

To the best of our knowledge, this is the first attempt to derive the purchasing, production, and sales policies of a production/inventory system with correlated and fluctuating purchasing and sales prices, random demand and raw material arrivals and random processing time. With this effort, we are able to investigate the impacts of limited production capacity and traffic intensity on the system performance measures. The use of this modeling technique also allows us to model the system as an infinite-horizon Markov decision process under the average cost criterion.

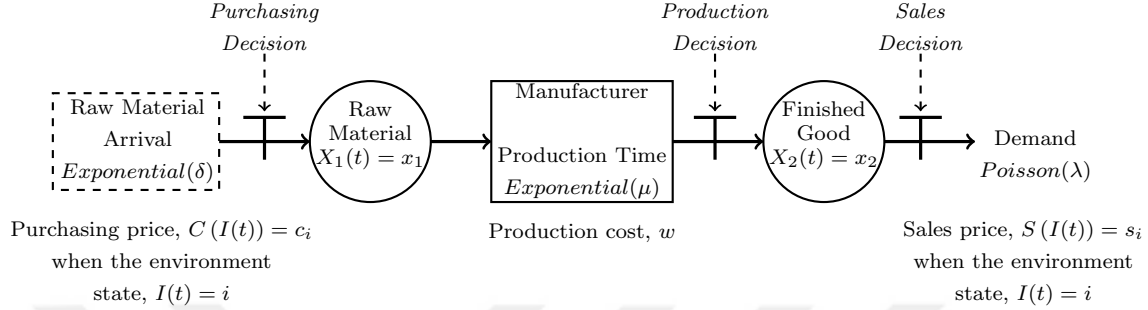


Figure 4.2: Illustration of the problem

4.2 The Model

In this section, we describe the problem setting and propose the dynamic programming model for the problem. Additionally, we derive the optimal purchasing, production, and sales policies for the manufacturer and the structural characteristics of these optimal control policies. A linear programming formulation is given to numerically obtain the parameters of the optimal purchasing, production, and sales policies.

4.2.1 Problem Definition

We consider a discrete-material flow production/inventory system where a single manufacturer with a limited production capacity operates in a make-to-stock manner to fulfill the demand of a single item. Figure 4.2 illustrates the considered system.

When a unit of raw material released into the manufacturing facility, it is processed there and then placed into the finished goods inventory. The manufacturing facility is capable of processing one item at a time. For the processing of a unit of raw material, the manufacturer incurs the production cost of w . The processing time is exponentially distributed at the rate μ .

Each customer arriving at the manufacturer requests only one unit of a finished good. Once a customer arrives to the facility, the manufacturer decides whether to satisfy the arriving customer from the finished goods inventory or reject it. That is, in

order to keep the existing products for future sales at a higher price, the manufacturer does not have to satisfy an arriving demand even though there are some goods in the finished goods inventory. When the arriving demand is satisfied, the manufacturer receives the market sales price for this transaction. If the arriving demand is rejected then it is lost without a penalty cost.

In order to analyze the purchasing policy in a discrete-material flow system, we model the system with raw materials arriving to the manufacturing facility individually with exponentially distributed inter-arrival times with the rate δ that is much higher compared to the other rates of change in the system. Once a unit of raw material arrives to the facility, the manufacturer decides whether to buy it or not. When the manufacturer decides to buy the arriving raw material, he pays the market purchasing price for this transaction and a unit of arriving raw material is added into the raw materials inventory.

The stock level of the raw materials inventory is $X_1(t)$ at time t where $X_1(t) \in \mathbb{N} = \{0, 1, 2, \dots\}$. The finished goods inventory level at time t is denoted by $X_2(t)$ where $X_2(t) \in \mathbb{N} = \{0, 1, 2, \dots\}$. A holding cost of keeping a unit of raw material in the raw materials inventory is h_1 per unit time whereas a holding cost of storing a unit of finished good in the finished goods inventory is h_2 per unit time. In the models where an upstream and a downstream inventory are used together, it is usually assumed that $h_2 > h_1$ in order to reflect a higher value added for the products in the downstream inventory. In our model, since the purchasing and market prices fluctuate, we do not make this restricting assumption.

The manufacturer's operating environment is subject to random changes that directly affect the unit prices for the raw materials and finished goods. The environment state evolves according to a continuous-time homogeneous Markov chain with a transition rate matrix Q . The elements q_{ij} in the transition matrix describe the rate departing from i and arriving in state $j \neq i$. The state of the environment at time t is represented by $I(t)$ where $I(t) \in \mathbb{E} = \{1, 2, \dots, L\}$.

The manufacturer is a price-taker, that is, he cannot individually exert influence over the market prices of finished goods and raw materials. Therefore, the manufacturer uses the market price when he sells a finished good or procures a raw material. The market purchasing and sales prices depend on the state of the environment. Specifically, for the environment $I(t) = i \in \mathbb{E}$, the market prices for purchasing and sales transactions are $C(I(t)) = c_i$ where $c_i \in \mathbb{C} = \{c_1, c_2, \dots, c_L\}$ and $S(I(t)) = s_i$ where $s_i \in \mathbb{S} = \{s_1, s_2, \dots, s_L\}$, respectively. In the setting where the sales price is lower than the purchasing price, the manufacturer would prefer not to continue his operations since he cannot generate a profit. In order to avoid this trivial case, we consider that the lowest possible minimum sales price is greater than or equal to the highest possible purchasing price, i.e., $\min \{s_1, s_2, \dots, s_L\} \geq \max \{c_1, c_2, \dots, c_L\}$. Specifically, it is profitable to purchase, produce, and sell in all environment states, but the profit margins are different.

The manufacturer is always able to observe the state of the environment, raw materials inventory level, and finished goods inventory level. Based on these observations, he seeks to find the optimal purchasing, production and sales policies that maximize his average reward per unit time over an infinite planning horizon.

4.2.2 Optimal Control Model

Since the system retains no memory as the time between each transition is exponentially distributed, the decision epochs in our model can be restricted to times when the state changes. Using these properties, we can formulate the problem as a Markov decision process (MDP) and restrict our attention only to the class of stationary Markovian policies (Puterman, 2014). For the class of stationary Markovian policies, the actions at each decision epoch depend solely on the current state. The current state of the system is therefore described as independent of time t and denoted by the variable $(i, \underline{\mathbf{x}})$. In the state variable, i is the state of the environment and it belongs to the set of $\mathbb{E}$. In addition, $\underline{\mathbf{x}}$ represents the stock levels of the raw materials and finished goods

inventories and it belongs to set of $\mathbb{F} = \{(x_1, x_2) | x_k \in \mathbb{N} \text{ where } k \in \{1, 2\}\}$. Hence, the state variable, $(i, \underline{\mathbf{x}})$, belongs to the state space $\mathbb{E} \times \mathbb{N}^2$.

For any given state, the manufacturer may choose either to purchase a raw material or to do nothing. These two actions are denoted by 1 and 0, respectively, and the action taken by u_b . If an action $u_b=1$ is taken when the environment state is i , a cost of c_i is incurred. He might also choose either to produce or not to produce. These two actions are represented by 1 and 0, respectively, and the action taken by u_p . When an action $u_p = 1$ is chosen, he pays a unit production cost w . When a demand arrives, it may either be immediately satisfied or rejected. These two actions are denoted by 1 and 0, respectively, and the action taken by u_r . If an action $u_r=1$ is taken when the environment state is i , a revenue of s_i is accrued.

For each state $(i, \underline{\mathbf{x}})$, a control policy ℓ specifies the action $u^\ell(i, \underline{\mathbf{x}}) = (u_b, u_p, u_r)$. Given a policy ℓ and an initial state $(i, \underline{\mathbf{x}})$, the manufacturer's average reward per unit time over an infinite planning horizon is defined as

$$v^\ell(i, \underline{\mathbf{x}}) = \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E}_{(i, \underline{\mathbf{x}})}^\ell \left[\int_0^T S(I(t)) dN_R(t) - \int_0^T w dN_P(t) - \int_0^T H(X_1(t), X_2(t)) dt - \int_0^T C(I(t)) dN_B(t) \right], \quad (4.1)$$

where $H(X_1, X_2) = h_1 X_1(t) + h_2 X_2(t)$ is the total holding cost function, $N_R(t)$ is the number of customers satisfied up to t , $N_P(t)$ is the number of products produced up to t , and $N_B(t)$ is the number of raw materials purchased up to t . In addition, $\mathbb{E}_{(i, \underline{\mathbf{x}})}^\ell$ denotes the expectation operation given an initial state $(i, \underline{\mathbf{x}})$ and a policy ℓ . The objective is to identify a control policy ℓ^* that satisfies $v^*(i, \underline{\mathbf{x}}) = \sup_{\ell} v^\ell(i, \underline{\mathbf{x}})$ for all states.

Following Lippman (1975), we work with a uniformized version of the original problem in which the transition rate in each state under any action is $\Lambda = \delta + \lambda + \mu + \sum_i \sum_{j \neq i} q_{ij}$ so that the transition times between decision epochs form a sequence of i.i.d. exponential random variables, each with a mean of $1/\Lambda$. The introduction of the

uniform transition rate allows us to build a discrete-time equivalent of the original system, simplifying the analysis considerably. To further simplify the analysis, we also rescale the time by letting $\Lambda = 1$. As a result of these efforts, we obtain the following optimality equation:

$$v(i, \underline{\mathbf{x}}) + g^* = \delta T_b v(i, \underline{\mathbf{x}}) + \mu T_p v(i, \underline{\mathbf{x}}) + \lambda T_r v(i, \underline{\mathbf{x}}) + T_e v(i, \underline{\mathbf{x}}) - h \underline{\mathbf{x}}, \quad (4.2)$$

where $h = (h_1, h_2)^T$. g^* is the optimal average reward whereas $v(i, \underline{\mathbf{x}})$ denotes the differential reward between the current reward and the optimal average reward. The operators $T_b f(i, \underline{\mathbf{x}})$, $T_p f(i, \underline{\mathbf{x}})$, $T_r f(i, \underline{\mathbf{x}})$, and $T_e f(i, \underline{\mathbf{x}})$ for any real-valued function $f(i, \underline{\mathbf{x}})$ are defined as follows:

$$T_b f(i, \underline{\mathbf{x}}) = \max \{f(i, \underline{\mathbf{x}} + e_1) - c_i, f(i, \underline{\mathbf{x}})\}, \quad (4.3)$$

$$T_p f(i, \underline{\mathbf{x}}) = \begin{cases} \max \{f(i, \underline{\mathbf{x}} - e_1 + e_2) - w, f(i, \underline{\mathbf{x}})\} & x_1 > 0 \\ f(i, \underline{\mathbf{x}}) & x_1 = 0 \end{cases}, \quad (4.4)$$

$$T_r f(i, \underline{\mathbf{x}}) = \begin{cases} \max \{f(i, \underline{\mathbf{x}} - e_2) + s_i, f(i, \underline{\mathbf{x}})\} & x_2 > 0 \\ f(i, \underline{\mathbf{x}}) & x_2 = 0 \end{cases}, \quad (4.5)$$

$$T_e f(i, \underline{\mathbf{x}}) = \sum_{j \in \mathbb{E} \setminus \{i\}} q_{ji} f(j, \underline{\mathbf{x}}), \quad (4.6)$$

where e_1 is $(1, 0)$ and e_2 is $(0, 1)$.

The operators $T_b f(i, \underline{\mathbf{x}})$, $T_p f(i, \underline{\mathbf{x}})$, and $T_r f(i, \underline{\mathbf{x}})$ respectively correspond to the purchasing, production, and sales decisions whereas $T_e f(i, \underline{\mathbf{x}})$ specifies the environmental changes. The state trajectory of the system corresponding to a unichain policy is eventually confined to the recurrent class of states. Because, the state space of the environment is finite and the manufacturer controls the purchasing, production and sales events. Since the system has this unique property, the average reward corresponding to all initial states as well as the differential rewards of the recurrent states are independent of the rewards obtained from the transient states (Bertsekas,

1995). This result assures us that the Bellman's equation $v^* + g^* = Tv^*$ holds and there exists a unique g^* .

4.2.3 Characterization of the Optimal Purchasing, Production, and Sales Policies

To define the optimality equation given in the previous section, we have employed the *event-based dynamic programming* approach that is originally proposed by Koole (1998). In the optimality equation, each certain event in the system is represented by a specific event operator. Representing each event with a specific event operator allows us to analyze the propagation of value function properties through the propagation properties of the event operators. Specifically, if the event operators have some structural properties under the given assumptions, then the value function of the system constructed by using these operators also has the same structural properties.

By using the structure of the event-based dynamic programming approach and the results obtained in the works of Altman et al. (2000) and Koole (2004), we establish that the optimal purchasing, production, and sales policies for the manufacturer are state-dependent threshold policies. In Theorem 1, 3, and 5, we propose the details related to the optimal purchasing, production, and sales policies, respectively. We also establish the monotonicity properties of the optimal purchasing, production, and sales policies in Theorem 2, 4, and 6. In the Appendix C.1, we present a detailed discussion on the proofs of the theorems.

Theorem 1. *The optimal purchasing policy for the manufacturer is a state-dependent threshold policy. That is, for any given state $(i', (x'_1, x'_2))$, there exists a corresponding threshold level, $Z_b^*(i', x'_2)$. It is optimal to buy if $x'_1 < Z_b^*(i', x'_2)$ and to do nothing otherwise, i.e.,*

$$u_b^*(i', (x'_1, x'_2)) = \begin{cases} 1, & \text{if } x'_1 < Z_b^*(i', x'_2), \\ 0, & \text{if } x'_1 \geq Z_b^*(i', x'_2). \end{cases} \quad (4.7)$$

To clarify the theorems, we use a problem instance analyzed optimally by using the approach given in Section 4.2.4 and characterize its optimal purchasing, production,

and sales policies. In Figure 4.3(a), we give the optimal purchasing policy for one of the environment states considered in the example denoted with the environment state i'' . Let us consider the state where there are 2 units in the raw material and 2 units in the finished goods inventories, i.e., the state $(i'', (2, 2))$. Theorem 1 implies that the purchasing threshold level for the given state is one of the points at $(i'', (x_1, 2))$ where $x_1 \in \mathbb{N}$. Figure 4.3(a) shows that the corresponding threshold level is $Z_b^*(i'', 2)=4$. Theorem 1 also implies that for all the points at $(i'', (x_1, 2))$ where $x_1 \in \mathbb{N}$, the purchasing threshold level is $Z_b^*(i'', 2)=4$. That is, for any given point $(i'', (x_1, 2))$ where $x_1 \in \mathbb{N}$, it is optimal to purchase if $x_1 < 4$ and not to purchase if $x_1 \geq 4$.

With the introduced problem instance, we observe that for any fixed i and x_2 , there exists a corresponding threshold level for purchasing decision and it is not optimal to buy a raw material when the raw materials inventory level for a given state is above a certain threshold level. To discuss this implication in more detail, let us modify the manufacturer's maximization problem into an equivalent minimization problem. In the modified version of the problem, the operator related to purchasing decision is defined as $T'_b v'(i, \underline{x}) = \min \{v'(i, \underline{x} + e_1) + c_i, v'(i, \underline{x})\}$ where $v'(i, \underline{x}) = -v(i, \underline{x})$. Also, let us define an operator $\nabla v'(i, \underline{x}) = v'(i, \underline{x} + e_1) - v'(i, \underline{x})$. Intuitively, for the modified problem, $\nabla v'(i, \underline{x})$ represents the benefit of having an extra raw material in the raw materials inventory when the environment state is i . $T'_b v'(i, \underline{x})$ implies that it is optimal not to buy a raw material in state $(i, \underline{x})$ if $\nabla v'(i, \underline{x}) > -c_i$. With the results obtained in the works of Koole (2004) and Altman et al. (2000), we also prove that the benefit of an extra item in the raw materials inventory is non-decreasing in x_1 for each environment state i when $v'(i, \underline{x})$ is multimodular. Whenever this benefit exceeds above a certain value, more specifically above the purchasing cost $-c_i$, it will remain above $-c_i$. This fact guarantees the existence of a threshold level for the purchasing decision. A similar discussion can also be adapted to Theorem 3 and Theorem 5.

Theorem 2. *The optimal purchasing policy for the manufacturer is non-increasing in x_1 and x_2 . That is, $Z_b^*(i, x_2)$ that defines the purchasing threshold level for any given*

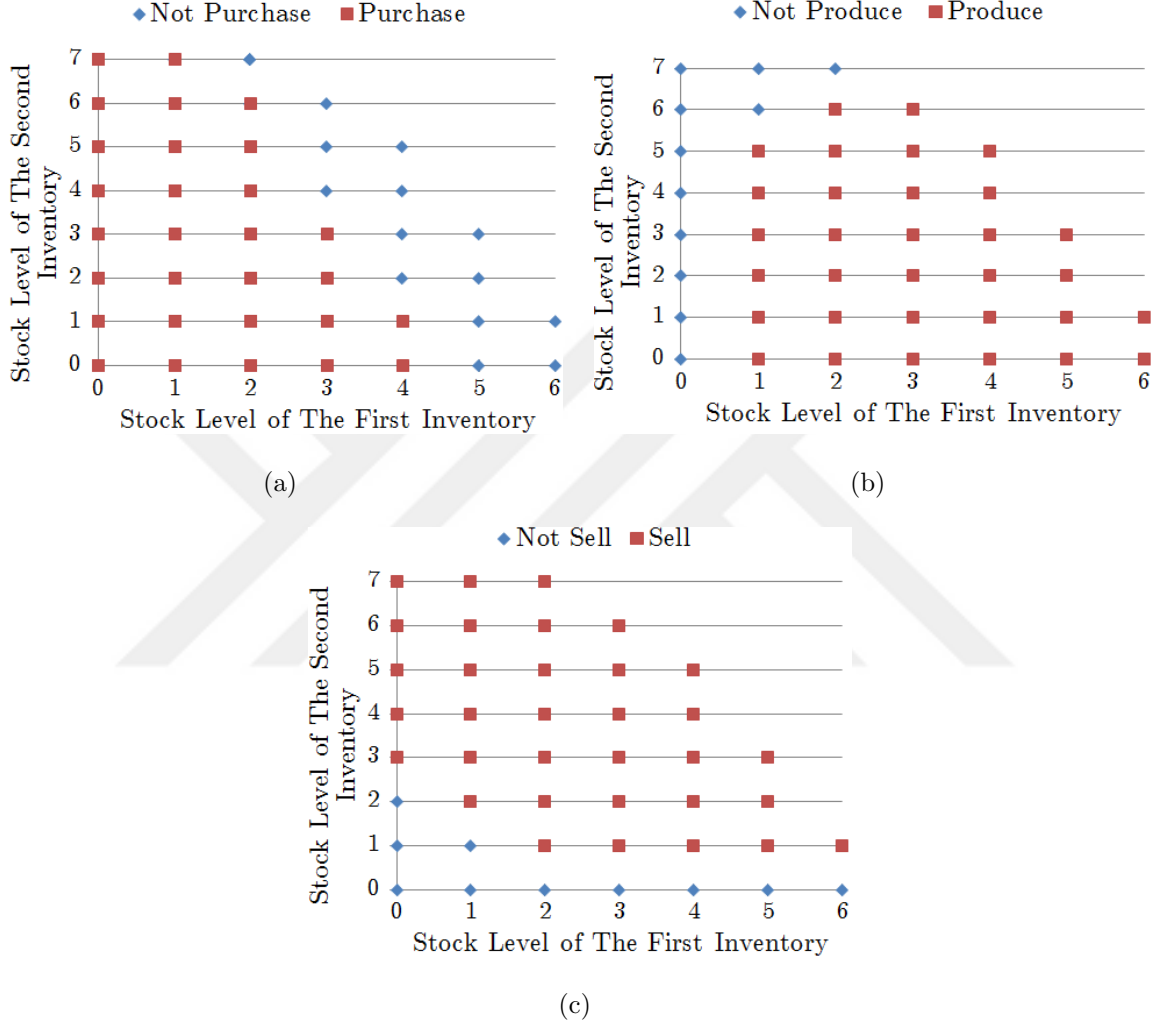


Figure 4.3: An illustration of the optimal (a) purchasing, (b) production, and (c) sales strategies derived for a particular environment state

state $(i, \underline{x})$ is non-increasing in x_2 .

Let us consider the state where there are 2 units in the raw material and 3 units in the finished goods inventories, i.e., the state $(i'', (2, 3))$. Theorem 2 implies that for any given state $(i'', (2, x_2''))$ where $x_2'' > 3$ the inequality $u_b^*(i'', (2, 3)) \geq u_b^*(i'', (2, x_2''))$ holds. In Figure 4.3(a), we observe that the optimal purchasing policy in the state $(i'', (2, 3))$ satisfies the given inequality, i.e., $u_b^*(i'', (2, 3)) = 1 \geq u_b^*(i'', (2, 4)) = 1 \geq$

$u_b^*(i'', (2, 5)) = 1 \geq \dots \geq u_b^*(i'', (2, 7)) = 0$. Let us also consider that $Z_b^*(i'', 3)$ and $Z_b'^*(i'', x_2'')$ are the purchasing threshold levels for the state $(i'', (2, 3))$ and any one of the states that satisfies $(i'', (2, x_2''))$ where $x_2'' > 3$. Theorem 2 implies that $Z_b^*(i'', 3) \geq Z_b'^*(i'', x_2'')$ holds due to the implication on the optimal purchasing policy and Equation (4.3). For instance, in Figure 4.3(a), the purchasing threshold levels for the states $(i'', (2, 3))$ and $(i'', (2, 6))$ are $Z_b^*(i'', 3) = 4$ and $Z_b'^*(i'', 6) = 3$.

Theorem 3. *The optimal production policy for the manufacturer is a state-dependent threshold policy. That is, for any given state $(i', (x_1', x_2'))$ where $x_1' + x_2' = k$, there exists a corresponding threshold level, $Z_p^*(i', (x_1', x_2'))$. It is optimal to produce if $x_1' > Z_p^*(i', (x_1', x_2'))$ and $x_2' < k - Z_p^*(i', (x_1', x_2'))$ and to stay idle otherwise, i.e.,*

$$u_p^*(i', (x_1', x_2')) = \begin{cases} 1, & \text{if } x_1' > Z_p^*(i', (x_1', x_2')) \text{ and } x_2' < k - Z_p^*(i', (x_1', x_2')), \\ 0, & \text{if } x_1' \leq Z_p^*(i', (x_1', x_2')) \text{ and } x_2' \geq k - Z_p^*(i', (x_1', x_2')). \end{cases} \quad (4.8)$$

In Figure 4.3(b), we give the optimal production policy for one of the environment states, i'' , considered in the example. Let us consider the state where there are again 2 parts in the raw materials inventory and 2 parts in the finished goods inventory, i.e., the state $(i'', (2, 2))$. Theorem 3 implies that the production threshold level for the given state is one of the points at $(i'', (x_1, 4 - x_1))$ where $x_1 \in \mathbb{N}$. Specifically, we can find the corresponding threshold value in Figure 4.3(b) by searching the line passing through the point $(i'', (2, 2))$ with a slope of -1. Figure 4.3(b) shows that the production threshold level for the given state is $Z_p^*(i'', (2, 2)) = 0$. Theorem 3 also implies that for all the points at $(i'', (x_1, x_2))$ where $x_1 + x_2 = 4$, the production threshold level is $Z_p^*(i'', (x_1, x_2)) = 0$. That is, for any given (i'', x_1, x_2) where $x_1 + x_2 = 4$, it is optimal to produce if $x_1 > 0$ and $x_2 < 4$, and not to produce if $x_1 \leq 0$ and $x_2 \geq 4$.

Theorem 4. *The optimal production policy for the manufacturer is non-decreasing in x_1 and non-increasing in x_2 . That is, $Z_p^*(i, (x_1, x_2))$ that defines the production threshold level for the given state $(i, (x_1, x_2))$ is non-increasing in x_2 .*

Let us consider the state where there are only 2 parts in the finished goods inventory, i.e., the state $(i'', 0, 2)$. Theorem 4 implies that for any given state $(i'', (0, x_2''))$ where $x_2'' > 2$ the inequality $u_p^*(i'', (0, 2)) \geq u_p^*(i'', (0, x_2''))$ holds. From Theorem 4, we also know that for any given state $(i'', (x_1'', 2))$ where $x_1'' > 0$ the inequality $u_p^*(i'', (0, 2)) \leq u_p^*(i'', (x_1'', 2))$ holds. In Figure 4.3(b), we observe that the optimal production policy obtained in the state $(i'', (0, 2))$ satisfies the given both inequalities, i.e., $u_p^*(i'', (0, 2)) = 0 \leq u_p^*(i'', (1, 2)) = 1 \leq u_p^*(i'', (2, 2)) = 1$ and $u_p^*(i'', (0, 2)) = 0 \geq u_p^*(i'', (0, 3)) = 0 \geq u_p^*(i'', (0, 4)) = 0$. Let us also consider that $Z_p^*(i'', (0, 2))$ and $Z_p'^*(i'', (0, x_2''))$ are the production threshold levels for the state $(i'', (0, 2))$ and any one of the states that satisfies $(i'', (0, x_2''))$ where $x_2'' > 2$. Theorem 4 implies that $Z_p^*(i'', (0, 2)) \leq Z_p'^*(i'', (0, x_2''))$ holds due to the implication on the optimal production policy and Equation (4.4). For instance, in Figure 4.3(b), the production threshold levels for the states $(i', (0, 2))$ and $(i', (0, 3))$ are $Z_p^*(i'', (0, 2)) = 0$ and $Z_p'^*(i'', (0, 3)) = 0$.

Theorem 5. *The optimal sales policy for the manufacturer is a state-dependent threshold policy. That is, for any given state $(i', (x_1', x_2'))$, there exists a corresponding threshold level, $Z_r^*(i', x_1')$. It is optimal to sell if $x_2' > Z_r^*(i', x_1')$, and to do nothing otherwise, i.e.,*

$$u_r^*(i', (x_1', x_2')) = \begin{cases} 1, & \text{if } x_2' > Z_r^*(i', x_1'), \\ 0, & \text{if } x_2' \leq Z_r^*(i', x_1'). \end{cases} \quad (4.9)$$

In Figure 4.3(c), we give the optimal sales policy for one of the environment states considered in the example, say, the environment state i'' . Let us consider that $(i'', (1, 1))$ is the given state. Theorem 5 implies that the sales threshold level for the given state is one of the points at $(i'', (1, x_2))$ where $x_2 \in \mathbb{N}$. Figure 4.3(c) shows that the corresponding threshold level is $Z_r^*(i'', 1) = 2$. Theorem 5 also implies that for all the points at $(i'', (1, x_2))$ where $x_2 \in \mathbb{N}$, the sales threshold level is $Z_r^*(i'', 1) = 2$. That is, for any given point $(i'', (1, x_2))$ where $x_2 \in \mathbb{N}$, it is optimal to sell if $x_2 > 2$ and not to sell if $x_2 \leq 2$.

Theorem 6. *The optimal sales policy for the manufacturer is non-decreasing in x_1 and x_2 . That is, $Z_r^*(i, x_1)$ that defines the sales threshold level for the given state $(i, (x_1, x_2))$ is non-increasing in x_1 .*

Let us consider the state where there are only 1 unit in the finished goods inventories, i.e., the state $(i'', (0, 1))$. Theorem 6 implies that for any given state $(i'', (x_1'', 1))$ where $x_1'' > 0$ the inequality $u_r^*(i'', (0, 1)) \leq u_r^*(i'', (x_1'', 1))$ holds. In Figure 4.3(c), we observe that the optimal sales policy obtained in the state $(i'', (0, 1))$ satisfies the given inequality, i.e., $u_r^*(i'', (0, 1)) = 0 \leq u_r^*(i'', (1, 1)) = 0 \leq u_r^*(i'', (2, 1)) = 1$. Let us also consider that $Z_r^*(i'', 0)$ and $Z_r'^*(i'', x_1'')$ are the sales threshold levels for the state $(i'', (0, 1))$ and any one of the states that satisfies $(i'', (x_1'', 1))$ where $x_1'' > 0$. Theorem 6 implies that $Z_r^*(i'', 0) \geq Z_r'^*(i'', x_1'')$ holds due to the implication on the optimal sales policy and Equation (4.5). For instance, in Figure 4.3(c), the sales threshold levels for the states $(i'', (0, 1))$ and $(i'', (1, 2))$ are $Z_r^*(i'', 0) = 2$ and $Z_r'^*(i'', 2) = 1$.

4.2.4 Linear Programming Formulation for Optimal Control Model

We use a linear programming formulation to validate the optimal purchasing, production, and sales policies derived in the previous section, as well as to numerically compute the policy parameters. The main advantage of this approach is that it derives the steady state probabilities for the system without an extra effort (Bertsekas, 1995). This fact allows us to readily examine the effects of system parameters on the performance measures. All of the sets and indices used in the linear programming formulation are listed in Table (4.2).

As a computational requirement of the linear programming approach, we should restrict the state spaces for the stock levels of the raw materials and finished goods inventories (Nadar et al., 2014). Therefore, we describe two new parameters M_1 and M_2 that are inventory truncation levels for the raw materials and finished goods inventories, respectively. These two truncation levels are chosen sufficiently high so that the globally optimal reward does not change with a further increase in one of them. With these

u_b :	Purchasing decision, $u_b \in \mathbb{B} = \{0, 1\}$
u_p :	Production decision, $u_p \in \mathbb{P} = \{0, 1\}$
u_r :	Sales decision, $u_r \in \mathbb{R} = \{0, 1\}$
x_1 :	Raw materials inventory level, $x_1 \in \mathbb{X}_1 = \{0, 1, \dots, M_1\}$
x_2 :	Finished goods inventory level, $x_2 \in \mathbb{X}_2 = \{0, 1, \dots, M_2\}$
i :	Environment state, $i \in \mathbb{E} = \{1, 2, \dots, L\}$
$\mathbf{x}$:	Inventory levels state, $\mathbf{x} \in \mathbb{F}' = \{(x_1, x_2) \mid x_k \in \mathbb{X}_k \text{ where } k \in \{1, 2\}\}$

Table 4.2: Sets and indices used in the linear programming formulation

efforts, the variables that denote the stock levels of the raw materials and finished goods inventories belong the sets $x_1 \in \mathbb{X}_1 = \{0, 1, 2, \dots, M_1\}$ and $x_2 \in \mathbb{X}_2 = \{0, 1, 2, \dots, M_2\}$, respectively. As a result, $\mathbf{x}$ that represents the inventory levels in the state variable belongs to the set $\mathbb{F}'$, i.e., $\mathbf{x} \in \mathbb{F}' = \{(x_1, x_2) \mid x_k \in \mathbb{X}_k \text{ where } k \in \{1, 2\}\}$.

The decision variable for the LP formulation is denoted by $Y_{i,\mathbf{x},u_b,u_p,u_r}$. The variable gives us the long-run fraction of the time that the system is in state $(i, \mathbf{x})$ when the actions u_b , u_p , and u_r are taken. With this decision variable and the sets and indices introduced in the above, the LP formulation for the problem is given as follows:

$$\max \phi = \sum_{i \in \mathbb{E}} \sum_{\mathbf{x} \in \mathbb{F}'} \sum_{u_b \in \mathbb{B}} \sum_{u_p \in \mathbb{P}} \sum_{u_r \in \mathbb{R}} Y_{i,\mathbf{x},u_b,u_p,u_r} (\lambda u_r s_i - \delta u_b c_i - \mu u_p w - x_1 h_1 - x_2 h_2), \quad (4.10)$$

subject to

$$\begin{aligned} \sum_{u_b \in \mathbb{B}} \sum_{u_p \in \mathbb{P}} \sum_{u_r \in \mathbb{R}} \left(Y_{i,\mathbf{x},u_b,u_p,u_r} - u_b \delta Y_{i,\mathbf{x}-e_1,u_b,u_p,u_r} - u_p \mu Y_{i,\mathbf{x}+e_1-e_2,u_b,u_p,u_r} \right. \\ \left. - u_r \lambda Y_{i,\mathbf{x}+e_2,u_b,u_p,u_r} - \sum_{j \in \mathbb{E} \setminus \{i\}} q_{ji} Y_{j,\mathbf{x},u_b,u_p,u_r} \right. \\ \left. - \left(1 - u_b \delta - u_p \mu - u_r \lambda - \sum_{j \in \mathbb{E} \setminus \{i\}} q_{ij} \right) Y_{i,\mathbf{x},u_b,u_p,u_r} \right) = 0, \quad \forall i \in \mathbb{E}, \forall \mathbf{x} \in \mathbb{F}', \quad (4.11) \end{aligned}$$

$$\sum_{i \in \mathbb{E}} \sum_{\mathbf{x} \in \mathbb{F}'} \sum_{u_b \in \mathbb{B}} \sum_{u_p \in \mathbb{P}} \sum_{u_r \in \mathbb{R}} Y_{i,\mathbf{x},u_b,u_p,u_r} = 1, \quad (4.12)$$

$$Y_{i,\underline{\mathbf{x}},u_b,u_p,u_r}=0, \forall i \in \mathbb{E}, \forall \underline{\mathbf{x}} \in \{(x_1, x_2) \mid x_1=0, x_2 \in \mathbb{X}_2\}, \forall u_b \in \mathbb{B}, u_p \in \{1\}, \forall u_r \in \mathbb{R}, \quad (4.13)$$

$$Y_{i,\underline{\mathbf{x}},u_b,u_p,u_r}=0, \forall i \in \mathbb{E}, \forall \underline{\mathbf{x}} \in \{(x_1, x_2) \mid x_1 \in \mathbb{X}_1, x_2=0\}, \forall u_b \in \mathbb{B}, \forall u_p \in \mathbb{P}, u_r \in \{1\}, \quad (4.14)$$

$$Y_{i,\underline{\mathbf{x}},u_b,u_p,u_r}=0, \forall i \in \mathbb{E}, \forall \underline{\mathbf{x}} \in \{(x_1, x_2) \mid x_1 \in \{-1, M_1+1\}, x_2 \in \mathbb{X}_2\}, \forall u_b \in \mathbb{B}, \forall u_p \in \mathbb{P} \quad (4.15)$$

$$\forall u_r \in \mathbb{R},$$

$$Y_{i,\underline{\mathbf{x}},u_b,u_p,u_r}=0, \forall i \in \mathbb{E}, \forall \underline{\mathbf{x}} \in \{(x_1, x_2) \mid x_1 \in \mathbb{X}_1, x_2 \in \{-1, M_2+1\}\}, \forall u_b \in \mathbb{B}, \forall u_p \in \mathbb{P} \quad (4.16)$$

$$\forall u_r \in \mathbb{R},$$

$$Y_{i,\underline{\mathbf{x}},u_b,u_p,u_r} \geq 0, \forall i \in \mathbb{E}, \forall \underline{\mathbf{x}} \in \mathbb{F}', \forall u_b \in \mathbb{B}, \forall u_p \in \mathbb{P}, \forall u_r \in \mathbb{R}. \quad (4.17)$$

The objective function defined in Equation (4.10) is to maximize the long-run average reward of the manufacturer. Constraint (4.11) is the balance equations that satisfy the flow into state $(i, \underline{\mathbf{x}})$ equals the flow out of state $(i, \underline{\mathbf{x}})$. Since the decision variables constitute a probability mass function, they must be non-negative real numbers and their summation must be equal to 1. Constraint (4.17) satisfies the condition on the non-negativity of the decision variables. Constraint (4.12) ensures that the sum of the decision variables equals to 1. Constraint (4.13) stipulates that production is not possible when the raw materials inventory is empty. Constraint (4.14) ensures that an incoming demand cannot be satisfied if there is no stock in the finished goods inventory. When x_1 is 0 or M_1 in the vector $\underline{\mathbf{x}}$, Constraint (4.11) yields the decision variables that are out of the state space due to $Y_{i,\underline{\mathbf{x}}-e_1,u_b,u_p,u_r}$ and $Y_{i,\underline{\mathbf{x}}+e_1-e_2,u_b,u_p,u_r}$. Constraint (4.15) eliminates these trivial decision variables from the formulation. Since a similar situation is observed when x_2 is 0 or M_2 in the vector $\underline{\mathbf{x}}$, Constraint (4.16) is also included into the formulation. In another words, Constraints (4.15) and (4.16) prevent probability leakage from the outside of the state space.

We analytically investigate the structure of the above linear programming problem by defining the number of decision variables and the number of constraints. Except the non-negativity constraint, the numbers of variables and constraints are $8L(M_1+1)(M_2+1)$ and $1+L(M_1+1)(M_2+1)+20L((M_1+1)+(M_2+1))$, respectively. Since the number of variables and constraints polynomially grow as the

size of state space increases, the size of the LP problem mostly stays at a manageable level. We also numerically examined the effect of the size of the state space on the computation time. For the examination, we used GAMS modeling environment with CPLEX 12.5 LP solver on a computer that has 2.7 GHz Intel core i5 processor and 8 GB RAM. The results confirmed our analytical findings and showed that the LP formulation manage to find the solution in less than one and half minute when the state space size is less than 2 million. We believe that a model including 2,000,000 states is sufficiently precise to deal with the fluctuating sales and purchasing prices in a production/inventory setting. For instance, this structure allows us to analyze a case in which there exist 400 different sales and purchasing prices combinations and truncation levels are 71.

4.3 Numerical Analysis

In this section, we examine the effects of variations in the purchasing and sales prices, the correlation between purchasing and sales prices, traffic intensity, and limited inventory capacities on the system performance measures through a range of numerical experiments. Before presenting results, we primarily introduce the long-run measures regarding the dynamics of the operating environment and manufacturing system and justify the chosen parameters.

4.3.1 The long-run measures regarding the dynamics of the operating environment and manufacturing system

In the numerical analysis, we consider the long-run average reward (ϕ), customer service level (α), average stock level in the raw materials inventory ($E[x_1]$), and average stock level in the finished goods inventory ($E[x_2]$) as the system performance measures. The definitions of these performance measures are given as follows:

$$\phi = \sum_{i \in \mathbb{E}} \sum_{\mathbf{x} \in \mathbb{F}'} \sum_{u_b \in \mathbb{B}} \sum_{u_p \in \mathbb{P}} \sum_{u_r \in \mathbb{R}} Y_{i, \mathbf{x}, u_b, u_p, u_r} (\lambda u_r s_i - \delta u_b c_i - \mu u_p w - x_1 h_1 - x_2 h_2), \quad (4.18)$$

$$\alpha = \sum_{i \in \mathbb{I}} \sum_{\underline{\mathbf{x}} \in \mathbb{F}'} \sum_{u_b \in \mathbb{B}} \sum_{u_p \in \mathbb{P}} \sum_{u_r \in \{1\}} Y_{i, \underline{\mathbf{x}}, u_b, u_p, u_r}, \quad (4.19)$$

$$\mathbb{E}[x_1] = \sum_{i \in \mathbb{I}} \sum_{\underline{\mathbf{x}} \in \mathbb{F}'} \sum_{u_b \in \mathbb{B}} \sum_{u_p \in \mathbb{P}} \sum_{u_r \in \mathbb{R}} x_1 Y_{i, \underline{\mathbf{x}}, u_b, u_p, u_r}, \quad (4.20)$$

$$\mathbb{E}[x_2] = \sum_{i \in \mathbb{I}} \sum_{\underline{\mathbf{x}} \in \mathbb{F}'} \sum_{u_b \in \mathbb{B}} \sum_{u_p \in \mathbb{P}} \sum_{u_r \in \mathbb{R}} x_2 Y_{i, \underline{\mathbf{x}}, u_b, u_p, u_r}. \quad (4.21)$$

In all the numerical instances, we examine a special setting where the sales and purchasing prices change only at High (H) and Low (L) states. In this setting, the sales prices in the low and high states are denoted by s_L and s_H whereas the purchasing prices in the low and high states are represented as c_L and c_H . To model such a setting with the framework introduced in this study, we map each possible binary combination of the purchasing and sales prices to a certain environment state. So, we define four different environment states and list them in Table 4.3.

1 = Purchasing and sales prices are High (HH), $c_1 = c_H$ and $s_1 = s_H$,
2 = Purchasing price is Low and sales price is High (LH), $c_2 = c_L$ and $s_2 = s_H$,
3 = Purchasing price is High and sales price is Low (HL), $c_3 = c_H$ and $s_3 = s_L$,
4 = Purchasing and sales prices are Low (LL), $c_4 = c_L$ and $s_4 = s_L$.

Table 4.3: Environment states in the numerical examples

With the considered setting, we can characterize the long-run probability distribution associated with the environment states by solving Equations (4.22) and (4.23), simultaneously.

$$\Pi^T Q = 0 \quad (4.22)$$

$$\Pi \mathbf{1} = 1 \quad (4.23)$$

Π^T is the vector including the long-run probability distribution associated with the environment states, i.e., $\Pi^T = [\pi_1 \ \pi_2 \ \pi_3 \ \pi_4]$. With this vector, we define the long-run expectation and variance of the purchasing price as in the following equations and

denote them by $E[C]$ and $\text{Var}[C]$, respectively.

$$E[C] = c_H (\pi_1 + \pi_3) + c_L (\pi_2 + \pi_4) \quad (4.24)$$

$$\text{Var}[C] = (c_H - c_L)^2 (\pi_1 + \pi_3) (\pi_2 + \pi_4) \quad (4.25)$$

Thus, the coefficient of variation for the purchasing price is defined as $CV_C = \sqrt{\text{Var}[C]}/E[C]$. The long-run expectation and variance of the sales price are also defined in below and denoted by $E[S]$ and $\text{Var}[S]$, respectively.

$$E[S] = s_H (\pi_1 + \pi_2) + s_L (\pi_3 + \pi_4) \quad (4.26)$$

$$\text{Var}[S] = (s_H - s_L)^2 (\pi_1 + \pi_2) (\pi_3 + \pi_4) \quad (4.27)$$

With the above expressions, the coefficient of variation for the sales price is $CV_S = \sqrt{\text{Var}[S]}/E[S]$. Additionally, the correlation between purchasing and sales prices, ρ_{CS} , is obtained as follows:

$$\rho_{CS} = \frac{\pi_4 \pi_1 - \pi_2 \pi_3}{\sqrt{(\pi_1 + \pi_3) (\pi_2 + \pi_4)} \sqrt{(\pi_1 + \pi_2) (\pi_3 + \pi_4)}}. \quad (4.28)$$

From Equation (4.28), we observe that when $\pi_2 \pi_3 > \pi_4 \pi_1$ there is a negative correlation between purchasing and sales prices. The same equation also implies that for a positive correlation between purchasing and sales prices, $\pi_2 \pi_3 < \pi_4 \pi_1$ condition should be satisfied. When $\pi_2 \pi_3 = \pi_4 \pi_1$ holds there is no correlation between these two market prices.

The correlation between sales and purchasing prices can only be manipulated with the transition matrix since it is a function of the long-run probability distribution of the environment states. Hence, in the numerical examples, we form the transition matrices in such a way that the specified correlation coefficients are obtained. While forming the transition matrices, we follow a two-step procedure. The procedure allows the correlation coefficient to set the specified level while keeping the expectations and variances of the sales and purchasing prices at the same levels. Thus, for the numerical instances being examined in the same group, we are able to observe the direct effects

of the correlation coefficient on the system. If the transition matrices are not formed in this way, the expectations and variances of the sales and purchasing prices change each time the correlation coefficient changes. In such a case, the analysis would yield biased and incorrect results. To initiate the procedure, $E[C]$, $\text{Var}[C]$, $E[S]$, $\text{Var}[S]$, ρ_{CS} , s_H , s_L , c_H , c_L , and the average time spent in each environment state, T_i where $i \in \{1, 2, 3, 4\}$, should be given as the input parameters. The details of the procedure are discussed in the Appendix C.2.

4.3.2 Parameter settings

In the numerical analysis, we study four different scenarios and list the parameters of each scenario in Table 4.4. In Scenario 1, 2, and 3, we consider a structure where $\delta > \mu > \lambda$ and normalize the demand and raw material arrival rates according to the production rate. With this structure, the manufacturer has a sufficient capacity and number of raw material purchasing opportunities to satisfy the arriving demand. This structure allows us to directly observe the impacts of the fluctuating and correlated purchasing and sales prices on the system when Scenario 1, 2, and 3 are considered. To obtain the correlation coefficients considered in the scenarios, we utilize the average amounts of time spent in the environments given in Table 4.5. One can notice that average time spent in each environment state is typically set to a large value compared to the average interarrival times assigned for the production, demand, and raw material processes. This implies that times to change the environment states are much longer than the ones for the other processes. Hence, the manufacturer is able to deduce and adjust to an environmental change in a relatively short time period.

In each scenario, we set the long-run averages of purchasing and sales prices in such a way that the relative difference between these two parameters does not exceed %60. We believe that this structure would provide a better representation for a production/inventory system in practice because it avoids the non-realistic environments where the long-run profit margins for the manufacturer are too low or

Scenario	The invariant parameters in the scenario				The changing parameters in the scenario
Scenario 1	$\mu=1.00$	$\delta=1.50$	$\lambda=0.80$	$w=0.10$	$CV_S \in \{0.30, 0.20, 0.10\}$
	$h_1=0.04$	$h_2=0.04$	$E[S]=1.80$	$E[C]=1.10$	$s_H \in \{2.35, 2.20, 2.00\}$
	$CV_C=0.10$	$c_H=1.20$	$c_L=1.00$		$s_L \in \{1.25, 1.40, 1.55\}$
					$\rho_{CS} \in \{-0.90, -0.80, \dots, 0.90\}$
Scenario 2	$\mu=1.00$	$\delta=1.50$	$\lambda=0.80$	$w=0.10$	$CV_C \in \{0.30, 0.20, 0.10\}$
	$h_1=0.04$	$h_2=0.04$	$E[C]=1.50$	$E[S]=2.40$	$c_H \in \{2.00, 1.80, 1.65\}$
	$CV_S=0.10$	$s_H=2.65$	$s_L=2.15$		$c_L \in \{1.00, 1.20, 1.35\}$
					$\rho_{CS} \in \{-0.90, -0.80, \dots, 0.90\}$
Scenario 3	$\mu=1.00$	$\delta=1.50$	$w=0.10$	$h_1=0.04$	$\lambda \in \{0.80, 0.90, \dots, 2.50\}$
	$h_2=0.04$	$E[S]=1.90$	$E[C]=1.20$	$CV_S=0.20$	$\rho_{CS} \in \{-0.60, 0, 0.60\}$
	$CV_C=0.15$	$s_H=2.30$	$s_L=1.50$	$c_H=1.40$	
	$c_L=1.00$				
Scenario 4	$h_1=0.04$	$h_2=0.04$	$w=0.10$	$E[S]=1.90$	$\lambda \in \{0.60, 0.70, \dots, 2.20\}$
	$E[C]=1.20$	$CV_S=0.20$	$CV_C=0.15$	$s_H=2.30$	$\mu \in \{1.00, 1.60\}$
	$s_L=1.50$	$c_H=1.40$	$c_L=1.00$	$\rho_{CS}=0$	$\delta \in \{1.60, 1.00\}$
					$M_1 + M_2 \in \{2, 3, \dots, 10\}$

Table 4.4: The scenarios specified to analyze the effects of the parameters on the system performance measures

high. While setting the values of the parameters whose impacts on the system would be analyzed, we utilize the specified coefficient of variation for the corresponding parameter and normalize all the market prices according to the lowest purchasing price considered in the corresponding scenario. In all scenarios, we ensure that the lowest sales price is higher than the highest purchasing price. Otherwise, the manufacturer would prefer not to operate in the setting where the sales price is lower than the purchasing price, and so, the results would be trivial. Additionally, in all the scenarios, we consider that the holding costs for the raw material and finished goods inventories

equal each other and set them as not-exceeding 4% of the long-run average of the purchasing prices.

From the preliminary numerical analysis results, we have observed that the truncation levels between 20 and 25 are typically sufficiently large to reach the optimal solution for the system parameters used. We have employed this observation while solving the problem instances generated with Scenario 1, 2 and 3. More specifically, we have primarily solved each problem instance by using two different truncation level settings, i.e., $M_1 = M_2 = 25$ and $M_1 = M_2 = 26$. Later on, for each problem instance, we have compared the results obtained with these two settings. The comparison results indicate that none of the reward functions in the problem instances improves when we change the truncation levels from 25 to 26. Accordingly, the setting where $M_1 = M_2 = 25$ guarantees that we obtain the globally optimal solution for each problem instance in all the scenarios.

4.3.3 *Effects of the correlation between sales and purchasing prices and sales price variation on the system*

To analyze the impacts of the correlation between sales and purchasing prices and sales price variation on the system, we use Scenario 1 given in Table 4.4. With this scenario, for each CV_S value, we generate 19 problem instances and depict the corresponding result in Figure 4.4.

Figure 4.4(a) shows that the manufacturer's profit increases with the sales price variability. When the sales price variability is high the profit margin per unit obtained in state 3 considerably declines. Therefore, in state 3, the manufacturer reduces the raw material purchases by lowering the threshold values regarding the purchasing decision. So, as Figures 4.4(c) and 4.4(d) indicate, the average stock levels in the raw materials and finished goods inventories decrease as the sales price variability increases. Figure 4.4(b) also indicates that the average service level reduces due a decrease in the average stock levels in the raw materials and finished goods inventories. Since the

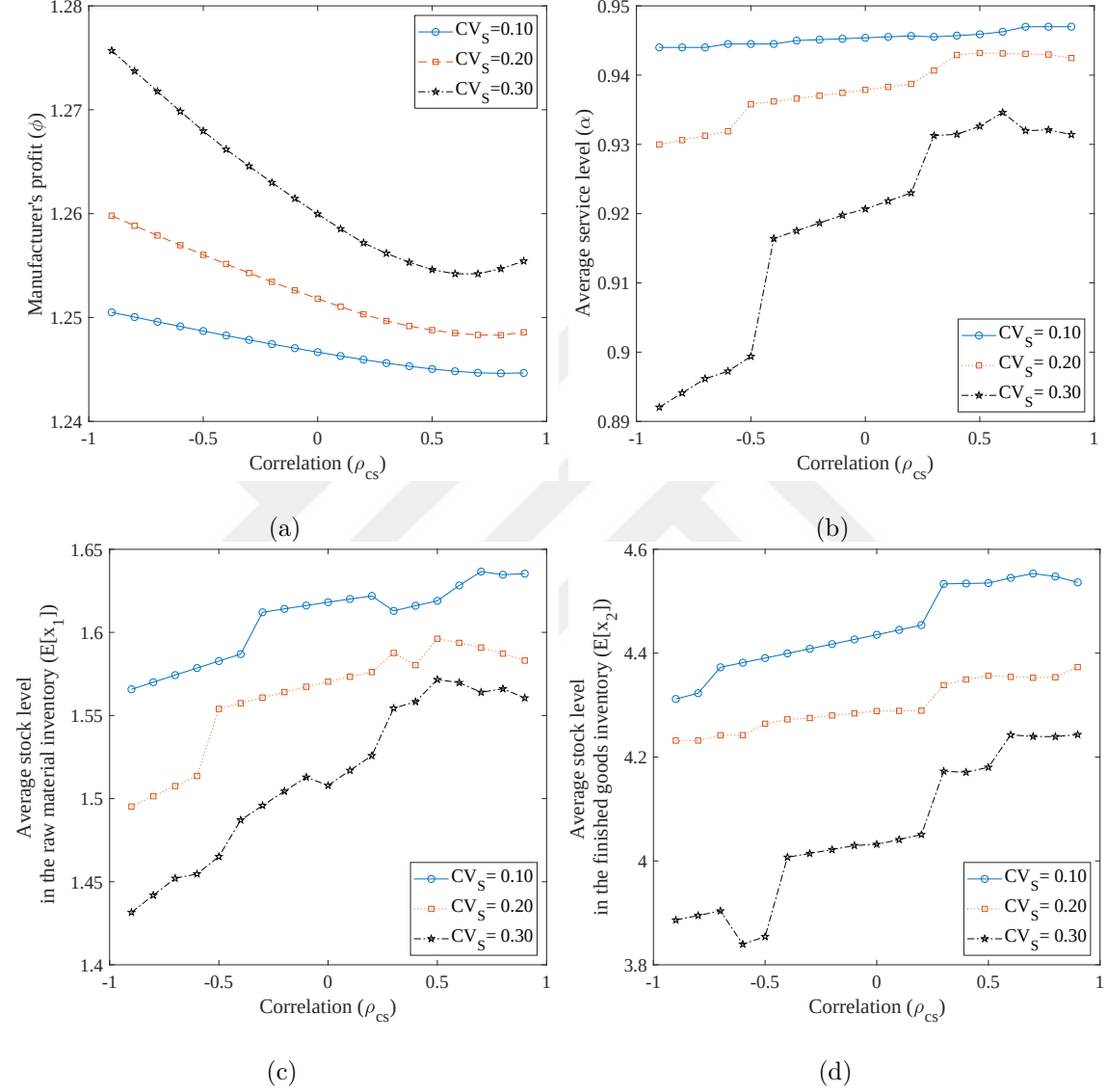


Figure 4.4: The impacts of the correlation between sales and purchasing prices and sales price variation on **(a)** the manufacturer's profit, **(b)** the average service level, **(c)** the average stock level in the raw materials inventory, and **(d)** the average stock level in the finished goods inventory

average stock levels in the raw materials and finished goods inventories decrease the manufacturer saves on the purchasing and inventory holding costs. Additionally, the profit margin in state 3 is the lowest one among the other states, because the sales

	ρ_{CS}																		
	-0.9	-0.8	-0.7	-0.6	-0.5	-0.4	-0.3	-0.2	-0.1	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
T_1	50	50	50	50	50	50	50	50	50	50	41	33	27	21	17	13	9	6	3
T_2	700	450	283	200	150	117	93	75	61	50	50	50	50	50	50	50	50	50	50
T_3	700	450	283	200	150	117	93	75	61	50	50	50	50	50	50	50	50	50	50
T_4	50	50	50	50	50	50	50	50	50	50	41	33	27	21	17	13	9	6	3

Table 4.5: The average time spent in environment state i for the given correlation coefficient between sales and purchasing prices

price is low and the purchasing price is high. As a result, the revenue loss due to less stock in state 3 is easily compensated by the sales in the other states and the savings from purchasing and inventory holding costs. These facts reveal the main rationale behind the increase in manufacturer's profit with an increase in sales price variability.

Figure 4.4(a) also shows that when the correlation between sales and purchasing prices shifts from -0.90 to 0.90 the manufacturer's profit decreases. In the case where the correlation between sales and purchasing prices is negative, the manufacturer reduces the raw material purchases in state 3 and saves on the purchasing and inventory holding costs. Figure 4.4(a) also implies that the amount of savings obtained in the negative correlation case increases as the variability of sales price increases. Lowering the raw material purchases in state 3 yields a decrease in the average service level, average stock level in the raw materials inventory, and average stock level in the finished goods inventory (see Figures 4.4(b), 4.4(c), and 4.4(d)). However, when the correlation proceeds from the negative values to the positive values the manufacturer starts to actively use four environment states. Hence, when the correlation is positive we observe an increase in the average service level, average stock level in the raw materials inventory, and average stock level in the finished goods inventory. An increase in these measures leads to a decrease in the amount of savings obtained from purchasing and inventory holding costs so that the manufacturer's profit reduces.

4.3.4 *Effects of the correlation between sales and purchasing prices and purchasing price variation on the system*

To analyze the impacts of the correlation between sales and purchasing prices and purchasing price variation on the system, we employ Scenario 2 given in Table 4.4. With this scenario, for each CV_C value, we generate 19 problem instances and depict the corresponding result in Figure 4.5.

Figure 4.5(a) indicates that the manufacturer's profit decreases when we shift the correlation between purchasing and sales prices from -0.90 to 0.90. When there is a

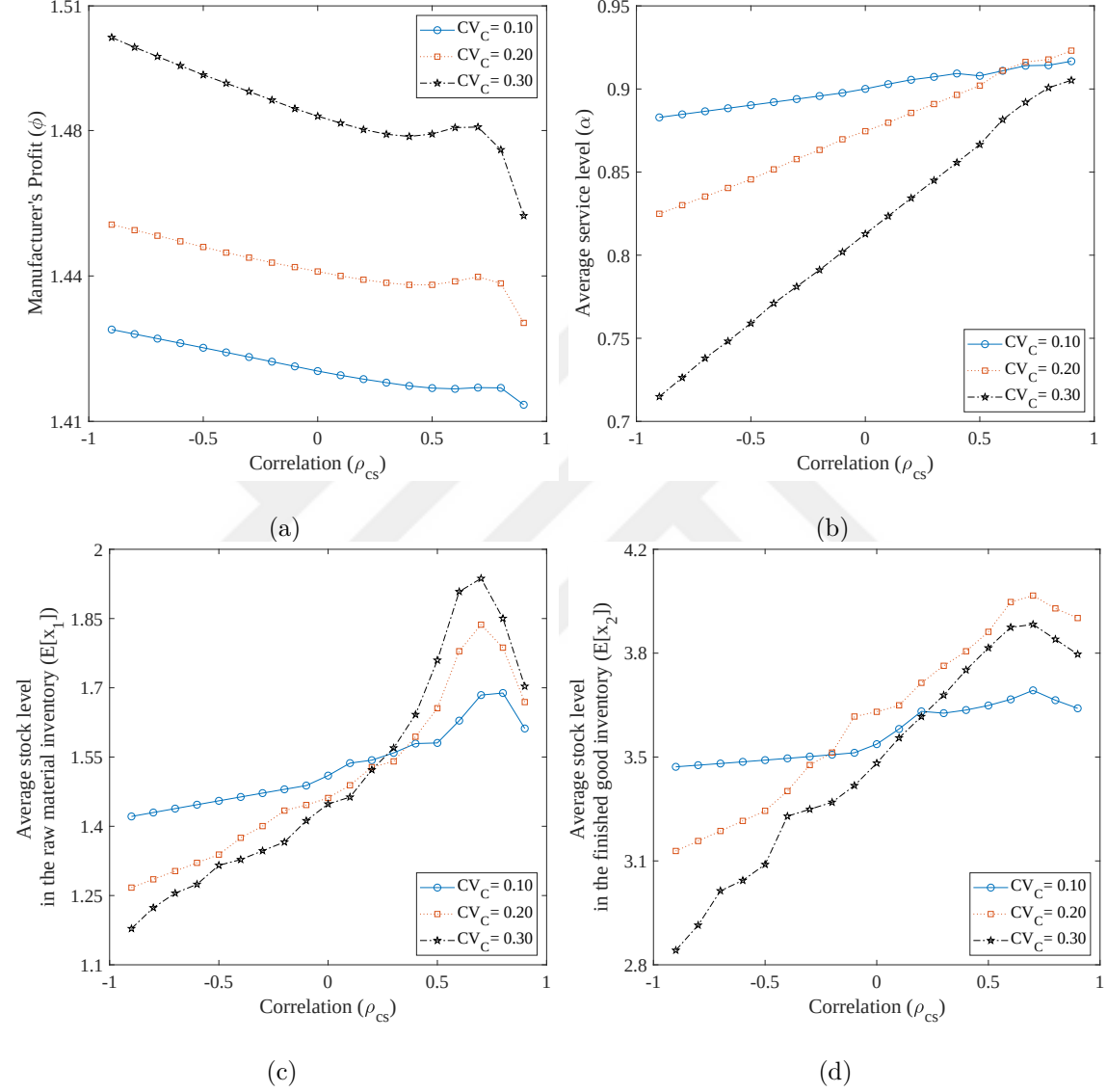


Figure 4.5: The impacts of the correlation between sales and purchasing prices and purchasing price variation on **(a)** the manufacturer's profit, **(b)** the average service level, **(c)** the average stock level in the raw materials inventory, and **(d)** the average stock level in the finished goods inventory

negative correlation between sales and purchasing prices the manufacturer reduces the raw material purchases in state 3. Figures 4.5(c) and 4.5(d) show that reducing the raw material purchases in state 3 declines the average stock levels in the raw

materials and finished goods inventories. With this policy, the manufacturer saves on the purchasing and inventory holding costs and increases his profit. Figure 4.5(a) shows that the amount of savings increases as the variation of the purchasing price rises. In addition, since the average stock levels in the raw materials and finished goods inventories decrease in the case where the correlation between sales and purchasing prices is negative, the average service level declines (see Figure 4.5(b)).

When the correlation between purchasing and sales prices shifts from the negative values to the positive values the manufacturer considerably increases the raw material purchases in state 2. Since the purchasing price is low in state 2 the manufacturer aims to save on the purchasing costs by implementing this policy. Figure 4.5(a) shows that the amount of this saving slightly rises when the purchasing price variation is high and the correlation coefficient is between 0.4 and 0.7. In Figures 4.5(c) and 4.5(d), we also observe that this policy causes a significant increase in the average stock levels in the raw materials and finished goods inventories when the correlation coefficient is between 0.4 and 0.7. Figure 4.5(b) indicates that since the average stock levels in both inventories increases with the positive correlation coefficient the average service level rises. The manufacturer could not raise the raw material stocks to the level that he aims because the average time spent in state 2 notably reduces when the correlation coefficient is greater 0.7. Hence, we observe that when the correlation coefficient is greater 0.7 the manufacturer's profit, average stock level in the raw materials inventory, and average stock level in the finished goods inventory decrease (see Figures 4.5(a), 4.5(c), and 4.5(d)).

4.3.5 Effects of the correlation between sales and purchasing prices and traffic intensity on the system

To examine the effects of the correlation between sales and purchasing prices and traffic intensity on the system, we utilize Scenario 3 given in Table 4.4. With this scenario, for each ρ_{CS} value, we generate 18 problem instances and depict the corresponding

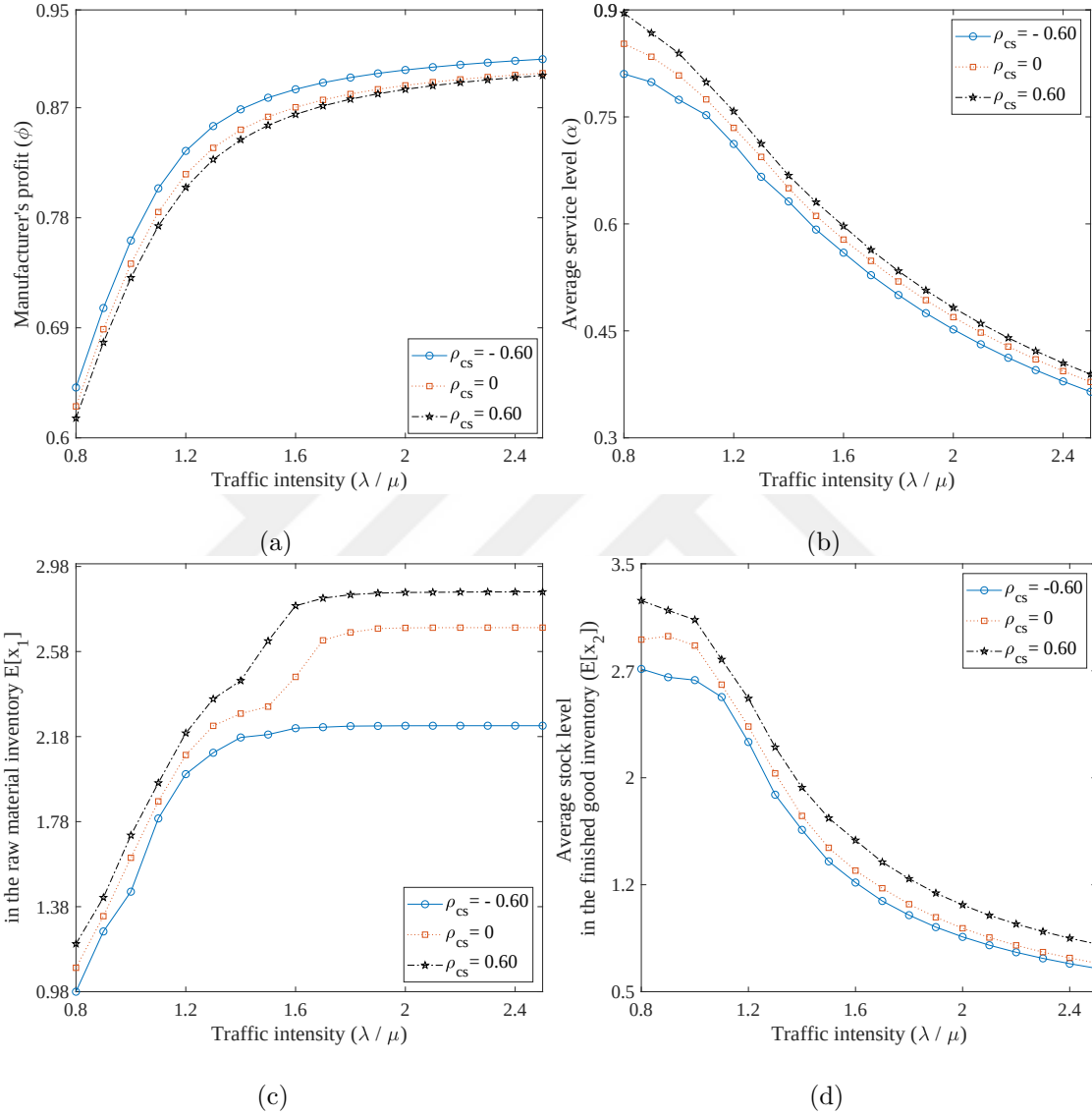


Figure 4.6: The impacts of the correlation between sales and purchasing prices and traffic intensity on **(a)** the manufacturer's profit, **(b)** the average service level, **(c)** the average stock level in the raw materials inventory, and **(d)** the average stock level in the finished goods inventory

result in Figure 4.6.

Figure 4.6(a) shows that the manufacturer's profit increases when the demand arrival rate raises. An increase in the demand arrival rate yields a higher number of

customers arriving at the system. To satisfy the increasing demand, the manufacturer increases the raw material purchases. Hence, in Figure 4.6(c), we notice that the average stock level in the raw materials inventory rises when the demand arrival rate increases. In Figure 4.6(d), we observe that since the manufacturer's production capacity is limited the average stock level in the finished goods inventory decreases with an increase in the demand arrival rate. As Figure 4.6(b) shows, the decreasing average stock level in the finished goods inventory due to an increase in the demand arrival rate yields a decrease in the average service level.

Figure 4.6(a) also indicates that the negative correlation between sales and purchasing prices leads to a slight increase in the manufacturer's profit. For each different correlation coefficient, the other performance measures, the average service level, average stock level in the raw materials inventory, and average stock level in the finished goods inventory, almost follow a similar pattern (see Figures 4.6(b), 4.6(c), and 4.6(d)). So, we conclude that the impacts of limited production and supply capacities on the system dominates the impact of the correlation between purchasing and sales prices on the system.

4.3.6 Effects of limited finished goods and raw materials inventories on the system

In practice, the manufacturer can restrict the capacities of the finished goods and raw materials inventories due to limited financial and physical resources. In such a case, the manufacturer must foresee the effects of the limited finished goods and raw materials inventories on the system and decides how to allocate the limited capacity to the inventories so as to maximize the profit. By considering this fact, in this section, we discuss how the capacitated finished goods and raw materials inventories affect the system.

To analyze the impacts of limited finished goods and raw materials inventories on the system, we utilize Scenario 4 given in Table 4.4. For each combination of given production, raw material arrival, and demand arrival rates, we generate a set

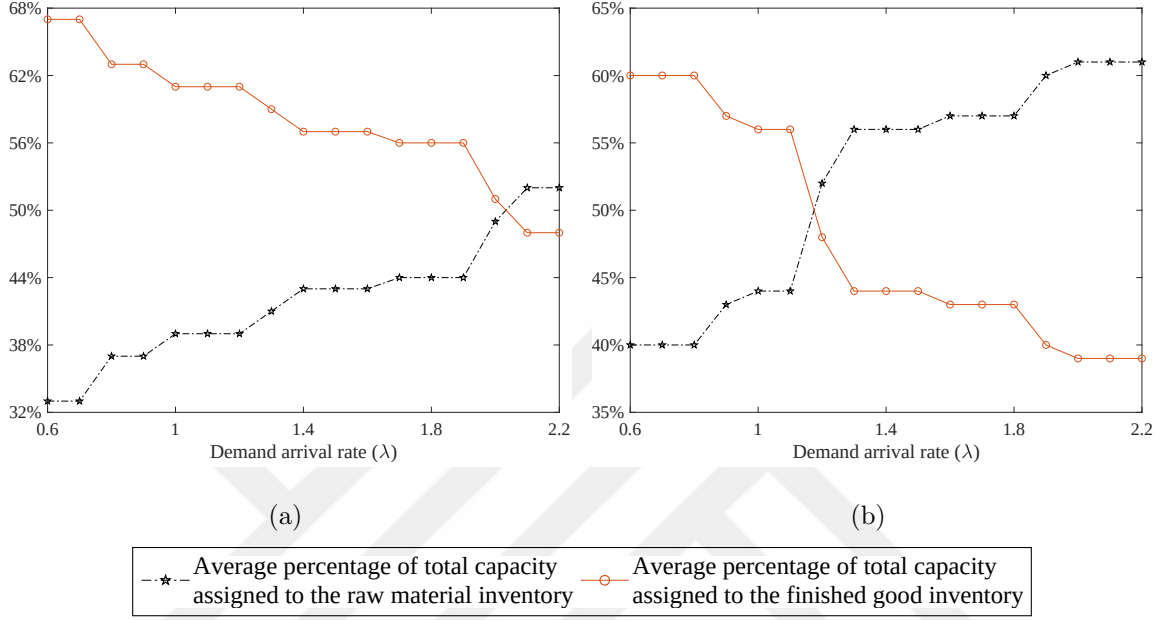


Figure 4.7: The averages of the percentages for total capacity assigned to the raw materials and finished goods inventories **(a)** when $\mu = 1.00 < \delta = 1.60$ **(b)** when $\mu = 1.60 > \delta = 1.00$

of problem instances by ranging the sum of M_1 and M_2 from 2 to 10. With this setting, we limit the capacities of the finished goods and raw materials inventories and obtain 306 problem instances for both $\mu < \delta$ and $\mu > \delta$ cases. For each given $M_1 + M_2$ value in a particular problem set, we obtain how the manufacturer assigns its limited capacity to the finished goods and raw material inventories by optimizing the profit. Thus, in each problem set, we are able to calculate the averages of the capacities allocated to the raw materials and finished goods inventories. We depict these results in Figure 2.4.

Figure 4.7(a) shows that the manufacturer allocates more capacity to the finished goods inventory than to the raw materials inventory when $\lambda < \mu < \delta$ holds. Figure 4.7(a) also indicates that as the demand rate increases the average amount of capacity allocated to the raw materials inventory increases. With an increase in the demand arrival rate, the production and raw material processes relatively slow down. This

fact forces the manufacturers to hedge against a starvation risk in the raw materials inventory. As a result, the average amount of capacity allocated to the raw materials inventory increases whereas the average amount of capacity allocated to the finished goods inventory decreases.

Figure 4.7(b) implies that the manufacturer allocates a higher capacity to the finished goods inventory up to the point where $\delta=\lambda=1.20$. At the point where $\delta=\lambda=1.20$, the average amount of capacity allocated to the raw materials inventory almost equals the average amount of capacity allocated to the finished goods inventory. Figure 4.7(b) shows that when the demand arrival rate is greater than 1.20 the average amount of capacity allocated to the raw materials inventory becomes to be higher than the average amount of capacity allocated to the finished goods inventory. The main rationale behind this trend is similar to that observed in the first version of the basic problem. When the demand arrival rate is greater than 1.20, the purchasing process would be the bottleneck of the system because of having the smallest rate compared to the demand arrival and production rates. This fact forces the manufacturer to avoid a starvation risk in the raw materials inventory. Consequently, an increase in the demand arrival rate leads to an increase in the average amount of capacity allocated to the raw materials inventory and a decrease in the average amount of capacity allocated to the finished goods inventory. With this analysis, we conclude that the manufacturer gives a priority to increase the capacity of inventory that is close to the system's bottleneck in terms of rates.

The impacts of limited finished goods and raw materials inventories on the system are also examined with the sales price variation, purchasing price variation, and correlation between sales and purchasing prices. However, we observe that the impacts of limited finished goods and raw materials inventories on the system are not affected by the sales price variation, purchasing price variation, and correlation between sales and purchasing prices. Due to the sake of clarity, we do not include these analyses in the current work.

4.3.7 Benefits of using the optimal policy to the profit when compared to the Buy Low and Sell High policy

The manufacturers which are subject to the random fluctuations in purchasing and sales prices may be inclined to adopt the *Buy Low and Sell High* naive policy where the manufacturer buys the raw materials only when the purchasing price is low and sells the finished goods only when the sales price is high. Although it is very easy to implement this policy, the naive policy leads to a profit loss for the manufacturer. By considering this fact, in this section, we discuss how much the manufacturer can improve the profit by using the optimal policy instead of using the naive one.

For the discussion, we consider Scenario 1, 2, and 3 given in Table 4.4. As done in the previous sections, the optimal control policies for the considered scenarios are numerically obtained by using the linear programming formulation introduced in Equations (4.10) - (4.17). In addition, the naive policies for the considered scenarios are numerically derived by adding two extra constraints to the original linear programming formulation. These two constraints are presented as follows:

$$Y_{i,\underline{\mathbf{x}},u_b,u_p,u_r} = 0, \forall i \in \{1, 3\}, \forall \underline{\mathbf{x}} \in \mathbb{F}', u_b \in \{1\}, \forall u_p \in \mathbb{P}, \forall u_r \in \mathbb{R}, \quad (4.29)$$

$$Y_{i,\underline{\mathbf{x}},u_b,u_p,u_r} = 0, \forall i \in \{3, 4\}, \forall \underline{\mathbf{x}} \in \mathbb{F}', u_b \in \mathbb{B}, \forall u_p \in \mathbb{P}, \forall u_r \in \{1\}. \quad (4.30)$$

Equation (4.29) implies that the manufacturer buys the raw materials only when the purchasing price is low. Equation (4.30) stipulates that the manufacturer sells the finished goods only when the sales price is high. For each scenario, we obtain the relative difference between the manufacturer's profit obtained with the use of the optimal policy and the manufacturer's profit obtained with the use of the naive policy. The results regarding Scenario 1, 2, and 3 are respectively depicted in Figures 4.8(a), 4.8(b), and 4.8(c). In the figures, a higher difference means that the manufacturer obtains a higher profit by using the optimal policy.

Figures 4.8(a) and 4.8(b) show that the positive impact of using the optimal policy on the profit decreases when the correlation between sales and purchasing prices shifts

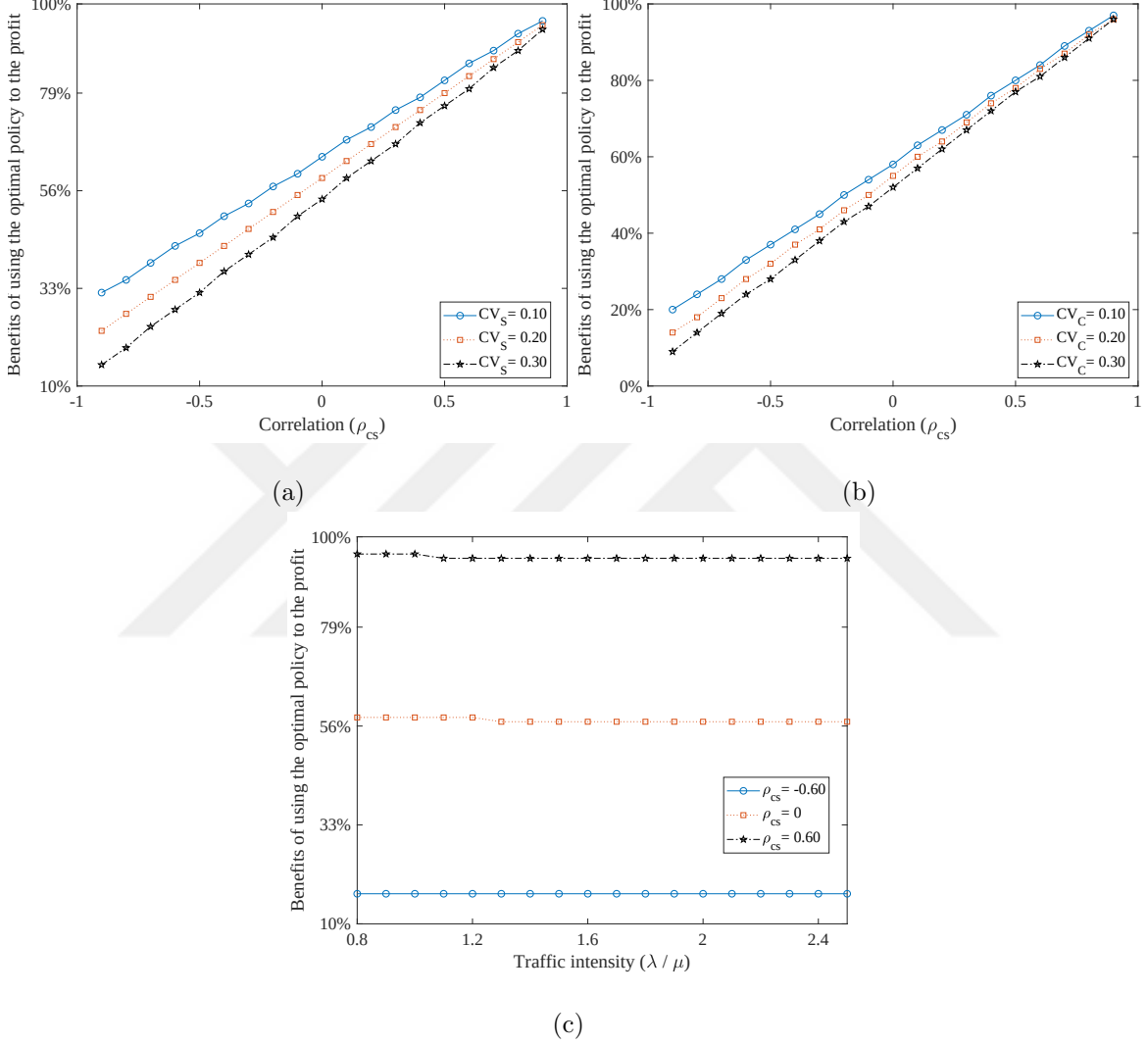


Figure 4.8: The benefit obtained by using the optimal policy instead of the naive policy **(a)** when Scenario 1 is considered **(b)** when Scenario 2 is considered **(c)** when Scenario 3 is considered

from 0.90 to -0.90. In the setting where the correlation coefficient is negative, the manufacturer that follows the optimal policy reduces the raw material purchases in state 3 to save on the purchasing and inventory holding costs. Thus, the optimal policy shows a notable similarity to the naive policy in which the manufacturer halts the raw material purchases in state 3. The similarity that emerges between the naive

and optimal policies with the negative correlation coefficient leads to a decrease in the positive impact of using the optimal policy on the profit.

Figure 4.8(a) indicates that an increase in the sales price variation yields a decrease in the positive impact of using the optimal policy on the profit. The main rationale behind this trend is similar to that observed in the negative correlation case. The manufacturer that follows the optimal policy reduces the raw material purchases in state 3 with an increase in the sales price variation. This result implies that as the sales price variation increases the optimal policy resembles the naive policy in which the manufacturer stops purchasing the raw materials in state 3. The resemblance that emerges between the naive and optimal policies with the high sales price variation yields a decrease in the positive impact of using the optimal policy on the profit. In addition, Figure 4.8(b) shows that the positive impact of using the optimal policy on the profit decreases with an increase in the purchasing price variation. The main reason behind this trend is similar to that observed in the negative correlation and high sales price variation cases. Figure 4.8(c) implies that there is no significant impact of the traffic intensity rate on the difference between the manufacturer's profit obtained with the use of the naive policy and the manufacturer's profit obtained with the use of the optimal policy.

4.4 Managerial Insights

In this section, we summarize our key findings that provide managerial insights into how the sales price variation, purchasing price variation, correlation between sales and purchasing prices, limited raw materials and finished goods inventories, and limited production capacity affect the considered system. We also give an insight into under which circumstances the use of the optimal policy significantly improves the profit when compared to the use of the naive policy in which the manufacturer buys only when the purchasing price is low and sells only when the sales price is high. A detailed list regarding these managerial insights is given below:

1. The negative correlation between sales and purchasing prices yields an increase in the manufacturer's profit. In the negative correlation, the manufacturer lowers the average stock levels in the raw materials and finished goods inventories. Therefore, the average service level decreases. Decreasing average stock levels in the raw materials and finished goods inventories yield a saving in the purchasing and inventory holding costs. The amount of saving obtained due to the negative correlation leads to an increase in the manufacturer's profit.
2. The positive correlation between sales and purchasing prices leads to a decrease in the manufacturer's profit. When the sales and purchasing prices are positively correlated, the manufacturer increases the average stock levels in the raw materials and finished goods inventories. Therefore, the average service level increases. Increasing the stock levels in the raw materials and finished goods inventories yield higher purchasing and inventory holding costs. This fact results a decrease in the manufacturer's profit when the correlation is positive.
3. The manufacturer's profit rises with an increase in the sales price variation. The main rationale behind this fact is that the increasing sales price variation allows the manufacturer to achieve a significant amount of savings in the purchasing and holding costs. As a result of this fact, when the correlation is negative and the sales price is high the manufacturer obtains the highest profit in the numerical instances.
4. The manufacturer's profit rises with an increase in the purchasing price variation. The main rationale behind this fact is similar to that observed in the negative correlation and high sales price variation cases. Specifically, when the purchasing price variation is high the manufacturer follows a policy that increases the profit by achieving a saving in the purchasing and inventory holding costs.
5. The manufacturer's profit increases as the demand arrival rate increases. With

an increase in the demand arrival rate, the number of customers arriving at the system per unit time rises. As a result, the revenue obtained from the sales rises thereby increasing the profit. To satisfy the increasing demand, the manufacturer raises the average stock level in the raw materials inventory. However, due to the limited production capacity, the average stock level in the finished goods inventory decreases with an increase in the demand arrival rate.

6. When the manufacturer has a limited capacity for assigning both raw materials and finished goods inventories, if the demand arrival rate is the smallest one between the raw material arrival and production rates, increasing the capacity of the finished goods inventory provides a higher profit for the manufacturer. If the raw material arrival rate is the smallest one between the demand arrival and production rates, increasing the capacity of the raw materials inventory yields a higher profit for the manufacturer. By following this policy, the manufacturer aims to avoid starvation that could arise in the inventory that is close to the bottleneck of the system.
7. The negative correlation between the sales and purchasing prices leads to a notable decrease in the difference between the profits achieved by using the optimal and naive policies. An increase either in the sales price variation or in the purchasing price variation also yields a decrease in the positive impact of using the optimal policy on the profit. These observations can be explained by the fact that the high sales price variation, high purchasing price variation, and negative correlation force the manufacturer to follow a policy that is similar to the naive policy.

4.5 A Summary of Findings

We analyze the purchasing, production, and sales policies for a continuous-review discrete material flow production/inventory system with fluctuating and correlated

purchasing and sales prices, exponentially distributed raw material and demand interarrival times, and processing time. The sales and purchasing prices are driven by the random environmental changes that evolve according to a discrete state space continuous-time Markov process. We model the system as an infinite-horizon Markov decision process under the average reward criterion.

We establish that the optimal purchasing, production, and sales strategies are state-dependent threshold policies. Additionally, the monotonicity properties of the optimal policies are examined. To numerically determine the optimal threshold levels and to validate the analytic results, we propose a solution procedure based on a linear programming formulation. We investigate the effects of sales price variation, purchasing price variation, correlation between sales and purchasing prices, limited raw materials and finished goods inventories, and limited production capacity on the system performance measures, through a range of numerical experiments. Based on the numerical results, we provide managerial insights regarding the effects of these parameters on the system.

The negative correlation between the sales and purchasing prices, high sales price variation, and high purchasing price variation leads to an increase in the system profit. The main rationale behind the increase in the profit is that these parameter specifications allow the manufacturer to save on the purchasing and inventory holding costs. When the capacity that can be assigned to the raw materials and the finished goods inventories is limited and the raw materials arrival rate is the smallest compared to the production and the demand arrival rates increasing the capacity of the raw materials inventory yields a higher profit for the system. However, if the demand arrival rate is the smallest, increasing the capacity of the finished good inventory yields a higher profit for the system. By using this policy, the manufacturer avoids starvation in the inventory that is close to the system's bottleneck.

We examine under which circumstances the use of the optimal policy considerably improves the profit compared to the use of the naive buy low and sell high policy where

the manufacturer buys only when the purchasing price is low and sells only when the sales price is high. The negative correlation between sales and purchasing prices, high sales price variation, and high purchasing price variation lead to a decrease in the positive impact of using the optimal policy on the profit. The main rationale behind this result is that the optimal policies derived with these parameter specifications resemble the naive policy.

Chapter 5

CONCLUSION

This dissertation consists of three essays. In the first two essays, we examine the group purchasing and e-auction practices based on an industrial case. In third essay, we study how the fluctuating and correlated sales and sales prices affect a production/inventory system, as well as deriving the optimal control policies for the system that operates in such an environment.

In the first essay, we study a setting where a group purchasing organization works with a set of buyers and suppliers under demand and price uncertainty. To analyze this setting, we develop a detailed two-period stochastic model. In this model, advance sales opportunities are available in the first period to all parties in the market. The GPO can operate when the buyers and suppliers decide to cooperate with the GPO in the first period. If the GPO is operational, it employs a uniform-price reverse auction to determine the procurement price and to select the suppliers to be used for procuring advance orders of its customers. This model captures the basic dynamics considered in the industrial case accurately described in Tan (2014).

For the setting considered in the first essay, we primarily analyze the buyers' decisions on participation in the GPO and how much to buy through advance order opportunities to maximize their profits. We then characterize how suppliers optimally decide whether to use the option of working with the GPO and capacity they would sell in the first period. Additionally, we establish an analysis of the auction mechanism that the GPO employs. By using these analyzes, we show that a group purchasing organization helps buyers and/or suppliers to mitigate demand and price risks in an effective way and benefits all parties subject to certain conditions.

Additionally, we investigate the effects of buyer's and supplier's market shares, share of GPO orders in the advance sales market, demand and price uncertainty, and variation in production cost on the operation of the supply chain, through a range of numerical experiments. The results show that an increase in the demand variation leads to a decrease in the GPO's profit because the revenue that the GPO obtains from advance sales decreases. When the demand variation increases, the marginal benefit of the GPO on the supplier's expected profit decreases due to the GPO-driven market downsizing in the first period. We also observe that when the buyer's market share is high or the supplier's market share is low participating in the GPO is beneficial for the supplier. Because, in these two cases, the GPO provides the suppliers a sizable advance sales market in the first period. It is found that an increase in the buyer's market share or a decrease in the supplier's market share yields a higher premium for the GPO and buyers. For the GPO and suppliers, the group buying benefit increases as the share of GPO orders in the advance sales market increases. We find that high variation in production cost improves the GPO's profit but adversely affects the supplier's profit. The main rationale behind this result is that an increase in the production cost variation leads to a decrease in the expected auction price.

The model developed in the first essay can be extended in several ways. First, the model can be extended to a supply chain with heterogeneous suppliers and buyers. Second, the model assumes information asymmetry between suppliers and the GPO. The GPO possibly generate a premium from this asymmetry. Extending this work to a setting with full information requires deriving an optimal bidding strategy for suppliers involving pricing and capacity decisions. Additionally, different contract types can be applied to this structure to determine how to incentivize the buyers and suppliers to participate in GPOs effectively. Finally, the risk behavior of parties in the supply chain can be considered. These are left for future research.

In the second essay, we empirically examine online procurement auctions managed by a third-party auction provider between March 2006 and March 2016. The dataset

includes the transaction details of 15458 e-auction events executed in 14 different product categories using three different auction formats. In the dataset, there are two types of buyers: the individual buyers that directly use the e-auction platform and the group purchasing organization that operates as a purchasing agent for a group of individual buyers.

By employing a standard Tobit model, we study the joint impacts of the product category, auction type, 2008 global financial crisis, and number of participating bidders on the buyer surplus obtained from the e-auctions. The results show that the product categories have notable impacts on the decrease in the procurement prices with respect to the minimum of the initial submitted bids. We find that in terms of the decrease in procurement prices, the *English* auctions outperform the *Dutch* auctions and the *Lot* auctions are superior to the *Split* auctions. The superiority of the *Lot* auctions over the *Split* auctions possibly stems from the economies of scale. The outperforming of the *English* auctions over the *Dutch* auctions could be related to the dynamics of the bidding rules. Because, in the *English* auctions, the bidders compete with each other by consecutively submitting bids whereas, in the *Dutch* auctions, the price of the auctioning item is iteratively increased by the auctioneer. Additionally, it is established that the 2008 global financial crisis led to an increase in the buyer surplus. The main rationale behind this result is that the economic downturn periods lead to a decrease in the market demand and force suppliers to a more intense competition in the auctions. Unlike the existing studies, we observe that the positive impact of having one more bidder in the auction on the buyer surplus is not constant and it decreases as the number of bidders is getting larger. Because the competition in the auction would not further increase after a certain number of suppliers participates in the event.

In addition, we indicate that the product categories can be classified into three different groups based on their impacts on the average decrease in procurement prices. On the basis of the classification results, we reveal that there is an opportunity of

achieving a large decrease in the procurement prices for the complex products such as advertisement, service, and high-tech manufacturing system.

We also study the impacts of the group purchasing, contract type, and platform ownership on the average price reduction achieved through the e-auctions. The empirical results imply that the option of group purchasing leads a higher decrease in the procurement prices compared to the option of individual buying. The main rationale behind this result is likely the economies of scale that is created with the group purchasing programs. It is found that there is no statistically significant difference between the *Fixed* and *Percentage* contract types. The analysis also indicates that there is no statistical difference between the average price reduction achieved through the use of the third-party's platform and the one achieved through the use of the private auction platform.

An interesting topic for future research would be a study that deals with the effects of incumbency, the supplier service quality, the contract duration, and the visual design parameters on the buyer surplus. Further investigations of what drives the suppliers' behaviors in the auction and which factors yield a benefit for the suppliers are needed. It is important for the practitioners to identify the source of price reduction achieved through the reverse auctions. Therefore, another topic would be to look at the question that is, how sustainable are the price reductions. In the second essay, due to lack of sufficient data, the main factors that drive the results regarding the group purchasing, contract type, and platform ownership could not be precisely derived. These issues are also left for future studies.

In third essay, we study a continuous-review discrete material flow production/inventory system with exponentially distributed raw material and demand interarrival times. In the system, the sales and purchasing prices are driven by the random environmental changes that evolve according to a discrete state space continuous-time Markov chain. The system has a limited production capacity because a single server processes raw materials individually with exponential processing times. With this

setting, the system is controlled by purchasing, production, and sales decisions.

To derive the optimal purchasing, production, and sales policies for the system, we propose an infinite-horizon Markov decision process model with the objective of maximizing the long-run average reward. As a result of this effort, we prove that the optimal purchasing, production, and sales strategies are state-dependent threshold policies. To numerically determine the corresponding optimal threshold levels and to validate the analytic results, we employ a solution procedure based on a linear programming formulation. Additionally, we examine the monotonicity properties of the optimal policies. The results reveal that the optimal sales and production policies are non-decreasing in the level of the raw materials inventory whereas the optimal purchasing policy is non-increasing in the level of the raw materials inventory. We also find that the optimal purchasing and production policies are non-increasing in the level of finished goods inventory and the optimal sales policy is non-decreasing in the level of finished goods inventory.

Based on a range of numerical experiment, we study the impacts of the sales price variation, purchasing price variation, correlation between sales and purchasing prices, limited raw materials and finished goods inventories, and customer arrival rate on the system performance measures. As a result of this effort, we ascertain that the negative correlation between the sales and purchasing prices, high sales price variation, and high purchasing price variation lead to an increase in the system profit. The increase in the system profit is explained by the fact that these parameter specifications allow the manufacturer to save on the purchasing and inventory holding costs. We also observe that as the customer arrival rate rises the system profit increases. If the manufacturer has a limited capacity to be assigned the raw materials and finished goods inventories the demand and raw materials arrival rates play an important role in the capacity allocation decision. We observe that when the raw materials arrival rate is the smallest one compared to the production and demand arrival rates increasing the capacity of the raw materials inventory yields a higher profit for the system. However, when the

demand arrival rate is the smallest one compared to the others increasing the capacity of the finished good inventory leads to a higher profit for the system. The system follows this policy to avoid starvation in the inventory that is close to the bottleneck.

Additionally, in the third essay, we study under which circumstances the use of the optimal policy considerably improves the profit compared to the use of the naive buy low and sell high policy where the manufacturer buys only when the purchasing price is low and sells only when the sales price is high. When the sales price variation or the purchasing price variation increases the benefit of using the optimal policy on the system profit decreases. It is also observed that the negative correlation between sales and purchasing prices leads to a decrease in the positive impact of using the optimal policy on the system profit. The main rationale behind this result is that the optimal policies derived with these parameter specifications are similar to the naive policy.

The model developed in the third essay can be extended in several ways. First, in the model, we consider exponentially distributed processing time. The raw materials and demand inter-arrival times are distributed exponentially and independent of the processing times. Markov arrival processes can be used to extend the model to a setting where correlated arrivals and service times. Second, this work provides the basic perspective for the optimal purchasing, production, and sales policies by considering a setting where the manufacturer produces a single product with a reliable machine. Studying the problem with multiple products and unreliable machine assumptions could be an interesting topic for future research. Third, this work can be extended by incorporating the pricing decision into the model. Extending this work to a setting with pricing decision would allow us to examine the impacts of different pricing strategies on the system. These issues are left for future studies.

We believe that the results derived in this dissertation will be of value to the producers planning to incorporate the e-auction and group purchasing practices into the procurement processes as the results help understanding of the dynamics of these practices and identify the conditions and factors motivating the use of them. This

dissertation also extends the state of art in the analyses of the group purchasing and e-auctions by dealing with the factors and settings that have not been addressed in the literature. Therefore, the analysis regarding both practices provides researchers a basis for further research and development on the new purchasing tools. The producers executing their operations in an international basis or operating in the sectors that rely on the commodity markets will utilize the results on the fluctuating sales and purchasing prices because they typically deal with random market prices. Additionally, we think that the results derived in this dissertation provide researchers the new understanding of how the fluctuating sales and purchasing prices affect the system performance measures and optimal policy structures because these factors have not been considered in the existing literature.

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Appendix A

SUPPLEMENTARY MATERIAL FOR: ANALYSIS OF A GROUP PURCHASING ORGANIZATION UNDER DEMAND AND PRICE UNCERTAINTY

A.1 Mathematical Proofs of Propositions

We first define the equations for the expected sales $S(\mathcal{A}, \mathcal{D})$, expected left-over inventory $I(\mathcal{A}, \mathcal{D})$, and expected lost sales $L(\mathcal{A}, \mathcal{D})$ for an on-hand inventory level of $\mathcal{A}$ and random demand $\mathcal{D}$ with a cumulative distribution function of $F_D(x)$ as

$$S(\mathcal{A}, \mathcal{D}) = E[\min(\mathcal{A}, \mathcal{D})] = \mathcal{A} - \int_0^{\mathcal{A}} F_D(x) dx \quad (\text{A.1})$$

$$I(\mathcal{A}, \mathcal{D}) = E[(\mathcal{A} - \mathcal{D})^+] = \mathcal{A} - S(\mathcal{A}, \mathcal{D}) \quad (\text{A.2})$$

$$L(\mathcal{A}, \mathcal{D}) = E[(\mathcal{D} - \mathcal{A})^+] = E[\mathcal{D}] - S(\mathcal{A}, \mathcal{D}). \quad (\text{A.3})$$

Proof of Proposition 1. If the buyer does not choose to work with the GPO, its expected profit is written as in Equation (2.1). The expected profit can also be expressed as

$$\begin{aligned} E[\Pi_r^{NG}(q_{NG})] &= (p - w_{sp} - e_r) E[\beta D_T] - (w_{fp} + e_r) q_{NG} \\ &\quad + (w_{sp} + e_r) S(q_{NG}, \beta D_T). \end{aligned} \quad (\text{A.4})$$

The expected profit $E[\Pi_r^{NG}(q_{NG})]$ is a concave function of q_{NG} , that is,

$$\frac{\partial^2 E[\Pi_r^{NG}(q_{NG})]}{\partial q_{NG}^2} = -(e_r + w_{sp}) f_B(q_{NG}) < 0. \quad (\text{A.5})$$

Under this setting, the first-order condition yields the solution of the buyer's

problem:

$$\begin{aligned} \frac{\partial E[\Pi_r^{NG}(q_{NG})]}{\partial q_{NG}} &= -(w_{fp} + e_r) + (w_{sp} + e_r) \frac{\partial S(q_{NG}, \beta D_T)}{\partial q_{NG}} = 0 \\ &= -(w_{fp} + e_r) + (w_{sp} + e_r) (1 - F_B(q_{NG})) = 0. \end{aligned} \quad (\text{A.6})$$

Rearranging the terms in the above equation gives

$$F_B(q_{NG}) = 1 - \frac{w_{fp} + e_r}{w_{sp} + e_r}. \quad (\text{A.7})$$

As a result, the optimal advance order quantity for a buyer who uses the market option in the first period is defined as in Equation (2.4).

When the buyer chooses to work with the GPO, its expected profit function is given as in Equation (2.2). The expected profit can be rewritten as

$$\begin{aligned} E[\hat{\Pi}_r^G(q_G)] &= \theta ((p - w_{sp} - e_r) E[\beta D_T] - w_r q_G + (w_{sp} + e_r) S(q_G, \beta D_T)) \\ &\quad + (1 - \theta) E[\Pi_r^{NG}(q_{NG})] \end{aligned} \quad (\text{A.8})$$

that is also a concave function of q_G , that is,

$$\frac{\partial^2 E[\hat{\Pi}_r^G(q_G)]}{\partial q_G^2} = -\theta (e_r + w_{sp}) f_B(q_G) < 0. \quad (\text{A.9})$$

The optimal quantity that maximizes the expected profit is determined from the first-order condition as

$$F_B(q_G) = 1 - \frac{w_r}{w_{sp} + e_r}. \quad (\text{A.10})$$

As a result, the optimal advance order quantity for a case where the buyer works with the GPO is given as in Equation (2.3). □

Proof of Proposition 2. The buyer prefers working with GPO in the first period if the expected profit for this option is greater than or equal to the profit obtained when it does not work with the GPO. The difference between the two expected profit functions, $E[\hat{\Pi}_r^G(q_G^*)] - E[\Pi_r^{NG}(q_{NG}^*)] \geq 0$, is written as

$$\theta [(w_{sp} + e_r) S(q_G^*, \beta D_T) - w_r q_G^* - (w_{sp} + e_r) S(q_{NG}^*, \beta D_T) + (w_{fp} + e_r) q_{NG}^*] \geq 0. \quad (\text{A.11})$$

Dividing both sides of the above equation with $\theta(w_{sp} + e_r)$ and writing $S(q_G^*, \beta D_T)$ and $S(q_{NG}^*, \beta D_T)$ explicitly give

$$q_G^* \left(1 - \frac{w_r}{w_{sp} + e_r}\right) - \int_0^{q_G^*} F_B(y) dy - q_{NG}^* \left(1 - \frac{w_{fp} + e_r}{w_{sp} + e_r}\right) + \int_0^{q_{NG}^*} F_B(y) dy \geq 0. \quad (\text{A.12})$$

From the proof of Proposition 1, $\left(1 - \frac{w_r}{w_{sp} + e_r}\right)$ and $\left(1 - \frac{w_{fp} + e_r}{w_{sp} + e_r}\right)$ can be replaced with $F_B(q_G^*)$ and $F_B(q_{NG}^*)$, respectively. Thus, the above inequality can be simplified as

$$q_G^* F_B(q_G^*) - q_{NG}^* F_B(q_{NG}^*) - \int_{q_{NG}^*}^{q_G^*} F_B(y) dy \geq 0. \quad (\text{A.13})$$

It can be shown that the above inequality holds only if $q_G^* \geq q_{NG}^*$. This result gives the condition in Proposition 2. $\square$

Proof of Proposition 3. Suppliers whose production costs are greater than or equal to the estimated auction price do not work with the GPO, that is, they do not allocate any capacity to the GPO.

Suppliers whose production costs are less than $\hat{w}_s$ prefer using the GPO option in the first period. In this case, the expected profit function of a supplier using the GPO option is given in Equation (2.6). In terms of Equation (A.1), the expected profit function is restated as

$$\begin{aligned} E\left[\hat{\Pi}_{s_j}^G(\Delta_G, \Delta_{NG}) | c < \hat{w}_s\right] &= \theta(\hat{w}_s \Delta_G + (w_{sp} - e_s) S(M - \Delta_G, D_s^G)) \\ &\quad + (1 - \theta)((w_{fp} - e_s) \Delta_{NG}) \\ &\quad + (1 - \theta)((w_{sp} - e_s) S(M - \Delta_{NG}, D_s^{NG})) - cM. \end{aligned} \quad (\text{A.14})$$

This is a concave function of Δ_G , namely,

$$\frac{\partial^2 E\left[\hat{\Pi}_{s_j}^G(\Delta_G, \Delta_{NG}) | c < \hat{w}_s\right]}{\partial \Delta_G^2} = -\theta(w_{sp} - e_s) f_{D_s^G}(M - \Delta_G) < 0. \quad (\text{A.15})$$

The optimal value of Δ_G that maximizes the expected profit subject to the constraint $0 \leq \Delta_G^* \leq \min \{M, Q_G^*\}$ is determined in accordance with the unconstrained solution for the problem, denoted as δ_G^* . The unconstrained solution for the problem is obtained from the first-order condition as

$$\delta_G^* = M - F_{D_s^G}^{-1} \left(1 - \frac{\hat{w}_s}{w_{sp} - e_s} \right). \quad (\text{A.16})$$

Equation (2.8) gives the solution of the constrained problem, using the concavity of the profit function.

If the supplier does not choose to work with the GPO, the expected profit can be written as in Equation (2.7) regardless of whether or not its production cost is less than $\hat{w}_s$. With Equation (A.1), the expected profit function is rewritten as

$$\begin{aligned} E \left[\Pi_{s_j}^{NG} (\Delta'_{NG}, \Delta_{NG}) | c \right] &= \theta ((w_{fp} - e_s) \Delta'_{NG} + (w_{sp} - e_s) S(M - \Delta'_{NG}, D_s^G)) \quad (\text{A.17}) \\ &+ (1 - \theta) ((w_{fp} - e_s) \Delta_{NG}) \\ &+ (1 - \theta) ((w_{sp} - e_s) S(M - \Delta_{NG}, D_s^{NG})) - cM. \end{aligned}$$

$E \left[\Pi_{s_j}^{NG} (\Delta'_{NG}, \Delta_{NG}) | c \right]$ is a concave function with respect to Δ_{NG} and Δ'_{NG} . That is,

$$\frac{\partial^2 E \left[\Pi_{s_j}^{NG} (\Delta'_{NG}, \Delta_{NG}) | c \right]}{\partial \Delta_{NG}^2} = - (1 - \theta) (w_{sp} - e_s) f_{D_s^{NG}}(M - \Delta_{NG}) < 0, \quad (\text{A.18})$$

$$\frac{\partial^2 E \left[\Pi_{s_j}^{NG} (\Delta'_{NG}, \Delta_{NG}) | c \right]}{\partial \Delta_{NG}'^2} = -\theta (w_{sp} - e_s) f_{D_s^G}(M - \Delta'_{NG}) < 0. \quad (\text{A.19})$$

With the same steps that yield the optimal solution for the previous case, the unconstrained optimization of $E \left[\Pi_{s_j}^{NG} (\Delta'_{NG}, \Delta_{NG}) | c \right]$, together with the concavity of the function, gives the solution of the optimal values of Δ_{NG}^* and $\Delta_{NG}'^*$ as given in Proposition 3. $\square$

Proof of Proposition 4. Supplier j , with $c \geq \hat{w}_s$, joins the GPO if its expected profit is higher with participation than non-participation. The difference in expected profits between these two options, $E \left[\hat{\Pi}_{s_j}^G (\Delta_{NG}^*) | c \geq \hat{w}_s \right] - E \left[\Pi_{s_j}^{NG} (\Delta_{NG}'^*, \Delta_{NG}^*) | c \right]$,

can be written as in the following expression.

$$(w_{sp} - e_s) \left(M - \int_0^M F_{D_s^G}(u) du \right) - (w_{fp} - e_s) \Delta'_{NG} - (w_{sp} - e_s) \left(M - \Delta'_{NG} - \int_0^{M - \Delta'_{NG}} F_{D_s^G}(u) du \right) \quad (\text{A.20})$$

Dividing both sides of the equation by $(w_{sp} - e_s)$ and using $F_{D_s^G}(M - \delta'_{NG})$, defined in the proof of Proposition 3, simplify the above equation as

$$\Delta'_{NG} \left(\frac{w_{sp} - w_{fp}}{w_{sp} - e_s} \right) - \int_{M - \Delta'_{NG}}^M F_{D_s^G}(u) du = \Delta'_{NG} F_{D_s^G}(M - \delta'_{NG}) - \int_{M - \Delta'_{NG}}^M F_{D_s^G}(u) du. \quad (\text{A.21})$$

When δ'_{NG} is smaller than zero, the above expression yields zero considering the definition of Δ'_{NG} . Otherwise, when δ'_{NG} is greater than or equal to zero, it will definitely be greater than or equal to Δ'_{NG} . With this argument and the basic properties of the cumulative distribution function, we can show that the above expression is less than or equal to zero. Therefore, given that supplier j 's production cost is greater than or equal to $\hat{w}_s$, choosing the market option is always at least as good as or better than choosing the GPO option. Accordingly, it never allocates a portion of its capacity to the GPO.

For suppliers whose production cost is less than $\hat{w}_s$, the GPO will be beneficial if and only if

$$E \left[\hat{\Pi}_{s_j}^G(\Delta_{NG}^*) | c < \hat{w}_s \right] - E \left[\Pi_{s_j}^{NG}(\Delta'_{NG}, \Delta_{NG}^*) | c \right] > 0. \quad (\text{A.22})$$

The above difference, $E \left[\hat{\Pi}_{s_j}^G(\Delta_{NG}^*) | c < \hat{w}_s \right] - E \left[\Pi_{s_j}^{NG}(\Delta'_{NG}, \Delta_{NG}^*) | c \right]$, can be restated more explicitly as in the following expression.

$$\hat{w}_s \Delta_G^* + (w_{sp} - e_s) S(M - \Delta_G^*, D_s^G) - (w_{fp} - e_s) \Delta'_{NG} - (w_{sp} - e_s) S(M - \Delta'_{NG}, D_s^G) \quad (\text{A.23})$$

The above function can be rewritten as

$$\Delta'_{NG} \left(1 - \frac{w_{fp} - e_s}{w_{sp} - e_s} \right) - \Delta_G^* \left(1 - \frac{\hat{w}_s}{w_{sp} - e_s} \right) + \int_0^{M - \Delta'_{NG}} F_{D_s^G}(u) du - \int_0^{M - \Delta_G^*} F_{D_s^G}(u) du. \quad (\text{A.24})$$

If the above expression is positive, supplier j prefers the GPO option given $c < \hat{w}_s$.

If $\hat{w}_s \geq w_{fp} - e_s$ and $w_r \leq w_{fp} + e_r$ hold, then Δ_G^* will be greater than or equal to Δ_{NG}^* due to their definitions. Therefore, the above expression can be simplified as

$$\Delta_{NG}^* \left(\frac{\hat{w}_s - w_{fp} + e_s}{w_{sp} - e_s} \right) - (\Delta_G^* - \Delta_{NG}^*) \left(1 - \frac{\hat{w}_s}{w_{sp} - e_s} \right) + \int_{M-\Delta_G^*}^{M-\Delta_{NG}^*} F_{D_s^G}(u) du. \quad (\text{A.25})$$

When $\Delta_G^* \geq \Delta_{NG}^*$, we can show that the above equation is positive. As a result, we conclude that given $c < \hat{w}_s$, supplier j definitely prefers working with the GPO when $\hat{w}_s \geq w_{fp} - e_s$ and $w_r \leq w_{fp} + e_r$. $\square$

Proof of Proposition 5. The capacity allocated to the GPO is exactly the same for all participating suppliers with $c < \hat{w}_s$. In addition, the allocated capacities are assumed to be sold in batches. Therefore, $k\Delta_G^*$ items are procured at the end of the auction. If the allocated capacities and the total amount of procured items at the end of the auction are normalized to Δ_G^* , the mechanism analyzed corresponds to an auction in which bidders bid for only one of k objects.

Milgrom (2004) proposes that if every bidder has a demand for just a single item and can bid for only a single unit, then the uniform-price auction would be a Vickrey auction. In this setting, truthful bidding is an optimal strategy for all bidders. Accordingly, we conclude, following Milgrom (2004), that truthful bidding is an optimal strategy for all bidders in our setting. $\square$

Proof of Proposition 6. Raghunandan and Patil (1972) derive the probability density and the moment generating functions of the order statistics where the sample size is random. The authors also propose a special case where the variables follow a uniform distribution over the interval $[0, 1]$ and the sample size follows a binomial distribution.

In our model, the sample size follows a binomial distribution as stated in Equation (2.14), and the production cost of a supplier participating in the auction is uniformly

distributed between $\underline{c}$ and $\hat{w}_s$. Therefore, we can directly use the approach given in Raghunandanan and Patil (1972) to obtain the expression. $\square$

A.2 The Closed Form Expressions of Propositions Under The Assumption of Uniform Demand

Proposition 7. For a given w_r quoted by the GPO, the buyer will work with the GPO in the first period when $E[\Pi_r^G(q_G^*)] - E[\Pi_r^{NG}(q_{NG}^*)] \geq 0$. Where D_T follows a uniform distribution between $\underline{d}_T$ and $\bar{d}_T$, the optimal advance order quantity, q_G^* , is defined as

$$q_G^* = \begin{cases} \beta \underline{d}_T + \beta (\bar{d}_T - \underline{d}_T) \left(1 - \frac{w_r}{w_{sp} + e_R}\right) & \text{if } w_{sp} + e_R \geq w_r \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (\text{A.26})$$

In addition, the total advance order quantity consolidated in the GPO is $Q_G^* = nq_G^*$.

On the other hand, if $E[\Pi_r^G(q_G^*)] - E[\Pi_r^{NG}(q_{NG}^*)] < 0$, the buyer will use the market option in the first period. Under this setting, when D_T is uniformly distributed between $\underline{d}_T$ and $\bar{d}_T$, the optimal advance order quantity, q_{NG}^* , is defined as

$$q_{NG}^* = \begin{cases} \beta \underline{d}_T + \beta (\bar{d}_T - \underline{d}_T) \left(1 - \frac{w_{fp} + e_R}{w_{sp} + e_R}\right) & \text{if } w_{sp} + e_R \geq w_{fp} + e_R \geq 0 \\ 0 & \text{otherwise} \end{cases} \quad (\text{A.27})$$

Proposition 8. Given that supplier j 's production cost is lower than the estimated auction price, the supplier will be eager to work with the GPO when the GPO option is more beneficial to him compared to the market option. Where D_T is uniformly distributed between $\underline{d}_T$ and $\bar{d}_T$, it allocates

$$\Delta_G^* = \begin{cases} \min \{\delta_G, Q_G^*\} & \text{if } w_{sp} - e_s \geq \hat{w}_s > 0 \\ 0 & \text{otherwise} \end{cases} \quad (\text{A.28})$$

where $\delta_G = M - (\bar{d}_T - Q_T^G) \psi \left(1 - \frac{\hat{w}_s}{w_{sp} - e_s}\right)$.

Supplier j never assigns a portion of its capacity for the GPO if its production cost c is greater than or equal to the estimated auction price, that is, $c \geq \hat{w}_s$.

Where D_T follows a uniform distribution between $\underline{d}_T$ and $\bar{d}_T$ and a GPO is operational and the supplier considers the market option more beneficial, the portion of capacity it will allocate to the buyers in the market is given as

$$\Delta'_{NG} = \begin{cases} \min \left\{ \delta'_{NG}, \psi \frac{nq_{NG}(1-\tau)}{\tau} \right\} & \text{if } w_{sp} - e_s \geq w_{sp} - w_{fp} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (\text{A.29})$$

where $\delta'_{NG} = M - (\bar{d}_T - Q_T^G) \psi \left(\frac{w_{sp} - w_{fp}}{w_{sp} - e_s} \right)$.

Where D_T is uniformly distributed between $\underline{d}_T$ and $\bar{d}_T$ and no GPO is operational, the portion allocated to the buyers in the market is defined as

$$\Delta^*_{NG} = \begin{cases} \min \{ \delta_{NG}, \psi Q_T^{NG} \} & \text{if } w_{sp} - e_s \geq w_{sp} - w_{fp} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (\text{A.30})$$

where $\delta_{NG} = M - (\bar{d}_T - Q_T^{NG}) \psi \left(\frac{w_{sp} - w_{fp}}{w_{sp} - e_s} \right)$.

Proposition 9. When the supplier's production cost is lower than the estimated auction price and D_T is uniformly distributed between $\underline{d}_T$ and $\bar{d}_T$, the supplier considers the GPO beneficial to him if and only if the following inequality holds.

$$\Delta_G^* \delta_G - \Delta_{NG}^* \delta'_{NG} - \frac{(\Delta_G^*)^2 - (\Delta_{NG}^*)^2}{2} \geq 0 \quad (\text{A.31})$$

On the other hand, suppliers whose production costs are greater than or equal to the estimated auction price would never consider the GPO beneficial to them. Therefore, they would never participate in the auction.

Appendix B

SUPPLEMENTARY MATERIAL FOR: AN EMPIRICAL ANALYSIS OF THE MAIN DRIVERS AFFECTING THE BUYER SURPLUS IN E-AUCTIONS

Product Category	Corresponding UNSPC Segment Codes and Segment Names
Direct Material	24000000 - Material Handling and Conditioning and Storage Machinery and Accessories and Supplies 27000000 - Tools and General Machinery 31000000 - Manufacturing Components and Supplies
Construction	22000000 - Building and Construction Machinery and Accessories 72000000 - Building and Facility Construction and Maintenance Services Supplies
Electrical Works	26000000 - Power Generation and Distribution Machinery and Accessories 39000000 - Electrical Systems and Lighting and Components and Accessories and Supplies
Metal	11000000 - Mineral and Textile and Inedible Plant and Animal Materials
Textile	53000000 - Apparel and Luggage and Personal Care Products
Logistics	78000000 - Transportation and Storage and Mail Services
Advertisement	82000000 - Editorial and Design and Graphic and Fine Art Services
Plastics	13000000 - Resin and Rosin and Rubber and Foam and Film and Elastomeric Materials
Manufacturing Sys.	73000000 - Industrial Production and Manufacturing Services 81000000 - Engineering and Research and Technology Based Services

Table B.1: The product categories considered in this study and the corresponding UNSPC segments

Product Category	Corresponding UNSPC Segment Codes and Segment Names
In-Direct Material	14000000 - Paper Materials and Products 44000000 - Office Equipment and Accessories and Supplies 48000000 - Service Industry Machinery and Equipment and Supplies 56000000 - Furniture and Furnishings
Health-Care	42000000 - Medical Equipment and Accessories and Supplies 51000000 - Drugs and Pharmaceutical Products 85000000 - Healthcare Services
Service	76000000 - Industrial Cleaning Services 77000000 - Environmental Services 80000000 - Management and Business Professionals and Administrative Services 84000000 - Financial and Insurance Services 86000000 - Education and Training Services 90000000 - Travel and Food and Lodging and Entertainment Services
Technological Eq.	32000000 - Electronic Components and Supplies 43000000 - Information Technology Broadcasting and Telecommunications 45000000 - Printing and Photographic and Audio and Visual Equipment and Supplies
Chemical	12000000 - Chemicals including Bio-Chemicals and Gas Materials 15000000 - Fuels and Fuel Additives and Lubricants and Anti-corrosive Materials

Table B.1: (cont'd) The product categories considered in this study and the corresponding UNSPC segments

Difference of Levels	Difference of Means	Standard Error of Difference	%95 Confidence Interval	t-value	Adjusted p-value
Logistics - Chemical	0.70	0.46	(-0.91; 2.30)	1.53	0.96
Health-Care - Chemical	-0.91	0.36	(-2.21; 0.39)	-2.50	0.41
Electrical Works - Chemical	3.33	0.46	(1.72; 4.94)	7.28	0.00
In-Direct Material - Chemical	4.73	0.40	(3.33; 6.13)	11.91	0.00
Construction - Chemical	4.70	0.38	(3.34; 6.06)	12.31	0.00
Metal - Chemical	4.37	0.60	(2.27; 6.48)	7.30	0.00
Technological Eq. - Chemical	4.39	0.56	(2.41; 6.37)	7.78	0.00
Textile - Chemical	5.44	0.57	(3.45; 7.43)	9.62	0.00
Direct Material - Chemical	5.27	0.39	(3.89; 6.65)	13.54	0.00
Service - Chemical	6.31	0.57	(4.30; 8.32)	11.03	0.00
Manufacturing Sys. - Chemical	7.38	0.93	(4.04; 10.71)	7.92	0.00
Plastics - Chemical	8.73	1.37	(3.73; 13.72)	6.35	0.00
Advertisement - Chemical	9.17	0.78	(6.41; 11.93)	11.69	0.00
Health-Care - Logistics	-1.60	0.29	(-2.63; -0.58)	-5.49	0.00
Electrical Works - Logistics	2.64	0.40	(1.21; 4.05)	6.53	0.00
In-Direct Material - Logistics	4.03	0.33	(2.86; 5.21)	12.10	0.00
Construction - Logistics	4.01	0.32	(2.90; 5.12)	12.71	0.00
Metal - Logistics	3.68	0.56	(1.71; 5.64)	6.58	0.00

Table B.2: Games-Howell Simultaneous Tests for Difference of Means

Difference of Levels	Difference of Means	Standard Error of Difference	%95 Confidence Interval	t-value	Adjusted p-value
Technological Eq. - Logistics	3.70	0.52	(1.86; 5.53)	7.09	0.00
Textile - Logistics	4.74	0.52	(2.91; 6.58)	9.08	0.00
Direct Material - Logistics	4.57	0.32	(3.44; 5.71)	14.13	0.00
Service - Logistics	5.62	0.53	(3.75; 7.48)	10.60	0.00
Manufacturing Sys. - Logistics	6.68	0.91	(3.43; 9.93)	7.37	0.00
Plastics - Logistics	8.03	1.36	(3.09; 12.97)	5.92	0.00
Advertisement - Logistics	8.47	0.75	(5.82; 11.12)	11.24	0.00
Electrical Works - Health-Care	4.24	0.30	(3.21; 5.28)	14.39	0.00
In-Direct Material - Health-Care	5.64	0.19	(4.98; 6.30)	30.07	0.00
Construction - Health-Care	5.61	0.15	(5.08; 6.15)	36.68	0.00
Metal - Health-Care	5.28	0.49	(3.58; 6.99)	10.87	0.00
Technological Eq. - Health-Care	5.30	0.44	(3.75; 6.86)	11.98	0.00
Textile - Health-Care	6.35	0.44	(4.79; 7.91)	14.31	0.00
Direct Material - Health-Care	6.18	0.17	(5.58; 6.78)	36.41	0.00
Service - Health-Care	7.22	0.45	(5.63; 8.81)	15.96	0.00
Manufacturing Sys. - Health-Care	8.29	0.86	(5.18; 11.40)	9.60	0.00
Plastics - Health-Care	9.64	1.33	(4.78; 14.50)	7.25	0.00
Advertisement - Health-Care	10.10	0.70	(7.61; 12.55)	14.37	0.00

Table B.2: (cont'd) Games-Howell Simultaneous Tests for Difference of Means

Difference of Levels	Difference of Means	Standard Error of Difference	%95 Confidence Interval	t-value	Adjusted p-value
In-Direct Material - Electrical Works	1.40	0.34	(0.22; 2.58)	4.17	0.00
Construction - Electrical Works	1.37	0.32	(0.26; 2.49)	4.33	0.00
Metal - Electrical Works	1.04	0.56	(-0.92; 3.01)	1.86	0.85
Technological Eq. - Electrical Works	1.06	0.52	(-0.78; 2.90)	2.03	0.75
Textile - Electrical Works	2.11	0.52	(0.27; 3.95)	4.03	0.00
Direct Material - Electrical Works	1.94	0.33	(0.80; 3.08)	5.96	0.00
Service - Electrical Works	2.98	0.53	(1.11; 4.85)	5.61	0.00
Manufacturing Sys. - Electrical Works	4.05	0.91	(0.79; 7.30)	4.46	0.00
Plastics - Electrical Works	5.40	1.36	(0.45; 10.34)	3.97	0.01
Advertisement - Electrical Works	5.84	0.76	(3.19; 8.49)	7.74	0.00
Construction - In-Direct Material	-0.03	0.22	(-0.80; 0.75)	-0.12	1.00
Metal - In-Direct Material	-0.36	0.51	(-2.15; 1.44)	-0.70	1.00
Technological Eq. - In-Direct Material	-0.34	0.47	(-1.99; 1.31)	-0.72	1.00
Textile - In-Direct Material	0.71	0.47	(-0.94; 2.37)	1.50	0.97
Direct Material - In-Direct Material	0.54	0.23	(-0.28; 1.36)	2.32	0.54
Service - In-Direct Material	1.58	0.48	(-0.11; 3.27)	3.30	0.06
Manufacturing Sys. - In-Direct Material	2.65	0.88	(-0.51; 5.80)	3.01	0.15
Plastics - In-Direct Material	4.00	1.34	(-0.89; 8.88)	2.98	0.17

Table B.2: (cont'd) Games-Howell Simultaneous Tests for Difference of Means

Difference of Levels	Difference of Means	Standard Error of Difference	%95 Confidence Interval	t-value	Adjusted p-value
Advertisement - In-Direct Material	4.44	0.72	(1.91; 6.97)	6.17	0.00
Metal - Construction	-0.33	0.50	(-2.09; 1.43)	-0.66	1.00
Technological Eq. - Construction	-0.31	0.46	(-1.92; 1.30)	-0.68	1.00
Textile - Construction	0.74	0.46	(-0.88; 2.35)	1.60	0.95
Direct Material - Construction	0.57	0.21	(-0.16; 1.29)	2.74	0.25
Service - Construction	1.61	0.47	(-0.04; 3.25)	3.44	0.04
Manufacturing Sys. - Construction	2.67	0.87	(-0.46; 5.80)	3.07	0.13
Plastics - Construction	4.02	1.33	(-0.85; 8.89)	3.01	0.16
Advertisement - Construction	4.47	0.71	(1.97; 6.97)	6.28	0.00
Technological Eq. - Metal	0.02	0.65	(-2.27; 2.30)	0.03	1.00
Textile - Metal	1.07	0.65	(-1.22; 3.35)	1.64	0.94
Direct Material - Metal	0.90	0.50	(-0.88; 2.67)	1.77	0.89
Service - Metal	1.94	0.66	(-0.37; 4.25)	2.95	0.16
Manufacturing Sys. - Metal	3.00	0.99	(-0.51; 6.52)	3.05	0.13
Plastics - Metal	4.35	1.41	(-0.76; 9.46)	3.08	0.13
Advertisement - Metal	4.80	0.85	(1.82; 7.78)	5.66	0.00
Textile - Technological Eq.	1.05	0.62	(-1.13; 3.22)	1.69	0.92
Direct Material - Technological Eq.	0.88	0.46	(-0.75; 2.51)	1.90	0.83

Table B.2: (cont'd) Games-Howell Simultaneous Tests for Difference of Means

Difference of Levels	Difference of Means	Standard Error of Difference	%95 Confidence Interval	t-value	Adjusted p-value
Service - Technological Eq.	1.92	0.63	(-0.28; 4.12)	3.07	0.11
Manufacturing Sys. - Technological Eq.	2.99	0.97	(-0.46; 6.43)	3.09	0.12
Plastics - Technological Eq.	4.34	1.40	(-0.73; 9.40)	3.10	0.13
Advertisement - Technological Eq.	4.78	0.82	(1.88; 7.67)	5.80	0.00
Direct Material - Textile	-0.17	0.47	(-1.80; 1.47)	-0.36	1.00
Service - Textile	0.87	0.63	(-1.33; 3.07)	1.39	0.98
Manufacturing Sys. - Textile	1.94	0.97	(-1.51; 5.38)	2.01	0.76
Plastics - Textile	3.29	1.40	(-1.78; 8.36)	2.35	0.52
Advertisement - Textile	3.73	0.82	(0.83; 6.63)	4.52	0.00
Service - Direct Material	1.04	0.47	(-0.62; 2.70)	2.20	0.63
Manufacturing Sys. - Direct Material	2.11	0.88	(-1.04; 5.25)	2.41	0.48
Plastics - Direct Material	3.46	1.34	(-1.42; 8.33)	2.59	0.37
Advertisement - Direct Material	3.90	0.72	(1.39; 6.41)	5.45	0.00
Manufacturing Sys. - Service	1.07	0.97	(-2.39; 4.52)	1.10	1.00
Plastics - Service	2.41	1.40	(-2.67; 7.50)	1.72	0.90
Advertisement - Service	2.86	0.83	(-0.06; 5.77)	3.45	0.04
Plastics - Manufacturing Sys.	1.35	1.58	(-4.33; 7.03)	0.85	1.00
Advertisement - Manufacturing Sys.	1.79	1.11	(-2.10; 5.69)	1.62	0.94
Advertisement - Plastics	0.44	1.50	(-4.96; 5.84)	0.30	1.00

Table B.2: (cont'd) Games-Howell Simultaneous Tests for Difference of Means

Appendix C

SUPPLEMENTARY MATERIAL FOR: PURCHASING, PRODUCTION, AND SALES STRATEGIES FOR A PRODUCTION SYSTEM WITH LIMITED CAPACITY AND FLUCTUATING SALES AND PURCHASING PRICES

C.1 Mathematical Proofs of Lemmas and Theorems

While deriving the optimal control policies for the purchasing, production, and sales decisions, we use a general framework that is proposed by Koole (2004) to derive convexity results and related properties on the value functions. To able to use this framework in our study, we first convert the manufacturer's maximization problem into an equivalent minimization problem as follows:

$$v'(i, \underline{\mathbf{x}}) + g^* = \delta T'_b v'(i, \underline{\mathbf{x}}) + \mu T'_p v'(i, \underline{\mathbf{x}}) + \lambda T'_r v'(i, \underline{\mathbf{x}}) + T_e v'(i, \underline{\mathbf{x}}) + h \underline{\mathbf{x}}, \quad (\text{C.1})$$

where $v'(i, \underline{\mathbf{x}}) = -v(i, \underline{\mathbf{x}})$ and the operators $T'_b f(i, \underline{\mathbf{x}})$, $T'_p f(i, \underline{\mathbf{x}})$, and $T'_r f(i, \underline{\mathbf{x}})$ for any real-valued function $f(i, \underline{\mathbf{x}})$ are

$$T'_b f(i, \underline{\mathbf{x}}) = \min \{f(i, \underline{\mathbf{x}} + e_1) + c_i, f(i, \underline{\mathbf{x}})\}, \quad (\text{C.2})$$

$$T'_p f(i, \underline{\mathbf{x}}) = \begin{cases} \min \{f(i, \underline{\mathbf{x}} - e_1 + e_2) + w, f(i, \underline{\mathbf{x}})\} & x_1 > 0 \\ f(i, \underline{\mathbf{x}}) & x_1 = 0 \end{cases}, \quad (\text{C.3})$$

$$T'_r f(i, \underline{\mathbf{x}}) = \begin{cases} \min \{f(i, \underline{\mathbf{x}} - e_2) - s_i, f(i, \underline{\mathbf{x}})\} & x_2 > 0 \\ f(i, \underline{\mathbf{x}}) & x_2 = 0 \end{cases}. \quad (\text{C.4})$$

With the modified version of the problem, we consider that the optimal value function satisfies a certain property for all states as specified in the following paragraph. Let $\mathcal{V}$ be a set of real-valued functions defined on $\mathbb{Z}^3$ such that if $v'(i, \underline{\mathbf{x}}) \in \mathcal{V}$, then

$$v'(i, \underline{\mathbf{x}}) + v'(i, \underline{\mathbf{x}} + d + d') \leq v'(i, \underline{\mathbf{x}} + d) + v'(i, \underline{\mathbf{x}} + d'), \quad (\text{C.5})$$

for all $\underline{\mathbf{x}} \in \mathbb{Z}^2$ and $d, d' \in \mathcal{D} = \{e_1, e_2 - e_1, -e_2\}$ with $d \neq d'$. The inequality defined in Equation (C.5) implies the multimodularity with respect to both x_1 and x_2 .

In Lemma 1, we extend the relation between multimodularity and component-wise convexity.

Lemma 1. *If $v'(i, \underline{\mathbf{x}}) \in \mathcal{V}$, then it also satisfies the inequality below:*

$$2v'(i, \underline{\mathbf{x}} + e_k) \leq v'(i, \underline{\mathbf{x}}) + v'(i, \underline{\mathbf{x}} + 2e_k), \quad \forall \underline{\mathbf{x}} \in \mathbb{Z}^2. \quad (\text{C.6})$$

Lemma 1 implies that if $v'(i, \underline{\mathbf{x}})$ satisfies the inequalities for the multimodularity, it is evidently component-wise convex. The proof related to this result is given in below.

Proof of Lemma 1: When any real-valued function $f(x)$ defined on $\mathbb{N}^2$ satisfies the inequalities for the multimodularity (MM), it evidently satisfies the inequalities for both the superconvexity ($SuperC$) and supermodularity ($Super$). Because $SuperC$ and $Super$ consist of exactly the same equations with the MM . For detailed definitions of $SuperC$ and $Super$, we refer to reader the work of Koole (2004). In particular, this proposition implies the following relationship:

$$MM = SuperC \cap Super. \quad (\text{C.7})$$

In addition, any real-valued function $f(x)$ defined on $\mathbb{N}^2$ satisfying the inequalities $SuperC$ and $Super$ is also component-wise convex (CC). Mathematically, it can be written as follows:

$$SuperC \cap Super \subset CC. \quad (\text{C.8})$$

As a result, we can obtain Lemma 1 by combining these two results presented in above. Specifically, for a fixed environment state i , if any real-valued function $v(i, \underline{\mathbf{x}})$

defined on $\mathbb{N}^3$ is multimodular with respect to x_1 and x_2 , then it is also component-wise convex with respect to x_1 and x_2 . Mathematically, this relationship can be shown as follows:

$$MM = SuperC \cap Super \subset CC. \quad (C.9)$$

□

In Lemma 2, the relation between multimodularity and joint convexity is described.

Lemma 2. *If $v'(i, \underline{\mathbf{x}}) \in \mathcal{V}$, then it is jointly convex with respect to both x_1 and x_2 .*

Proof of Lemma 2: Lemma 2 is a direct result obtained from the work of Altman et al. (2000). The author proves that if any real-valued function $f(x)$ defined on $\mathbb{N}^m$ is multimodular, then it is evidently jointly convex. For more detailed discussion, we refer to reader the work of Altman et al. (2000). □

Lemma 3 establishes that for each environment i , the operator T preserves multimodularity, component-wise convexity, and joint convexity properties with respect to x_1 and x_2 .

Lemma 3. *If $v'(i, \underline{\mathbf{x}}) \in \mathcal{V}$, then $Tv'(i, \underline{\mathbf{x}}) \in \mathcal{V}$ where $Tv'(i, \underline{\mathbf{x}}) = \delta T'_b v'(i, \underline{\mathbf{x}}) + \mu T'_p v'(i, \underline{\mathbf{x}}) + \lambda T'_r v'(i, \underline{\mathbf{x}}) + T_e v'(i, \underline{\mathbf{x}}) + h\underline{\mathbf{x}}$. Furthermore, $Tv'(i, \underline{\mathbf{x}}) \in \mathcal{V}$ also preserves the properties proposed in Lemma 1 and Lemma 2.*

Proof of Lemma 3: The operators, $T'_b f(i, \underline{\mathbf{x}})$, $T'_p f(i, \underline{\mathbf{x}})$, and $T'_r f(i, \underline{\mathbf{x}})$ are variations to the operators introduced in the work of Koole (2004). In his work, it is already shown that these operators preserve the multimodularity and component-wise convexity when any real-valued function $f(i, \underline{\mathbf{x}})$ is multimodular. For more detailed discussion, we refer to reader the work of Koole (2004). The operator described for the environment transitions, $T_e f(i, \underline{\mathbf{x}})$, is just a linear combination of any real-valued function $f(i, \underline{\mathbf{x}})$. By assumption, the holding cost is defined as linear. With these facts, we can conclude that the operator T where $Tv'(i, \underline{\mathbf{x}}) =$

$\delta T'_b v'(i, \underline{\mathbf{x}}) + \mu T'_p v'(i, \underline{\mathbf{x}}) + \lambda T'_r v'(i, \underline{\mathbf{x}}) + T_e v'(i, \underline{\mathbf{x}}) + h \underline{\mathbf{x}}$ preserves the multimodularity, joint convexity, and component-wise convexity. Because, it is a linear combination of the operators that preserve the multimodularity, joint convexity, and component-wise convexity. $\square$

Lemma 3 implies by the value iteration principle that the optimal value function $v^*(i, \underline{\mathbf{x}})$ is jointly convex and satisfies the inequalities for component-wise convexity. Since the optimal value function satisfies both joint and component-wise convex and the event operators preserve these convexity properties, there exists a corresponding threshold level for purchasing, production, and sales decisions. Hence, we are able to give the proofs that establish the optimality of threshold policies for purchasing, production, and sales decisions.

Proof of Theorem 1: Let $v^*(i, \underline{\mathbf{x}}) \in V$. Due to Lemma 1, we can say that $v^*(i, \underline{\mathbf{x}})$ is convex with respect to x_1 for each i and x_2 , i.e.,

$$v^*(i, \underline{\mathbf{x}} + e_1) - v^*(i, \underline{\mathbf{x}}) \geq v^*(i, \underline{\mathbf{x}}) - v^*(i, \underline{\mathbf{x}} - e_1). \quad (\text{C.10})$$

If it is optimal to buy in a state $(i, \underline{\mathbf{x}})$, from Equation (C.2) we have:

$$v^*(i, \underline{\mathbf{x}} + e_1) + c_i < v^*(i, \underline{\mathbf{x}}) \iff v^*(i, \underline{\mathbf{x}} + e_1) - v^*(i, \underline{\mathbf{x}}) < -c_i. \quad (\text{C.11})$$

Then, by convexity, we have:

$$-c_i > v^*(i, \underline{\mathbf{x}} + e_1) - v^*(i, \underline{\mathbf{x}}) \geq v^*(i, \underline{\mathbf{x}}) - v^*(i, \underline{\mathbf{x}} - e_1), \quad (\text{C.12})$$

implying that it has to be optimal to buy in state $(i, \underline{\mathbf{x}} - e_1)$, as well. Therefore, whenever an optimal policy is to buy in a state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}} = (x_1, x_2)$, it is optimal to buy in all states $(i, \tilde{\underline{\mathbf{x}}})$ where $\tilde{\underline{\mathbf{x}}} = (\tilde{x}_1, x_2)$ and $\tilde{x}_1 < x_1$. A similar discussion can also be adapted to show that if an optimal policy does not buy in a state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}} = (x_1, x_2)$, it continues not to buy in all states $(i, \hat{\underline{\mathbf{x}}})$ where $\hat{\underline{\mathbf{x}}} = (\hat{x}_1, x_2)$ and $\hat{x}_1 \geq x_1$. These two statements together imply the existence of an optimal purchasing threshold

level. Specifically, for any given state $(i', \mathbf{x}')$ where (x'_1, x'_2) , the purchasing threshold level is defined as

$$Z_b^*(i', x'_2) = \arg \min_{x_1} \{ (i', (x_1, x'_2)) | u_b^*(i', (x_1, x'_2)) = 0 \}, \quad (\text{C.13})$$

where $u_b^*(i', (x_1, x'_2))$ is the optimal purchasing decision in the state $(i', (x_1, x'_2))$. The above problem gives us a unique level, $Z_b^*(i', x'_2)$, and it is optimal to buy if the raw materials inventory level for the given state is smaller than $Z_b^*(i', x'_2)$ and to do nothing otherwise.

□

Proof of Theorem 2: In the proof of Theorem 1, we observe that if an optimal policy does not buy in a state $(i, \mathbf{x})$ where $\mathbf{x} = (x_1, x_2)$, it continues not to buy in all states $(i, \hat{\mathbf{x}})$ where $\hat{\mathbf{x}} = (\hat{x}_1, x_2)$ and $\hat{x}_1 \geq x_1$. This result directly implies that the optimal purchasing policy for the manufacturer is non-increasing in x_1 .

Let $v'^*(i, \mathbf{x}) \in V$. From Equation (C.9), we know that if any real-valued function $v'^*(i, \mathbf{x})$ is multimodular with respect to x_1 and x_2 , then it evidently satisfies the inequalities for supermodularity. So, we have:

$$v'^*(i, \mathbf{x} + e_1 + e_2) - v'^*(i, \mathbf{x} + e_2) \geq v'^*(i, \mathbf{x} + e_1) - v'^*(i, \mathbf{x}). \quad (\text{C.14})$$

If it is optimal not to buy in a state $(i, \mathbf{x})$, from Equation (C.2) we have:

$$v'^*(i, \mathbf{x} + e_1) - v'^*(i, \mathbf{x}) > -c_i. \quad (\text{C.15})$$

Then, we obtain:

$$v'^*(i, \mathbf{x} + e_1 + e_2) - v'^*(i, \mathbf{x} + e_2) \geq v'^*(i, \mathbf{x} + e_1) - v'^*(i, \mathbf{x}) > -c_i, \quad (\text{C.16})$$

implying that it has to be optimal not to buy in state $(i, \mathbf{x} + e_2)$, as well. Therefore, whenever an optimal policy is not to buy in a state $(i, \mathbf{x})$ where $\mathbf{x} = (x_1, x_2)$, it is optimal not to buy in all states $(i, \mathbf{x}'')$ where $\mathbf{x}'' = (x_1, x_2'')$ and $x_2'' > x_2$. This result means that the optimal purchasing policy for the manufacturer is non-increasing in x_2 .

Specifically, $u_b^*(i, (x_1, x_2)) \geq u_b^*(i, (x_1, x_2''))$ holds for any given two states $(i, (x_1, x_2))$ and $(i, (x_1, x_2''))$ where $x_2'' > x_2$. Let $Z_b^*(i, x_2)$ and $Z_b'^*(i, x_2')$ are the purchasing threshold levels for the states $(i, (x_1, x_2))$ and $(i, (x_1, x_2'))$ where $x_2' > x_2$. By using the previous result and Equation (4.7), we can conclude that $Z_b^*(i, x_2) \geq Z_b'^*(i, x_2')$. This result implies $Z_b^*(i, x_2)$ that defines the purchasing threshold level for the given state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}}=(x_1, x_2)$ is non-increasing in x_2 . $\square$

Proof of Theorem 3: Let $v^*(i, \underline{\mathbf{x}}) \in V$. Due to Lemma 1 and 2, we can say that $v^*(i, \underline{\mathbf{x}})$ is convex in $(e_2 - e_1)$, i.e.,

$$v'^*(i, \underline{\mathbf{x}} - e_1 + e_2) - v'^*(i, \underline{\mathbf{x}}) \geq v'^*(i, \underline{\mathbf{x}}) - v'^*(i, \underline{\mathbf{x}} + e_1 - e_2). \quad (\text{C.17})$$

If it is optimal to produce in a state $(i, \underline{\mathbf{x}})$, from Equation (C.3) we have:

$$v'(i, \underline{\mathbf{x}} - e_1 + e_2) + w < v'(i, \underline{\mathbf{x}}) \iff -w > v'(i, \underline{\mathbf{x}} - e_1 + e_2) - v'(i, \underline{\mathbf{x}}). \quad (\text{C.18})$$

Then, by convexity in $(e_2 - e_1)$, we have:

$$-w > v'^*(i, \underline{\mathbf{x}} - e_1 + e_2) - v'^*(i, \underline{\mathbf{x}}) \geq v'^*(i, \underline{\mathbf{x}}) - v'^*(i, \underline{\mathbf{x}} + e_1 - e_2), \quad (\text{C.19})$$

implying that it has to be optimal to produce in state $(i, \underline{\mathbf{x}} + e_1 - e_2)$, as well. Therefore, whenever an optimal policy is to produce in a state $(i, (x_1, x_2))$, it is optimal to produce in all states $(i, (\hat{x}_1, \hat{x}_2))$ where $\hat{x}_1 > x_1$ and $\hat{x}_2 < x_1 + x_2 - \hat{x}_1$. A similar discussion can also be adapted to show that if an optimal policy does not produce in a state $(i, (x_1, x_2))$, it continues not to produce in all states $(i, (\check{x}_1, \check{x}_2))$ where $\check{x}_1 \leq x_1$ and $\check{x}_2 \geq x_1 + x_2 - \check{x}_1$. These statements together mean the existence of an optimal threshold level for the production decision. Specifically, for any given state $(i', (x'_1, x'_2))$, the purchasing threshold level is defined as

$$Z_p^*(i', (x'_1, x'_2)) = \arg \max_{x_1} \{ (i', (x_1, x'_1 + x'_2 - x_1)) | u_p^*(i, (x_1, x'_1 + x'_2 - x_1)) = 0 \}. \quad (\text{C.20})$$

In the above equation, $u_p^*(i, (x_1, x'_1 + x'_2 - x_1))$ is the optimal production decision in state $(i, (x_1, x'_1 + x'_2 - x_1))$. For any given line $x'_1 + x'_2 = k$ and environment i' , the above problem gives us a unique level, $Z_p^*(i', (x'_1, x'_2))$. That is, it is optimal to produce if $x'_1 > Z_p^*(i', (x'_1, x'_2))$ and $x_2 < k - Z_p^*(i', (x'_1, x'_2))$ and to stay idle otherwise. $\square$

Proof of Theorem 4: Let $v'^*(i, \underline{\mathbf{x}}) \in V$. From Equation (C.9), we know that if any real-valued function $v'^*(i, \underline{\mathbf{x}})$ is multimodular with respect to x_1 and x_2 , then it evidently satisfies the inequalities for superconvexity. So, we have:

$$v'^*(i, \underline{\mathbf{x}}) + v'^*(i, \underline{\mathbf{x}} + e_2) \leq v'^*(i, \underline{\mathbf{x}} - e_1 + e_2) + v'^*(i, \underline{\mathbf{x}} + e_1). \quad (\text{C.21})$$

By manipulating the above inequality, we obtain:

$$v'^*(i, \underline{\mathbf{x}} + e_2) - v'^*(i, \underline{\mathbf{x}} + e_1) \leq v'^*(i, \underline{\mathbf{x}} - e_1 + e_2) - v'^*(i, \underline{\mathbf{x}}). \quad (\text{C.22})$$

If it is optimal to produce in a state $(i, \underline{\mathbf{x}})$, from Equation (C.3) we have:

$$v'(i, \underline{\mathbf{x}} - e_1 + e_2) - v'(i, \underline{\mathbf{x}}) < -w. \quad (\text{C.23})$$

Then, we obtain:

$$v'^*(i, \underline{\mathbf{x}} + e_2) - v'^*(i, \underline{\mathbf{x}} + e_1) \leq v'^*(i, \underline{\mathbf{x}} - e_1 + e_2) - v'^*(i, \underline{\mathbf{x}}) < -w, \quad (\text{C.24})$$

implying that it has to be optimal to produce in state $(i, \underline{\mathbf{x}} + e_1)$, as well. Therefore, whenever an optimal policy is to produce in a state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}} = (x_1, x_2)$, it is optimal to produce in all states $(i, \hat{\underline{\mathbf{x}}})$ where $\hat{\underline{\mathbf{x}}} = (\hat{x}_1, x_2)$ and $\hat{x}_1 > x_1$. This result means that the optimal production policy for the manufacturer is non-decreasing in x_1 . Specifically, $u_p^*(i, (x_1, x_2)) \leq u_p^*(i, (\hat{x}_1, x_2))$ holds for any given two states $(i, (x_1, x_2))$ and $(i, (\hat{x}_1, x_2))$ where $\hat{x}_1 > x_1$. A similar analysis can also be adapted to prove that the optimal production policy for the manufacturer is non-increasing in x_2 . Let $Z_p^*(i, (x_1, x_2))$ and $Z_p'^*(i, (x_1, \tilde{x}_2))$ are the production threshold levels for the states $(i, (x_1, x_2))$ and $(i, (x_1, \tilde{x}_2))$ where $\tilde{x}_2 > x_2$. By using the previous results and Equation (4.8), we can conclude that $Z_p^*(i, (x_1, x_2)) \leq Z_p'^*(i, (x_1, x_2))$. This result implies $Z_p^*(i, (x_1, x_2))$ that defines the production threshold level for the given state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}} = (x_1, x_2)$ is non-increasing in x_2 . $\square$

Proof of Theorem 5: Let $v'^*(i, \underline{\mathbf{x}}) \in V$. Due to Lemma 1, we can say that $v'^*(i, \underline{\mathbf{x}})$ is convex with respect to x_2 for each i and x_1 , i.e.,

$$v'^*(i, \underline{\mathbf{x}} + e_2) - v'^*(i, \underline{\mathbf{x}}) \geq v'(i, \underline{\mathbf{x}}) - v'^*(i, \underline{\mathbf{x}} - e_2). \quad (\text{C.25})$$

If it is optimal to sell in a state $(i, \underline{\mathbf{x}})$, from Equation (C.5) we have:

$$v'^*(i, \underline{\mathbf{x}} - e_2) - s_i < v'^*(i, \underline{\mathbf{x}}) \iff -s_i < v'^*(i, \underline{\mathbf{x}}) - v'^*(i, \underline{\mathbf{x}} - e_2). \quad (\text{C.26})$$

Then, by convexity, we have:

$$v'^*(i, \underline{\mathbf{x}} + e_2) - v'^*(i, \underline{\mathbf{x}}) \geq v'^*(i, \underline{\mathbf{x}}) - v'^*(i, \underline{\mathbf{x}} - e_2) > -s_i, \quad (\text{C.27})$$

meaning that it has to be optimal to sell in state $(i, \underline{\mathbf{x}} + e_2)$, as well. Hence, whenever an optimal policy is to sell in a state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}} = (x_1, x_2)$, it is optimal to sell in all states $(i, \dot{\underline{\mathbf{x}}})$ where $\dot{\underline{\mathbf{x}}} = (x_1, \dot{x}_2)$ and $\dot{x}_2 > x_2$. For a fixed i and x_1 , a similar discussion can also be adapted to show that if it is not optimal to sell in a certain state, it continues not to sell in all states that have a lower level of the finished goods inventory. These two statements together imply the existence of an optimal threshold level for the sales decision. Specifically, for any given state $(i', \underline{\mathbf{x}}')$ where (x'_1, x'_2) , the sales threshold level is defined as

$$Z_r^*(i', x'_1) = \arg \min_{x_2} \{(i', (x'_1, x_2)) | u_r^*(i', (x'_1, x_2)) = 1\}, \quad (\text{C.28})$$

where $u_r^*(i', (x'_1, x_2))$ is the optimal sales decision in state $(i', (x'_1, x_2))$. The above problem gives us a unique level, $Z_r^*(i', x'_1)$, and it is optimal to sell if the level of the finished goods inventory is greater than $Z_r^*(i', x'_1)$ and not to sell otherwise.

□

Proof of Theorem 6: In the proof of Theorem 5, we observe that whenever an optimal policy is to sell in a state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}} = (x_1, x_2)$, it is optimal to sell in all states $(i, \dot{\underline{\mathbf{x}}})$ where $\dot{\underline{\mathbf{x}}} = (x_1, \dot{x}_2)$ and $\dot{x}_2 > x_2$. This result directly implies that the optimal sales policy for the manufacturer is non-increasing in x_2 .

Let $v'^*(i, \underline{\mathbf{x}}) \in V$. From Equation (C.9), we know that if any real-valued function $v'^*(i, \underline{\mathbf{x}})$ is multimodular with respect to x_1 and x_2 , then it evidently satisfies the inequalities for supermodularity. So, we have:

$$v'^*(i, \underline{\mathbf{x}} + e_1 - e_2) - v'^*(i, \underline{\mathbf{x}} + e_1) \leq v'^*(i, \underline{\mathbf{x}} - e_2) - v'^*(i, \underline{\mathbf{x}}). \quad (\text{C.29})$$

If it is optimal to sell in a state $(i, \underline{\mathbf{x}})$, from Equation (C.4) we have:

$$v'^*(i, \underline{\mathbf{x}} - e_2) - v'^*(i, \underline{\mathbf{x}}) < s_i. \quad (\text{C.30})$$

Then, we obtain:

$$v'^*(i, \underline{\mathbf{x}} + e_1 - e_2) - v'^*(i, \underline{\mathbf{x}} + e_1) \leq v'^*(i, \underline{\mathbf{x}} - e_2) - v'^*(i, \underline{\mathbf{x}}) < s_i, \quad (\text{C.31})$$

implying that it has to be optimal to sell in state $(i, \underline{\mathbf{x}} + e_1)$, as well. Therefore, whenever an optimal policy is to sell in a state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}} = (x_1, x_2)$, it is optimal to sell in all states $(i, \underline{\tilde{\mathbf{x}}})$ where $\underline{\tilde{\mathbf{x}}} = (\tilde{x}_1, x_2)$ and $\tilde{x}_1 > x_1$. This result means that the optimal sales policy for the manufacturer is non-decreasing in x_1 . Specifically, $u_r^*(i, (x_1, x_2)) \leq u_r^*(i, (\tilde{x}_1, x_2))$ holds for any given two states $(i, (x_1, x_2))$ and $(i, (\tilde{x}_1, x_2))$ where $\tilde{x}_1 > x_1$. Let $Z_r^*(i, x_1)$ and $Z_r'^*(i, \tilde{x}_1)$ are the sales threshold levels for the states $(i, (x_1, x_2))$ and $(i, (\tilde{x}_1, x_2))$ where $\tilde{x}_1 > x_1$. By using the previous result and Equation (4.9), we can conclude that $Z_r^*(i, x_1) \geq Z_r'^*(i, \tilde{x}_1)$. This result implies $Z_r^*(i, x_1)$ that defines the sales threshold level for the given state $(i, \underline{\mathbf{x}})$ where $\underline{\mathbf{x}} = (x_1, x_2)$ is non-increasing in x_1 . $\square$

C.2 The Two-Step Procedure Forming The Transition Matrices For The Numerical Instances

In this section, we introduce the procedure forming the transition matrices that are necessary to obtain the specified correlation coefficients between sales and purchasing prices. In the procedure, we suppose that $E[C]$, $\text{Var}[C]$, $E[S]$, $\text{Var}[S]$, ρ_{CS} , s_H , s_L , c_H , and c_L are given as the input parameters. Additionally, the average time spent in each environment state is given. For the environment state i , it is denoted by T_i .

In the first step, by using the parameters $E[C]$, $\text{Var}[C]$, $E[S]$, $\text{Var}[S]$, ρ_{CS} , s_H , s_L , c_H , and c_L , we construct the linear equation system given in Equation (C.32). The solution of this system yields the long-run probabilities of being in each environment state. It has a unique solution for the given parameters as far as $s_H \neq s_L$ and $c_H \neq c_L$ hold.

$$\begin{bmatrix} E[S] \\ E[C] \\ \rho_{CS}\sqrt{\text{Var}[C]\text{Var}[S]} + E[C]E[S] \\ 1 \end{bmatrix} = \begin{bmatrix} s_H & s_H & s_L & s_L \\ c_H & c_L & c_H & c_L \\ s_H c_H & c_L s_H & c_H s_L & c_L s_L \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} \pi_1 \\ \pi_2 \\ \pi_3 \\ \pi_4 \end{bmatrix} \quad (\text{C.32})$$

In the second step, we substitute the solution of the above equation system into Equation (4.22). With this effort, we can define a transition matrix ensuring that $E[C]$, $\text{Var}[C]$, $E[S]$, $\text{Var}[S]$, and ρ_{CS} are the same as given at the beginning of the procedure. Since the time between each transition is exponentially distributed, the transition matrix should not allow the sales and purchasing prices to change at the same time. Therefore, the transition matrix always preserves the structure illustrated in the transition diagram in Figure (C.1). Specifically, it implies that $q_{23}=q_{32}=q_{14}=q_{41}=0$ in all the numerical instances. The exponentially distributed transition times also imply that the average time spent in environment state i can be defined as $T_i = \frac{1}{q_{ii}}$ where $q_{ii} = \sum_{j \in \mathbb{E} \setminus \{i\}} q_{ij}$. This relationship allows us to characterize the diagonal elements of the transition matrix since the average time spent in each environment state is already given. By considering these facts, we simplify the equation system obtained with Equation (4.22) as follows:

$$\frac{\pi_2 q_{21}}{\pi_1} + \frac{\pi_3 q_{31}}{\pi_1} = \frac{1}{T_1}, \quad (\text{C.33})$$

$$\frac{\pi_1 q_{12}}{\pi_2} + \frac{\pi_4 q_{42}}{\pi_2} = \frac{1}{T_2}, \quad (\text{C.34})$$

$$\frac{\pi_1 q_{13}}{\pi_3} + \frac{\pi_4 q_{43}}{\pi_3} = \frac{1}{T_3}, \quad (\text{C.35})$$

$$\frac{\pi_2 q_{24}}{\pi_4} + \frac{\pi_3 q_{34}}{\pi_4} = \frac{1}{T_4}. \quad (\text{C.36})$$

Let suppose that q_{12} and q_{21} equal a and b , respectively. Since the sum of the elements in a row of the transition matrix equals zero, q_{13} is $1/T_1 - a$ and q_{24} is $1/T_2 - b$. By substituting $q_{21} = b$ into Equation (C.33), we define the transition rate from state 3 to 1 as $q_{31} = (\pi_1 - bT_1\pi_2)/T_1\pi_3$. Replacing $q_{12} = a$ into Equation

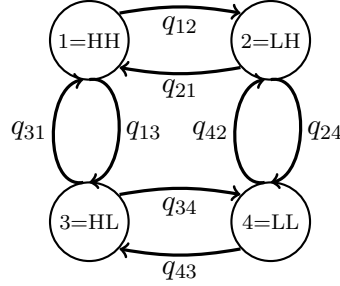


Figure C.1: Illustration for the structure of the transition matrix considered in the numerical examples

(C.34) yields the transition rate from state 4 to 2, that is, $q_{42} = (\pi_2 - a\pi_1 T_2)/T_2 \pi_4$. The values of q_{13} and q_{24} are also substituted into Equations (C.35) and (C.36), respectively. With this effort, we find that $q_{34} = (T_2 \pi_4 - T_4 \pi_2)/T_1 T_4 \pi_3 + \pi_2 b/\pi_3$ and $q_{43} = (T_1 \pi_3 - T_3 \pi_1)/T_1 T_3 \pi_4 + \pi_1 a/\pi_4$. So, for the given a and b values, the solution of the above equation system is expressed as follows:

$$Q = \begin{bmatrix} -\frac{1}{T_1} & a & \frac{1}{T_1} - a & 0 \\ b & -\frac{1}{T_2} & 0 & \frac{1}{T_2} - b \\ \frac{\pi_1 - bT_1\pi_2}{T_1\pi_3} & 0 & -\frac{1}{T_3} & \frac{T_2\pi_4 - T_4\pi_2}{T_1T_4\pi_3} + \frac{\pi_2 b}{\pi_3} \\ 0 & \frac{\pi_2 - a\pi_1 T_2}{T_2\pi_4} & \frac{T_1\pi_3 - T_3\pi_1}{T_1T_3\pi_4} + \frac{\pi_1 a}{\pi_4} & -\frac{1}{T_4} \end{bmatrix}. \quad (\text{C.37})$$

As a transition matrix, the off-diagonal elements of Q should be non-negative and the sum of each row should be zero. These facts imply the following conditions on a , b , and T_i , respectively.

$$a \in \left(\max \left\{ 0, \frac{T_1\pi_3 - T_3\pi_1}{\pi_1 T_1 T_3} \right\}, \min \left\{ \frac{1}{T_1}, \frac{\pi_2}{\pi_1 T_2} \right\} \right) \quad (\text{C.38})$$

$$b \in \left(\max \left\{ 0, \frac{T_4\pi_2 - T_2\pi_4}{\pi_2 T_1 T_4} \right\}, \min \left\{ \frac{1}{T_2}, \frac{\pi_1}{\pi_2 T_1} \right\} \right) \quad (\text{C.39})$$

$$\pi_1/T_1 + \pi_4/T_4 = \pi_2/T_2 + \pi_3/T_3 \text{ and } T_i > 0 \text{ where } i \in \{1, 2, 3, 4\} \quad (\text{C.40})$$

As far as the above conditions are satisfied for the input parameters, the matrix defined in Equation (C.37) will be a proper transition matrix ensuring that $E[C]$, $\text{Var}[C]$, $E[S]$, $\text{Var}[S]$, and ρ_{CS} are the same as given at the beginning of the procedure.

We follow the above-mentioned procedure to form the transition matrices that are used to obtain the specified correlation coefficients between sales and purchasing prices. All the input parameters used to initiate this procedure are specified at the beginning of each subsection within the Numerical Analysis section. For each given correlation coefficient, we construct the equation system defined in Equation (C.32) and solve it. While forming the equation system for the specified correlation coefficients, we keep the expectations and variances of the sales and purchasing prices at the same levels for the numerical examples to be examined in the same group. Hence, we avoid the case in which the expectations and variances of the sales and purchasing prices change each time the correlation coefficient changes. Subsequently, for each correlation coefficient, we substitute the obtained solution into Equation (C.37) and define the corresponding transition matrix. While defining the transition matrices for the specified correlation coefficients, we consider that $T_1 = T_4$, $T_2 = T_3$, $a = 1/2T_1$, and $b = 1/2T_2$. This setting allows the conditions defined in Equations (C.38), (C.39), and (C.40) to be immediately satisfied. As a result of this effort, we define the transition matrices so as to give the desired correlation coefficients.