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Procurement Auctions in Logistics and Transportation

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Abstract

This thesis studies different issues which complicate sourcing decisions. Specifically it looks at procurement decisions which are made (1) under demand uncertainty, (2) under capacity restrictions and (3) under the presence of economies of scale. Taking a new approach, it looks at problems which exist at both the operational and strategic level. At the strategic level, decisions about designing an auction, about choosing a contract format and about capacity investments must be made before production can start. In order to make the right strategic decisions, it is necessary to also consider the influence strategic decisions have on the operational level. This includes decisions concerning capacity levels, which require knowledge about how a given level of capacity will influence later production decisions. It also includes decisions concerning the choice of an auction format, whereby certain formats influence bidding decisions in different ways. In addition, when different strategic decisions are made in unison, they can also influence each other. Here, for example, choosing a specific auction or contract format can influence the capacity decision process. While a company's production decision under demand uncertainty can be solved with techniques from operations research, the interaction of different companies through competitive bidding or a capacity competition makes it necessary to use game theory approaches. Thus the interdependence of strategic and operational tasks, as well as the mix of operations research and game theory approaches, makes this thesis a challenging but also very worthwhile task.

Through looking at three specific situations where procurement decisions are made, this thesis provides new insights on (1) how procurement auction should be designed under the presence of demand uncertainty in order to maximize either the companies or the whole supply chain profit, (2) how companies with limited capacities should act when they participate at repeated bidding events and (3) how procurement auctions should be designed under the presence of economies of scale. This thesis therefore helps on the one hand the sourcing company to find the right auction design in order to minimize procurement cost and on the other hand provides new insights to the bidding company on the optimal bidding behaviour as well as on capacity strategies.

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Chapter 1

Introduction

1.1 Motivation

Nowadays procurement represents a very large fraction of total economic activity. While the value of public procurement transactions in EU countries is about 16 percent of their GDP and around 20 percent in the United States, it is even larger in the private sector. Additionally, private procurement transactions are steadily increasing, which is, in part, driven by a recent trend in outsourcing (Dimitri et al., 2006). As a result, procurement is increasingly recognized as a key driver in a more and more competitive business environment, since an efficient procurement is essential to a company's success (van Weele, 2005).

To keep costs low, procurement auctions are widely used in both government procurements and private enterprise purchases. In addition, online reverse auctions have especially received a lot of attention since electric commerce has matured. Instead of paper-based bid submission, suppliers now communicate their best offer via an online system. Today, most large industrial companies use online reverse auctions to procure their materials. For example, Hewlett-Packard has spent more than $30 billion through e-sourcing. At some business units they purchase more than 80 percent through e-sourcing (Moody, 2006).

Used in the right way, reverse auctions, compared to traditional purchasing methods, allow high cost savings (Tunca and Wu, 2009). Unit cost reductions in reverse auctions compared to traditional sourcing range from 5-40 percent and lead to gross savings of 15-20 percent, while an average manufacturer spends 55 percent of its revenue on purchased goods and services (Hawkins et al., 2010).

If companies decide to conduct their procurement via reverse auctions, they are faced with suppliers whose production cost they do not know. The purchaser's target therefore is to find the supplier that can supply the service for the lowest price. On the opposite end, the suppliers aim to find a strategy that maximizes their profits. The procuring company therefore has to search for the (overall) cost minimizing auction design, while many factors that influence the design of an optimal auction have to be taken into account, such as the structure of the demand, the suppliers' cost and their capacity structure.

Even though many problems have to be addressed when searching for the right design, procurement auctions also promise high savings, if they are conducted in the right way.

This is also reflected in a growing interest in studying procurement auctions by scholars in e.g. economics, operations research, management science, etc. (see Rothkopf and Whinston, 2007). This thesis contributes to this field by covering different problems that arise when procuring via reverse auctions. It answers first off, how an optimal auction should be designed depending on the designers objective, and secondly, how the optimal bidding strategy for the supplier should look like depending on the given auction situation. Section 1.2 will present the different procurement situations that will be analyzed in this thesis.

1.2 Analyzed problems

Although this thesis addresses more generally the topic of procurement auctions, it looks specifically at procurement auctions in three given situations: (1) under demand uncertainty, (2) under capacity restrictions and (3) under the presence of economies of scale. This section introduces each of these three analyzed problems.

1.2.1 Procurement auctions under demand uncertainty

The first issue looked at is uncertainty concerning future demand and the implications of demand uncertainty on the optimal auction design. Observing the current business practice, fixed quantity procurement auctions are the predominant form of auctions used today, even though they are often not optimal, especially when faced with demand uncertainty. Many practical auction examples exist where demand can be adjusted after the price has been determined (McAdams, 2007; Li and Scheller-Wolf, 2011) and flexible auctions receive increasing attention. Take for example the newsvendor as the simplest single-product problem under demand uncertainty. In this case, the optimal order quantity for a retailer (buyer) depends on the purchasing price. It is therefore not appropriate to treat these procurement problems as simple single-unit auctions. It has already been shown that abandoning fixed quantity auctions and allowing the possibility of adjusting quantities after procurement prices are known results in lower purchasing prices (Hansen, 1988) and enables higher profits for the purchasing company (McAdams, 2007). However, allowing to adjust quantities after observing prices makes the computation of optimal bidding strategies more complex.

Although there are many possibilities for allocating demand risk within a supply chain, the two extremes of push and pull contracts are simple and easy to implement. Because their only parameter is the wholesale price, they find higher acceptance in practice than complex multi-attribute auctions (Elmaghraby, 2007; Li and Scheller-Wolf, 2011). Under a push contract, the retailer has to decide about the purchasing quantity before demand is known and the manufacturer produces the order quantity. The retailer bears all the risk of ordering too many or too few. Under a pull contract, the retailer postpones the order until demand is known. In this case, the supplier bears all the demand risk and must produce or build capacity when demand is still uncertain (e.g. Cachon, 2004). If the retailer or the suppliers are risk-averse, there is an additional benefit from using push or pull contracts as an effective instrument to shift demand risk within the supply chain.

To look at procurement auctions under demand uncertainty, we analyze and compare simple auction and contract formats in a newsvendor sourcing problem under information asymmetry about the suppliers' manufacturing cost and flexible order quantities. To do this we evaluate the allocation of profits from the retailer's, the supplier's, and the entire supply chain's perspective. The options considered for auction design are the two most prominent first- and second-price auctions. For contract design, we limit the choice to simple, pure push and pull contracts. We extend the work of Li and Scheller-Wolf (2011) by 1) additionally including first-price auctions, 2) enforcing supply contract compliance by introducing a common outside procurement option, and 3) considering risk-averse decision makers either on the supply or retail side. We show the dominance of first-price auctions and the clear preferences of a push contract under risk-neutrality and full contract compliance. Furthermore, the numerical results show the impact of competition (number of bidders), cost and demand uncertainty, and the degree of risk-aversion on supply chain efficiency and profit allocation in the supply chain through the investigated auction and contract formats. This thesis contributes to the literature by applying known formats and results from auction theory to the supply contracting problems and enabling the comparison of different format-contract setups under risk-neutral and risk-averse decision making.

1.2.2 Procurement auctions under capacity restrictions

The second topic of this thesis is motivated by the circumstance that nowadays, procurement in companies is not limited to tangible products such as semi-finished products, raw materials or equipment. Companies today are increasingly buying services. For example, a steadily increasing number of companies across industries makes use of third party logistics providers (Marasco, 2008), which provide convenient, low-cost and reliable logistic services (Monczka et al., 2009). Third party logistics companies (3PLs) perform tasks that were previously done in-house, such as: transportation, warehousing, light manufacturing, managing reverse logistics, etc. (Mangan et al., 2008). Another example is public procurement of constructions.

There are significant differences between providing a physical product and providing a service. Physical products can be produced in high numbers and it is possible to build up inventories to cover fluctuations in demand. In contrast, capacities of service providers are much more limited. Most construction companies will only be able to work on a limited number of construction sites at a time, and since a service typically cannot be stored, even in times of low demand, it is not possible to produce to stock. Thus, service providers face the problem of how to determine the right capacity level. If capacity is high, a company can provide services to more customers. A higher overall capacity increases competition and lowers market prices. Once capacity is set up, it normally cannot be changed on short notice. Capacity is not set up for only one project. Instead, it serves several sequential projects. Thus, the company faces a trade-off between capacity utilization and being able to work on several projects in parallel.

In order to minimize procurement costs, companies and public institutions often purchase services via reverse auctions. An important aspect of the bidding process is that service providers tend to participate in more than one auction; they repeatedly submit bids to several auctions. Therefore, they must take the described problem of limited capacity into account. When a provider wins a contract, he has to commit some capacity such as machines, human resources, etc. for the duration of carrying out the contract. Since providers can only submit a bid when they have free capacity, they might not be able to submit a bid for an auction while they are still working on a contract won in an earlier auction. One accompanying problem includes not always knowing when such auctions take place and that requests for auctions arrive rather randomly. This raises a question that must be answered before setting up capacity. How do capacity constraints influence the bidding behavior?

Examples of such repeated bidding events include public procurement activities, such as contracts for highway and street construction in the U.S., which had an annual cost of \$3.7bn in 2013. This is also relevant for the European Union which plans to invest €50bn in infrastructure from 2014-2020. Auctions are used to achieve full and open competition (see Gupta and Chen, 2013). Jofre-Bonet and Pesendorfer (2003) already found that bids in a repeated auction with capacity constrained bidders are 18% higher than those made by unconstrained bidders. A similar observation was made by Gallien and Wein (2005) in their business example with FreeMarkets.

This thesis studies how capacity constraints influence the bidding behavior and how a bid is influenced by the average duration of a project or the expected interarrival time between two auctions. We study a Markov Decision Process with a sealed-bid first-price auction as the choice of the auction format (the second-price auction is discussed in the extensions). After showing general characteristics of the repeated procurement auction, we derive a closed form solution of a model with a maximum capacity of one. In doing so, we are able to gain insights on how different parameters influence the bidding decision, as well as the expected procurement cost. In a second step, we look at the influence of the maximum capacity level on expected cost and profits. This reveals insights on the optimal capacity decision, including how it depends on different parameters, such as production time or capacity cost. We discuss how the capacity problem can end up in a prisoner's dilemma when both service providers build up higher levels of capacity, but as a result both are worse off than without any investments. The contribution to the literature is therefore (1) to show how capacity restrictions influence bidding in repeated auctions and (2) to provide insight on optimal capacity decisions in such cases of repeated competitive bidding events.

1.2.3 Procurement auctions under the presence of economies of scale

A third issue arises when we consider economies of scale in procurement. As mentioned, more an more companies are using the services of third party logistics providers in order to keep their cost down and to be able to focus on their core competencies. If we consider e.g. warehousing or transportation, it appears that economies of scale exist, especially if a supplier provides this logistics service for several products rather than for only one product.

Economies of scale also appear in another challenge that has received a lot attention in the last years: risk management in procurement, especially in the provision of physical products. Nowadays many successful companies share procurement risks with their suppliers such as the risk of demand uncertainty (Segerberg et al., 2010). As a result contracts have been designed to include risk sharing elements such as advanced purchase discounts and buy back or pull contracts (see e.g. Cachon, 2004, or Chapter 3 of this thesis). Similar to the provision of logistics services, being able to combine the procurement of different products can lead to cost savings due to reduced demand uncertainty.

Similar to the situations describe before, the companies searching for a provider of such goods or services are faced with a problem of information asymmetry because they do not know the exact cost of their potential supplier. Therefore, in suche cases a popular tool is also a reverse auction, which determines both the supplier and the procurement cost. Companies often source, instead of just a single product or service, several similar products or services which could be supplied by either only one or several different companies. The sourcing company then has to decide whether they should procure those products as a bundle or if they should procure them separately. Since there might be economies of scale if one supplier wins several contracts, the supplier's cost of providing a service or supplying a good depends on what other contracts he wins. Since lower costs on the supplier side usually also lead to lower procurement costs for the auctioneer, such economies of scale would be an incentive to source several services from one company in order to exploit synergies. One way to achieve this would be to bundle several services in one auction. In such a bundle auction, the buyer would offer a contract that allows the supplier to submit bids that take cost reductions through economies of scale into account.

On the other hand, if several services are bundled into one auction, the individual service might not always be supplied by the company having the lowest cost for that service. If there is a high variance in the cost of providing such a service among the companies for the different services, it might be beneficial to exploit the differences in cost by sourcing the services from several providers, even though this might decrease potential economies of scale. Thus, if services are sourced separately from each other, cost reductions through synergies are not ensured, which then is also reflected in the submitted bid. It appears that taking synergies into consideration makes the procurement of goods and services more complex. Yet a good purchasing strategy offers possibilities to save procurement cost and to gain a cost advantage against other companies.

Grimm (2007) studies recurring procurement auctions, where current success positively or negatively affects future market opportunities, since they increase or decrease future production cost. By allowing to sub-contract production in the bundle auction, she shows a clear preference towards bundling by comparing the bundle with a simple sequential auction. Building on her work, we show that this result no longer holds if there is no option of sub-contracting and that there might be an incentive to source products in a sequential auction. The contribution to the literature is the application of a modified version of Grimm's model to particular problems in the procurement of logistics services. To do this we consider two procurement problems. In the first problem the supply cost follows the cost structure of a Vendor Managed Inventory service provider, where the provider takes over responsibility for production, transportation and storage of the product. Thus, in contrast to a supplier just producing a product, the service provider is faced with inventory holding and transportation costs in addition to production costs. The second problem is a newsvendor model, where production must be completed before final demand is known. We consider the case of a buyer wanting to source the product via a pull contract, whereby the supplier has to bear the supply risk. By using flexible resources he is able to pool demand in e.g. the case of winning two auctions, and thus can reduce the demand risk and, through this, the overall cost. In contrast to Grimm (2007), we do not allow subcontracting in order to (1) not give a one-sided advantage to the bundle auction, to (2) make both sourcing strategies comparable and (3) because in practice, subcontracting is not always possible and allowed by the contracting party due to quality reasons.

1.3 Field of research

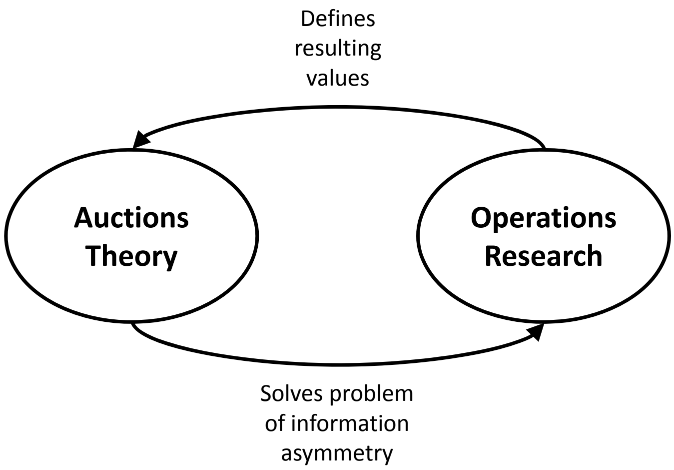


Figure 1.1: Auction theory vs. operations research

By analyzing the problems mentioned above, this thesis combines two different research streams: The general field of auction theory and the field of operations research. Both fields are relevant for the research stream of procurement auctions, because approaches from both areas help to deal with problems a buyer (or seller) could be confronted with.

Insights from auction theory, for example, help to design mechanisms that find the best supplier in order to e.g. minimize total procurement cost. It does not help to find optimal production or order quantities though. Therefore, a procurement manager also needs insights from operations research in order to find the right procurement strategies, when e.g. a specific seller is chosen and the per unit procurement cost is determined. Thus, approaches from operations research help to determine the optimal procurement quantity, for example, if the purchase price per unit is known but the future demand is still uncertain, a problem which is better known as the newsvendor problem. Another problem operations research helps to deal with involves a service provider who has to determine an order strategy under the presence of fixed and variable ordering costs (better known as the Economic Order Quantity (EOQ) problem). Thus, the theory of operations research helps to find the best strategy and further define total logistic costs that result from e.g. a given single unit procurement (or production) cost (see Figure 1.1). To outline this approach, we provide a short introduction to the general idea of procurement auctions and discuss two basic auction models as well as two models of operations research in Chapter 2.

1.4 Structure of the thesis

The remainder of this thesis is organized as follows:

In **Chapter 2** we discuss how auction design in general works and present some basic methods of auctions theory and operations research. This chapter further reviews the relevant literature.

Chapter 3 studies the auction model under demand uncertainty, as introduced in Section 1.2.3. The results of this chapter have been published in the European Journal of Operational Research (Budde and Minner, 2014b).

In **Chapter 4** we analyze repeated sourcing events with suppliers that have limited capacities, as presented in Section 1.2.2. This chapter is based on a working paper by Budde and Minner (2014c).

Chapter 5 investigates procurement auctions under the presence of economies of scale, as introduced in Section 1.2.3. This chapter is based on a working paper by Budde and Minner (2014a).

Finally, **Chapter 6** provides concluding remarks and suggestions for future research.

Chapter 2

Fundamentals and literature review

In general, procurement auctions (also known as reverse auctions) can be seen as an instrument to solve a problem of asymmetric information. In the models discussed in following three chapters, asymmetric information usually concerns the knowledge about production cost. For example, a buyer who wants to procure a product can choose from several suppliers whose production costs he does not know. His lack of knowledge is based upon the suppliers, who hold private information about their individual production costs. The retailer's problem here is to find the best (which is in most cases the cheapest) supplier. The retailer now, instead of negotiating with every single supplier, conducts an auction, which determines a winner and a price that has to be paid for the product. Thus, procurement auctions reverse the traditional auction setting, in which buyers bid and sellers try to achieve a high price. In such a reverse auction the sellers have to compete against each other by submitting bids to earn the right to deliver a product or service. Here the buyer's goal is generally to reduce the price in order to minimize the procurement cost (see e.g. Jap, 2002). It is therefore up to the sourcing company to design a mechanism that creates the highest value for itself. The relevant value does not necessarily result from the profit of the firm though, it can also result from a utility function or from a company seeking to maximize the system wide profits. Such a mechanism defines the game of asymmetric information and in general has three components: a set of possible messages (bids), an allocation rule and a payment rule. The allocation rule determines the probability that a bidder will win the contract and is dependent upon the bid he submits and the bids all the other bidders submit. The payment rule then determines the expected payment of a bidder as a function that depends again on his and all other submitted bids. In order to provide an equilibrium, these mechanism must fulfill the properties of incentive compatibility and truthful bidding (for further explanation, see e.g. Krishna, 2010).

The issue of asymmetric information described above is a crucial problem in many markets. Historically, auctions have been utilized since antiquity and the earliest reports of auctions date back to 500 B.C. (Krishna, 2010). However, auction theory, as we know it today, has not started to be analyzed and defined before the second half of the 20th century. The first equilibrium theory analysis on auctions was provided by Vickrey (1961) in his seminal paper on counterspeculation, auctions, and competitive sealed tenders. The clarification of the Bayesian-Nash equilibrium concept (provided in Harsanyi, 1967, 1968a,b) further helped to push auctions forward. Ever since, a vast body of work has been developed in the field of auction theory. By using input from the general mechanism design theory, which e.g. provides the fundamental theory of the revelation principle (introduced by Gibbard (1973) and further developed by Myerson (1979)) or pushed forward by e.g. the definition of the revenue equivalence theorem (Myerson, 1981; Riley and Samuelson, 1981), auctions now are widely used in the design of procurement mechanisms. Since it would exceed the scope of this work to cover all developments in auction theory, we refer the interested reader to McAfee and McMillan (1987), Milgrom (1989) and Klemperer (1999) who provide an overview of the actual state of the art in auctions theory. Even though many of these references refer to forward auctions, they are basic and applicable to reverse auctions. Furthermore, Elmaghraby (2000, 2007), and Pinker et al. (2003) provide comprehensive surveys about sourcing, online auctions, and internet-enabled marketplaces.

As a result of this research on the theoretical and also on the practical level, nowadays, there exist many incentive compatible designs in which an auction can be conducted that lead to truthful bidding. The formats of this range, though, between the two extrema of an open or a sealed-bid auction (Jap, 2002). In general, there are four basic types of auctions that have been both used in practice and analyzed in research. On the sealed-bid side, these are the first-price and the second-price auction, while under the open-bid auctions there are the so-called English and Dutch auction (see e.g. Klemperer, 1999). In our work we will mainly use two sealed-bid formats, the first-price and the second-price auction and will neglect the other two formats on the other extreme side, the English and the Dutch auction. One reason for the focus on the sealed-bid auction is the given strategic equivalence, most of the time, of the open formats of a Dutch or an English auction to the closed formats of a first- or second-price auction. Nevertheless, we will also discuss examples, where e.g. the strategic equivalence of the English and the second-price auction is not given anymore (see Chapter 3.3). For further information on general similarities and differences between those four standard auctions we refer to Krishna (2010) and Klemperer (1999).

Before studying in Chapters 3-5 how bidding strategies for specific procurement situations look like as well as how the choice of an auction or contract format influences expected cost and profits, we will discuss some general factors that influence bidding behavior and the outcome of an auction. Since these factors have a huge impact on a company's profits when sourcing with a reverse auction, they should be understood and considered by any procurement manager before setting up an auction. After this survey on influencing factors, we present two basic theorems in auction theory, the revenue equivalence theorem and the revelation principle. As mentioned above, both theorems are important cornerstones of auction theory and will, explicitly or implicitly, be used later in this thesis. Since the focus of this thesis is on sealed-bid auctions, we further introduce equilibrium bidding strategies for simple single unit first- and the second-price sealed-bid auctions, in order to ease the reading of the rest of this thesis. As mentioned this thesis combines auctions theory and operations research. We therefore introduce the newsvendor model as well as the economic order quantity model, since we will use modified versions of these models in the main body of this thesis. This chapter than closes with a review of the relevant literature for this thesis.

2.1 Influencing factors in procurement auctions

As stated by Klemperer (2002): "Good auction design is not 'one size fits all'. It must be sensitive to the details of the context." Therefore, we will discuss some factors that have to be taken into consideration in order to achieve, from the designer's point of view, the best solution feasible. Even though this list of factors is not exhaustive, it provides a first impression of the influencing factors which should be considered when managers look to design an auction. Since the design of an auction is highly influenced by the later bidding process, these factors are also highly relevant for any manager who is about to participate in a competitive bidding process and has to think about the optimal bidding strategy for his company.

2.1.1 Objective

When designing an auction, the most important aspect is the objective of the party who designs the auction. This is in most cases the party procuring the product. Thus, before conducting an auction, the designer has to answer the question: What is the objective of the mechanism I want to design? Examples of such objectives include minimizing procurement costs, achieving efficient allocation (i.e. awarding the lots to the firms with the lowest cost) or maximizing system-wide profits. This thesis mainly focuses on the minimization of procurement costs, but will also consider how the choice of a specific auction influences the system wide profits. Since we do not always consider risk neutral agents, the designer's goal might also shift from cost minimization to utility maximization (see. e.g. Chapter 3.2).

2.1.2 Expected cost, profit and utility

After defining the objective of the auction, the next step should aim to understand how a specific objective such as profit or cost is determined and how it is related to the submitted bid in order to make a well-grounded decision concerning the auction design (see also Chapter 1.3). While in some procurement situations the relevant cost is equal to the amount paid to the winning supplier, in some set-ups, such as the newsvendor model, the relevant cost depends on more than just the price of a specific product. In such cases the price paid per product is just one element of the total relevant cost. This also holds for the supplier's side. The more a decision maker knows about e.g. how private and common cost components influence the total relevant cost, the more he will know about how different auction formats influence the objective. Thus, only if a procurement manager knows e.g. how the price paid per item influences the companies profits or how variable production cost influence the total cost a supplier has for providing a specific service, he will be able to make a proper decision on the auction design.

Since the structure of the total relevant cost differs from one case to another, each situation requires a different model to best fit the problem. In this thesis we study different procurement situations, such as procurement under demand uncertainty or under consideration of inventory holding and transportation cost. In some settings stochastic models must be used to determine expected cost and profits under demand uncertainty, while for some inventory and transportation problems deterministic models can be used to describe the cost structure. We further study situations where actors are rather risk-averse and therefore, the expected utility not only depends on the resulting profit, but on the variance of these profits as well.

2.1.3 Private vs. common components

While in the first step of designing an auction, a decision maker must know both his objective and how it is determined, he should also be aware of how and why bids differ from one supplier to another. Bids tend to be different for several reason, and often rest on differences in the factors which influence the cost of providing a service. In general a bid will depend on two components: On the one hand there will be a private component, that is specific to a company and which is part of the total cost. Most of the time, the private component is only known to the bidder. On the other hand, there will be a common component, that is, factors that also influence the total cost, but are common knowledge and the same for all bidders (see Dimitri et al., 2006). In this thesis the private component is mainly the direct production cost, that is, the cost of producing a single product or service, while the common component will, depending on the model, concern different variables. In the newsvendor auction studied in Chapter 3, a common component is the cost of an emergency order but also the distribution of the expected demand, which is a common uncertainty that has to be taken into account for the supplier to determine the expected cost of a pull contract. When procuring items with economies of scale, the common component might include fixed set-up cost, transportation time or interest rate. These will be common for all suppliers. It therefore is important to know which components are private and which ones are common in order to make a proper guess on the outcome of the auction. The higher the influence of common components, the less potential a proper auction design has. If all components are common and there is no private part in the cost we would face a situation with perfect information and the auction model would be relatively easy to solve (Klemperer, 1999). A factor which is actually one of the most influential on the outcome of the auction is the uncertainty concerning the private component influence. The higher e.g. the spectrum of possible production cost, the higher the information rent a procuring company has to pay. In contrast, under high competition (this factor will be explained this later) a large range of possible production costs also offers potential for lower bids. In the extreme case, where there is no uncertainty concerning the private component, the procurer would be faced with a case of perfect information again. Therefore, the influence of the combination of competition and variance in production cost on the outcome will also be addressed in this thesis.

2.1.4 Competition

Another important aspect in procurement auctions is competition in the supplier market. Even though the procuring company has in general no or only little influence on the competitiveness of a market, it is still important to know the competition, as it might influence a company's decisions concerning the auction design. If there are, for example, not enough bidders, since e.g. a monopoly on the supplier market exists, it might not make any sense to conduct and auction, and thus would rather be better to have a form of structured negotiations (Klemperer, 2002). But even if the supplier market is competitive enough to conduct an auction, it is still important to know about the degree of competition. One widely recognized important determinant is the number of bidders, while in general a large number of firms create a competitive environment (Gupta, 2002). Besides the effect that, in general, a higher number of bidders leads to lower procurement cost (see Li and Scheller-Wolf (2011) for an example where this is not the case), this thesis shows that the number of bidders has a crucial influence on the optimal design of a specific auction. An auction design that is optimal for a low number of bidders is not necessarily optimal if there are many bidders (see e.g. Chapter 5). Therefore, knowing about the competitiveness of the market can be a big advantage when a decision about the auction format must be made. A procurement manager might also come to the conclusion that the design of the auction is no longer important if e.g. the number of bidders is very high (Klemperer, 2002). In such a case the focus of the auctioneer might be to design a rather simple auction, even though it might not be the optimal one.

While the number of bidders is one important determinant for competitiveness of the market, there are also others. In Chapter 4 for example we show that competition is also driven by the amount of available capacities and by the number of auctions that are conducted per period, rather than only be the pure number of bidders. For example, reducing available capacities on the supplier side decreases competition and leads to a higher procurement cost, while if there are less requests to participate at auctions, competition increases which then leads to a more aggressive bidding and a lower procurement cost.

2.2 Basic theorems of auction theory

In the following we will introduce the revelation principle and the revenue equivalence theorem. Even though many other important theorems in auctions theory exist (and many of them will be used and discussed in this thesis), these two theorems are among the most important. The revelation principle and the revenue equivalence theorem are both central to auction theory and are highly relevant in later chapters of this thesis. Therefore, a basic understanding of these both theorems helps to follow the thesis when e.g. a benchmark in the form of an optimal auction is to be set or when different auction formats are compared.

2.2.1 Revelation principle

The revelation principle is a useful principle of mechanism design that helps to identify benchmarks for different auction designs. It answers the question: How efficient can contracting under asymmetric information be? (Bolton and Dewatripont, 2005). We first define:

Definition 1. *A direct mechanism is called a truthful mechanism, if it is incentive compatible for the agent to announce his true type for any type.*

The revelation principle then states:

Definition 2. *Any allocation that can be implemented by some mechanism, which allows to infer the agent's type correctly, can also be implemented with a truthful direct revelation mechanism.*

Therefore, the revelation principle guarantees that, when looking for a profit maximizing (often referred to as the optimal) mechanism, there is no loss of generality in restricting the analysis to direct mechanisms (see e.g. Laffont, 1993, for proof). The revelation principle also provides insights for indirect mechanisms such as auctions, as it enables to set a benchmark (e.g. in Chapter 3.4 and 5.1.4).

Since each outcome that can be implemented by an indirect mechanism such as an auction can also be implemented by a direct mechanism, finding the optimal direct mechanism also means defining the maximum profit that can be achieved by any truthful incentive compatible mechanism. Thus, an auction that leads to the same profit as the optimal direct mechanism is also an optimal mechanism. This is especially interesting, since in many cases it is easier to implement an indirect mechanism than to implement a direct mechanism.

2.2.2 Revenue equivalence theorem

In the following we will have a short look at the revenue equivalence theorem. This theorem can be very useful to reduce the number of auction designs that have to be studied, since it shows under which conditions different auctions lead to the same outcome. The revenue equivalence theorem states that:

Definition 3. *Every auction where risk-neutral bidders sell a single unit yields the same expected prices and revenues, if:*

(i) The bidders' costs are independently drawn from a common, strictly-increasing atomless distribution.

(ii) The bidder with the lowest signal always wins.

(iii) The bidder with the highest-feasible signal expects zero surplus.

This theorem was established by Myerson (1981) as well as Riley and Samuelson (1981), while the definition above is adapted for the reverse auction. Thus, whenever two auctions fulfill those requirements, they both lead to the same outcome. This is, for example, the case for the first- and second- price auction, as well as for both open formats (the Dutch and English auction) when studying single unit procurement auctions as presented in Chapter 2.3. Thus, whenever a buyer just wants to buy a single product, the procurement cost stays the same, no matter which of those four formats he chooses as the sourcing mechanism. One great advantage of defining the revenue equivalence theorem is that whenever this theorem holds, the buyer is able to restrict his attention to finding the mechanism easiest to implement, rather than looking for the profit maximizing contract.

Nevertheless, the revenue equivalence only holds under specific conditions. As we will see later in this thesis, revenues differ a lot among different auction designs, if we e.g. consider multi-unit auctions, risk aversion, or asymmetries.

2.3 Optimal bidding in a single unit procurement auction

At this point we present a reversed version of the simple single unit auction model as e.g. presented in Krishna (2010). This helps in understanding the basic idea behind first- and second-price sealed-bid auctions and how optimal bidding strategies in procurement auctions can be determined (see also Holt, 1980 and Cohen and Loeb, 1990 for further information on especially the first-price auction). Even though in the models discussed later in this thesis we do not consider simple single-unit auctions, discussing a simplified set-up helps to understand the general nature of auctions, especially since the general methods used here can also be applied to more complex models.

Consider an auction with a number of $n \geq 2$ ex ante symmetric suppliers that compete for the right to supply a product. Assume that n is common knowledge. The supplier i's marginal cost to produce the product is c_i and private knowledge. Beliefs about a competitor's marginal cost c are distributed according to $F(c)$ with density $f(c) > 0$ which is continuous over $[\underline{c}, \overline{c}]$. Thus, bidder i only knows his own marginal cost c_i and knows that the other bidders' marginal costs are independently distributed according to $F(c)$. Further assume that bidders are risk neutral and are trying to maximize their profits.

The first- and second-price auction now differ as follows: While in the reverse first-price auction the supplier with the lowest bid wins the auction, delivers the product and gets paid the amount he bid, in the reverse second-price auction, the supplier with the lowest bid wins the auction, delivers the product, but gets paid the second lowest bid. In both auctions the bidders try to maximize their profits by choosing a bid $b(c_i) \in \mathbb{R}_+$. Further assume that if there is a tie (thus, if two or more bidders submit the same bid), the contract goes to each bidder with equal probability.

2.3.1 Reverse first-price auctions

The profit of supplier i in the single unit first-price auction is given as follows:

$$\pi_i = \begin{cases} b_i - c_i & \text{if } b_i \leq min_{j \neq i} b_j \\ 0 & \text{if } b_i > min_{j \neq i} b_j \end{cases} \tag{1}$$

One can see that the submitted bid, contrary to the second-price auction, directly influences the payment. Since the profit in case of winning is the difference between the cost and the submitted bid, it is obvious that it cannot be optimal to bid at cost. Thus, in order to be able to make a profit greater than zero, the submitted bid should always be higher than the cost. Since we consider a symmetric auction, in equilibrium, bidders with the same cost will submit the same bid. Therefore, in equilibrium, the probability to win the auction is equal to the probability of having the lowest cost (this property also holds for the second-price auction). We define $b(c)$ as the equilibrium bidding strategy of a bidder with cost c. Thus, if a bidder follows the equilibrium bidding strategy, his probability of winning an auction by submitting the bid $b(c_i)$ is given as $(1 - F(c_i))^{n-1}$.

As a result, the expected profit in the first price auction is: $(b(c_i) - c_i)(1 - F(c_i))^{n-1}$

Consider the profit of a bidder that has cost of c but by submitting a bid of $b = b(x)$ reveals having cost of x. We define his profit as $\pi(c, x)$, which depends on the actual cost c and the signaled cost x. We then get:

$$\frac{\partial \pi(c, x)}{\partial x} = (b'(x))(1 - F(x))^{n-1} - f(x)(n-1)(b(x) - c)(1 - F(x))^{n-2} \tag{2}$$

Assume that all other bidders follow the equilibrium bidding strategy. It then holds that $\pi(c, x) = (b(x) - c)(1 - F(x))^{n-1}$. For $b(c)$ to be an equilibrium, $\pi(c, x)$ has to be maximized at $x = c$. In that case there is no incentive to deviate from the equilibrium strategy. It therefore has to hold that $\frac{\partial \pi(c,x)}{\partial x} = 0$ for $x = c$ and by replacing x with c we get:

$$\frac{\partial \pi(c, x)}{\partial x} = (b'(c))(1 - F(c))^{n-1} - f(c)(n-1)(b(c) - c)(1 - F(c))^{n-2} = 0, \text{for } x = c \tag{3}$$

Define $\pi'(c)$ as the deviation of $\pi(c)$ for a change in the real cost c. Since in equilibrium $\frac{\partial \pi(c,x)}{\partial x} = 0$, we can simplify $\pi'(c)$ and get:

$$\pi'(c) = -(1 - F(c))^{n-1} \tag{4}$$

Since it has to hold that $\Pi(\overline{c}) = \Pi(\overline{c}, \overline{c}) = 0$ we have:

$$\pi(c) = \int_{\overline{c}}^{c} \pi'(z) dz \tag{5}$$

and thus (by rearranging the integral limits) we get:

$$\pi(c) = \int_{c}^{\overline{c}} (1 - F(z))^{n-1} dz \tag{6}$$

In equilibrium it has to hold that $\Pi(c, c) = \Pi(c)$. This yields:

$$(b(c) - c)(1 - F(c))^{n-1} = \int_{c}^{\overline{c}} (1 - F(z))^{n-1} dz \tag{7}$$

and thus for the equilibrium bid we get:

$$b(c) = c + \frac{\int_c^{\overline{c}} (1 - F(z))^{n-1} dz}{(1 - F(c))^{n-1}} \tag{8}$$

We see that the bid always increases in the cost and that, for all $c < \overline{c}$, there always is a markup on the cost, thus $b(c) > c$, $\forall c < \overline{c}$. While for the standard first-price single unit auction it is easy to derive the equilibrium bid, this thesis will show that this is not the case anymore, when studying more complex set-ups. This is especially true if we remove assumptions as e.g. single unit auctions and risk neutrality or if auctions are conducted repeatedly. As a result it might not even be possible anymore to derive closed-form solutions for the general case.

2.3.2 Reverse second-price auctions

Deriving the equilibrium bid in the second-price auction is usually much simpler than in the first-price auction. Again, consider the profits depending on the bids:

$$\Pi = \begin{cases} min_{j \neq i} b_j - c_i & \text{if } \; b_i \leq min_{j \neq i} b_j \\ 0 & \text{if } \; b_i > min_{j \neq i} b_j \end{cases} \tag{9}$$

The equilibrium bid for the second-price auction is to always submit a bid equal to cost, thus $b^*_{second}(c) = c$. The proof is straightforward. Consider a supplier i submitting a bid equal to c_i. Assume that all other bidders submit a bid higher than c_i. In this case, he would win the auction and would get paid the second lowest bid. Submitting a bid lower than c_i would not change the profit at all. He would still win and would still get paid the same amount. Assume now that there is one bidder that submits a bid below c_i. In this case, if the bidder submits a bid $b(c_i) = c_i$ he does not win and his profit is zero. What would happen if he now lowers his bid? Assume the bidder submits a bid $b(c_i) < c_i$ that is low enough to win. In this case, he would have cost of c_i to supply the product but he would get paid less than c_i and thus his profit would be negative. Thus, it can never pay off for bidder i to submit a bid lower than c_i. Consider in contrast submitting a bid higher than c_i. In case of winning, the submitted bid does not influence the winner's payment. Therefore, increasing the bid can never be beneficial, since it would just decrease the probability of winning without increasing the expected payment. As we see, in the standard second-price sealed-bid auction, the bidding strategy is very simple and it is always a dominant strategy to submit a bid equal to the cost. But nevertheless, this thesis will also study auctions, where it is not optimal anymore for the supplier to bid at his cost, if e.g. we consider repeated auctions (see Chapter 4).

2.4 Basic operations research models

In this section we study two models, the newsvendor model and the economic order quantity model. Both are well known approaches in logistics and also basic to this thesis.

At this point we will present the models with very basic assumptions. Later in this thesis some of this assumptions might be removed, as e.g. in the newsvendor model we will add the option to place an emergency order or in the economic order quantity model we will consider joint replenishment and also include the issue of transportation. However, the basic insights of the models will be the same.

2.4.1 The newsvendor model

We now briefly introduce the newsvendor model, an approach of optimizing order quantities under demand uncertainty by balancing out the expected cost of understocking and the expected cost of overstocking. In general the newsvendor problem is not a new issue and studies of this problem can be traced back to Edgeworth (1888). However, it did not become a topic of operations research studies before the 1950's when Scarf et al. (1958) defined and analyzed the newsvendor problem as we know it today (Petruzzi and Dada, 1999). Ever since, it has been a subject of much research, and thus, has been further developed and extended (see also below for some examples of these extensions). Nevertheless, the basic idea remained the same: The newsvendor model is the problem of a company that must choose an order or production quantity before the start of a single selling season that has stochastic demand. In the essential formulation of the model there is no option of placing a second order or to produce after the season has started (and the demand is known). Besides the demand uncertainty, a further aspect is that the products are perishable. Thus the products lose their value after the selling season because, for example, a discount is used to sell the left over units or the product is disposed of when the selling season is over (Khouja, 1999). While there are further aspects of the newsvendor problem that can be named (see e.g. Silver et al., 1998, for a detailed list of properties of the newsvendor model), demand uncertainty and the perishability of the products are the most crucial ones.

We now define the following set-up in order to analyze the basic newsvendor model: Consider a company facing uncertain market demand x, drawn from a continuous distribution on $[0, \infty)$ with cumulative probability $\Phi(x)$ and probability density $\phi(x) > 0$. $\Phi(x)$ has a finite mean μ and an inverse $\Phi^{-1}(x)$. Assume a market price p and ordering cost c. The company now has to determine an order quantity q before the final demand is known. We further assume that left-over inventory can be sold at the end of the season for a salvage value v, with $v < c$. Assume that unsatisfied demand is lost and that there is no option to place an emergency order in case of a stock-out. The objective of the newsvendor is now to maximize his expected profit $E(\Pi(q))$ by choosing an order quantity q:

$$E(\Pi(q)) = -q \cdot c + \int_0^q (x \cdot p + (q - x) \cdot v)\phi(x)dx + \int_q^\infty q \cdot p\phi(x)dx \tag{10}$$

Since (10) is concave in the order quantity, the sufficient optimality condition is:

$$\frac{\partial E(\Pi(q))}{\partial q} = 0 \tag{11}$$

Solving (11) leads to:

$$\Phi(q^*) = \frac{p-c}{p-v}$$
$$\Leftrightarrow q^* = \Phi^{-1}\left(\frac{p-c}{p-v}\right) \tag{12}$$

(12) provides the well known fractile formula for the optimal order quantity of the newsvendor. The formula shows that the order quantity always decreases in costs, while (since $c < v$) it increases in selling price and salvage value. This is a quite intuitive property of the newsvendor quantity. Higher procurement cost or a lower salvage price increase the cost of having left overs and thus lead to an incentive, to decrease the expected amount of left overs. On the other hand, if the procurement price is lower or the selling price is higher, the newsvendor loses more money when he is out of stock and therefore tries to decrease the probability of having not enough on stock.

A further property of the newsvendor solution is that the order quantity only depends on the fractile and not the total values of the costs. Thus, for a given demand distribution, two companies would order (or produce) the same quantity whenever their fractile is the same. This enables approaches to coordinate the supply chain, such as a buy-back contract or revenue sharing (Cachon, 2003). In this thesis, for example, we will use this property to show whether or not a contract coordinates the supply chain by saying it maximizes the overall profit of the whole supply chain rather than the profit of a single actor.

So far we considered the newsvendor as a maximization problem: the company tries to find the order quantity that maximizes the expected profit. Another approach that provides the same result is to minimize expected cost of ordering too much or too few. To follow this approach, define overage cost (c_o) as the cost that appears per unit of having too much, if the company ordered more than the final realization of the demand D. This cost is the difference between the order cost and the salvage value: $c_o = c - v$. The total cost of having too much is then the overage cost times the quantity that has been over-ordered: $c_o \cdot (q - D)$ (assuming $q > D$). The underage cost (c_u) on the other hand is the cost that appears per unit that is missing if the company did order less then the final demand. Since there is no option of an emergency order we have: $c_u = p - c$, thus the profit margin of a single product. Therefore, the total cost of not having ordered enough is: $c_u \cdot (D - q)$ (assuming $q < D$).

Defining the expected newsvendor cost $C(q)$ as the sum of total overage and total underage cost we get:

$$C(q) = c_o \cdot \int_0^q (q-x)\phi(x)dx + c_u \cdot \int_q^\infty (x-q)\phi(x)dx \tag{13}$$

Minimizing this cost leads to the same result that we obtain from the maximization of (10). The minimization of (13) leads to the following expression:

$$\begin{aligned}
c_o \cdot \Phi\left(q^*\right) &= c_u \cdot \left(1 - \Phi\left(q^*\right)\right) \\
\Leftrightarrow \Phi\left(q^*\right) &= \frac{c_u}{c_u + c_o} \\
\Leftrightarrow q^* &= \Phi^{-1}\left(\frac{c_u}{c_u + c_o}\right)
\end{aligned} \tag{14}$$

In this way, the optimal order quantity can be broken down to a very simple, intuitive equation that also shows that the optimal order quantity only depends on the relation of relevant cost and prices rather than their total values. An advantage of writing the newsvendor formula as a relation of overage and underage cost is that it reveals another intuitive result of the newsvendor model: Whenever the overage cost is higher than the underage cost, it is optimal to order less than the expected demand ($\Phi^{-1}(q^*) < 0.5$) while if the cost of not ordering enough is higher than the cost of ordering too much, it is optimal to order more than the expected demand.

The derivation of the newsvendor formula shows that it is a very practical tool to support manufacturing or ordering decision in e.g. the fashion and sporting industries. It is relevant for a supermarket manager deciding on quantities of fresh meat or vegetables and helps a farmer to decide on quantities of different crops to be planted in a certain season. It can further be used in managing capacity decisions but also to evaluate advanced booking of orders in service industries, including airlines and hotels (Khouja, 1999; Axsäter, 2006). While the set-up presented here is very basic, many extension of the newsvendor model exist, including the option of emergency orders (Khouja, 1996), risk-aversion (Eeckhoudt et al., 1995) or the pricing decision of a newsvendor (Petruzzi and Dada, 1999). A survey of several issues and extensions of the newsvendor that are especially relevant for the problems studied in this thesis, including the coordination of the newsvendor, risk-aversion and newsvendor networks, will be provided in Section 2.5.

2.4.2 The economic order quantity model

In this section we discuss the well-known economic order quantity (EOQ) model, a framework that analyzes the trade offs between set-up and holding costs, which is basic to Chapter 5 of this thesis. The classic EOQ model was introduced by Harris (1913) and was made popular by Wilson (1934). It is based the following assumptions:

- Demand is constant and continuous at a rate of d items per time unit
- Holding cost of h (per unit and time unit) is constant over time
- A fixed set-up cost of A is incurred every time an order is placed
- Infinite planning horizon
- No shortages are allowed
- The whole order quantity Q is delivered at the same time with zero lead time

Since no shortages are allowed and further no safety stock is needed, the inventory level will vary over time as presented in Figure 2.1. A new batch arrives exactly at that point in time when the previous batch is finished and the time between the arrival of the two batches is equal the order quantity divided by the demand per time unit.

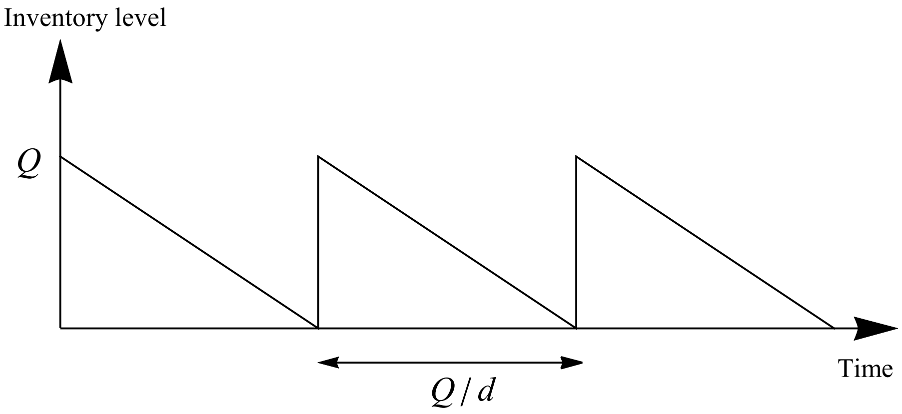


Figure 2.1: Development of inventory over time

The objective of the EOQ model is now to find the order quantity Q^* that minimizes the total cost C per time unit which is given as:

$$C = \frac{Q}{2}h + \frac{d}{Q}A \tag{15}$$

The first term in 15 represents the holding cost, which is equal the average stock $\frac{Q}{2}$ multiplied with the holding cost h. The second term is the average ordering cost per time unit which is obtained by multiplying the ordering cost A with the average number of orders per time unit $\frac{d}{Q}$. Since relevant costs are only costs that vary with the order quantity, the classic EOQ model does not consider the variable ordering cost (price per unit ordered). This changes, for example, if quantity discounts are considered (see e.g. Axsäter, 2006). Since C is convex in Q, the optimal order quantity Q^* can be derived from the first order condition:

$$\frac{dc}{dQ} = \frac{h}{2} - \frac{d}{Q^2}A = 0 \tag{16}$$

which leads to the following square root formula, the well-known economic order quantity:

$$Q^* = \sqrt{\frac{2Ad}{h}} \tag{17}$$

and a minimized cost C^* of:

$$C^* = \sqrt{2Adh} \tag{18}$$

Figure 2.2 allows a grafical interpretation of the EOQ Model: The total cost is minimized at the intersection of the average holding cost and the average ordering cost.

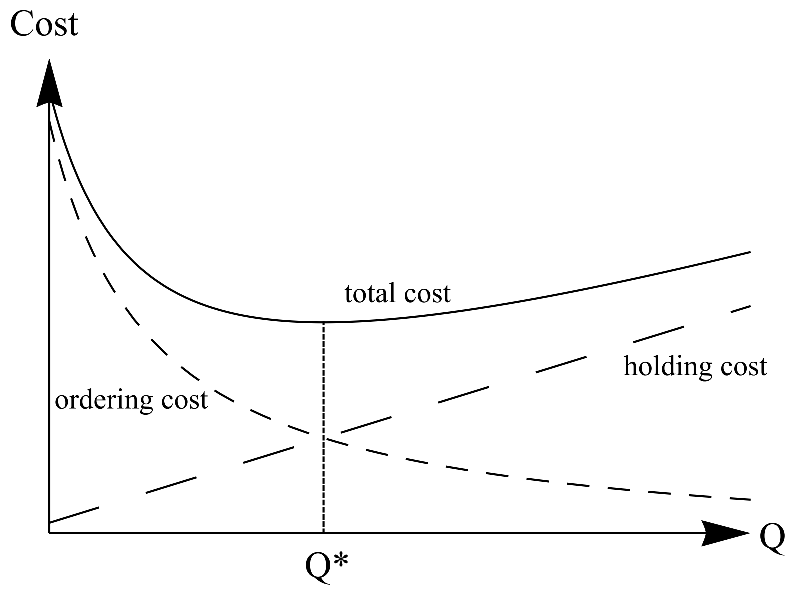


Figure 2.2: EOQ Cost function

Even though this model is a simplified version of the reality and some assumptions of e.g. a fixed demand over the whole time horizon, seem to be unrealistic, it is a good approximation and many assumptions can be easily relaxed while maintaining a relatively simple optimal policy (Simchi-Levi et al., 2005). Therefore, the EOQ Model is a useful tool to determine order quantities, whenever 1) demand is fairly stable over time, 2) the cost to place an order is reasonably stable and independent of the quantity ordered and 3) replenishments are delivered all at once, which are conditions that can be found in many purchasing situations (Hopp, 2011). There further exist several extensions of this model, including finite horizon, multi-item problems (as in Chapter 5), quantity discounts, finite production rates, backorders or time-varying demand, making this model a practical tool for many procurement situations (see e.g. Axsäter, 2006 or Simchi-Levi et al., 2005).

2.5 Literature review

In this section we provide a review of the most important works in the fields of auctions and supply chain management relevant for the topics covered in this thesis. This helps to follow this thesis, to provide suggestions for further reading, and to distinguish the contribution of this thesis to the already existing body of literature on procurement auctions. The review thus discusses the relevant literature for the specific problems discussed in the main body of this thesis. It does not only cover literature on auction theory though; it also outlines relevant literature for logistic problems such as supply contracts under demand uncertainty or transportation and inventory problems.

2.5.1 Supply contracts under demand uncertainty

Qin et al. (2011) provide a review of the newsvendor problem, including the issue of risk-aversion. Cachon (2003) provides a survey of supply contracts and coordination. Lariviere and Porteus (2001) analyze wholesale price contracts in the context of the newsvendor problem with a manufacturer selling to a retailer that faces uncertain demand. They all show how market size and demand variability influences the optimal wholesale price set by the manufacturer. Cachon and Lariviere (2001) address the problem of information asymmetry about demand forecasts and study contracts that allow for sharing demand forecasts credibly. Cachon (2004) compares push and pull contracts and proposes an advance-purchase discount where the risk of demand is shared by shifting the excess inventory risk from the supplier to the manufacturer. This advance-purchase discount, contrary to the push and pull contracts, allows to coordinate the supply chain and achieves an efficient production quantity. Comparing push and pull, he shows that the pull contract leads to a higher efficiency than the push contract. Perakis and Roels (2007) compare push and pull contracts and characterize efficiency depending on various supply chain configurations, such as different numbers of stages in the supply chain and the number of competing suppliers or competing retailers. They show that under a push contract more competition always leads to higher efficiency. However, in a pull contract more competition can also decrease supply chain efficiency.

2.5.2 Procurement auctions under demand uncertainty

While in simple single-unit auctions the format does not matter and simple first- and second-price auctions lead to optimal results, the optimal design of an multi-unit auction is more complicated, since, for example, fixed quantity auctions might not be optimal anymore. An important work to mention in that field is Dasgupta and Spulber (1990), who studied different procurement auctions for companies facing downward sloping demand curves. Chen (2007) enhances this model and derives general conditions for a firm's optimal auction mechanism that selects a supplier and determines the procurement quantity and corresponding payments. He proposes an auction where the retailer determines the optimal quantity-payment schedule. The retailer needs specific information concerning the cost distribution of the suppliers to be able to set up this optimal schedule. As opposed to Chen (2007), we consider price-only auctions where the retailer does not need any specific information about the suppliers' cost distribution to select the optimal contract. Duenyas et al. (2013) provide an extension of Chen (2007) by studying a more simple auction and show its optimality for ex-ante asymmetric suppliers and a class of non-linear production costs. Li and Scheller-Wolf (2011) compare different auction designs for a buyer facing uncertain demand using an open descending price-only auction format (English auction). Using an open auction format and letting the supplier determine the service level of supply, they show that intense competition in pull contracts can lead to lower retailer profits. They propose an enhanced pull contract that enables a certain service level and they establish how characteristics of demand and supply influence the retailer's preferences between a push and an (enhanced) pull mechanism. The authors show that the retailer prefers a push mechanism if supplier competition is high and a pull mechanism if demand uncertainty or the supplier cost level is relatively high. In contrast to Li and Scheller-Wolf (2011), we consider sealed-bid auctions and thus are able to implement a first-price auction which leads to lower purchasing prices in push contracts than in an open auction format. By enforcing contract compliance using an outside option rather than choosing a service level in pull contracts, we can establish that more competition between suppliers always leads to higher expected retailer profits.

Hansen (1988) considers the impact of endogenous quantities in procurement auctions under deterministic, price-sensitive demand. He shows that the auctioneer always prefers a first-price to a second-price auction and that even from the perspective of the total surplus of the considered economy, the first-price dominates the second-price auction. Spulber (1995) and Lofaro (2002) analyze a similar framework for Bertrand competition where rivals costs are unknown. Further, Ausubel and Cramton (2002) show how inefficiency occurs under multi-unit forward auctions if large bidders have an influence on the price under a uniform price auction. They show that efficiency and revenue rankings of the uniform-price and pay-as-bid auctions are inherently ambiguous. In some situations, the pay-as-bid auction leads to an efficient outcome while the uniform-price auction does not and vice versa.

2.5.3 Risk aversion in procurement auctions

For a risk-averse newsvendor, Cachon (2003) provides an overview of the literature. Eeckhoudt et al. (1995) determine comparative-static effects for changes in price and cost parameters. Agrawal and Seshadri (2000) investigate the role of intermediaries offering the possibility of emergency orders and buy-back options in supply chains with risk-averse retailers. Gan et al. (2004) study the coordination of supply chains with risk-averse agents. Keren and Pliskin (2006) set a benchmark by deriving a closed form solution of the risk-averse newsvendor for a special case of uniform demand. Wang et al. (2009) provide insights on how selling prices influence the risk-averse newsvendor and thus investigate some limitations of the expected utility theory.

We follow the common modeling philosophy in supply chain management to analyze a stand-alone newsvendor. This restrictive assumption of independence from market considerations is relaxed in Anvari (1987) who uses the capital asset pricing model for studying a newsvendor facing uncertain demand. If the relevant risk of the inventory investment is considered in the market-valuation model, results differ in comparison to the classical expected benefit maximization framework and order quantities are lower. Gaur and Seshadri (2005) study the impact of financial hedging in a newsvendor set-up, where demand is correlated with the price of a financial asset. They show that hedging reduces the variance of profit and increases the expected utility of a risk-averse decision maker. Ding et al. (2007) consider financial hedging against exchange risks and show how financial hedging influences operational strategy and can lead to altering global supply chain choices of a risk-averse firm.

Concerning auctions with risk-averse agents, Maskin and Riley (1984), Matthews (1987) and Waehrer et al. (1998) provide seminal results for single-unit auctions. Maskin and Riley (1984) show that first-price auctions are optimal for a risk-neutral seller with risk-averse buyers whereas Matthews (1987) examines the buyer's point of view. Waehrer et al. (1998) consider risk-averse bid takers and risk-neutral bidders and show that first-price auctions are optimal in this case. This thesis contributes to this field by investigating how effects of risk-averse bidding and risk-averse capacity planning affect each other and influence resulting profits. A combined study allows to investigate how risk-aversion shifts the preferences towards specific auction and contract designs.

2.5.4 Capacity provision for repeated auctions

Chapter 4 is related to two streams of the literature, 1) industrial organization literature on how capacities influence competitions and profits, where we refer to Tirole (1988) and more recently Belleflamme and Peitz (2010) for comprehensive surveys and 2) repeated (procurement) auctions. The existing literature in this second field shows that much work has already been done on sequential auctions with a finite horizon. Weber (1981) provides a survey on multi-object auctions and gives intuition for why prices fall in the sequential auction for identical objects when bidders have limited purchasing capacity. Bernhardt and Scoones (1994) investigate repeated auctioning where several different objects are auctioned off in sequential auctions and show that mean prices fall. They further show which objects should be auctioned first if valuations are not identically distributed across objects. While Milgrom and Weber (1982) show that for independent private values prices in repeated sales auctions should remain constant, a so-called declining price anomaly can be observed in repeated auctions of e.g. wine and art (see Ashenfelter, 1989). McAfee and Vincent (1993) explain these decreasing prices in repeated auctions of identical products with the risk aversion of bidders. Said (2011) discusses a model of discounted sequential second-price (forward) auctions with an infinite horizon, where objects and buyers (with single-unit demand) arrive randomly. He shows that bidders take the option value of participating in future auctions into consideration and as a result they decrease their bids.

A further stream in repeated auctions are studies on collusion where bidders communicate before an auction in order to maximize their profits. Graham and Marshall (1987) are among the first discussing this topic for second-price auctions and McAfee and McMillan (1992) analyze collusion for first-price auctions. However, even though this is an interesting and highly relevant field, we do not consider collusion in this thesis. For an introduction to this topic, we refer to Hendricks and Porter (1989) and Pesendorfer (2000), as well as Krishna (2010). Another topic in repeated auctions is the possibility to learn about the bidders' cost structure from previous auctions. However, even though learning effects can appear in repeated auctions, we do not consider them in our model. For further information on this topic, see e.g. Jeitschko (1998), who gives a comprehensive survey on the topic and provides new insights on the benefits of being able to learn in sequential auctions.

Next, we focus on the literature that considers the aspect of capacity constraints in repeated procurement auctions. Elmaghraby (2003) studied the sequencing problem of a buyer wishing to procure two heterogeneous objects in two (sequential) auctions while facing suppliers with capacity constraints. She shows the critical influence ordering can have on the efficiency of an auction. For a similar set-up, Reiß and Schöndube (2010) studied revenue equivalence in a sequential auction with capacity constrained bidders. While these models consider bidders who only participate in an auction once, we consider bidders who participate repeatedly. Jofre-Bonet and Pesendorfer (2000), and Jofre-Bonet and Pesendorfer (2003) present empirical work in the field of repeated auctions with capacity constraints by looking at repeated highway construction procurement auctions and estimating the bids of the competing companies. They show that bids increase in relation to the fraction of the capacity already committed to other jobs. Similarly, Saini (2012) provides a numerical approach to a repeated procurement model where production costs increase in the usage of capacity. Under high capacity utilization, competition becomes weaker and procurement costs increase. A further interesting work by Römhild (1997) develops a decision theory model without explicit (game theoretic) interaction and studies the problem a producer with limited capacity has when faced with the option of participating in several bids. By considering a finite-horizon model with known auction events, known times of production, and externally given winning probabilities, this problem was solved via backward induction. He also shows that there is a markup for the opportunity cost of using capacity and that, consequently, bids are higher than in non-capacitated bidding events.

Considering investment decisions in the auction environment, Arozamena and Cantillon (2004) provide insights on incentives to invest in cost reduction and their effects on bidding behavior in first- and second-price sealed-bid auctions. By showing that second-price auctions, in comparison to first-price auctions, lead to higher investment incentives, they provide relevant information on the general aspect of capacity decision for procurement auctions. Budde and Göx (2000) study an investment problem where a supplier can invest in cheaper capacity before the bidding process, or else wait until after the bidding and then buy more expensive capacity if needed. They show that only companies with a lower production cost will invest in advance, while bidders with a higher cost will wait with their investment until the outcome of the auction is known. Another interesting work is provided by Perrone et al. (2010), who, in addition to the price, take the production time as an attribute in service procurement auctions into account. They provide new insights by e.g. proving revenue equivalence for different auction schemes and further show that increasing the number of bidders but not the duration of projects has an impact on prices.

While most of these papers consider finite horizon models where capacity is only used once (during that horizon), there are - apart from empirical or numerical work - no models which consider auctions with an infinite horizon and capacity only committed for a specific time and its later reuse. In contrast to Römhild (1997), we further consider the effect limited capacity has on competition among service providers, as well as how capacity decisions influence the outcome.

Concerning Markov Decision Processes, Tijms (2003) and Puterman (2009) provide great introductions to this topic with several applications. Filar and Vrieze (1996) cover the more specific topic of stochastic games, similar to Hu and Yue (2007) who provide an overview of several applications in the field of game theory and auctions in Markov Decision Processes.

2.5.5 Recurring auctions with economies of scale

Grimm (2007) derives general results for recurring procurement auctions of complementary or substitutionary goods. She studies a set-up of successive procurement situations where current success influences future production cost. By allowing subsequent resale for bundling auctions, it can be shown that bundling auctions always dominate the standard sequential auction. As a benchmark Grimm (2007) derives the optimal sequential auction, where the allocation for the second product depends on new defined virtual cost function rather then on the actual cost. The optimal sequential auction then dominates the bundling auction. We extend her paper by first making both auctions more comparable by not allowing subsequent resale under the bundling auction and further applying it to specific procurement problems of companies. We are then able to show that the choice for a bundle or sequential auction is dependent on e.g. the number of bidders and the cost structure. Further related to this thesis is the work of Jofre-Bonet and Pesendorfer (2006) who derive conditions for an optimal sequential procurement auction and build the basis for the benchmark auction in Grimm (2007). Jeitschko and Wolfstetter (2002) compare first- and second-price forward auctions for a sequential bidding game with either economies or diseconomies of scale. They show that economies of scale lead to declining expected prices, whereas diseconomies of scale do not always lead to higher prices. They further show that first- and second-price auctions are no longer always revenue equivalent and that in the presence of scale economies, second-price auctions lead to higher profits for the seller than first-price auctions. De Silva (2005) shows empirical results of synergies in recurring procurement auctions and their impact on bidder behavior. He empirically shows that if bidders with potential synergies participate in an auction, their probability of winning increases and they bid more aggressively. This finding goes hand in hand with the results of our work.

2.5.6 Bundling in auctions

Our work is also closely related to the general theory on bundle auctions. A seminal work in that field is provided by Palfrey (1983), who studies a monopolist selling several products using an auction mechanism. He shows that with a small number of buyers, a profit maximizing seller will bundle all his output while with a larger number of buyers, the seller will have a tendency to unbundle his output. Chakraborty (1999) studies a situation where an auctioneer has the option to bundle two or more objects before selling them. He shows that under any auction which fulfills the requirements of the revenue equivalence theorem there is a unique critical number for each pair of objects such that when the number of bidders is fewer than that critical number the seller strictly prefers to bundle the products. When there are more bidders, the seller prefers not to bundle the products. Armstrong (2000) provides similar results while deriving an optimal auction for the sale of two products with binary distributed values. Avery and Hendershott (2000) extend the work of Amstrong by deriving further properties for optimal revelation mechanism. Levin (1997) and Branco (1997) give additional characteristics of optimal multi-unit auctions for complementary products. While Levin (1997) studies the influence of bundling on the seller's revenue and social welfare, Branco (1997) derives the equilibrium bids for a sequential auction of products with superadditive values. A further stream in literature where economies of scale play an important role is the topic of combinatorial auctions. In such combinatorial auctions multiple items are sold simultaneously and, in contrast to e.g. the model we study later on, it is allowed to submit "‘all-or-nothing"’ bids on combinations of these items. Thus, two characteristics that distinguish combinatorial auctions from standard auction models are the complexity of winner determination and further a cooperative aspect (Pekeč and Rothkopf, 2003). For an excellent survey and summary on the topic of combinatorial auctions we refer to the work of Cramton et al. (2006) who puts together insights from theory as well as from practice.

2.5.7 Third party logistics with economies of scale

As mentioned, in this thesis we apply two particular problems that appear in the procurement of logistic services to a modified version of the procurement model of Grimm (2007).

Therefore, the first application emerges from the field of transportation and inventory management. One focus we set lies on the topic of inventory models with joint replenishment. Here we refer the reader to e.g. Hall (1987), Aksoy and Erenguc (1988), Goyal and Satir (1989) or Khouja and Goyal (2008), who provide comprehensive surveys on this topic. In our work we apply the model of Balintfy (1964), one of the first researchers to develop models for multi-item inventory problems. He compares different classes of multi-item inventory problems where a joint order of several products can save a part of the fixed order cost. He also introduces the can-order policy as one of the first types of a continuous coordinated replenishment policy. We combine his research with the work of Blumenfeld et al. (1985), who determine optimal shipping strategies on freight networks by taking effects such as transportation, inventory and production set-up costs into account.

The second topic covers providing goods in an uncertain environment (see Section 2.5.1 for the single item case). The literature shows that bundling products in a supply chain with uncertain demand can lead to huge economies of scale. Van Mieghem (1998) studies optimal investment strategies for flexible resources in a newsvendor environment. He shows that besides demand correlation, differences in price and cost have a significant influence on the optimal capacity provision and the value of flexibility. We study a simplified version of this model as an application of the sequential sourcing problem that will be discussed later. A vast number of other works exist which study the investment in product-flexible capacity in newsvendor networks.

Netessine et al. (2002), for example, study the impact on demand correlation of optimal capacity provision. They provide intuitive results if there are two demand classes by showing that increasing correlation leads to a shift from flexible to dedicated capacity. They expand their study to more than two demand classes and show that there are also adjustments to the resources not directly affected by the correlation change and which follow, along with a rising correlation, an alternating pattern.

Another example is Bish and Wang (2004), who add ex-post pricing to the capacity decisions. They study the optimal investment strategy for two products of a price-setting firm, which employs a postponed pricing scheme and has the option to invest in dedicated resources as well as a more expensive, flexible resource that can satisfy both products. The capacity decision is made under demand uncertainty, while pricing and resource allocation decisions are postponed until the demand is known. They show that the optimal investment strategy depends on demand parameters as well as on investment cost. Due to risk pooling effects, investment in the flexible resource can be optimal, even if demand patterns are perfectly correlated. On the other hand, they show that depending on the profitability of the two products, even for perfectly negatively correlated demand patterns an investment in the flexible resource might not be optimal. For a further overview on the literature of newsvendor networks and flexible resources we refer to Van Mieghem (2003) who presents a comprehensive review on capacity management, investment and hedging.

However, besides the two models we discuss in Chapter 5, there exists a vast number of other tasks that can be addressed by Third Party Logistics providers. For a general overview on possible topics, we refer to Sink et al. (1996), Marasco (2008), Selviaridis and Spring (2007) and further Andersson and Norrman (2002), who provide excellent surveys on the topic of Third Party Logistics. Especially related to our work are Third Party Logistic Situations with economies of scale. Examples for such economies of scale include investment in special equipment (Skjoett-Larsen, 2000) or the ability to use large truck fleets (Vasiliauskas and Jakubauskas, 2007). These examples are further possible applications of the auction framework discussed in Chapter 5.

Chapter 3

First- and second-price sealed-bid auctions applied to push and pull supply contracts

In this chapter we investigate a newsvendor-type retailer sourcing problem under demand uncertainty who has the option to source from multiple suppliers. The suppliers' manufacturing costs are private information. We compare the combinations of different simple auction formats (first- and second-price) and risk sharing supply contracts (push and pull) under full contract compliance, both for risk-neutral and risk-averse retailer and suppliers. We show the superiority of a first-price push auction for a risk-neutral retailer. However, only the pull contracts lead to supply chain coordination. If the retailer is sufficiently risk-averse, the pull is preferred over the push contract. If suppliers are risk-averse, the first-price push auction remains the choice for the retailer. Numerical examples illustrate the allocation of benefits between the retailer and the (winning) supplier for different number of bidders, demand uncertainty, cost uncertainty, and degree of risk-aversion.

3.1 Model analysis

Consider a supply chain with a dominant retailer and several competing and identical suppliers. The retailer faces uncertain market demand x, drawn from a continuous distribution on $[0, T]$ with cumulative probability $\Phi(x)$ and probability density $\phi(x) > 0$. $\Phi(x)$ has a finite mean μ and an inverse $\Phi^{-1}(x)$. The distribution is assumed to be common knowledge. The market price p is fixed and exogenously given. Without loss of generality we assume zero salvage value.

A number of $n \geq 2$ ex ante symmetric suppliers compete for the right to sell a good to the retailer through contract-bidding. Manufacturers have no production capacity limitations. Supplier i's marginal cost is c_i and private knowledge. Beliefs about competitor's marginal costs c are distributed according to $F(c)$ with density $f(c) > 0$ continuous over $[\underline{c}, \overline{c}]$. We further assume that $c + F(c)/f(c)$ is increasing in c, a regularity condition to ensure unique solutions (see e.g. Chen, 2007).

In the event of a stockout, the retailer and all suppliers have the option of sourcing unlimited additional quantities from a secondary market at a cost z per unit ($p \geq z \geq \overline{c}$, compare e.g. Gallego and Moon (1993)). In order to be able to provide customized products at a short lead time, this outside option has to be highly responsive. Therefore, these products can only be supplied by manufacturers with short reaction times. This high responsiveness leads to the high cost of the outside option (e.g. for investments in responsive capacities, use of faster supply modes etc.). The manufacturers that participate at the auction considered here cannot supply to this market and take advantage of the high price z, as they have a long reaction time and their production has to start before demand is known. Left-overs cannot be sold to this market either, as they are customized for the particular sourcing company. Instead of an outside option, one might also assume that demand is lost if it cannot be satisfied. If the supplier has to compensate the retailer for lost sales under a pull contract, an obvious compensation would be the retailer's margin $p - w$, where w denotes the wholesale price. This is equal to setting $z = p$. For a study of pull contracts without second order option and where suppliers do not have to compensate the retailer for lost sales, we refer to Li and Scheller-Wolf (2011).

The retailer chooses the auction format (first-price sealed-bid or second-price sealed-bid to select a supplier and to determine the wholesale price) and the supply contract (push or pull). In the first-price auction, the lowest bid wins and the winner has to supply the product at the bidding price. In the second-price auction, the lowest bid wins but the buyer pays the second lowest bid for the supplied product.

3.1.1 Auctioning a push contract

The suppliers compete for the right to supply the retailer through price bidding. The contract is fully awarded to the lowest bidder and the supply quantity q_R is determined directly after the auction and thus after the determination of the wholesale price w through an auction, but before the final demand is realized. The retailer determines the optimal order quantity, which maximizes the expected retailer profit for a given wholesale price w.

$$E(\Pi_R^{Push}|w) = -wq_R + \mu p - z \int_{q_R}^{\infty} (x - q_R)\phi(x)dx. \tag{19}$$

(19) is concave in the order quantity q_R and the optimal solution is $q_R(w) = \Phi^{-1}[(z - w)/z]$.

In a first-price auction, each bidder $i = 1, 2, ..., n$ submits a sealed-bid $b(c_i)$ for the right to sell the good to the retailer. In an equilibrium, the bidding strategy $b(c)$ defines the cost dependent bid for every supplier and the probability to win the auction with the bid $b(c_i)$ is equal to $(1 - F(c_i))^{n-1}$, the probability that costs of all the other $n - 1$ suppliers are higher than c_i. In equilibrium, the expected profit of each supplier is

$$E(\Pi_S^{f,Push}) = (1 - F(c_i))^{n-1} q_R(b(c_i))(b(c_i) - c_i), \tag{20}$$

where $q_R(b(c_i))$ is the quantity the retailer will order if $w = b(c_i)$. Since the retailer's order quantity decreases with the resulting wholesale price, the supplier has to anticipate the retailer's order for any wholesale price and the sales quantity becomes endogenous. For a common bidding strategy $b(c)$ with symmetric suppliers, the first-order condition is

$$\frac{dE(\Pi_S^{f,Push})}{db(c)}\frac{db(c)}{dc} = 0 \Leftrightarrow \frac{db(c)}{dc} = \frac{f(c)(n-1)(b(c)-c)q_R(b(c))}{(1-F(c))\left[q_R(b(c)) + (b(c)-c)\frac{dq_R(b(c))}{db(c)}\right]}, \tag{21}$$

i.e. requires to solve a differential equation.

On the right-hand side of equation (21), the numerator is obviously always positive. The same holds for the denominator. A negative denominator would imply that the bidder could, by decreasing the bid, increase the profit in case of winning and the probability of winning at the same time, which is not an equilibrium. Therefore, the whole term is always positive and bids are increasing in costs since in an equilibrium it has to hold that $b(c) > c$ for all $c \in [\underline{c}, \overline{c})$ while the seller with the highest possible cost $\overline{c}$ has zero expected profit and thus $b(\overline{c}) = \overline{c}$.

In a second-price auction for push contracts, it is optimal for the supplier to bid marginal costs $b(c) = c$. The comparison of the resulting expected prices from both auction formats yields the first result.

Proposition 1. *Under a push contract, the first-price auction leads to lower expected prices than the second-price auction.*

In the first-price auction, the bidder has to consider that the quantity sold decreases with the bid. This leads to more aggressive bidding, whereas the bid in the second-price auction does not depend on whether the quantity sold is fixed or variable. The expected profit for the retailer under a first-price push auction is

$$E(\Pi_R^{f,Push}) = \mu p - \int_{\underline{c}}^{\overline{c}} nf(c)(1-F(c))^{n-1}\left(b(c)q_R(b(c)) + z\int_{q_R(b(c))}^{\infty}(x - q_R(b(c)))\phi(x)dx\right)dc. \tag{22}$$

Inserting the optimal bid for the second-price push auction $b(c) = c$ into the retailer's profit function (19) and integrating for the costs of the second lowest bidder with probability density $f_{II:n}(c) = n(n-1)F(c)(1-F(c))^{n-2}f(c)$ (see Arnold et al., 1993), we get the expected profit for the retailer in the second-price push auction

$$E(\Pi_R^{s,Push}) = \mu p - \int_{\underline{c}}^{\overline{c}} n(n-1)F(c)(1-F(c))^{n-2}f(c)\left(cq_R(c) + z\int_{q_R(c)}^{\infty}(x - q_R(c))\phi(x)dx\right)dc. \tag{23}$$

3.1.2 Auctioning a pull contract

The retailer's order quantity is specified after observing demand and the supplier has to produce before the retailer specifies the order and bears the whole demand risk. The optimal order quantity is $q_S(c) = \Phi^{-1}[(z-c)/z]$ and does not depend on the wholesale price w but on the production cost c and the secondary market cost z, i.e. this is the optimal quantity a central planner would choose. For a first-price auction, the expected profit for the bidding supplier is

$$E(\Pi_S^{f,Pull}(b(c_i))) = (1-F(c_i))^{n-1}\left(-c_i q_S(c) + b(c_i)\mu - z\int_{q_S(c)}^{\infty}(x-q_S(c))\phi(x)dx\right). \tag{24}$$

For $b(c)$ being an equilibrium bid, the first-order condition (25) provides the differential equation for the first-price pull contract.

$$\begin{aligned} \frac{dE(\Pi_S^{f,Pull})}{db(c)}\frac{db(c)}{dc} &= 0 \\ \Leftrightarrow \frac{db(c)}{dc} = \frac{f(c)(n-1)(-cq_S(c)+b(c)\mu - z\int_{q_S(c)}^{\infty}(x-q_S(c))\phi(x)dx)}{(1-F(c))\mu} \end{aligned} \tag{25}$$

Since in an equilibrium the bidder submits a bid that at least covers expected cost, this expression strictly increases in c for all $c \in [\underline{c}, \overline{c})$. Since the supplier with the highest cost expects zero surplus, it holds that $b(\overline{c}) = \frac{\overline{c}q_S(\overline{c}) + z\int_{q_S(\overline{c})}^{\infty}(x-q_S(\overline{c}))\phi(x)dx}{\mu}$.

In a second-price pull auction, all suppliers' dominant strategy is to bid at expected unit costs. In the push contract, the winning supplier delivers a given quantity, i.e. the total cost is the supplied quantity multiplied by the marginal cost. However, in the pull contract the winning supplier has to build up capacity before knowing how much to deliver and eventually has to buy extra units if demands exceed capacity. Thus, the total cost depends on the realized demand and at the time of bidding, a supplier can only assess expected total cost of the pull contract. Therefore, the ex-ante bid is equal to the expected and not the ex-post cost. Therefore, an equilibrium bid $b(c)$ satisfies that expected supplier profits in case of supplying the good at a wholesale price $w = b(c)$ must be zero. Otherwise, a supplier could increase the chance to win the auction by decreasing the bid without changing the outcome as the realized price is determined according to the second-price logic. However, as we consider a pull contract, the bid has to account for the extra cost of taking the entire demand risk. Note that when taking the realized wholesale price into account, the expected supplier profit is positive.

$$-cq_S(c) + b(c)\mu - z\int_{q_S(c)}^{\infty}(x-q_S(c))\phi(x)dx = 0 \tag{26}$$

Inserting the optimal quantity $q_S(c)$ and solving for b provides the optimal bidding function. We further get the expected profit for the retailer:

$$E(\Pi_R^{s,Pull}) =$$

$$\mu p - \int_{\underline{c}}^{\bar{c}} n(n-1)F(c)(1-F(c))^{n-2}f(c)\left(cq_S(c) + z\int_{q_S(c)}^{\infty}(x-q_S(c))\phi(x)dx\right)dc \tag{27}$$

Lemma 1. *Under a pull contract the revenue equivalence theorem holds. The first-price and the second-price auctions lead to the same expected prices and profits for the retailer and every supplier.*

Under a push contract, the first-price auction always leads to lower expected prices than the second-price auction because the order quantity is endogenous and decreasing in the wholesale price w. Under both pull contracts, the order quantities are independent of the wholesale price and thus the outcome is independent of the auction format. Since the revenue equivalence theorem holds for the pull contract, an open-bid auction such as an English auction would also lead to the same result as the considered sealed-bid auctions. From the revenue equivalence theorem, the optimal bid of a bidder in the first-price auction must be equal to the expected lowest bid of the remaining bidders in the second-price auction, assuming that this bidder has the lowest costs. Thus,

$$b^f(c) = \int_c^{\bar{c}} b^s(c_r)(n-1)(1-V(c_r,c))^{n-2}v(c_r,c)dc_r \tag{28}$$

,whereas the cost of the $n-1$ remaining bidders are distributed according to $V(c_r, c)$, with density $v(c_r, c) = \frac{f(c_r)}{1-F(c)}$.

3.1.3 Comparison of auction formats and contract types

Pull contracts lead to supply chain coordination, because $q_S^{pull}(c) = \Phi^{-1}[(z-c)/z]$ for first- and second-price auctions and the lowest cost bidder always wins the auction. Push contracts lead to an inefficiently low production volume because $q_R^{push}(w(c)) = \Phi^{-1}[(z - w(c))/z]$ and $w(c) > c \;\forall\; c < \bar{c}$. Therefore, total supply chain profits are higher under a pull contract than under a push contract and a social planner would choose a pull contract. The auction design (first- or second-price auction) is irrelevant.

When comparing both push auctions, we find two opposing effects. On the one hand, the profit function of the retailer is convex in the resulting wholesale price (see the appendix for a proof). Since the spread of resulting wholesale prices is now higher under the second-price auction than under the first-price auction, this effect favors the second-price auction. On the other hand, we have shown that the first-price auction leads to lower prices than the second-price auction.

Conjecture 1. *The first-price push contract yields higher expected retailer profits than the second-price push contract.*

Lemma 2. *The second-price push contract leads to the same expected retailer profits as a (first- or second-price) pull contract.*

The conjecture is confirmed by all numerical results and will be proven for special cases (see Section 5).

The pull contract coordinates the supply chain, but under a wholesale price-only contract, the retailer cannot benefit from the higher overall supply chain profit. If the retailer chooses a pull contract instead of a second-price push contract, the retailer's profit remains the same while the supplier receives the whole surplus created through the supply chain coordinating pull contract.

This is caused by the fact that under the second-price contract, no matter if push or pull, the suppliers bid at their actual (in case of push) or expected (in case of pull) cost and therefore the retailer's profit depends on the cost of the supplier with the second lowest cost. For the supply chain profits we can observe a change in the dependency. If a pull contract is chosen, the bidder with the lowest cost determines the total production quantity. Under a push contract, the quantity depends on the cost of the supplier with the second lowest cost. Consequently, as the suppliers profits are equal to the difference of the supply chain profits and the retailer profits, they increase with a switch from the push to the pull contract. Comparing both push contracts, a supplier prefers the first-price contract, as the quantity sold is higher (see Hansen, 1988 and Milgrom, 1989).

As the first-price push contract enables lower expected prices than the second-price push contract and the retailer is indifferent between a second-price push and a pull contract, the retailer would never prefer a pull contract to a push contract. The retailer's dominant strategy is to not choose the supply chain coordinating contract (see Table 3.1).

Table 3.1: Format ranks

	First-price	Second-price
Push	Retailer: #1 Supplier: #3 Supply Chain: #3	Retailer: #2 Supplier: #4 Supply Chain: #4
Pull	Retailer: #2 Supplier: #1 Supply Chain: #1 (Coordinating)	Retailer: #2 Supplier: #1 Supply Chain: #1 (Coordinating)

This result on overall supply chain efficiency and retailer benefit is reinforced by increasing competition between bidders. The retailer and the supply chain always benefit from increasing supply competition and have an incentive to let as many suppliers participate in the auction as possible.

Corolary 1. *For both push and pull contracts expected retailer and supply chain profits increase in the number of bidders.*

This result might not be surprising, but in pull contracts where the suppliers can choose their own service level (see e.g. Li and Scheller-Wolf, 2011), the retailer profit does not necessarily increase with supplier competition.

3.2 The influence of risk-aversion

In the previous section, demand risk allocation was implicitly incorporated through the choice of a push or pull contract. There are additional benefits from shifting the risk in a supply chain if the decision makers are risk-averse, rather than risk-neutral. Next, we analyze how one-sided risk-aversion, both on the retail and supply-side, affects the contract and auction format choice. We define the utility function $u(z)$ to be increasing, concave, and differentiable, $u'(z) > 0$, $u''(z) \leq 0$, $u(0) = 0$ (compare Eeckhoudt et al., 1995).

3.2.1 The risk-averse retailer

Consider the case of a risk-averse retailer and risk-neutral suppliers. The retailer's expected utility for a given wholesale price w, $H_R(q|w)$ is

$$H_R(q|w) = \int_0^q u(px - wq)\phi(x)dx + \int_q^T u(px - wq - z(x - q))\phi(x)dx. \tag{29}$$

$H_R(q|w)$ is concave in q and the first-order condition is

$$\frac{dH_R(q)}{dq} = -w \int_0^q u'(px - wq)\phi(x)dx + (z - w) \int_q^T u'(px - wq - z(x - q))\phi(x)dx = 0. \tag{30}$$

Theorem 1. *(i) A risk-averse retailer sourcing via a pull contract always prefers the first-price auction.*
(ii) A retailer with a low risk aversion prefers the push contract to the pull contract, but if the risk aversion is high enough, the retailer prefers the first-price pull contract.
(iii) If the utility function fulfills the property decreasing absolute risk aversion (DARA, which includes constant absolute risk aversion (CARA)), the first-price push auction leads to lower expected prices than the second-price push auction.

Under a pull contract, the supplier takes the whole demand risk. For a retailer with low risk-aversion, the first-price push contract is preferred because of more aggressive bidding under endogenous quantities. However, a retailer with high risk-aversion prefers the pull contract to avoid demand risk. Since the bidding behavior in the second-price push and second-price pull contract does not change, the retailer always prefers the second-price pull contract to the second-price push contract (for a proof see Theorem 2.1 in Agrawal and Seshadri, 2000). This implies that the first-price pull contract dominates the second-price push contract. As the wholesale prices remain the same, a risk-averse retailer prefers the contract where the supplier bears the entire risk.

3.2.2 Risk-averse suppliers

Assume a risk-neutral retailer and risk-averse suppliers with symmetric utility functions $u(z)$.

Lemma 3. *If the suppliers are risk-averse and the retailer sources via a push contract, the prices for the first-price push auction are lower than with risk-neutral bidders.*

As the supplier does not take any inventory risk in a push contract, the only risk is not to win the auction. Therefore, lower bids than under risk neutrality are submitted. Under a second-price auction, it is optimal to bid at cost. Thus, the degree of risk-aversion has no influence on the bidding strategy and bids are still higher than under the first-price auction.

Under a pull contract, the winning supplier's expected utility $H_M(q_S(w,c)))$ is

$$H_M(q_S(w,c)) = \int_0^{q_S(w,c)} u(wx - cq_S(w,c))\phi(x)dx$$
$$+ \int_{q_S(w,c)}^{T} u(wx - cq_S(w,c) - z(x - q_S(w,c)))\phi(x)dx. \tag{31}$$

The supplier's optimal quantity and expected utility now depend on the costs and the bid. The derivation of the optimal order quantity $q_S^*(b(c),c)$ is analogous to that for the risk-averse retailer. Since z is constant and higher than w, the optimal order quantity is a decreasing function of the wholesale price. For the first-price auction the supplier's optimal bidding strategy is

$$\frac{db(c)}{dc} = \frac{f(c)(n-1)H_M(q_S^*(b(c),c))}{(1-F(c))\frac{dH_M(q_S^*(b(c),c))}{d(b(c))}}. \tag{32}$$

The bidder with the highest cost expects zero utility $H_M(q_S^*(b(\overline{c}),\overline{c})) = 0$. The optimal bid for the second-price contract can be derived as the one for the risk-neutral supplier (compare (26)), with the difference that for the risk-averse supplier the expected utility (see (31)) rather than the expected profit must be zero.

Theorem 2. *With risk-averse suppliers, the first-price push contract remains the dominant choice for the retailer. The second-price push contract always dominates the second-price pull contract. The dominances between the second-price push and first-price pull contract are indeterminate. Depending on the demand distribution and the cost structure, the first-price pull contract can either lead to higher or to lower expected retailer profits than the second-price push contract.*

Introducing risk-aversion has two effects on the first-price pull auction. Risk-averse suppliers bid more aggressively, but their cost of supplying the good increases because (due to their risk aversion) the production quantities are not efficient anymore. Taking $r(z)$ as the measure for risk aversion, it holds that $\lim_{r(z)\to\infty} b(c) = z$ for the pull contract. Therefore, the retailer's profit can increase and decrease in the suppliers' risk attitude. In the second-price push auction, the retailer's profits are independent from the suppliers' risk-aversion as the suppliers always bid at cost.

Table 3.2: Preference ranking under risk aversion

		risk-averse retailer				risk-averse supplier			
		low risk-aversion		high risk-aversion		low risk-aversion		high risk-aversion	
		first-price	second-price	first-price	second-price	first-price	second-price	first-price	second-price
Push	Retailer:	#1	#4	#3	#4	#1	#2 or #3	#1	#2
	Supplier:	#3	#4	#3	#4	#3	#4	#1 or #2	#1 or #2
	Supply Chain:	#3	#4	#3	#4	#3	#4	#1	#2
Pull	Retailer:	#2	#3	#1	#2	#2 or #3	#4	#3	#4
	Supplier:	#1	#1	#1	#1	#1 or #2	#1 or #2	#3 or #4	#3 or #4
	Supply Chain:	#1	#1	#1	#1	#1 or #2	#1 or #2	#3 or #4	#3 or #4

The inefficient production of the supplier leads to a lower overall supply chain profit under the pull contract. Therefore, for high risk-aversion, the supply chain profit is maximized under the first-price push contract and not under a pull contract. For low risk-aversion, it depends on the parameters whether the first- or second-price pull contract maximizes the supply chain profit. For instance, it depends on the utility function or the price itself, whether a higher selling price leads to a higher or lower production quantity and thus a higher or lower efficiency (see e.g. Eeckhoudt et al., 1995 or Wang et al., 2009 for the effect of price changes on the order quantities of a risk-averse newsvendor).

A risk-averse supplier prefers the pull contract if risk-aversion is low. If risk-aversion is high, the inefficient production quantity cause preferences to switch to the push contract. Within the contract formats, there is no clear preference for a first- or a second-price auction. While a first-price auction leads to a lower spread of bids (under a push contract) and to a higher quantity sold, it will also lead to lower prices than the second-price contract. For the extreme case without demand uncertainty, pay-offs are a linear function of the wholesale price and according to Matthews (1987), for IARA (increasing absolute risk-aversion) the bidder prefers the first-price, for CARA there is indifference, and for DARA preference for the second-price auction. With demand uncertainty, the pay-offs are no longer a linear function of the resulting wholesale price and it depends on the specific parameters, such as the utility function and demand or cost distributions, as to whether the first- or second-price auction is preferred. The results for the risk-averse retailer and for the risk-averse supplier are summarized in Table 3.2.

3.3 Closed-form results

Lofaro (2002) analyzes the equilibrium for Bertrand competition with incomplete cost information which can be interpreted as a push auction model. This framework assumes that demand is uniformly distributed on $[0, 1]$ and marginal costs c of each single supplier are independently and uniformly distributed on $[0, 1]$. Further, we assume $p \geq z = 1$.

3.3.1 Push contract

For the first-price auction $b^{f,Push}(c) = \frac{1}{1+n} + \frac{n}{1+n}c$ is the unique strictly monotone function which solves the differential equation (21) and is thus the unique symmetric Bayesian-Nash equilibrium. The expected values for wholesale price $w^{f,Push}$, retailer profit $\Pi_R^{f,Push}$, and supply chain profit $\Pi_{SC}^{f,Push}$ are

$$E(w^{f,Push}) = \frac{2n+1}{(1+n)^2}, E(\Pi_R^{f,Push}) = \frac{1}{2}\left(p - \frac{4n^2+5n+2}{(n+1)^2(n+2)}\right),$$
$$E(\Pi_{SC}^{f,Push}) = \frac{p}{2} - \frac{2n+1}{2(n+1)^2}.$$

For the second-price push auction, the respective expressions are

$$E(w^{s,Push}) = \frac{2}{n+1}, E(\Pi_R^{s,Push}) = \frac{1}{2}\left(p - \frac{4n+2}{(n+1)(n+2)}\right), E(\Pi_{SC}^{s,Push}) = \frac{p}{2} - \frac{1}{n+1}.$$

3.3.2 Pull contract

As first- and second-price auctions are revenue equivalent for the pull contract, it is sufficient to analyze the second-price auction. From (26), $b^{s,Pull}(c) = c(2-c)$. The expected values for wholesale price $w^{s,Pull}$, retailer profit $\Pi_R^{s,Pull}$, and supply chain profit $\Pi_{SC}^{s,Pull}$ are

$$E(w^{s,Pull}) = \frac{4n+2}{(n+1)(n+2)}, E(\Pi_R^{s,Pull}) = \frac{1}{2}\left(p - \frac{4n+2}{(n+1)(n+2)}\right),$$
$$E(\Pi_{SC}^{s,Pull}) = \frac{p}{2} - \frac{1}{n+2}.$$

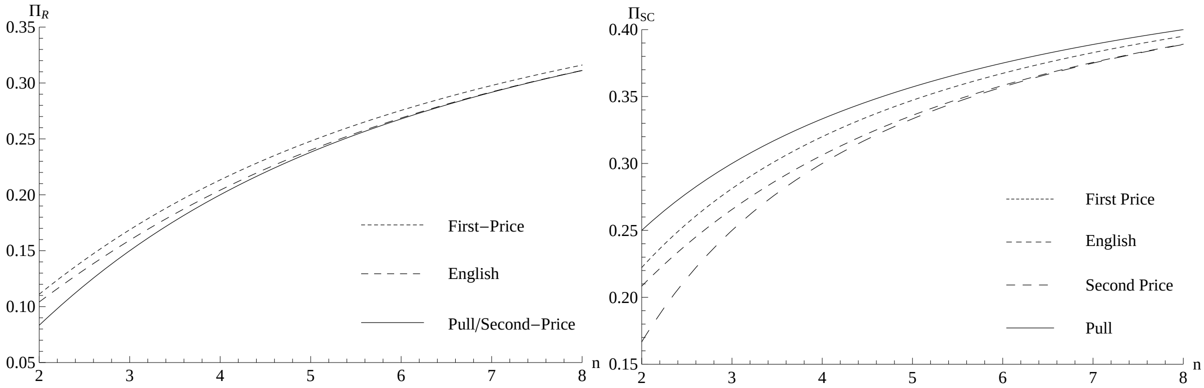
3.3.3 English auction

An open descending price-only auction (English auction) is proposed in Li and Scheller-Wolf (2011). Under our assumptions, the English auction will lead to the same results as a second-price auction for a pull contract. Therefore, we only analyze the English auction for a push contract. A dominant strategy for a supplier with cost c is to bid starting with the price that maximizes the profit if no other supplier exists, and then descend to the break-even price c. The ideal starting price under the above conditions is $\frac{1+c}{2}$. Then,

$$E(w^{e,Push}) = \frac{2-2^{-n}}{1+n}, E(\Pi_R^{e,Push}) = \frac{p}{2} - \frac{1+2n-2^{-(1+n)}n}{2+3n+n^2},$$
$$E(\Pi_{SC}^{e,Push}) = \frac{p}{2} - \frac{1-2^{-(1+n)}}{1+n}.$$

3.3.4 Comparing auction and contract formats

As $\Delta_R^{Pull} = E(\Pi_R^{f,Push}) - E(\Pi_R^{Pull}) = \frac{n}{2(n+1)^2(n+2)} > \Delta_R^e = E(\Pi_R^{f,Push}) - E(\Pi_R^{e,Push}) = \frac{2^{-(1+n)}(2^n-1-n)}{(n+1)^2(n+2)} > 0$, the retailer's profit in the first-price push auction is the highest of all considered auction formats for any number of bidders. For the supply chain profit, the pull contract dominates the push contract, $\Delta_{SC}^f = E(\Pi_{SC}^{Pull}) - E(\Pi_{SC}^{f,Push}) = \Delta_R^{Pull} < \Delta_{SC}^e = E(\Pi_{SC}^{Pull}) - E(\Pi_{SC}^{e,Push}) = \frac{1-2^{-(n+1)}(n+2)}{2+3n+n^2} < \Delta_{SC}^s = E(\Pi_{SC}^{Pull}) - E(\Pi_{SC}^{s,Push}) = \frac{1}{2+3n+n^2}$. Since for any realization of c, the wholesale price in the second-price push auction is not lower than the wholesale price in the English auction, the expected retailer and supply chain profits in the English auction are higher than in the second-price push auction. The retailer profits are therefore also higher than in the pull contract. Compared to the first-price push auction, the English auction leads to lower profits for the retailer and the supply chain. However, the gaps close with an increasing number of bidders. Since $\Delta_{SC}^f = \Delta_R^{Pull}$ if the product is purchased with a pull auction instead of a first-price push auction, the winning supplier gets exactly one half of the profit increase from the higher total supply chain profit and the other half from the reduced retailer profit.



(a) Retailer profits (b) Supply Chain profits

Figure 3.1: Auction formats, profits and number of bidders

Figure 3.1 illustrates an example with $p = 1$. Both retailer and supply chain profits increase in n, but with decreasing increments per extra supplier. The profits of the English auction are always between those of the first-price and the second-price push contract. The retailer's fractions of total supply chain profits under first-price auctions are

$$\frac{\Pi_R^{f,Push}}{\Pi_{SC}^{f,Push}} = \frac{n}{n+2}, \frac{\Pi_R^{Pull}}{\Pi_{SC}^{Pull}} = \frac{n-1}{n+1}, \Delta_\Pi = \frac{\Pi_R^{Push}}{\Pi_{SC}^{Push}} - \frac{\Pi_R^{Pull}}{\Pi_{SC}^{Pull}} = \frac{2}{(n+1)(n+2)}.$$

For the first-price push contract, the retailer's share increases from 50% for $n = 2$ to 100% for $n \to \infty$. For the pull contracts, the share is $\frac{1}{3}$ for $n = 2$ and approaches 100% under perfect competition. $\Delta_\Pi > 0 \ \forall\, n$ shows that supplier competition is higher under the first-price push contract than under a pull contract and even compensates the additional total supply chain profit under pull contracts from the retailer's perspective.

3.4 Numerical results

Although general results on the ranking of simple auction and contract formats were obtained and the closed-form expressions in the previous section allowed for further insights into the magnitude of certain effects, especially the distributional assumptions were rather restrictive. Therefore, we numerically provide further insights into the dependency of the results on the different parameter values: number of bidders, degree of demand uncertainty, degree of cost uncertainty, and the impact of risk-aversion. The effects are driven by competition, cost and demand uncertainty and result in price and quantity effects of different magnitudes. Similar to Chen (2007) and Li and Scheller-Wolf (2011), we assume that the suppliers' marginal costs are drawn from a uniform distribution and that demand follows a truncation of the normal distribution with mean μ and standard deviation σ. The base-set of parameters is $n = 2, 4$; $(\underline{c}, \overline{c}) = (1, 10), (3, 8)$; $p = z = 10$; $\mu = 10$; $\sigma = 2, 4, 6, 8, 10$. The two cost settings exhibit a mean preserving spread and the secondary procurement cost is set to the maximum reasonable value to exclude distortions of the results from further second sourcing benefits. The supplier profits (or utility) refer to the winning supplier.

3.4.1 Risk neutrality

The results for risk-neutral decision makers are summarized in Table 3.3. Let $\Delta_i = \frac{\Pi_i^{Push} - \Pi_i^{Pull}}{\Pi_i^{Push}} \cdot 100$, $i \in \{R, S, SC\}$ define the percentage difference between the first-price push and the pull contracts. Comparing the results with the optimal benchmark shown in the columns opt (see e.g. Chen, 2007), the optimal contract always leads to higher profits for the retailer, while the supply chain profit and the retailer profit are lower than in the simple auction formats. One reason is that under the optimal mechanism there is no trade if the lowest marginal cost among the suppliers is too high (since the optimal order quantity is given as $q(c) = \Phi^{-1}[c + \frac{F(c)}{f(c)}]$, there is no trade if $c \geq c_*$ with $z = c_* + \frac{F(c_*)}{f(c_*)}$). Competition under the optimal mechanism increases while supply chain efficiency decreases.

Table 3.3: Performance comparison

			Retailer Profit				Supplier Profit				Supply Chain Profit				α				
n	$(\underline{c}, \overline{c})$	σ	Opt.	push	pull	Δ_R	Opt.	push	pull	Δ_S	Opt.	push	pull	Δ_{SC}	Opt.	push	pull	$\frac{\Pi_R^{Push}}{\Pi_{SC}^{Push}}$	$\frac{\Pi_R^{Pull}}{\Pi_{SC}^{Pull}}$
2	(1,10)	2	32.85	25.76	24.41	5.3	13.37	25.47	29.08	-14.2	46.22	51.23	53.49	-4.4	0.67	0.86	0.93	0.50	0.46
		4	28.37	21.79	19.10	12.3	11.80	21.80	28.08	-28.8	40.17	43.59	47.19	-8.2	0.59	0.74	0.86	0.50	0.40
		6	25.04	19.01	15.51	18.4	10.58	19.09	26.82	-40.5	35.62	38.10	42.32	-11.1	0.53	0.65	0.81	0.50	0.37
		8	22.87	17.30	13.42	22.4	9.76	17.24	25.62	-48.6	32.63	34.54	39.03	-13.0	0.50	0.59	0.76	0.50	0.34
		10	21.43	16.19	12.15	25.0	9.20	15.99	24.64	-54.1	30.63	32.18	36.79	-14.3	0.47	0.55	0.73	0.50	0.33
	(3,8)	2	31.41	29.83	29.51	1.1	11.26	15.17	16.23	-7.0	42.68	45.00	45.74	-1.6	0.80	0.88	0.92	0.66	0.65
		4	25.51	23.34	22.65	3.0	9.51	13.72	15.73	-14.7	35.02	37.06	38.39	-3.6	0.69	0.77	0.85	0.63	0.59
		6	21.23	18.83	17.83	5.3	8.15	12.26	14.95	-22.0	29.38	31.09	32.78	-5.4	0.60	0.68	0.78	0.61	0.54
		8	18.58	16.19	15.00	7.3	7.24	11.05	14.10	-27.6	25.82	27.24	29.10	-6.8	0.54	0.61	0.73	0.59	0.52
		10	16.89	14.57	13.29	8.8	6.64	10.17	13.38	-31.6	23.53	24.75	26.68	-7.8	0.50	0.56	0.69	0.59	0.50
4	(1,10)	2	49.20	47.46	46.91	1.2	13.79	17.59	18.98	-7.9	62.99	65.05	65.90	-1.3	0.87	0.93	0.96	0.73	0.71
		4	43.47	41.18	40.06	2.7	12.95	17.26	19.89	-15.2	56.42	58.44	59.95	-2.6	0.80	0.86	0.92	0.70	0.67
		6	39.09	36.45	34.86	4.3	12.19	16.72	20.29	-21.4	51.25	53.17	55.16	-3.7	0.74	0.81	0.89	0.69	0.63
		8	36.09	33.34	31.45	5.7	11.57	16.09	20.28	-26.1	47.66	49.43	51.73	-4.6	0.70	0.76	0.86	0.67	0.61
		10	34.06	31.27	29.18	6.7	11.11	15.51	20.10	-29.5	45.16	46.78	49.28	-5.3	0.67	0.73	0.83	0.67	0.59
	(3,8)	2	42.77	42.44	42.28	0.4	9.00	9.76	10.17	-4.2	51.77	52.20	52.44	-0.5	0.90	0.92	0.94	0.81	0.81
		4	35.74	35.14	34.81	0.9	8.29	9.50	10.30	-8.4	44.03	44.64	45.11	-1.0	0.82	0.84	0.88	0.79	0.77
		6	30.44	29.67	29.19	1.6	7.59	9.07	10.18	-12.1	38.04	38.74	39.36	-1.6	0.75	0.77	0.83	0.77	0.74
		8	27.00	26.14	25.57	2.2	7.02	8.59	9.88	-15.1	34.02	34.72	35.45	-2.1	0.69	0.72	0.79	0.75	0.72
		10	24.75	23.85	23.23	2.6	6.58	8.16	9.57	-17.2	31.33	32.01	32.80	-2.4	0.65	0.68	0.75	0.75	0.71

Retailer Profit

The first-price push contract always leads to higher expected retailer profits than the pull contract, which confirms Conjecture 1. The gap Δ_R between the first-price push and the pull contracts increases if demand uncertainty increases, the spread of unit production cost increases, or the number of bidders decreases. If $n = 2$, the retailer's absolute profit decreases with the spread of production cost under the first-price push contract for small demand uncertainty and increases for high demand uncertainty. For $n = 2$, the expected cost of the second-lowest bidder increases in a mean preserving spread of production cost and thus the suppliers bid less aggressively with a higher spread. A second effect is that the suppliers bid more aggressively if the demand uncertainty is higher. The higher the spread of production cost, the more this effect influences the retailer's profit. Thus, for low demand uncertainty the retailer's profit decreases, whereas for a high demand uncertainty it increases in production cost uncertainty.

Supply Chain Profit and Profit Allocation

The pull contract maximizes the supply chain profits while the differences Δ_{SC} between pull and push become smaller in the number of bidders, but increase in demand uncertainty. The supply chain profits (stronger under push than under pull contracts) increase in the spread of production cost as this decreases the expected cost of the lowest bidder. Although expected supply chain profit and expected retailer profit decrease in demand uncertainty for the pull contract, the supplier's profit can increase because the cost of offering a pull contract for a given production cost c increases in demand uncertainty, which lowers supply competition. In Table 1, this effect only appears for $n = 4$ when supply competition is relatively high. For a push contract, the cost of supplying the product is equal to unit production cost and there is no such effect. Besides the obviously deteriorating effect of increasing demand uncertainty on absolute retailer and supply chain profits, increasing demand uncertainty decreases the retailer's share of total supply chain profit for both auction formats, which, however, is less pronounced for the first-price push contract. For the pull contract, lower competition for higher demand uncertainty drives this effect. For the push contract, this effect is caused by higher demand risk purely allocated to the retailer. Only for a high cost uncertainty and a low number of possible suppliers, this share does not decrease under a push contract, because the retailer's demand is highly sensitive to price changes and competition is relatively low. For an increasing number of bidders and a decreasing cost spread, the retailer's profit and its relative share of supply chain profits increases for both auction formats. Under the pull contract, the retailer's expected profit always decreases in the spread of production cost if $n = 2$, as the suppliers do not bid more aggressively when demand uncertainty is higher. For $n = 4$, the retailer's profit always increases in the spread of production cost, independent of the contract, as with a higher number of bidders the expected cost of the second lowest bidder decreases in the spread.

Define α as the share of the products procured from the supplier and $1 - \alpha$ as the share of the products procured (by the retailer or, under pull, by the supplier) from the outside option. The study shows that α is the highest under the pull contract, while it is the lowest under the optimal push contract (for the case that under the optimal push contract there is no trade between the retailer and the supplier, it is assumed that the retailer satisfies demand from the outside option). Not surprisingly, we can further observe that α increases in the number of bidders and decreases in demand uncertainty.

3.4.2 The risk-averse retailer

Under risk-aversion, additional effects arise from the possibility of allocating risks through the different auction and contract formats. In addition to the previous assumptions, we specify the utility function to be of the CARA-type, $u(k) = 1 - e^{-rk}$. Let $\Delta_r = \frac{H_R^{f,Pull} - H_R^{f,Push}}{H_R^{f,Push}} \cdot 100$. For our numerical study, we varied r on $[0, 0.1]$ and computed results for $n = 2, 4$; $(\underline{c}, \overline{c}) = (1, 10), (3, 8)$; $p = z = 10$; $\mu = 10$; $\sigma = 2, 4, 6$. We find similar patterns for different set-ups and thus summarize our findings. Since we know from Theorem 1 that the retailer always chooses a first-price auction, we will focus on that format. Figure 3.2 and 3.3 illustrate the results for the example of $(\underline{c}, \overline{c}) = (1, 10)$ and $n = 2$.

Retailer Utility

The results of our numerical study show that the push contract dominates the pull contract for low risk-aversion, but a retailer with high risk-aversion prefers the pull contract (see Figure 3.2). For sufficiently large risk-aversion, we face a win-win situation: the retailer and the winning supplier both prefer the first-price pull contract. A lower cost spread further promotes the pull contract because a lower spread lowers the possible informational rent for both strategies and the retailer prefers to shift the demand risk to the supplier.

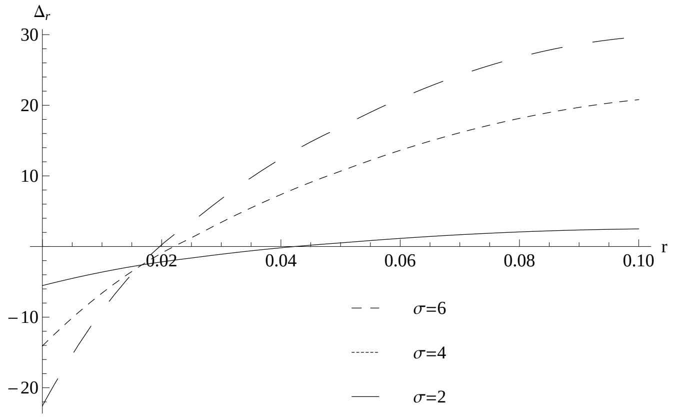
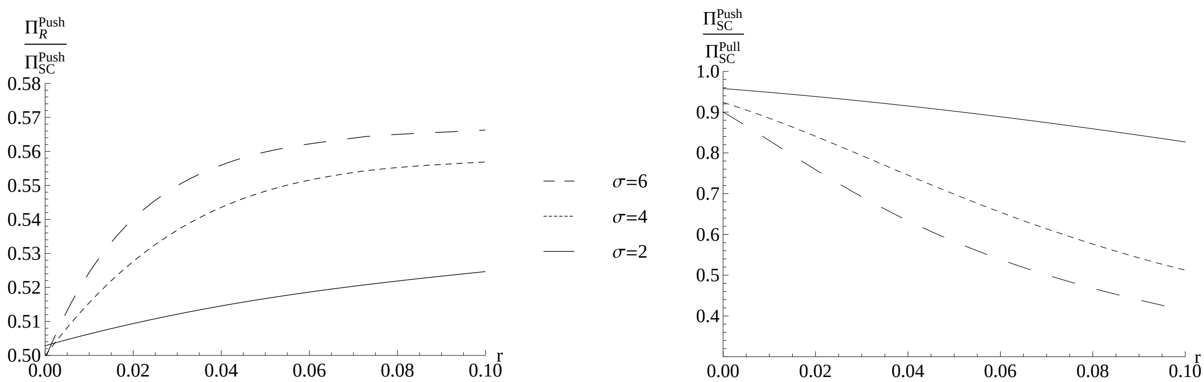


Figure 3.2: Ratio of push and pull contracts for a risk-averse retailer

Supply Chain Profit and Profit Allocation



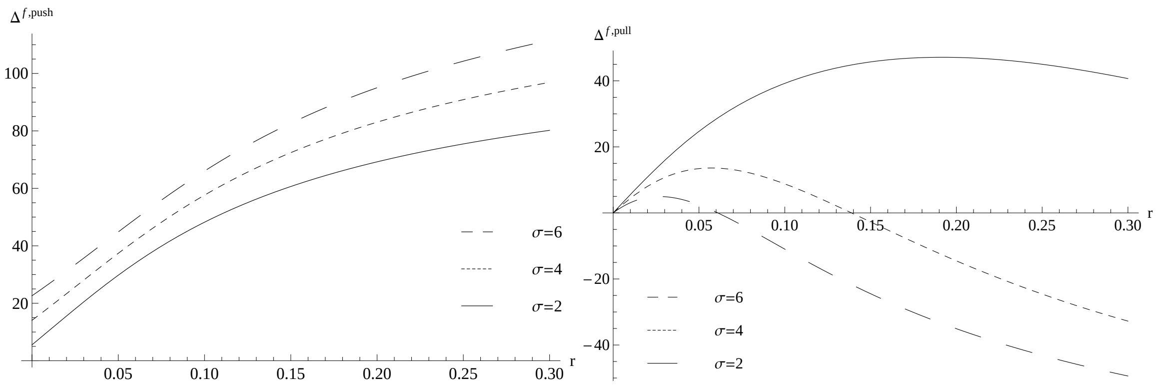
(a) Retailer Share (b) Supply Chain Efficiency

Figure 3.3: First-price push auction with the risk-averse retailer

Under the first-price push contract, the retailer's share of the supply chain profit increases in risk-aversion while the supply chain efficiency decreases due to the lower order quantity of the retailer (see Figure 3.3, where the supply chain profit of a coordinating pull contract under risk neutrality is taken as the benchmark for efficiency). Under the pull auctions, the retailer orders realized demand and the profit and its allocation are not affected by risk-aversion.

3.4.3 Risk-averse suppliers

In order to show how the choice of the contract format influences the profits and their allocation, we again compare the first-price push and the first-price pull auction. Using the same CARA-utility function for all suppliers with r on $[0, 0.3]$, we will again summarize our findings.



(a) First-price push contract

(b) First-price pull contract

Figure 3.4: Relative retailer profit with risk-averse suppliers

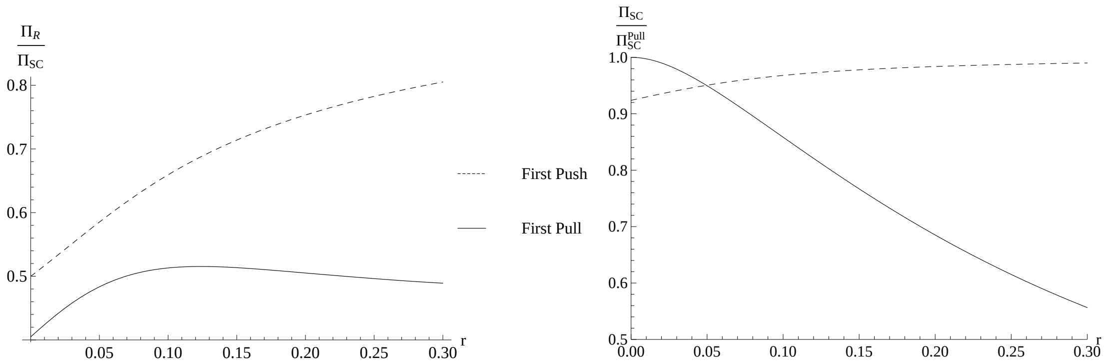
Retailer Profit

Defining $\Delta^{i,j} = \frac{H^{i,j} - H^{s,Push}}{H^{s,Push}} \cdot 100$, Figure 3.4 shows how the retailer profit develops under the suppliers' risk-aversion (with $(\underline{c}, \overline{c}) = (1, 10)$ and $n = 2$). Since the retailer profit under the second-price push auction does not change with the suppliers' risk-aversion, this is taken as the reference value. The first-price push contract is the dominant choice for the retailer and the second-price pull is the least preferred contract. The first-price push contract takes maximum advantage of the suppliers' risk-aversion and the retailer's expected profit increases with increasing supplier risk-aversion (see Figure 3.4a). Furthermore, while under risk neutrality we observe that for a low number of bidders the retailer's profit decreases in the spread of production cost for low demand uncertainty and increases for high demand uncertainty, this effect disappears if risk aversion increases. Thus, for high risk aversion, the retailer's profit increases in the spread of production cost even for a lower demand uncertainty. The reason is that risk aversion leads to a more aggressive bidding on the supplier's side, which has a stronger effect if the spread of production cost is higher.

For the first-price pull contract, we can observe that for low risk-aversion the effect of aggressive bidding dominates the effect of higher cost of supplying the product (see Section 3.2.2 for further explanation). If the risk-aversion is high, this result changes and the retailer profit decreases in the risk-aversion of the suppliers (see also Figure 3.4b). The study further showed that higher demand uncertainty enforces these effects, while a higher number of bidders leads to an earlier decrease of $\Delta^{f,pull}$. The reason is that the competition increases in n, which reduces the effect of aggressive bidding under risk aversion and thus the effect of higher cost becomes more dominant.

Supply Chain Profit and Profit Allocation

For the push auction, one can observe that supplier risk-aversion has a coordinating effect and the supply chain profit increases with the suppliers' risk-aversion because the suppliers bid more aggressively. Suppliers are willing to give up some profit in order to reduce the risk of not winning the auction and consequently not making any profit at all.



(a) Retailer Share

(b) Supply Chain Efficiency

Figure 3.5: Supply chain profit and allocation for the risk-averse supplier

This effect changes the allocation of profits and the retailer gets a higher share of the total supply chain profit. While supply chain efficiency under the push contract increases in the suppliers' risk-aversion, it decreases under the pull contract. This is because under the pull contract a risk-neutral supplier maximizes the supply chain profit, whereas risk-aversion leads to an inefficient production quantity.

Consider now the retailer's share of the total supply chain profit under the pull format. There are several effects that influence the profit allocation. Risk-aversion leads to more aggressive bidding and the supplier further follows a less risky capacity strategy and gives up some expected profit to reduce demand risk. These effects lead to an increase of the retailer's share. On the other hand, a risk-averse supplier needs a higher compensation to take over the demand risk. Thus, if this effect dominates, the retailer's share of the supply chain decreases. We can now observe that the retailer's share first increases, but decreases again if risk-aversion is strong (see also Figure 3.5, where the supply chain profit of the pull contract under risk neutrality is again taken as the benchmark).

3.5 Conclusion

The analysis provides clear preferences between push and pull contracts and proves that a risk-neutral retailer should source via a push contract in a reverse auction. One benefit of the push contract presented is its simplicity. The retailer does not have to set up a price-quantity scheme (see e.g. Chen, 2007; Duenyas et al., 2013) and the order quantity follows the well-known newsvendor model. The retailer chooses the first-price sealed-bid auction rather than a second-price sealed-bid auction in order to minimize the procurement price. If we consider a social planner who maximizes the total supply chain profit, the pull contract is preferred as it leads to supply chain efficiency and the auction format does not matter. Therefore, under pull contracts first-price and second-price sealed-bid auctions lead to the same profits as does an open bidding format like the English auction. Sourcing through a push contract and using a first-price sealed-bid auction leads to an aggressive bidding. This is enabled by introducing a flexible auction where the retailer can decide about the order quantity after the wholesale price has been determined.

Compared to other papers that propose pull contracts leading to an inefficient low production volume (see e.g. Li and Scheller-Wolf, 2011), we provide new insights on the efficiency of those contracts. We show that only the supplier can benefit from such an efficient pull contract, whereas the retailer profit is maximized under a push contract. For both push and pull contracts we show that retailer and total supply chain profit increases in the number of suppliers participating at the auction. Consequently, more competition on the supply side increases efficiency and further lowers the difference between auction designs.

For a risk-averse retailer, the push auction is no longer always preferred. A retailer with a high risk-aversion prefers the first-price pull contract avoiding demand risk. With risk-averse suppliers, a risk-neutral retailer prefers first-price to second-price pull contracts, but the preferences towards first-price pull and second-price push are not unique anymore.

Chapter 4

Optimal capacity provision for service providers with subsequent auctioning of projects

In this chapter repeated sourcing events with suppliers that have limited capacities are studied. Sealed-bid reverse auctions are used to select the providers. A service provider that wins an auction has to allocate some capacity to that project for a certain duration. If all capacities are utilized, a provider is unable to participate in upcoming auctions until a project is finished. The decision problem is for every service provider to determine the optimal bidding strategy for a given capacity level and to set up the optimal capacity. Our research shows that in repeated auctions, it is optimal for a provider to submit higher bids than in a single, non-repeated auction. In addition, we investigate how production times and the interarrival time of auctions influence the bidding behavior. Our findings show that the bidding service providers' profits do not always increase with a higher capacity level. By studying a capacity game of two service providers, we show the potential existence of a prisoner's dilemma, which occurs when both providers increase capacity, even though they would have been better off with both having a lower capacity level. Finally, our results show a first mover advantage when capacity decisions are sequential rather than simultaneous.

4.1 Model analysis

We split the service providers' problem into a strategic capacity decision and an operational part of bidding. Both decisions depend on each other. Therefore, we first study how capacity restrictions influence the bidding behavior and then analyze the problem of capacity decision (see e.g. Schneeweiss, 1998).

Consider an auction where n service providers compete through a first-price sealed-bid auction to win a contract for a project. For the general model and its insights it does not yet matter if n is known. Nevertheless, we will later discuss both cases with a known and with an unknown number of providers. Each service provider submits a sealed-bid of b, the lowest bid wins and the winner sells the service to the buyer for the auctioned price. Provider i's marginal cost c_i of carrying out the project is private knowledge and c_i is constant over the time horizon. Beliefs about competitors' marginal costs are distributed according to $F(c)$, with density $f(c)$ and is continuous over $[\underline{c}, \overline{c}]$. Without loss of generality, we assume that the buyer's reservation price is $\overline{c}$, thus he does not accept bids over the highest possible production cost. This assumption ensures that for cases where service providers assume to be the only participating company, they do not set an infinite bid.

We assume a market with an exogenously given set of auctioneers who offer contracts for sale. Since these companies do not coordinate their procurement activities, requests to participate in auctions arrive randomly with an exponentially distributed interarrival time with mean λ. If a provider wins the auction, it takes an exponentially distributed length of time with mean ρ to finish the project. Ex ante, ρ is the same for all providers. The maximum capacity of every service provider is K. Thus, he is unable to work on more than K projects at a time. We define states i with free capacity level of i units. The allowable set of actions in state i is to submit a bid $b(c)_i \in [0, \overline{c}]$. If the provider wins an auction, he moves from i to $i-1$, receives the payment of $b(c)_i$, and the cost of c to carry out the project occurs. If the provider looses the auction, he stays in state i and no payment or cost occurs. Whenever he finishes a project, one capacity level is set free again and he moves from i to $i+1$. If there is a request to participate in an auction, the provider can only submit a bid if there is free capacity ($i \geq 1$). While K is known, we assume the actual state of a service provider to be private information.

We assume that service providers do not actively incorporate learning about the competitors' cost into their decisions. This is of course a limiting assumption, but supported by the belief that costs of competitors might change over time. This allows us to study the auction as a Markovian, and thus memoryless process. We suggest further research on this topic and also refer to the wide body of literature covering this aspect (see Section 2.5). This enables us to focus on the expected average profit per time unit over the infinite time horizon. For an example of a discounted sequential (forward) auction, see e.g Said (2011). In Section 4.4.3, we further discuss an extension of production cost, which are a random for each new project.

4.1.1 General model

The described optimization problem is analyzed as a continuous time Markov decision process with an infinite horizon. In equilibrium $P(b(c)_i)$ is the probability that the submitted bid is the lowest bid of all service providers if the provider is in state i and has cost c (see Figure 4.1).

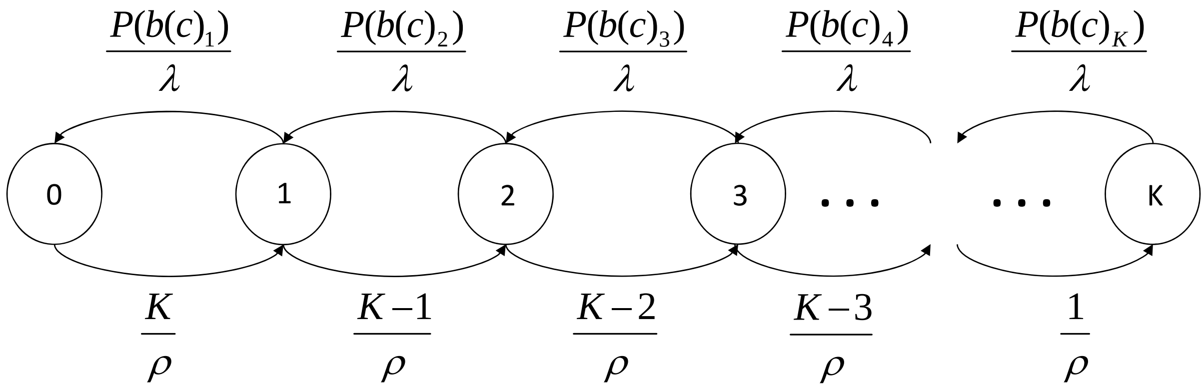


Figure 4.1: Markov chain of capacity states

$P(b(c)_i)$ is therefore the probability to win an auction and depends on the state as well as on the cost. This defines the transition rates $t(i|i-1, b(c)_i)$ and $t(i|i+1, b(c)_i)$. If the service provider is in state $i \geq 1$, the transition rate to move to state $i-1$ by winning an arriving auction is $t(i|i-1, b(c)_i) = \frac{P(b(c)_i)}{\lambda}$. The probability that production of a previously won auction terminates, and thus the transition rate from i to $i+1$, is $t(i|i+1, b(c)_i) = \frac{K-i}{\rho}$. Whenever the provider moves from i to $i-1$, he receives a reward of $b(c)_i - c$. Define p_i as the long-term fraction of time a service provider is in state i. The steady-state probabilities are given by the following system of linear equations:

$$p_{i-1} \cdot \frac{K-(i-1)}{\rho} + p_{i+1} \cdot \frac{P(b(c)_{i+1})}{\lambda} = p_i \cdot \left(\frac{P(b(c)_i)}{\lambda} + \frac{K-i}{\rho} \right) \forall i \neq 0, K$$
$$p_{K-1} \cdot \frac{1}{\rho} = p_K \cdot \frac{P(b(c)_K)}{\lambda}, p_0 \cdot \frac{K}{\rho} = p_1 \cdot \frac{P(b(c)_1)}{\lambda}, \sum_{i=0}^{K} p_i = 1 \tag{33}$$

Solving this set of linear equations (33) gives the steady state probabilities:

$$p_i = \frac{\left(\prod_{a=i+1}^{K} P(b(c)_a) \right) \lambda^i \cdot \rho^{K-i} \cdot \frac{K!}{(K-i)!}}{\sum_{j=0}^{K} \left(\prod_{a=j+1}^{K} P(b(c)_a) \right) \lambda^j \cdot \rho^{K-j} \cdot \frac{K!}{(K-j)!}} \tag{34}$$

The objective is to maximize expected average profit per time unit $E(\Pi)$ by setting a bidding strategy $b(c)_i$ for every state $i = 1, .., K$.

$$E(\Pi) = \max_{b(c)_i \in [0, \bar{c}]} \sum_{i=1}^{K} (b(c)_i - c) \cdot p_i \cdot \frac{1}{\lambda} \cdot P(b(c)_i) \tag{35}$$

The service provider wants to maximize the expected profit in each state by choosing the optimal bid. In equilibrium, the bids are therefore defined by the following set of non-linear differential equations:

$$\frac{dE(\Pi)}{db(c)_i} = 0, \quad i = 1, .., K \tag{36}$$

As those equations cannot be solved to a closed expression, we derive general properties of the bids in repeated auctions. We therefore define b_{nr} as the bid in the non-repeated auction and get:

Theorem 3. $b(c)_{nr} < b(c)_i < b(c)_{i-1}$

Consequently, the higher the level of free capacity units, the lower the bid and the bids will always be higher than a bid in a non-repeated auction.

While we provide the proof for this theorem in the appendix, the reason for this effect can be explained as follows: If a service provider facing an auction has only one unit of capacity left, he knows that if he wins the auction, he will not be able to participate in auctions that arrive while working on full capacity. Thus, this factor needs to be considered as an opportunity cost and a higher bid than without limited capacity will be submitted. If, for example, a service provider has two free capacities, he already takes into account that winning an auction and moving to state 1 increases the probability of working under full capacity in the future. Therefore, the submitted bid in state 2 is also above the bid in the non-repeated game. Nevertheless, since the provider first moves from state 2 to state 1 where he is still participating in arriving auctions, the increase of the bid in state 2 is not as high as in state 1. The same holds for all other states. The bid decreases with a higher capacity as it gets closer to the bid in a non-repeated auction.

4.1.2 The special case

Assume that the maximum capacity is $K = 1$. The expected average profit per unit of time is:

$$E(\Pi) = \frac{(b(c) - c) \cdot P(b(c))}{\lambda + P(b(c)) \cdot \rho} \tag{37}$$

In most auctions it is assumed that the number of competing bidders is common knowledge. However, it is more likely that the bidder might not know how many other service providers compete. Possible competing providers might enter or exit the market or they may not have free capacity to participate in an arriving auction.

Define $\eta = 1, 2, ..., N$ as the set of potential providers and let $n \subseteq \eta$ be the set of actual providers participating in the arriving auction and having free capacity. Assume that the number of participating providers is uncertain, but that the probability of a certain number of providers participating in the auction is common knowledge. Further, assume that all providers hold the same beliefs about the likelihood of meeting different numbers of rivals. These beliefs do not depend on the type (cost, amount of free capacity) of the provider (see also Krishna, 2010). All potential providers draw their values independently from the same distribution, where $\omega(i)$ denotes the probability that $n = i$.

From Harstad et al. (1990), we know that in the first-price auction the unique symmetric equilibrium bidding function with a random number of bidders is:

$$b(c) = \sum_{n=1}^{N} \omega(n) b_n(c) \tag{38}$$

where $b_n(c)$ is the bid if the number of bidders is n. The optimal bid is thus the average of the bids for a known number of n participants, weighted with the probability that the actual number of bidders is n. To derive the optimal bid, it is sufficient to know what the bid for a given number of providers looks like.

Theorem 4. *For a maximum capacity of $K = 1$ and a given number n of service providers, the optimal bid $b(c)$ is:*

$$b(c) = c + \frac{(\frac{\lambda}{\rho} + (1 - F(c))^{n-1}) \cdot \int_c^{\overline{c}} \frac{(1-F(z))^{n-1}}{\frac{\lambda}{\rho}+(1-F(z))^{n-1}} dz}{(1 - F(c))^{n-1}} \tag{39}$$

The optimal bid depends only on the ratio of ρ and λ, and thus on the relation of the service time and the average time between two auctions. As long as $\frac{\rho}{\lambda}$ is the same, ceteris paribus, the optimal bid is also the same. For comparison, the bid in the non-repeated auction (see Holt, 1980 and Cohen and Loeb, 1990) is:

$$b(c) = c + \frac{\int_c^{\overline{c}} (1 - F(z))^{n-1} dz}{(1 - F(c))^{n-1}} \tag{40}$$

Comparing Theorem 4 with Equation (40) reveals that the bid in the repeated auction will always be higher than in the non-repeated auction, since $\frac{\lambda}{\rho} + (1 - F(c))^{n-1} > \frac{\lambda}{\rho} + (1 - F(z))^{n-1} \forall z > c$. Service providers submit consistently higher bids in a repeated first-price auction than in a non-repeated first-price auction (see Theorem 3). Hence, the expected price in a repeated first-price auction is higher than the expected price in a single auction. The optimal bid increases in cost and in service time ρ and decreases in the interarrival time λ. Thus the opportunity costs of winning the auction (compared to the possibility to win a later auction with a higher bid) increase and as a result the bid increases. If there is a longer time period between two auctions, the provider will miss fewer auctions while working on a won project.

Combining Theorem 4 and Equation (38), we obtain the optimal bidding function for an unknown number of service providers:

$$b(c) = c + \frac{(\lambda + G(c) \cdot \rho) \cdot \int_c^{\bar{c}} \frac{G(z)}{\lambda + G(z) \cdot \rho} dz}{G(c)}, \; \textit{with } G(c) = \sum_{n=1}^{N} \omega(n)(1 - F(c))^{n-1} \tag{41}$$

4.2 Capacity expansion problem

While so far we assumed the capacity level to be externally given and to be the same for all service providers, we now study the optimal choice of the capacity level. In order to do this, we analyse under what conditions a company should invest in capacity and under what conditions it should not. For simplicity, we assume $N = 2$ service providers and a choice between a capacity of 1 or 2. Each company starts with a basic capacity of one unit and has the choice to increase its capacity level to two units. Having an extra capacity available will cause a fix cost of k per time period. The fix cost for the first capacity unit is considered to be sunk. For simplicity, we assume that the service providers learn their final cost c after capacity is set up and that the capacity decision is observable. Even though we assume the general effects of capacity expansion to be similar, knowing about cost before setting up capacities will have some impact on the service provider's decision. Since service providers with low costs will have a higher incentive to invest in capacity because they will have a higher utility rate of their capacity, setting up capacity could therefore be a signal of having lower costs and will therefore influence the opponents' bidding behaviour. We suggest further research on this topic. We define $E(\Pi)^{i,j} = \max_{b(c)_k \in [0,\bar{c}]} \sum_{k=1}^{K} (b(c)_k - c) \cdot p_k \cdot \frac{1}{\lambda} \cdot P(b(c)_k^{i,j})$ as a service provider's expected profit if he sets up a capacity of i and his competitor sets up a capacity of j, where $P(b(c)_k^{i,j}$ is the probability to win an auction by submitting a bit of $b(c)_k$ (see Figure 4.2).

		Player B	
		K=1	K=2
Player A	K=1	$E(\Pi)^{1,1}$, $E(\Pi)^{1,1}$	$E(\Pi)^{1,2}$, $E(\Pi)^{2,1}$
	K=2	$E(\Pi)^{2,1}$, $E(\Pi)^{1,2}$	$E(\Pi)^{2,2}$, $E(\Pi)^{2,2}$

Figure 4.2: Payoff matrix

Due to higher competition and without having the option to compensate this with a higher capacity, it always holds that $E(\Pi)^{1,1} > E(\Pi)^{1,2}$. A provider who invested in extra capacity always bids lower prices than a provider who did not invest. This also holds if he already has one capacity in use. The reason is that if a service provider with $K = 2$ is in state 1 and were about to win an auction, he does not stay in state 0 as long and misses less auctions than a winning provider with $K = 1$, since the probability of leaving state 0 is $\frac{K}{\rho}$ and increases in the installed capacity. Therefore, since he misses less auctions in state 0 if K is higher, the opportunity cost of winning decreases in K and as a result the bid decreases too. For a similar reason, it always holds that $E(\Pi)^{2,1} > E(\Pi)^{2,2}$.

In a capacity expansion problem with $N = 2$ service providers and capacity options of $K = 1 \vee K = 2$, possible equilibria can be categorized in four partitions. In partition I setting up an extra capacity does not pay off, even if the competitor does not expand his capacity to $K = 2$ ($E(\Pi)^{1,1} > E(\Pi)^{2,1}$). As a result, none of the providers expand their capacities. In partition II expanding from $K = 1$ to $K = 2$ only increases profits if the competitor did not already set up a second capacity unit. Thus, in partition II $E(\Pi)^{1,1} < E(\Pi)^{2,1}$, but $E(\Pi)^{1,2} > E(\Pi)^{2,2}$. Partition III defines the so-called prisoner's dilemma. In this case, both service providers have an incentive to invest in capacity since $E(\Pi)^{1,1} < E(\Pi)^{2,1}$ and $E(\Pi)^{1,2} < E(\Pi)^{2,2}$. But if both invest, they increase competition and are both worse off ($E(\Pi)^{1,1} > E(\Pi)^{2,2}$). The well-known dilemma is that even though they know that they are both worse off if they both invest, individual incentives will always lead to investment. In partition IV the providers always have an incentive to invest ($E(\Pi)^{1,1} < E(\Pi)^{2,1}$ and $E(\Pi)^{1,2} < E(\Pi)^{2,2}$), but in contrast to partition III, the investment pays off ($E(\Pi)^{1,1} < E(\Pi)^{2,2}$). The four partitions are summarized in Table 4.1. We later show how the partitions $I - IV$ depend on specific investment costs, the interarrival time and the service time.

Table 4.1: Partitions

Part.	Condition	Result
I	$E(\Pi)^{1,1} > E(\Pi)^{2,1}$	No company expands
II	$E(\Pi)^{1,1} < E(\Pi)^{2,1} \wedge E(\Pi)^{1,2} > E(\Pi)^{2,2}$	One company expands
III	$E(\Pi)^{1,1} < E(\Pi)^{2,1} \wedge E(\Pi)^{1,2} < E(\Pi)^{2,2} \wedge E(\Pi)^{1,1} > E(\Pi)^{2,2}$	Prisoner's dilemma
IV	$E(\Pi)^{1,1} < E(\Pi)^{2,1} \wedge E(\Pi)^{1,2} < E(\Pi)^{2,2} \wedge E(\Pi)^{1,1} < E(\Pi)^{2,2}$	Both profits increase

The structure of the partitions shows that if one company is able to signal a capacity investment early (or if capacities are observable and are determined sequentially), it might have a first mover advantage. This is the case in partition II. If the early mover signals that he invests, the follower will not invest anymore, and the early mover is able to increase profits. This can also be analyzed as a capacity investment similar to Belleflamme and Peitz (2010) in their chapter on strategic incumbents and entry. Since in this case the investment in higher capacity leads to lower opportunity costs, because the probability to work on full capacity decreases, the effect is the same as investing in capacity that reduces the cost. In both cases, the bids decrease, which makes it harder for the incumbents to make enough profits to pay off the investments.

On the other hand, if it is not possible to deter the competitor from building up capacity or if capacity decisions are made simultaneously, service providers should look for strategic collusion to avoid ending up in in the prisoner's dilemma. Since service providers face a repeated game for an infinite horizon, it would be possible to set up other equilibria with punishing strategies. It would, for example, be possible to avoid the prisoner's dilemma by setting up a Tit for Tat strategy. If one provider decides to deviate from the agreement to stay with one capacity unit, the other will follow and from then on, both will compete with two capacity units and achieve lower average profits.

4.3 Numerical results

4.3.1 Expected bids and profits for different capacity levels

Assume the cost to be uniformly distributed on $[\underline{c}, \overline{c}]$: $[1, 10], [3, 8]$, and a maximum capacity of K units with a total number of $N = 5$ or 2 service providers. $E[b]$ denotes the expected price per auction and thus gives the expected procurement cost of a company sourcing a service via a repeated auction. $E(\Pi)$ denotes the expected average profit (per time unit) of a service provider. We vary λ and ρ fixed at 1. To show the influence of a λ, we vary it on a range of $[1/20, 5]$ for $N = 5$ and $[\underline{c}, \overline{c}] = [1, 10]$. Since the effect is similar for other set-ups, we only consider $\lambda = 1/2, 1, 2$ when varying the other parameters, which keeps the number of variations low. In the non-capacitated case ($K \to \infty$), service providers face several single auctions, since winning an auction today does not influence the capacity level for the future.

Table 4.2: Numerical example

$[\underline{c}, \overline{c}]$	N	λ	K	$E[b]$	$E(\Pi)$	K	$E[b]$	$E(\Pi)$	% in State i				K	$E[b]$	$E(\Pi)$	% in State i	
									0	1	2	3				0	1
[1, 10]	5	1/20	∞	4.0	6.0	3	6.54	5.01	38.5	21.2	17.6	22.8	1	9.86	4.13	94.8	5.2
		1/2		4.0	0.6		4.32	0.57	2.0	6.5	16.3	75.2		7.84	1.45	48.5	51.5
		2/3		4.0	0.4		4.27	0.44	1.2	4.7	14.6	79.5		7.32	1.06	38.1	61.9
		1		4.0	0.3		4.25	0.30	0.5	2.8	12.0	84.6		6.56	0.64	25.4	74.6
		3/2		4.0	0.2		4.24	0.20	0.2	1.5	9.4	88.8		5.88	0.37	16.3	83.7
		2		4.0	0.15		4.24	0.15	0.1	1.0	7.7	91.3		5.46	0.25	11.8	88.2
		5		4.0	0.06		4.24	0.06	0.0	0.2	3.6	96.2		4.61	0.08	4.3	95.7
	2	1/2		7.0	3.0		7.64	2.71	6.2	17.1	32.0	44.7		9.42	2.48	62.3	37.7
		1		7.0	1.5		7.59	1.46	1.7	8.0	26.7	63.6		8.96	1.58	42.5	57.5
		2		7.0	0.75		7.58	0.75	0.3	2.9	18.1	78.7		8.43	0.86	24.6	75.4
[3, 8]	5	1/2		4.67	0.33		4.83	0.32	2.0	6.5	16.3	75.2		6.80	0.80	48.5	51.5
		1		4.67	0.17		4.80	0.16	0.5	2.8	12.0	84.6		6.09	0.36	25.4	74.6
		2		4.67	0.08		4.80	0.08	0.1	1.0	7.7	91.3		5.48	0.14	11.8	88.2
	2	1/2		6.33	1.67		6.54	1.51	6.2	17.1	32.0	44.7		7.68	1.38	62.3	37.7
		1		6.33	0.83		6.51	0.81	1.7	8.0	26.7	63.6		7.42	0.88	42.5	57.5
		2		6.33	0.42		6.50	0.41	0.3	2.9	18.1	78.7		7.13	0.48	24.6	75.4

Table 4.2 summarizes the results. A first effect the numerical study shows is the influence λ/ρ on the service providers' profits and the expected procurement cost of the sourcing company. If λ decreases, this has two effects on the retailer profit: A direct effect of more auctions arriving and therefore being able to win more auctions per time unit, and an indirect effect, since as there are more requests to participate at auctions, more capacity is in use and therefore, competition decreases and prices increase. Both effects lead to a higher profit of the service provider, while the second effect leads to higher procurement cost for the sourcing company, too.

The study further shows how bids and profits change with the number of participating service providers. A decrease in the number of providers leads to higher procurement prices, higher profits for the providers and a higher utilization rate of capacities. This effect is more pronounced if K is lower. Because a lower number of providers has two effects: A direct effect of less competition due to a lower number of providers, and an indirect effect through a higher utilization rate and a higher number of bidders that might operate under full capacity utilization, which also reduces competition. Both effects lead to higher bids.

Another issue is the influence of the variance in possible service cost on bids and profits. To study this issue, we vary the spread of possible production cost by keeping the expected cost the same. When doing so, we observe the standard outcome for procurement auctions. For a low number of service providers a lower spread ($[\underline{c}, \overline{c}] : [3, 8]$) leads to lower procurement cost, while for a high number of providers a lower spread increases the expected procurement cost. Concerning the providers' profits, a lower spread always leads to a decrease in profits, since a lower spread increases competition. For a high spread in cost, a service provider is able to achieve a higher mark-up on his actual cost, which is no longer the case if the costs differ only slightly among the providers.

The numerical results further provide insight on the influence of the capacity on bids and profits. The results show that if the capacity decreases the bids increase but the providers' expected profits do not necessarily increase. We observe that for the game with low capacity ($K = 1$), when λ is not too small, the expected profits decrease with a higher capacity (increase to $K = 3$). In contrast, if capacity is already high ($K = 3$), a further increase in capacity also leads to a higher average profit. If capacity is equal to one, providers who win the auction always leave the bidding process while they are working under full capacity. This leads to a lower competition for the remaining providers, as there are less service providers competing for the contract. Thus, it is possible to increase the bids such that the bid increase in comparison to the un-capacitated case overcompensates, so that the winner of the auction cannot participate for some time. However, this observation only holds for relatively high interarrival times between the auctions. If there are many auctions arriving, the service provider would be better off with a higher capacity, even if all other providers have a higher capacity. There is a reservation price for the highest bid, where the maximum bid is $\overline{c}$. Consequently, if he misses too many auctions during production, he cannot compensate this with a bid if $\overline{c}$ too low. If capacity is higher, this is no longer the case. Competition is higher, since the average number of providers participating in the auction is higher. Therefore, a provider who has only one free capacity left cannot raise the bid to the same extent as he could if all the other providers also had low capacity. And as a result, he is not able to compensate missed auctions while running on full capacity and thus his average profits are lower. It would therefore be beneficial to have a higher capacity, even if all other providers have a higher capacity. Then, the probability not to participate in an auction will decrease. Thus, setting up more capacity has two effects. On the one hand it decreases competition and therefore lowers the prices, which decreases the service providers' profits. On the other hand it enables the service providers to participate at more auctions, an effect that increases profits. It now depends on other parameters, such as the service time, the time between two auctions or the number of service providers, if a higher capacity increases or decreases the service providers's profits.

4.3.2 Capacity expansion

Assume the ex-ante expectation for the cost to be uniformly distributed on $(\underline{c}, \overline{c}) = (1, 10)$ and $\rho = 1$. Figure 4.3 shows how the Nash equilibrium depends on the investment cost k and $\frac{\rho}{\lambda}$.

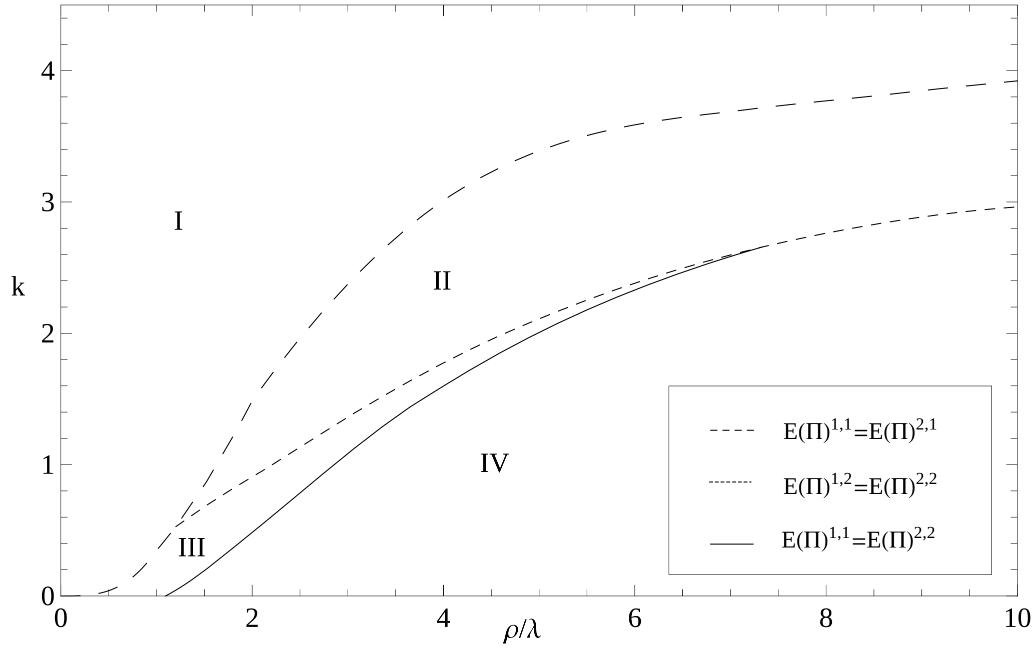


Figure 4.3: Capacity expansion

The figure is divided into the four partitions $I-IV$ defined in Section 4.2. The thresholds $E(\Pi)^{1,1}=E(\Pi)^{2,1}$,$E(\Pi)^{1,2}=E(\Pi)^{2,2}$ and $E(\Pi)^{1,1}=E(\Pi)^{2,2}$ directly follow from the definitions of the partitions (see Table 4.1). The study shows that if the costs are high or $\frac{\rho}{\lambda}$ is small, no provider invests in additional capacity. If now the frequence of auctions arriving increases ($\frac{\rho}{\lambda}$ increases), the outcome switches, while the result further depends on the investment cost. If k is relatively high, such that $E(\Pi)^{1,2}>E(\Pi)^{2,2}$, only one provider invests in capacity (Partition II). In this case the investing service provider is able to increase his profit, while the profit of the other provider decreases. If k is lower than this threshold, both providers will build up an extra capacity unit. Depending on $\frac{\rho}{\lambda}$ (whether it is higher than the threshold where $E(\Pi)^{1,1}=E(\Pi)^{2,2}$, or lower), the equilibrium will be in partition III or IV. In partition III, both providers invest in capacity, but they are worse off than in partition I. The study shows that this case can also occur if building up capacity does not cause any extra cost. In partition IV, both providers invest and are better off. The cost-thresholds increase in $\frac{\rho}{\lambda}$, thus the more auctions one might miss while working on a project, the more attractive it becomes to invest in capacity.

Thus, the study shows that a lower investment cost for capacity does not always lead to a higher profit for a provider. In Partition III, one or even both providers might be better off if the investment cost were higher and less capacity were built up (depending on whether higher investment cost would lead to Partition II or I). A higher capacity level leads to higher competition, and a higher competition leads to lower prices. In Partition III this overcompensates the benefits of being able to participate in more auctions when investing in capacity.

4.4 Extensions

So far we made restrictive assumptions concerning e.g. the auction design, the development of cost over time, or information concerning the competitors state. Therefore, we now study how results change, if e.g. auctions are conducted via a second-price auction, or if the state of a service provider is observable by the competitors.

4.4.1 Second-price auctions

The expected average profit in the second-price auction is:

$$E(\Pi) = \sum_{i=1}^{K} \left(\int_{b(c)_i}^{\bar{c}} (b - c) \cdot \phi(b) db \right) \cdot p_i \cdot \frac{1}{\lambda} \tag{42}$$

where b is the lowest bid submitted by the $n - 1$ remaining providers and $\phi(x)$ denotes its probability density function aggregated over all possible states. As in the first-price auction, the service provider wants to maximize $E(\pi_i)$ at each state by choosing the optimal bid. In the first-price auction, the provider has a direct influence on the resulting price in case of winning while in the second-price auction, it depends on the bids submitted by the competitors. While in the standard non-repeated auction, it is optimal to submit a bid equal to cost, this does not hold for the repeated auction. The provider now has to take into account how he might miss auctions if he works on full capacity. Therefore, the provider should submit a bid that is higher than his own costs. An asymmetric game is e.g. the game described in Section 4.2, where service providers set up different capacities and thus are, for the subsequent bidding game, no longer symmetric. In a symmetric game, K is the same for all providers. Ex-ante symmetry also holds if K differs from one provider to another, but K is private information and not observable by other providers. If then each provider holds the same beliefs in their competitors' capacity levels, the bidding game is still symmetric.

Theorem 5. *For the symmetric repeated auction with capacity constraints, the revenue equivalence theorem holds.*

Since the revenue equivalence theorem holds, the provider is indifferent between the two auction formats and the auctioneer will face the same expected cost, independent of the auction format. However, revenue equivalence only holds for the symmetric game. If the game is asymmetric, first- and second-price auctions lead to different revenues. For a study on the differences of investment incentives between first- and second-price auctions, we refer to Arozamena and Cantillon (2004). Even though they study investment incentives in cost reduction for a single non-repeated auction, their insights are transferable to our set-up, where we interpret investment in a higher capacity level as a reduction of opportunity cost.

As mentioned, the capacity expansion in Section 4.2 leads to an asymmetric game. Thus, first- and second-price auctions lead to different results. However, the general insight derived from the first-price auction still holds for the second-price auction. The general effects of an investment and its influences on the participants' profits are the same. Nevertheless, there are two differences in the outcome between the first- and the second-price auction. One the one hand, we know from Proposition 3 in Arozamena and Cantillon (2004) that if capacity decisions are sequential, rather then simultaneous, in the second-price auction the incentive to invest for the first mover is higher in comparison to the first-price auction. On the other hand, Arozamena and Cantillon (2004) and Maskin and Riley (2000) suggest that for a given but asymmetric capacity level, the first-price auction may lead to a lower expected cost than the second-price auction. We can confirm this with numerical examples.

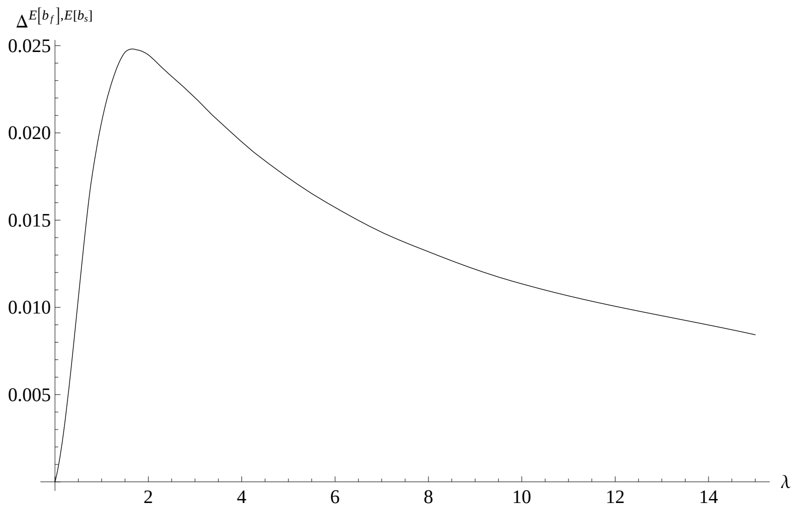


Figure 4.4: Difference in the expected procurement cost

For illustration, we compare first- and second-price auctions in Figure 4.4 (the set-up is the same as in Section 4.3.2). Define for the asymmetric case where the first mover sets $K = 2$ and the follower sets $K = 1$, $\Delta^{E[b_f],E[b_s]}$ as $\frac{E[b_s]-E[b_f]}{E[b_f]}$ with $E[b_f]$and $E[b_s]$ as the expected procurement cost in the first- and second-price auctions. Since for $\lambda = 0$ (requests to participate at an auction auction arrive constantly) the bid is $b[c] = \overline{c}$ in both auctions. For $\lambda \to \infty$ bids in both auctions approach the single, non-repeated auction, where the revenue equivalence theorem holds again. As a result the gap for $\lambda = 0$ and $\lambda \to \infty$ is zero. For all other values, we can observe that the first-price auction leads to a lower expected cost than the second-price auction. This leads to an interesting result. If investment costs have a value where the leader in the second-price auction would invest in capacity, while under the first-price auction he would not, the second-price auction leads to a lower expected cost. On the other hand, if in both cases the first mover were to invest, while the follower would not (*Partition II* in Figure 4.3), the first-price auction leads to a lower expected cost.

The reason for the different outcomes of the auction formats is that under the first-price auction, the follower reacts to both the higher capacity level and the more aggressive bidding of the leader by lowering his bids. Under the second-price auction, the followers do not adapt their bids (only indirectly over their lower opportunity cost) and thus the bidding behavior is less aggressive under the second-price auction, leading to a higher procurement cost. This higher cost also leads to increased profits for the service provider, which is the reason why the investment incentive is higher under the second-price auction.

If both providers invest, the revenue equivalence theorem holds again.

4.4.2 Observable states

In Section 4.1.2 we assumed that the available capacity states are not observable, thus service providers do not know how many competitors can actually participate in an upcoming auction. We now study how, for a basic example, the results change if we assume that states are observable. To be able to derive closed form solutions, we assume the number of service providers on the market to be $N = 2$ and the capacity level to be $K = 1$. We then get a two-dimensional Markov chain with four states.

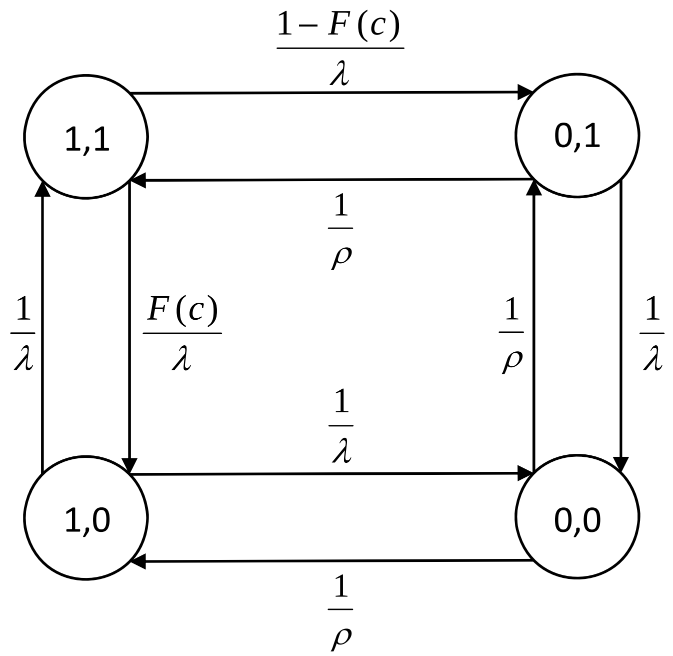


Figure 4.5: Markov chain for two service providers (from the provider's view)

In state $(0,0)$, both providers are working on a project and have no available capacity. In state $(1,0)$ and $(0,1)$, one of the providers is working while the other provider has available capacity. In state $(1,1)$, both providers have available capacity and can participate in the auction.

In equilibrium it must hold that for a provider with cost c and free capacity, the probability to win is $1 - F(c)$ if his competitor has available capacity. If the other provider has no available capacity, the probability of winning an upcoming auction is 1 while the optimal bid is $b(c)_{1,0} = \bar{c}$. The equilibrium state probability equations for a provider with cost of c are given by the following system of linear equations where (i,j) denotes the available capacity i of the provider, j of his competitor and $p_{i,j}$ denotes the probability for this state (see Figure 4.5 for the Markov Chain).

$$2 \cdot p_{0,0} \cdot \frac{1}{\rho} = (p_{0,1} + p_{1,0}) \cdot \frac{1}{\lambda}$$

$$p_{1,0} \cdot (\frac{1}{\lambda} + \frac{1}{\rho}) = p_{0,0} \cdot \frac{1}{\rho} + \cdot p_{1,1} \cdot \frac{1}{\lambda} \cdot F(c)$$

$$
\begin{aligned}
p_{0,1} \cdot (\frac{1}{\lambda} + \frac{1}{\rho}) = p_{0,0} \cdot \frac{1}{\rho} + \cdot p_{1,1} \cdot \frac{1}{\lambda} \cdot (1 - F(c)) \\
p_{1,1} \cdot \frac{1}{\lambda} = (p_{0,1} + p_{1,0}) \cdot \frac{1}{\rho} \\
p_{0,0} + p_{1,0} + p_{0,1} + p_{1,1} = 1
\end{aligned} \tag{43}
$$

Which leads to the following probabilities:

$$
\begin{aligned}
p_{0,0} = \frac{\rho^2}{2\lambda^2 + 2\lambda\rho + \rho^2}, p_{1,0} = \frac{\lambda\rho(\rho + 2\lambda F(c))}{2\lambda^3 + 4\lambda^2\rho + 3\lambda\rho^2 + \rho^3}, \\
p_{0,1} = \frac{\lambda\rho(2\lambda(1 - F(c)) + \rho)}{2\lambda^3 + 4\lambda^2\rho + 3\lambda\rho^2 + \rho^3}, p_{1,1} = \frac{2\lambda^2}{2\lambda^2 + 2\lambda\rho + \rho^2}
\end{aligned} \tag{44}
$$

This leads to the expected profit of:

$$
E[\Pi(c)] = \frac{2\lambda(\lambda + \rho)(b(c)_{1,1} - c)(1 - F(c)) + (\bar{c} - c)\rho(\rho + 2\lambda F(c))}{(\lambda + \rho)\left(2\lambda^2 + 2\lambda\rho + \rho^2\right)} \tag{45}
$$

As for Theorem 4, we can derive the equilibrium bid for state $(1, 1)$ and get:

$$
b(c)_{1,1} = c + \frac{\int_c^{\bar{c}}(1 - F(z))\, dz}{1 - F(c)} + \frac{\rho\left(\int_c^{\bar{c}}(F(z))\, dz - (\bar{c} - c)(F(c))\right)}{(\lambda + \rho)(1 - F(c))} \tag{46}
$$

since $\int_c^{\bar{c}} F(z)\, dz > (\bar{c} - c)F(c) \forall c < \bar{c}$, one can see that also for observable capacities, providers submit higher bids than in the non-capacitated case. We can rearrange to:

$$
b(c)_{1,1} = c + \frac{\lambda \int_c^{\bar{c}}(1 - F(z))\, dz}{(\lambda + \rho)(1 - F(c))} + \frac{\rho\,(\bar{c} - c)}{(\lambda + \rho)} \tag{47}
$$

an expression that helps us to compare the outcome of a model with observable states with a model with unobservable states. Since in both cases the optimal bid in state $(1, 0)$ (no competitor) is to submit $b(c) = \bar{c}$, it is sufficient to compare the model with observable states to the one with unobservable states for the case that there are two providers with one free capacity (state (1,1)). Consider (41) from Section 4.1.2, for a given number of $n = 2$ providers and thus $G(c) = 1 - F(c)$. Now, since $(\lambda + \rho) \int_c^{\bar{c}} \frac{1-F(z)}{\lambda+\rho(1-F(z))} dz < \int_c^{\bar{c}} 1 - F(z) dz\ \forall c > \underline{c}$ and further $\int_c^{\bar{c}} 1 - F(z) dz < \bar{c} - c$, one can see that (41) < (47), thus providers in the auction with observable states submit higher bids than the ones where states are not observable.

This is due to the assumption that, in the model with observable states, winning or losing an auction has an influence on the expected capacity level of the remaining providers, whereas in the unobservable model, losing or winning an auction is assumed to just influence the provider's capacity level while not having any influence on the provider's beliefs about the competitor's capacity. Thus, if the provider takes the influence of winning an auction on the capacity level of the competitor into consideration, he submits higher bids, since if he loses the auction, there is a high chance that he will not face any competition during the next auction. Consequently, he can submit a bid $b[c] = \overline{c}$ and will win with certainty.

4.4.3 Randomly varying production cost

We have assumed that service costs do not change over the time horizon. Since this might be a critical assumption, we now analyze the outcome under the assumption that service providers' production costs change from one project to the next. Assume service providers only know their production cost for an occurring auction, while they do not know their cost for future auctions with certainty. Further, assume that the costs for different projects are independent, thus learning the cost for one project has no impact on the beliefs about the cost for future projects. Service providers' beliefs about their future marginal costs are distributed according to $F(c)$ with density $f(c)$. Beliefs about a competitor's current and future marginal costs are also distributed according to $F(c)$. Consider the case with $K = 1$ and n providers. For simplification, assume that n is known and constant over the time horizon (the equilibrium for an unknown number of providers can be derived in the same manner as in Section 4.1.2).

The expected average profit per time unit if costs are random over time ($E(\Pi)^{rand}$) now depends on the expected future cost, where in equilibrium the probability to win is $(1 - F(c))^{n-1}$.

$$E(\Pi)^{rand} = \int_{\underline{c}}^{\overline{c}} \frac{(b(c) - c) \cdot (1 - F(c))^{n-1}}{\lambda + (1 - F(c))^{n-1} \cdot \rho} f(c)dc \tag{48}$$

A service provider who wins an auction produces for an average time of ρ and - on average - misses a potential income of $\rho \cdot E(\Pi)^{rand}$. Since this expression does not depend on the current cost, it is the same for all service providers. Therefore, a current auction can be simplified to a standard single auction with procurement cost c and common opportunity cost $\rho \cdot E(\Pi)^{rand}$. This leads to the optimal bidding function (see Holt, 1980 and Cohen and Loeb, 1990):

$$b(c)^{rand} = c + \frac{\int_c^{\overline{c}} (1 - F(z))^{n-1} dz}{(1 - F(c))^{n-1}} + \rho \cdot E(\Pi)^{rand} \tag{49}$$

Inserting this expression in (48) leads to:

$$E(\Pi)^{rand} = \int_{\underline{c}}^{\overline{c}} \frac{\frac{\int_c^{\overline{c}}(1-F(z))^{n-1}dz}{(1-F(c))^{n-1}} \cdot (1 - F(c))^{n-1}}{\lambda + \rho(1 - F(c))^{n-1}} f(c)dc +$$

$$\int_{\underline{c}}^{\overline{c}} \frac{E(\Pi)^{rand} \cdot \rho(1-F(c))^{n-1}}{\lambda + \rho(1-F(c))^{n-1}} f(c)dc \tag{50}$$

and for the expected average profit we get:

$$E(\Pi)^{rand} = \frac{\frac{1}{\rho}\int_{\underline{c}}^{\overline{c}} \frac{\int_{c}^{\overline{c}}(1-F(z))^{n-1}dz}{\frac{\lambda}{\rho}+(1-F(c))^{n-1}} f(c)dc}{1-\int_{\underline{c}}^{\overline{c}} \frac{(1-F(c))^{n-1}}{\frac{\lambda}{\rho}+(1-F(c))^{n-1}} f(c)dc} \tag{51}$$

In contrast to the model with constant cost over time, a service provider with production cost $\overline{c}$ submits a bid that is higher than his cost. While in the constant cost model a provider with $c = \overline{c}$ has opportunity cost of zero, because he will never win an auction, this is not the case if production costs vary over time. A provider with a current cost of $\overline{c}$ might have lower cost in the future and therefore be able to win an auction. As shown above, the opportunity cost does not depend on current cost and therefore, even for cost of $\overline{c}$, the bid is higher than the pure service cost. Figure 4.6 compares the bid for constant cost $(b(c)^{const})$ with the bid for changing marginal cost for the example of $n = 3$ providers, where $\Delta^{rand} = b(c)^{rand} - b(c)^{const}$ $[\underline{c}, \overline{c}] : [1, 10]$ and $\lambda = \rho = 1$.

While for high cost the example shows that the model with random cost leads to higher bids, it shows that, for low cost, the bid with a random cost over time is lower than the bid with a constant cost. This is because the opportunity cost for the random cost case does not depend on the realization of the actual cost, while they increase for the case of constant cost over time. Thus, for a relatively low production cost, opportunity costs in the constant cost model are higher than in the random cost model. This shows that when participating at an auction, managers of service providers have to take the characteristics of their future costs into consideration when submitting a bid. In case of randomly varying production cost, they should bid aggressively if current costs are low, but less aggressively if costs are high. In that case it might be beneficial to not win the current auction and to wait for lower cost in the future.

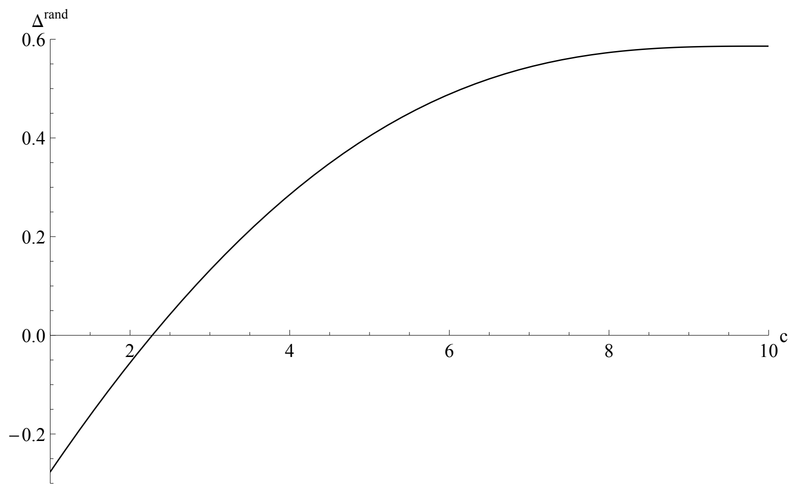


Figure 4.6: Bids: Constant vs. randomly varying production cost

4.5 Conclusion

We derive the general equilibrium conditions for repeated first-price sealed-bid auctions with capacity constraints. The analysis shows that repeated auctions always cause higher expected prices than single auctions. We show that only the ratio of the production time and the expected time between two auctions, rather than their absolute values, influences bidding behavior, where a long production time or a high frequency of auctions leads to higher bids. The analysis further shows that the providers' profit does not always increase with a higher capacity level. While it might be beneficial to invest in capacity if interarrival times between auctions are relatively short, it does not always pay off to invest if interarrival times are long. By studying a capacity game where two service providers have the option to set up either one or two capacity units, we show that a prisoner's dilemma could occur such that both providers invest in increasing their capacity, even though they are worse off than with having just one capacity unit. If a service provider is able to signal a capacity investment early, we can detect cases where this provider would have a first-mover advantage by deterring others from building up capacity, as well. For observable capacities, we discuss that it is also possible to avoid the prisoner's dilemma by having agreements on the capacity levels with the competitors and following a Tit for Tat strategy if one company deviates from the agreement.

As a result, this chapter provides valuable managerial insight for service providers. It supports capacity planners by showing how capacities influence profits and how their optimal level is driven by the amount and the duration of projects. This work further shows managers how signaling capacity early or strategic interaction with competitors can increase a company's profits. Our results also help to understand the value of capacity in the service sector and how it influences competitive bidding. A comparison of first- and second-price auctions supports procurement managers in choosing the right auction format for their purchasing activities.

Chapter 5

The impact of economies of scale on bidding for logistics services

This chapter investigates successive procurement situations for transportation and logistic services with economies of scale. Two services are auctioned via second-price sealed-bid auctions. In the case that a service provider wins both auctions, economies of scale appear which cannot be realized if contracts are assigned to two different providers. We compare sequential and bundle auctions to show under which conditions it is beneficial to either procure the services separated from each other or to bundle the services in one auction event. We apply this set-up to actual problems of the procurement of logistics services including vendor managed inventory and supply contracts under demand uncertainty. Our findings show the decision for or against bundling has a huge impact on expected procurement cost. When the number of competing service providers is low, bundling is the right choice in order to minimize procurement cost, while under high competition, a sequential auction should be choosen. Our results further show that economies of scale reduce the differences in expected cost between bundling and sequential selling.

5.1 The auction model

We consider a supply chain with a dominant retailer and several competing providers of logistic services. The retailer wants to procure two contracts. Due to e.g. different lead times or because requirements for different parts of a new product are specified at different times, we assume that the contracts need to be acquired in two successive periods. Service providers privately observe their cost at the beginning of each period (the second period costs are not known in the first period). A number of $n \geq 2$ ex ante symmetric service providers compete for the right to provide their service for one or both of the contracts through contract-bidding. Service provider i's marginal cost in period j is c_j^i and of private knowledge. Beliefs about competitor's marginal costs c are distributed according to $F_j(c)$ with density $f_j(c) > 0$ continuous over $[\underline{c_j}, \overline{c_j}]$. The competitor's belief about his second period cost c_2 also follows the distribution $F_2(x)$ while he privately learns his cost at the beginning of period 2. As a result, bids submitted in the bundle or in the first period of the sequential auction only depend on c_1, which allows for the determination of unique solutions. Each auction involves a business volume of d_1

or d_2. When winning the auction the service provider's total cost function is given by $C_{d_1+d_2}(c_1, c_2)$, which is assumed to be concave in the total business volume. Examples for such concave cost functions are given in Section 5.2. For simplification define the cases $C_{d_1+0}(c_1, c_2)$ and $C_{0+d_2}(c_1, c_2)$, thus whenever only one service is supplied as $C_{d_1}(c_1)$ and $C_{d_2}(c_2)$. Further define $E[C_{bundle}]$ and $E[C_{seq}]$ as the expected procurement cost in the bundle and sequential auction.

5.1.1 Equilibrium bid in the sequential auction

We first study the optimal bidding behavior in the sequential auction. We consider an auction with two bidding events, where the service providers submit their bids in a second-price sealed-bid auction. Since this problem has a finite horizon, we can solve the game via backward induction. We know from Vickrey (1961) that in the second period it is a (weakly) dominant strategy for the service providers to bid their true cost that occurs with this last auction. The optimal bidding strategy now depends on the marginal cost c_i as well as on the outcome of the auction in the first period. If the provider won the auction in the first period the optimal strategy is to bid

$$b^{won}(c_1, c_2) = C_{d_1+d_2}(c_1, c_2) - C_{d_1}(c_1) \tag{52}$$

where C_j is the cost that occurs if a contract with volume of j is supplied. If the provider did not win the first auction his optimal bid is

$$b^{lost}(c_2) = C_{d_2}(c_2), \tag{53}$$

thus exactly the cost that occurs when just providing the second contract with volume d_2 to the retailer. Consider now the expected prices and profits that occur in the second period. If the service provider won the first auction, his expected profit for the second auction is given as:

$$E(\Pi(c_1, c_2))^{won} = \int_{b^{won}(c_1,c_2)}^{b^{lost}(\overline{c_2})} (X - (C_{d_1+d_2}(c_1, c_2) + C_{d_1}(c_1))) f_{C_2}^{I,r(win)}(X)dX \tag{54}$$

where $f_C^{I,r(win)}(x)$ denotes the density function of the lowest cost service provider of the remaining service providers for having total cost of $C_{d_2}(c_2) = x$. If the provider did not win the first auction, his expected profit on the other hand will be

$$E(\Pi(c_1, c_2))^{lost} = \int_{b^{lost}(c_2)}^{b^{lost}(\overline{c_2})} (X - C_{d_2}(c_2)) f_{C_2}^{I,r(lost)}(X)dX \tag{55}$$

where $f_{C_2}^{I,r(lost)}(X)$ denotes the density function the lowest cost provider of the remaining service providers to supply the second service, including the providers who won the first auction, where the total costs X are given as $C_{d_2}(c_2)$ for those who lost and $C_{d_1+d_2}(c_1, c_2) - C_{d_1}(c_1)$ for the one who won the first auction.

Comparing both profits we can observe several effects. First, winning the first contract leads to a lower cost of providing the second service (since $C(d)$ is concave in d, $(C(d_1 + d_2) - C(d_1) < C(d_2))$. Thus, for a given retail-price the profits in the second auction are higher, if the service provider wins the first contract, compared to not winning the first contract. Secondly, the probability to win the the second contract increases if the service provider already wins the first contract. There are two effects that influence this: First of all, the provider's costs are lower. Thus, he can submit a lower bid. And second, competition is lower than in the case where another provider would have won the first auction. This also leads to a third effect. For a given low-bid, the expected resulting price is higher, if the winning bid is submitted by the provider who won the first auction than if it would be the bid of one of the other providers. Thus, the expected profit margin, in case of winning, is higher for the provider who won the first auction.

We further define $E(P_2)$ as the expected procurement cost for the second period:

$$E(P_2) = \int_{\underline{c_1}}^{\overline{c_1}} \left(\int_{b^{won}(c_1,\underline{c_2})}^{b^{lost}(\overline{c_2})} (x) f_{C_2}^{II}(x) dx \right) f_1^I(c_1) dc_1 \tag{56}$$

where $f_{C_2}^{II}(X)$ denotes the density function the provider with the second lowest cost X of supplying the second service, including the service provider who won the first auction and $f_1^I(c_1) = n(1 - F_1(x))^{n-1} f_1(c_1)$, is the density function of the lowest marginal cost c_1 for the first period.

We now consider the first period bidding problem. In the first period the service provider is not only confronted with his cost of supplying the good, but also with the effect that winning or not winning the first auction will have on the expected profit in the second period. Now, the optimal strategy is to bid at his cost minus the effect winning has on the expected profit in the second auction: $b(c_1) = C(d_1) - (E(\Pi(c_1, c_2))^{won} - E(\Pi(c_1, c_2))^{lost})$. Since the costs for the second period are not known yet, this expression changes to (see also Grimm, 2007):

$$b(c_1) = C_{d_1}(c_1) - \int_{\underline{c_2}}^{\overline{c_2}} (E(\Pi(c_1, x))^{won} - E(\Pi(c_1, x))^{lost}) f(x) dx \tag{57}$$

Which leads to expected procurement cost for the first service of:

$$E(P_1) = \int_{\underline{c_1}}^{\overline{c_1}} \left(C_{d_1}(c_1) - \int_{\underline{c_2}}^{\overline{c_2}} (E(\Pi(C_1, x))^{won} - E(\Pi(C_1, x))^{lost}) f_2(x) dx \right) f_1^{II}(c_1) dc_1 \tag{58}$$

with $f_1^{II}(x) = n(n-1)F_1(x)(1 - F_1(x))^{n-2} f_1(x)$, as the density function of the second lowest marginal cost. Equation (56) and (58) further give an expression for $E[C_{seq}]$:

$$E[C_{seq}] = E(P_1) + E(P_2) \tag{59}$$

5.1.2 Equilibrium bid in the bundle auction

We now consider the optimal bid in the bundle auction. In the bundle auction, the providers submit their bids for both services at the same time in a second-price sealed-bid auction. At the moment of submitting the bids, the service provider does not know the cost for the second service yet. Thus, his optimal bid is

$$b(c_1) = \int_{\underline{c}}^{\overline{c}} C_{d_1+d_2}(c_1, x) f_2(x) dx \tag{60}$$

which leads to expected procurement cost of:

$$E[C_{bundle}] = \int_{\underline{c_1}}^{\overline{c_1}} \left(\int_{\underline{c}}^{\overline{c}} C_{d_1+d_2}(c_1, x) f_2(x) dx \right) f_1^{II}(c_1) dc_1 \tag{61}$$

While we study here the bundled buying of the two services, one could alternatively consider buying both services in a separated, but simultaneous auction. But since at that point the service providers do not know their cost for the second service, the outcome for such a separated auction would be the same as for the bundle auction. The reason is that all providers have ex ante the same beliefs about their cost c_2 while winning the auction leads to economies of scale. In any possible equilibrium, the providers bid at expected cost and since $\frac{\partial E(C_{d_1+d_2}(c_1,c_2))}{\partial c_i} > 0, i = 1,2$ and $E[c_2]$ is the same for all service providers, the provider with the lowest c_1 has to win both auctions. Any auction where the provider with the lowest c_1 does not win the contract for both services cannot be a Nash equilibrium. One possible equilibrium that fullfills the requirements of the Nash equilibrium would be to always bid $b_2 = E(C_{d_2}(c_2)) + \epsilon \cdot c_1$ and to bid $b_1 = E(C_{d_1+d_2}(c_1, c_2) - C_{d_2}(c_2)) - \epsilon \cdot c_1$, where adding and subtracting $\epsilon \cdot c_1$ makes sure that in the second period, the provider with the lowest c_1 always wins the contract, where ϵ refers to a very small number. Alternatively, one could conduct the auction with the rule that in case of a tie of bids for one service, the contract is allocated to the provider who has submitted the lowest bid for the other contract. Following this rule, there is no incentive to e.g. submit a higher or a lower bid. Submitting e.g. a higher bid for b_2 and a lower one for b_1 would never increase, but could decrease profits if all other service providers follow the described bidding strategy. In that case, it could be that the service provider wins the contract for the first service, but that he might not win the contract for the second service. It then can happen that he has to provide the first service for less than his cost and thus will make a loss. There is an unlimited amount of possible combinations for equilibrium contracts, but the outcome is always the same and the expected cost for the procurer are always: $\int_{\underline{c_1}}^{\overline{c_1}} \left(\int_{\underline{c}}^{\overline{c}} C_{d_1+d_2}(c_1, x) f_2(x) dx \right) f_1^{II}(c_1) dc_1$, thus the same as in the bundle auction.

5.1.3 Sequential vs. bundled procurement

Denote $X_1 = C_{d_1+d_2} - C_{d_1}$ as the extra cost of supplying the second contract for the service provider who won the first contract (the incumbent), and $X_{\neq 1} = C_{d_2}$ as the cost for the provider who did not win the first contract (the contestant). Then $X^{-1}_{(j)}$ and $X^{-C}_{(j)}$ denote the jth order statistics of all random variables in X except for X_1, (the incumbent's cost) and respectively, X_C, one representative contestant's cost. It then holds that:

Theorem 6. *If $E[X_1 - X^{-1}_{(2)}; X^{-1}_{(2)} \leq X_1] > E[X^{-C}_{(1)} - X_C; X_C \leq X^{-C}_{(1)}]$, then $E[C_{bundle}] > E[C_{seq}]$ and vice versa.*

It further follows from the bidding functions that if there are no economies of scale the bundling contract leads to lower procurement cost, if $E[X] < E[X_{(2)}]$. Thus the buyer prefers to bundle the auctions if the expected cost in the second stage are lower than the expected cost of the service provider with the second lowest cost in the second stage. Since $E[X]$ does not change in n while $E[X_{(2)}]$ decreases in n, this leads to the result that the sequential auction is preferred, if the number of providers is high enough, while for a low number of providers the bundling is preferred, which is a generally known result for the comparison of bundled and not bundled auctions (see e.g. Chakraborty, 1999).

Theorem 7. *If $X_1(c, \overline{c_2}) \leq X_{\neq 1}(\underline{c_2})\ \forall\ c \in [\underline{c_1}, \overline{c_1}]$, then $E[C_{bundle}] = E[C_{seq}]$.*

Thus, the bundle and the sequential auction lead to the same expected procurement cost, whenever the economies of scale are so high, such that in the sequential auction the winner of the first auction will always win the second auction, even for the case that the winner realizes $c_2 = \overline{c_2}$ while one of the competitors realizes $c_2 = \underline{c_2}$.

Corolary 2. *If Theorem 7 is not fulfilled, it holds that*

(i) If $n = 2$, then $E[X_1 - X^{-1}_{(2)}; X^{-1}_{(2)} \leq X_1] = 0$ and $E[X^{-C}_{(1)} - X_C; X_C \leq X^{-C}_{(1)}] > 0$.

(ii) If $n \to \infty$, then $E[X_1 - X^{-1}_{(2)}; X^{-1}_{(2)} \leq X_1] < E[X^{-C}_{(1)} - X_C; X_C \leq X^{-C}_{(1)}]$.

Corollary 2 states that if $n = 2$, bundling leads to lower procurement cost than the sequential auction, while the opposite holds for $n \to \infty$. Thus, if $n > 2$, it now depends (besides on n) on the cost structure and cost distribution, whether the bundle or sequential auction should be preferred.

5.1.4 The optimal sequential auction

To define a benchmark for the performance of the sequential and bundle auction studied above, we now derive the expected total procurement cost of the optimal sequential auction. Stage one and stage two allocation rules are denoted by $\theta^1_j(q)$ and $\theta^2_j(q)$ with $j = I$ for the incumbent and $j = C$ for the contestant. It is assumed that the auctioneer has to commit to a set of rules prior to period one and cannot modify those rules after the first period (see also Grimm, 2007).

Definition 4. *Define the virtual cost $\psi(x_j)$ of the two service provider types in the second of the sequential auctions as follows:*

$$\begin{aligned} \psi_(x_I) &= x_I \quad \textit{for the incumbent} \\ \psi_(x_C) = x_C &+ \frac{n}{n-1}\frac{F_{2,C,t}(x_C)}{f_{2,C,t}(x_C)} \quad \textit{for the contestant} \end{aligned} \tag{62}$$

where further $F_{1,t}(C(x))$, $F_{2,I,t}(C(x))$ and $F_{2,C,t}(C(x))$ with density $f_j(C(x))$ denote the distribution of the total cost $C(x)$, which can easily be derived from the cost distribution of the marginal cost $F(x)$ using the given cost structure $C(x)$ as defined above. This leads to:

Theorem 8.

(i) The procurement cost of the sequential auction are minimized if the auction in the first period follows a simple first- or second-price auction, while the contract in the second period is allocated to the service provider with the lowest virtual cost $\psi_C(x_i)$ as defined in Definition 4. This service provider is paid the highest cost he could have had, such that his virtual cost were still the lowest.

(ii) In the cost minimizing, incentive compatible procurement mechanism where service providers participate voluntarily at each stage, expected procurement cost is given by:

$$\begin{aligned} E(P_1) = &\int_{C_{d1}(\underline{c_1})}^{C_{d1}(\overline{c_1})} \left(C_{d1}(x) + \frac{F_{1,t}(C_{d1}(x))}{f_{1,t}(C_{d1}(x))}\right) n(1-F_{1,t}(C_{d1}(x)))^{n-1} f_{1,t}(C_{d1}(x)) dC_{d1}(x) \\ &+ \int_{\underline{c_1}}^{\overline{c_1}} \int_{C_{d1+d2}(c_1,\underline{c_2})-C_{d1}(c_1)}^{C_{d1+d2}(c_1,\overline{c_2})-C_{d1}(c_1)} (C_{d1+d2}(c_1,x) - C_{d1}(c_1))\, \theta_I^2(x) f_{2,I,t}(C_{d1+d2}(c_1,x) - C_{d1}(c_1)) dx \\ &+ \int_{C_{d2}(\underline{c_2})}^{C_{d2}(\overline{c_2})} \left((n-1)\left(C_{d2}(x) + \frac{n}{n-1}\frac{F_{2,C,t}(C_{d2}(x))}{f_{2,C,t}(C_{d2}(x))}\right)\theta_C^2(x)\right) f_{2,C,t}(C_2(x)) dx f_{I:n}(c_1) dc_1 \end{aligned} \tag{63}$$

Theorem 8 shows that the optimal strategy favors the incumbent. By doing so, the auctioneer makes winning the first contract more valuable, and thus the difference between the incumbent's and the contestants' expected profits for the second period increases. The definition of the incumbent's virtual cost also shows that it is crucial for the optimal sequential auction, that the auctioneer has to commit to the announced allocation scheme. If the rule is not binding for the second period, the auctioneer would prefer to implement another allocation rule (following a regular first- or second-price auction), because this would minimize the expected procurement cost in the second period. The benefit of committing to the payment scheme in Theorem 8 is in increasing the value of winning by increasing the expected profit of the winner in the second period and decreasing the profit of the loser. As a result, the service provider bids more aggressively in the first period. In the optimum the allocation rule balances out the marginal decrease of the first period procurement cost with the marginal increase of the second period procurement cost (see also Jofre-Bonet and Pesendorfer, 2006). The difference between the real and the virtual cost is $\frac{n}{n-1}\frac{F_{2,C,t}(x_C)}{f_{2,C,t}(x_C)}$ thus $\frac{n}{n-1}$ times the information rent of a standard procurement auction.

5.2 The supply chain

Especially in logistics cost functions are often driven by economies of scale. In many cases providers of logistic services are able to decrease cost when the can combine two or more contracts. Two examples for drivers of such economies of scale are depot and portfolio effects (see e.g. Eppen, 1979 and Eppen and Schrage, 1981). We now present two particular supply chain problems, with typical a cost structure. The first model will discuss a Vendor Managed Inventory problem while the second model describes a capacity decision model under demand uncertainty. While both models describe two different situations in the supply chain, they both have in common that economies of scale appear, when not only one, but two or more services are supplied together. In the Vendor Managed Inventory problem the depot effects lead to cost reduction, while in the second problem, the service provider can take advantage of the portfolio effect by using the same capacity for several products.

5.2.1 Vendor Managed Inventory

Assume a retailer or manufacturer (we will later refer to him as the retailer) who wants to procure a Vendor Managed Inventory (VMI) service: The products the retailer wants to buy will, after production and shipping, be stored at the retailer's warehouse. The products will be shipped on a consignment base, thus the retailer does not pay before he consumes the good. One could alternatively assume that the retailer pays a fixed fee for the whole contract independent on when he is consuming the good. Since the provider's cost still depend on the point of time the retailer consumes the good, the results are the same. The price the retailer pays per unit he takes out of the warehouse (or as mentioned, for the whole contract) will be determined via a reverse auction. The relevant costs of the service provider are the cost for storing the good at his production site (e.g. interests for bounded capital which depend on the production cost), the cost for storing at the inventory warehouse, the cost for production and the cost for transportation of the goods from the production site to the warehouse. While the service provider can freely organize the shipping and inventory control by himself, it will be part of the VMI-agreement, that the product must always be available when needed. We assume a deterministic demand model where the retailer consumes the parts (product 1 and product 2) at a steady rate (d_1, d_2). It is assumed that the service provider, who is also the manufacturer of the product, produces at the same steady rate. As stated in Section 5.1, we assume that even though the auctions are sequential, the service will be conducted over the same period of time. Thus, if a provider wins both contracts, he is able to achieve economies of scale by shipping both products with one truck. The bidding process has been described in Section 5.1.

The presented supply chain problem is a modified version of the model from Blumenfeld et al. (1985) where we add the production cost per unit to obtain the service provider's cost per unit of supplying the VMI service. Define T as the transportation time and t as the reorder cycle length. The fixed cost per transport from the production site to the warehouse are given by A and the maximum capacity of one single transport vehicle is W. Since these values depend on the transportation mode rather than the product, we assume A and W to be the same for different products. Thus each product uses up the same capacity of the transport vehicle and the cost per transport does not depend on how many units of Product 1 and how many units of Product 2 are shipped. The inventory is in average half a shipment at the origin waiting to be shipped, and half a shipment at the destination waiting to be consumed, plus $d \cdot T$ parts in transit. Assume h to be the average holding cost (as a percentage of the production cost), for simplification to be assumed the same at the origin, destination and during transport. Thus, even though the value for h is the same for two different products, the total holding cost per product differ if the production cost differ. Consider the one product case with marginal production cost c. From Blumenfeld et al. (1985) it is known that the optimal shipment size S^* is given by:

$$S^* = Min\,(Z, W) \tag{64}$$

where

$$Z = \sqrt{\frac{A \cdot d}{c \cdot h}} \tag{65}$$

Thus the optimal total cost for a single item shipment problem are given by:

$$C^*(c) = \begin{cases} d \cdot c + 2\sqrt{d \cdot c \cdot h \cdot A} + d \cdot c \cdot h \cdot T & \text{if } Z \leq W \\ d \cdot c + \frac{d \cdot A}{W} + c \cdot h \cdot W + d \cdot c \cdot h \cdot T & \text{if } Z > W \end{cases} \tag{66}$$

While Blumenfeld et al. (1985) consider the optimal shipping size for the single product case, we now, by applying Balintfy's approach on the multi-item economic order quantity (EOQ) problem, derive the optimal shipment size for the joint shipment. Therefore, define c_i as the marginal production cost for product i. For simplification and without loss of generality we assume the demands for both products and therefore the production rates for both products to be even ($d_1 = d_2 = d$) (see Balintfy, 1964, for cases with differing production rates). We first consider how the reorder period for the items influences the cost. This interval then defines the optimal shipping size. Since the fixed costs are the same, whether one or two products are shipped, the total cost function for joint shipping (TCJ) is given as:

$$TCJ = d \cdot (c_1 + c_2) + h \cdot (c_1 + c_2) \cdot d \cdot t + \frac{A}{t} + d \cdot (c_1 + c_2) \cdot h \cdot T \tag{67}$$

which leads to

$$t^* = \sqrt{\frac{A}{h \cdot (c_1 + c_2) \cdot d}} \tag{68}$$

and further

$$t^{opt} = \begin{cases} \sqrt{\frac{A}{h \cdot (c_1+c_2) \cdot d}} & \text{if } t^* \cdot (2 \cdot d) \le W \\ \frac{W}{2 \cdot d} & \text{if } t^* \cdot (2 \cdot d) > W \end{cases} \tag{69}$$

The optimal order quantities are now given by

$$q_i^* = t^{opt} \cdot d \tag{70}$$

and we get the optimal total cost for the joint shipment problem:

$$C_j^*(c_1, c_2) = \begin{cases} d \cdot (c_1 + c_2) + 2\sqrt{h(c_1 + c_2) \cdot d \cdot A} + d \cdot (c_1 + c_2)h \cdot T & \text{if } 2d \cdot t^* \le W \\ d \cdot (c_1 + c_2) + \frac{h(c_1+c_2) \cdot d \cdot W}{2d} + \frac{2d \cdot A}{W} + d \cdot (c_1 + c_2)h \cdot T & \text{if } 2d \cdot t^* > W \end{cases} \tag{71}$$

The transit time T has no influence on the optimal shipping size, since each item, independent of when it will be shipped, has to spend T time units in transit. Thus a longer shipping time only has a linear influence on the total cost, which is depended on the price dependent holding cost per item. The comparison of equations (66) and (71) shows that there are economies of scale if two products are supplied together rather then separately.

5.2.2 The flexible newsvendor

In the following we will study a stochastic program with recourse: the newsvendor model with flexible capacities. Since our focus lies on the sourcing strategy, we consider a very simple example with only one flexible capacity while auction design presented in Section 5.1 also works for other set-ups, including a mix of flexible and dedicated resources as in e.g. Van Mieghem (1998).

We consider a capacity decision problem for the provision of two products. Assume that due to long set-up times companies have to decide on the amount of installed capacities before final demand vector $D \in \mathbb{R}_+^2$ of the two products is known, which is a standard assumption of the newsvendor. In the later sourcing design this will be right after both auctions have been conducted. Thus the service providers know which auctions they have won, but they do not know the final demand. The sourcing company faces uncertain market demand for product i. D is drawn from a continuous distribution on $[0, \infty)$ with cumulative probability $\Phi_i(D)$ and probability density $\phi_i(D) > 0$. $\Phi_i(D)$ has a finite mean μ_i and an inverse $\Phi_i^{-1}(D)$. The distributions are assumed to be common knowledge. We assume that the service providers offer pull contracts by saying that the sourcing company can wait untill it observes demand and then orders what it needs. Thus, part of the service the provider offers is, besides the pure production of the product, to take over and handle the demand risk the retailer faces. Therefore, instead of a retailer ordering under demand uncertainty, we now consider a problem of a service provider, setting up his capacities while demand is still uncertain. Assume now that the capacity that has to be installed is flexible and can be used for the production of both products. The cost to invest in one unit of that resource is k and the same for all service providers. K denotes the capacity level the companies decide to set up. The differentiation of the products takes place during production and causes variable manufacturing cost c_1 and c_2 whenever Product 1 or Product 2 is produced. Thus, while k occurs whenever capacity is set up, independent on whether it will be used or not, the manufacturing cost only occurs, when the product is produced and thus depends on the later production quantity rather then on the capacity level. The manufacturing cost differs among the providers and products and are private knowledge. We assume that the service provider has to fulfill a service level of 100%, thus he always has to fullfill demand. In the case that demand exceeds the installed production capacities, there is the option of an emergency supply. We assume that the cost for this outside option is common knowledge and the same for all providers. The prices of the emergency supply of Product i is u_i and the quantity ordered at the emergency market of Product i is z_i. To avoid trivial solutions assume that $k + c_i \leq u_i$. While the assumption of an emergency market is one extreme case, many other options extist concerning how shortages could be managed. Examples include a penalty cost for shortages, agreements on a specific service level, or the provider might choose the service level that maximizes his profit (see e.g. Li and Scheller-Wolf, 2011). Nevertheless, these assumptions would not change the general insights of our model. After demand is known, the service provider chooses, while constrained by its earlier resource investment, a vector $x = (y_1, y_2, z_1, z_2) \in \mathbb{R}_+^4$ of production quantities, where y_i represents the quantities produced of product i. The studied model is a simplified version of Van Mieghem (1998) and thus follows its model description, with the difference that the goal is to minimize cost rather than to maximize profits. The firm's manufacturing process and production decisions are modeled as follows. After the company has chosen the capacity level K, the provider observes a demand vector D and chooses its production vector x in order to maximize its profit. Since after conducting the auction the prices are fixed and the provider always has to fulfill demand, his profit is maximized when his cost is minimized. Thus the optimization problem is given as:

$$\min_{y_i, z_i \in \mathbb{R}_+^2} y_1 \cdot c_1 + y_2 \cdot c_2 + z_1 \cdot u_1 + z_2 \cdot u_2 \tag{72}$$

$$s.t$$

$$y_1 + y_2 \leq K \tag{73}$$

$$y_1 \leq D_1 \tag{74}$$

$$y_2 \leq D_2 \tag{75}$$

$$y_1 + z_1 = D_1 \tag{76}$$

$$y_2 + z_2 = D_2 \tag{77}$$

The optimal objective value of the product mix problem (72)-(77) is the minimal operating cost and is denoted by $\kappa(K, D) = (c_1, c_2, u_1, u_2)'x(K, D)$ where $x(K, D)$ is an associated optimal production vector.

We now consider the investment problem of the service provider. Define $C(K) = k \cdot K$ as the service providers total investment cost if he chooses the capacity level K. Thus, the company's total cost of supplying a pull service are given as:

$$V(K) = E\kappa(K, D) + C(K), \tag{78}$$

the expected operational cost plus resource investment cost. We denote the optimal minimal value of $V(\cdot)$ by V^* and call any minimizer of $V(\cdot)$ an optimal investment vector.

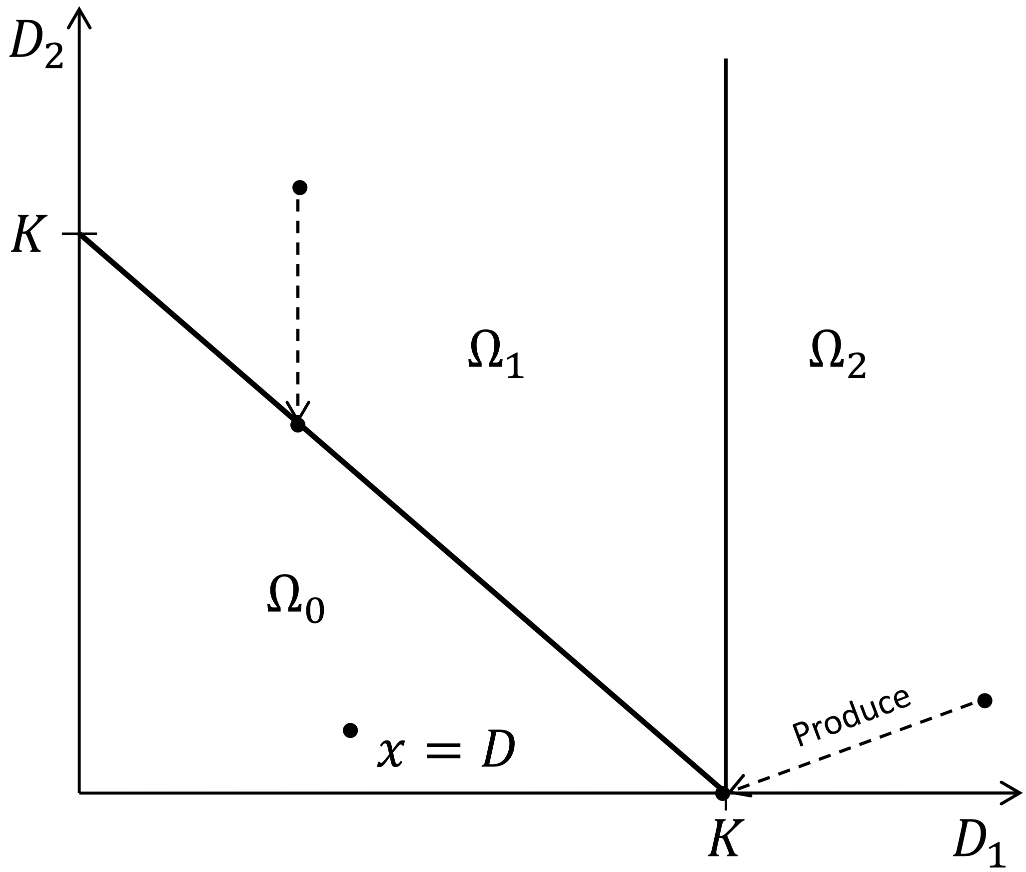


Figure 5.1: Production quantities and shadow prices

We can solve that capacity decision problem backwards by first solving for the optimal contingent production decisions $x(K, D)$ and the associated variable $\lambda(K, D)$ of the optimal dual variables of the capacity constraint (73). To reduce the number of cases that need to be discussed, we define the product with the higher difference between manufacturing cost and emergency order cost as Product 1, so that $u_1 - c_1 \geq u_2 - c_2$. Analyzing the linear program leads to a partition of the demand space $\mathbb{R}^2_+$ for a given K into three domains as shown in Figure 5.1, where the thick-lined $\Omega(K)_0$ is the service provider's capacity region. In Ω_0 production equals demand, in Ω_1 production of Product 1 equals demand while for the second product the remaining capacity is used up and demand that exceeds this will be ordered at the emergency market. In Ω_2 the whole capacity is used to supply (parts of) the demand for Product 1. All demands that exceed that capacity are satisfied from the emergency market. The optimal contingent primal and dual variables then are: $x = (D_1, D_2, 0, 0)$ and $\lambda = 0$, if $D \in \Omega_0$; $x = (D_1, K - D_1, 0, D_1 + D_2 - K)$ and $\lambda = u_2 - c_2$, if $D \in \Omega_1$; $x = (D_1, 0, D_1 - K, D_2)$ and $\lambda = u_1 - c_1$, if $D \in \Omega_2$. Since $V(\cdot)$ is convex, the Kuhn-Tucker first-order conditions are necessary and sufficient to minimize $V(\cdot)$. Define $P(\Omega_i(K))$ as the probability that demand falls into partition Ω_i, if the provider invests K. We can now reformulate *Proposition 1* from Van Mieghem (1998) to:

Proposition 2. *An investment K is optimal if and only if a ν exists such that*

$$(u_2 - c_2)P(\Omega_1(K^*)) + (u_1 - c_1)P(\Omega_2(K^*)) = k - \nu \tag{79}$$

$$\nu K^* = 0 \tag{80}$$

where K^* is unique.

For a given capacity K and given cost c_1 and c_2 we get the following expected procurement cost:

$$\begin{aligned} V(K) = k \cdot K + \int_0^K \int_0^{K-d_1} (c_1 d_1 + c_2 d_2)\phi_2(d_2) dd_2 \phi_1(d_1) dd_1 \\ + \int_0^K \int_{K-d_1}^{\infty} (c_1 d_1 + c_2(K - d_1) + u_2(d_2 - K + d_1))\phi_2(d_2) dd_2)\phi_1(d_1) dd_1 \\ + \int_K^{\infty} \left(\int_0^{\infty} (c_1 K + u_1(K - d_1) + u_2 d_2)\phi_2(d_2) dd_2 \right) \phi_1(d_1) dd_1 \end{aligned} \tag{81}$$

Equation (81) together with Proposition 2 now determine, for given per unit manufacturing and capacity costs, the expected minimized total cost of supplying a pull contract.

While the model above fits if the provider has to deliver two products in a pull contract, we now shortly study the one-dimensional problem, in case a provider only needs to supply one product. In the single-product case, the problem changes to the standard newsvendor problem. Assume the provider has to deliver product i. His optimization problem then is the following:

$$V(K) = k \cdot K + \int_0^K d_i \cdot c_i \phi(d_i) dd_i + \int_K^{\infty} (K \cdot c_i + (d_i - K)u_i)\phi(d_i) dd_i \tag{82}$$

Since (82) is concave in the order quantity k_i, the optimal solution is $k_i(c_i)^* = \Phi^{-1}[(u_i - c_i)/u_i]$. Defining $V(k_i(c_i)^*)$ $(V(k_{i+j}(c_i, c_j)^*))$ as the expected total cost of supplying product i (i and j), it always holds that $V(k_{1+2}(c_1, c_2)^*) \leq V(k_1(c_1)^*) + V(k_2(c_2)^*)$ (for given c_1 and c_2). Thus, having flexible capacities allows economies of scale, if two products are sourced from one service provider rather than having them supplied by different companies.

5.3 Numerical study

In Section 5.1 we showed that there are no unique preferences towards bundling or sequential auctioning when products with economies of scale are purchased. In Section 5.2 we presented sourcing situations, where economies of scale appear and thus provided applications for the theoretic auction framework in Section 5.1. In this section we present numerical results that, on the one hand, show under which circumstances it is better to bundle products rather than selling in sequential auctions and, on the other hand, quantify the effect the auction design has on the expected cost. We first study a general model with economies of scale to show some general effects of the auction model and then present numerical examples for the applications introduced in Section 5.2.

5.3.1 A simple model with concave cost

For the first numerical study we assume a simple set-up, where the service providers' marginal costs are drawn from a uniform distribution with $(\underline{c_1}, \overline{c_1}) = (1, 10)$ and $(\underline{c_2}, \overline{c_2}) = (1, 10), (3, 8)$. Since a mean preserving spread of the cost distribution in the first period cost has no effect on the expected profits, we only vary the spread for the second period cost. The total costs are defined as $C_{d_1+d_2}(c_1, c_2) = c_1 \cdot d_1 + c_2 \cdot d_2 + \sqrt{2A(d_1 + d_2)h}$. The cost structure involves a direct variable cost c_1, c_2, holding cost h (per piece and unit of time) and indirect concave overhead costs A (economies of scale driver). Thus the cost structure follows a simple EOQ model with constant holding cost h that does not depend on the production cost. Therefore, the production cost has no influence on the economies of scale and is rather a fixed term, determined by A,h and the demand. While a more complex model with holding cost, dependent on production cost and thus having cost dependent economics of scale, is discussed in Section 5.3.2, this simplified model allows us to study the influence of differences in the demand of the two products on the outcome of the sourcing process. For the parameters we have chosen $A = 10, 20$, $d_1 = 10, 20$, $d_2 = 10, 20, 30, 40$, $h = 1$ and $n = 2, 3, 4, 5$ with $\Delta^{i,j} = \frac{E[C_j]-E[C_i]}{E[C_i]} \cdot 100$, where s, b, o refer to *sequential*, *bundle* and *optimal*. Since changing h leads to the same effect as changing A by the same factor, we keep h fixed and only vary A.

Table 5.1 shows that the sequential auction becomes more attractive when the number of service providers increases. The reason is that while $E[X]$ does not change in n, $E[X_{(2)}]$ decreases in n. Since the bid in the bundle auction is based on $E[X]$ and the one of the sequential auction results from $X_{(2)}$, a higher number of potential service providers leads to a preference towards the sequential auction. Therefore, if $n \geq 3$ a higher demand for the second period product favors the sequential auction, while for $n = 2$ we get the opposite result. While the gap between the expected procurement cost in the sequential and the optimal sequential auction decreases if the number of service providers increases, this does not hold for bundling. Comparing the gap between bundling and the optimal sequential (or also normal sequential) auction, one can see that, even for a high n, it does not close and rather increases. The reason is that for the second period, all providers in the bundle auction will always bid their expected cost, which is ex-ante the same for all providers and therefore does not change in n. In the sequential auction, on the other hand, the second period cost will be the lowest actual cost of all providers around and therefore, always decrease in n.

Table 5.1: Cost comparison

$(\underline{c_2}, \overline{c_2})$	d_1	d_2	A	n	$E[C_{seq}]$	$E[C_{bundle}]$	$\Delta^{b,s}$	$E[C_{optimal}]$	$\Delta^{o,s}$	$\Delta^{o,b}$
(1,10)	10	10	10	2	155.90	145.00	7.52	141.26	10.36	2.65
				3	129.75	130.00	-0.20	121.83	6.49	6.70
				4	113.74	121.00	-6.00	109.16	4.20	10.85
				5	103.01	115.00	-10.43	100.17	2.83	14.80
			20	2	162.12	153.28	5.76	149.99	8.08	2.19
				3	138.00	138.28	-0.20	131.07	5.29	5.50
				4	122.68	129.28	-5.11	118.78	3.28	8.84
				5	112.41	123.28	-8.82	110.09	2.11	11.99
	20	10	10	2	229.62	219.50	4.61	216.12	6.25	1.56
				3	189.23	189.50	-0.14	183.04	3.38	3.52
				4	164.50	171.50	-4.08	162.06	1.51	5.82
				5	147.95	159.50	-7.24	147.37	0.39	8.22
	10	20	10	2	230.02	204.50	12.48	195.66	17.56	4.51
				3	189.11	189.50	-0.20	169.66	11.47	11.69
				4	164.59	180.50	-8.81	151.98	8.30	18.76
				5	148.10	174.50	-15.12	139.25	6.36	25.31
		30		2	303.62	263.28	15.32	249.25	21.81	5.63
				3	247.83	248.28	-0.18	216.81	14.31	14.52
				4	214.57	239.28	-10.33	194.20	10.49	23.22
				5	192.20	233.28	-17.61	177.73	8.14	31.26
		40		2	376.83	321.62	17.17	302.37	24.63	6.37
				3	306.12	306.62	-0.16	263.58	16.14	16.33
				4	264.02	297.62	-11.29	236.06	11.85	26.08
				5	235.74	291.62	-19.16	215.85	9.21	35.10
(3,8)	10	10	10	2	148.18	145.00	2.19	143.39	3.34	1.12
				3	129.82	130.00	-0.14	126.45	2.66	2.81
				4	117.66	121.00	-2.76	115.81	1.59	4.48
				5	109.50	115.00	-4.78	108.46	0.97	6.03
		20		2	215.91	204.50	5.58	202.24	6.76	1.12
				3	189.20	189.50	-0.15	180.42	4.87	5.03
				4	172.52	180.50	-4.42	166.28	3.75	8.55
				5	161.32	174.50	-7.55	156.46	3.10	11.53
		30		2	283.00	263.28	7.49	259.64	9.00	1.40
				3	247.91	248.28	-0.15	233.30	6.27	6.42
				4	226.51	239.28	-5.34	215.88	4.92	10.84
				5	212.11	233.28	-9.08	203.73	4.12	14.51
		40		2	349.66	321.62	8.72	316.30	10.55	1.68
				3	306.20	306.62	-0.14	285.61	7.21	7.36
				4	279.97	297.62	-5.93	265.03	5.64	12.30
				5	262.33	291.62	-10.05	250.59	4.69	16.38

For example, consider the set-up with $A = 10$, $(\underline{c_1}, \overline{c_1}) = (\underline{c_2}, \overline{c_2}) = (1, 10)$ and $d_1 = d_2 = 10$ and let the number of service providers run towards infinity. The expected cost for the sequential auction is 47.9: the total cost of two separate providers with production cost of $\underline{c_1}$ and $\underline{c_2}$ minus the expected profit of the provider who wins the first auction. For the bundling auction the expected payment is the cost of a service provider with $c_1 = \underline{c_1}$ and being able to achieve economics of scale while bidding on the estimated cost $E[c_2]$, which in this case leads to expected procurement cost of 85. Thus, the lower bound for the bundle is almost 100% higher than the one of the sequential auction.

When considering the demand rates, one can see that d_2 has a high influence on the preference for one specific auction format since the gap between the two auction formats increases in d_2. Thus, for a higher number of service providers, a high level of d_2 favors the sequential auction. If, on the other hand, d_1 increases, the differences between both auction formats become smaller since the second period has less influence. If e.g. $d_1 \to \infty$ or $d_2 \to 0$ both auctions would lead to the same result and they would basically be just a one product auction. Therefore, the higher the influence of the second period product, the more important becomes the right choice of the auction format.

The study shows that the differences between the auction formats decrease in the fixed cost A. This goes in hand with Theorem 7 since higher fixed cost also lead to higher economies of scale and therefore, the higher A is, the higher the probability is to win both sequential auctions.

An interesting result comes up when studying a mean preserving spread of the second period production cost. While a change in the spread of production costs for the first good (as long as mean preserving) has no influence on the expected procurement cost, this does not hold for a change in the spread of the cost for the second good. Whereas under the pooling contract, the spread does not influence the result as long as the mean is preserved (the bid is based on expected values and total costs are a linear of the production costs), it has an influence on the sequential auction. For the sequential auction we can therefore observe that for a low number of providers costs decrease in a lower spread. In contrast, if the number of providers is high, costs increase in a lower spread. As a result, for a low number of providers, a higher spread favors the bundle auction, while for a high number of providers, it favors the sequential auction.

One can further observe that if the spread becomes very small, the bundle and sequential auction lead to the same result. This threshold is reached as soon as $d_2 \cdot (\overline{c_2} - \underline{c_2}) \leq \sqrt{2Ad_1h} + \sqrt{2Ad_2h} - \sqrt{2A(d_1 + d_2)h}$, thus the maximum cost difference for the second product, weighted by its demand, is lower than the economies of scale if one provides both products. In this case, in the sequential auction the incumbent will always win the second auction. The expected cost for both auction formats then will be the same (see Theorem 7), even though, ex post, they might differ, since in the bundle, the service provider bids on the expected cost for the second period, while for the sequential auction, the second period cost depends on the lowest cost of the remaining incumbents. This shows that the variance in possible production cost of the second product has a large influence on the retailer's preferences: If 1) the variance as well as the number of competing service providers are high, the retailer prefers to procure the items in a sequential auction. If 2) the variance is high, but there are only a few service providers that compete against each other, the retailer prefers to bundle the items in one auction. And finally, if 3) the variance is very low the retailer is indifferent between bundling and sequential auctioning, independent on the number of service providers.

5.3.2 The transportation and inventory model

This section presents a numerical study on the transportation and inventory model presented in Chapter 5.2.1 to show how different paremeters influence the preferences towards bundling or separate selling. Since the general influence of a change in the spread of production cost as well as a change in demand is already studied in the previous section, we now vary parameters such as holding costs, fixed order costs, transportation time or transportation capacity.

Table 5.2: Transport auction

A	h	T	W	n	$E[C_{seq}]$	$E[C_{bundle}]$	$\Delta^{b,s}$	$E[C_{optimal}]$	$\Delta^{o,s}$	$\Delta^{o,b}$
10	1	2	$\geq \overline{W}$	2	487.78	445.02	9.61	427.13	14.20	4.19
				3	404.12	395.53	2.17	364.84	10.77	8.41
				4	346.63	365.72	-5.22	323.23	7.24	13.15
				5	307.51	345.79	-11.07	292.97	4.96	18.03
		3		2	627.80	570.02	10.14	543.57	15.50	4.87
				3	514.55	505.53	1.78	462.19	11.33	9.38
				4	438.84	466.72	-5.97	407.84	7.60	14.44
				5	387.69	440.79	-12.05	368.36	5.25	19.66
		2	3	2	501.81	460.42	8.99	450.92	11.29	2.11
				3	414.46	413.17	0.31	385.78	7.44	7.10
				4	361.76	384.82	-5.99	342.81	5.53	12.26
				5	324.06	365.92	-11.44	312.19	3.80	17.21
	$\frac{1}{2}$		$\geq \overline{W}$	2	327.93	299.51	9.49	289.03	13.46	3.62
				3	272.34	266.34	2.25	246.83	10.34	7.90
				4	233.90	246.35	-5.05	218.65	6.97	12.67
				5	207.71	232.98	-10.85	198.21	4.79	17.55
	2		$\geq \overline{W}$	2	795.88	724.02	9.92	690.67	15.23	4.83
				3	655.18	642.68	1.95	588.78	11.28	9.15
				4	560.07	593.70	-5.67	520.69	7.56	14.02
				5	495.63	560.97	-11.65	471.16	5.19	19.06
5	1			2	467.95	424.51	10.23	405.44	15.42	4.70
				3	382.77	376.34	1.71	344.15	11.22	9.35
				4	326.12	347.35	-6.11	303.25	7.54	14.54
				5	287.89	327.98	-12.23	273.59	5.23	19.88
20				2	516.81	474.02	9.03	457.72	12.91	3.56
				3	434.62	422.62	2.84	393.95	10.32	7.28
				4	375.89	391.70	-4.04	351.31	7.00	11.50
				5	335.44	370.97	-9.58	320.22	4.75	15.85

The service providers' marginal costs are drawn from a uniform distribution with $(\underline{c_1}, \overline{c_1}) = (\underline{c_2}, \overline{c_2}) = (1, 10)$. For the further parameters we have chosen $A = 10, 20$, $d_1 = d_2 = 10$, $h = 0.5, 1, 2$, $A = 5, 10, 20$, $T = 2, 3$, $W =\geq \overline{W}, 3$ and $n = 2, 3, 4, 5$. Define

$\overline{W} = (d_1 + d_2) \cdot \sqrt{\frac{A}{h \cdot (\underline{c_1} \cdot d_1 + \underline{c_2} \cdot d_2)}}$. Whenever $W \geq \overline{W}$, the vehicle size is no constraint, since the optimal batch size (compare Equation 69 and 70) would be less than or equal to the vehicle size, even if both products would be sold for the minimum possible cost.

The numerical results (see Table 5.2) show again that for a low number of service providers, the bundling auction should be chosen, while for a high number of providers, the sequential auction is the preferred format while the gap increases with the number of providers. The thresholds for $n \to \infty$ for the example of $A = 10$, $h = 1$, $T = 2$, $W \geq \overline{W}$, $(\underline{c_1}, \overline{c_1}) = (\underline{c_2}, \overline{c_2}) = (1, 10)$ and $d_1 = d_2 = 10$ are 129.67 for the sequential and 271.42 for the bundle auction. Thus, the lowest expected cost for the bundle that can be achieved through a high number of providers is still more than double the cost of the sequential auction. The reasons are the same as in Section 5.3. As a result one can further see that in comparison to the optimum, the gap between the sequential and optimal sequential auction becomes smaller with a higher number of providers while the one between the bundle and optimal sequential auction increases with the number of providers.

A very interesting observation comes up when varying the transportation capacity. The study shows that that a lower transportation capacity favors the sequential auction, since it reduces economies of scale, especially for service providers with higher cost, since order quantities decrease in cost. Thus if the transportation volume is limited, it becomes more beneficial when the contract is awarded to two different providers, since economies of scale decrease, especially if production costs are low. Regarding the fixed cost, we can observe that if $n = 2$, higher fixed cost lead to a lower gap between the two formats, since the higher the fixed cost, the closer both formats converge (see also Theorem 7). Thus, for $n = 2$ lower fix cost favor the bundle auction. On the other hand, if $n \geq 3$, lower fixed costs favor the sequential auction, since lower fixed costs increase the potential benefit of allocating the contract to two different companies.

5.3.3 The flexible resource model

In this section we present a numerical study on the flexible resource model that we presented in chapter 5.2.2. Providers' marginal costs are drawn from a uniform distribution with $(\underline{c_1}, \overline{c_1}) = (1, 10)$ and $(\underline{c_2}, \overline{c_2}) = (1, 10), (1, 5), (3, 8), (6, 10)$ and $u_1 = u_2 = 20$. For the further parameters we have chosen $k = 2, 5, 10$, $\mu_1 = \mu_2 = 10$, $\sigma_{1,2} = 0, 4, 6, 8$ and $n = 2, 3, 4, 5$.

If $\sigma_{1,2} = 0$ we actually have a case without demand uncertainty and thus without economies of scale. Therefore, this case can be taken as a benchmark that enables to separate the effect of economies of scale on the bundling decision from general preferences concerning bundling and seperate sourcing. For $(\underline{c_2}, \overline{c_2}) = (1, 10)$ and without economies of scale, bundling leads to lower costs than the sequential auction if $n = 2$, to the same cost if $n = 3$ and to higher costs, whenever $n > 3$ (see also Chakraborty, 1999, who analyses such thresholds for forward auctions with independent values). Thus, for the flexible resource problem economies of scale support sequential auctioning, even though it reduces the total differences between the formats. The higher the demand uncertainty, the higher this effect wil be. This does not hold anymore, if expected production cost for the second product decrease. For this case, we observe that bundling becomes more attractive, while the opposite is true, if expected production cost for the second product increase. A reason for this effect is that when the expected cost for the second product is higher, the benefits of changing the service provider in the second period are higher than for lower expected cost. A lower mean preserving spread of these costs lead to smaller differences between the different auction designs. For bundling, a lower spread always leads to higher cost, while for the sequential auctions this is only true for $n \geq 3$.

Table 5.3: Newsvendor auction

$\underline{c_2}$	$\overline{c_2}$	k	σ_1	σ_2	n	$E[C_{seq}]$	$E[C_{bundle}]$	$\Delta^{b,s}$	$E[C_{optimal}]$	$\Delta^{o,s}$	$\Delta^{o,b}$
1	10	5	0	0	2	240.00	225.00	6.67	220.00	9.09	2.27
					3	210.00	210.00	0.00	199.20	5.42	5.42
					4	192.00	201.00	-4.48	185.50	3.50	8.36
					5	180.00	195.00	-7.69	175.76	2.41	10.95
			4	4	2	256.74	251.16	2.22	240.36	6.82	4.50
					3	236.20	237.56	-0.57	226.47	4.30	4.90
					4	222.66	229.20	-2.85	217.38	2.43	5.44
					5	213.54	223.54	-4.47	210.74	1.33	6.08
			6	6	2	264.15	261.07	1.18	250.40	5.49	4.26
					3	246.38	248.04	-0.67	237.78	3.62	4.31
					4	234.53	239.95	-2.26	229.65	2.12	4.49
					5	226.48	234.44	-3.40	224.00	1.11	4.66
			8	8	2	269.88	268.07	0.68	256.11	5.38	4.67
					3	253.75	255.44	-0.66	244.40	3.82	4.52
					4	243.04	247.56	-1.83	237.18	2.47	4.38
					5	235.72	242.17	-2.67	232.16	1.53	4.31
		10	4	4	2	344.84	343.01	0.53	327.46	5.31	4.75
					3	330.30	331.93	-0.49	318.47	3.72	4.23
					4	320.18	324.87	-1.45	313.60	2.10	3.59
					5	313.20	319.92	-2.10	308.38	1.56	3.74
		2			2	191.99	181.79	5.61	172.06	11.58	5.66
					3	166.80	167.21	-0.25	155.61	7.19	7.45
					4	150.88	158.40	-4.74	144.69	4.28	9.48
					5	140.25	152.50	-8.03	136.71	2.59	11.55
1	5	5			2	229.25	227.19	0.91	206.69	10.92	9.92
					3	214.97	214.28	0.32	202.34	6.24	5.90
					4	205.42	206.36	-0.46	194.99	5.35	5.83
					5	198.80	201.00	-1.09	191.63	3.74	4.89
3	8				2	253.49	251.63	0.74	237.64	6.67	5.89
					3	238.06	238.18	-0.05	227.06	4.84	4.90
					4	227.78	229.84	-0.90	222.09	2.56	3.49
					5	220.93	224.16	-1.44	215.68	2.44	3.93
6	10				2	275.36	274.96	0.15	252.52	9.05	8.89
					3	260.14	260.61	-0.18	239.16	8.77	8.97
					4	250.41	251.79	-0.55	230.49	8.64	9.24
					5	243.76	245.85	-0.85	224.40	8.63	9.56

A reason for this effect is that for a high number of providers, the expected cost for the second-lowest provider increases in a mean-preserving spread, while it decreases for

$n = 2$. Further, since the cost function is convex (see Van Mieghem, 1998, for proof of convexity), expected costs further decrease with a higher, mean-preserving spread in potential production cost. As a result, for the sequential auction, bids first increase with a higher spread and then decrease again. Since under bundling the expected cost for the second-product does not depend on the number of service providers and thus always decreases in a mean-preserving spread, we observe that under bundling expected procurement costs always decrease in a mean-preserving spread of potential production cost.

5.4 Conclusion

We have shown that the decision of procuring two services or products as a bundle or in a sequential auction has big influence on the expected cost. In contrast to Grimm (2007) we show that bundling is no longer dominant if there is no subcontracting. For a low number of service providers, the bundle will be preferred while for a high number of bidders the sequential auction will be the contract of choice. We further show that high economies of scale lead to lower differences between both auction formats and if these economies are high enough, it does not matter anymore which format is chosen. Another interesting insight is that for these auctions it does not hold that the differences between the auction formats become marginal for a high number of service providers. For a high number of service providers with economies of scale that are not to high, there will always be a significant gap between bundling and sequential auctioning, no matter how many providers participate at the auction. This is especially interesting, since in many other sourcing situations, the differences between the auction formats decrease when competition increases (see e.g. Chapter 3).

We additionaly applied this model to actual sourcing problems. By doing so, we were able to show what impact the choice of bundling or sequential ordering can have on the expected cost in a VMI contract and in a newsvendor setting.

As a result, this work is a helpful tool for managers confronted with the decision of either pooling their services into one auction, or buying them separately. It helps managers to incorporate the cost-structure of the service providers into their sourcing strategy, in order to better understand how different parameters such as competition, differences in production cost or drivers of economies of scale have an outcome on different sourcing strategies. Finally it supports them in finding the fitting strategy for their sourcing situation.

Chapter 6

Summary, limitations and future research

This thesis has shed new light on different procurement problems including procurement under demand uncertainty (Chapter 3), optimal capacity provision and bidding for service providers (Chapter 4) and procurement auctions under the presence of economies of scale (Chapter 5). By providing new insights on these topics this thesis contributes to the emerging field of literature on procurement auctions. While we studied different problems and settings that occur in supply chain management, our major focus lies in the optimization of the procurement and bidding processes. In doing so, we have provided useful insights for both buying and selling companies.

In Chapter 3, we investigated procurement auctions under the assumptions of the newsvendor model. By studying two simple sourcing contracts, the push and pull contract, we showed the importance of the right auction design in order to minimize procurement cost. We also showed how a procurer would always choose the push contract, while a social planner prefers the pull contract. Further, we studied the influence of risk aversion and showed how preferences concerning the auction design switch when agents do not have linear utility functions anymore. The findings of this chapter help procurement managers to find the right auction which fits their specific goals.

In Chapter 4 we covered the aspect of capacity restriction in repeated auctions. We showed how and why bids increase, if bidders have limited production capacities. We then showed the influence of the total capacity level on bids and profits and investigated how a supplier should set up capacity. By doing so, we discovered a prisoners dilemma, in which suppliers are given incentive to invest in further capacities, even though these investments end up in lower profits. This chapter helps buyers on the one hand to have an appropriate idea of expected procurement cost and helps suppliers on the other hand to set up the right bidding and capacity strategy.

Chapter 5 discussed auctions for products with economies of scale. Here we showed how the preferences of a buyer concerning sequential buying or bundled buying depend on parameters such as the number of bidders or the service providers' cost structure. We applied this model to concrete procurement problems and showed the differences between sequential and bundle auction for a VMI model as well as a newsvendor set-up. As a result, this chapter provides helpful insights to decision makers wanting to procure products in the presence of scale economies.

The three topics covered in this thesis reveal that procurement auctions are an interesting and challenging field that have a high relevance to both buyers and sellers. Nevertheless, even though this thesis provides many new insights, there is still a lot of research to do.

Concerning newsvendor auctions, we have, for example, shown that while a simple pull auction maximizes the supply chain profit, it does not maximize the retailer's profit. Therefore, a challenge would be to find mechanisms which are able to allocate more profit to the retailer when choosing a coordinating pull contract. It might also be interesting to investigate combined push-pull contracts, rather than just the two extremes. The outside option is also an interesting aspect for further research. So far we have assumed the external market to be given. It might be interesting to investigate how contracts should be designed when a supplier acts on both the primary market and the emergency market. Another limitation of our analysis has been the assumption of symmetric suppliers. Therefore, asymmetries in cost and demand information are an important next step for research.

While for the repeated auction model in Chapter 4 we basically studied single unit auctions, it might be very interesting to investigate how the results change if project sizes differ and winning an auction does not always consume the same amount of capacity. While it might be obvious that bids will increase in project size, it will be challenging to study how exactly the project size would influence the bid. We further do not consider learning or collusion, although it might be an interesting topic for future research to investigate how learning or strategic interaction of providers would influence the bidding behavior in repeated auctions with capacity constraints.

Concerning economies of scale in procurement auctions, it might be interesting to apply apply the third approach (in Chapter 5) to other relevant problems in the field of supply chain management. Also, in our model the distribution of the costs were independent from each other. It would therefore be interesting to study how the insights change when the distributions of the costs of the different products are correlated, for example, by saying that a company that has a low production cost for the first product will most probably also have a relatively low production cost for the next product and vice versa. Another challenge would be to look for an easy way of how to implement an optimal auction and to further extend this model to the case of more than two services. In addition, it would be interesting to have a look at first-price auctions and how the results differ in comparison to the studied second-price auction set-up. While for the bundle the choice of the auction format would have no influence, it will have an influence under the sequential auction. The results of Arozamena and Cantillon (2004), who study the influence of investment into cost reduction on the bidding behavior, suggest that the prices for the second contract would be lower under the first-price auction in comparison to the second-price auction. On the other hand, the benefit of winning the first contract might therefore be higher under the second-price auction, which would lead to an incentive to bid more aggressive in the first stage. A buyers preference for the second-price auction is supported by the results of Jofre-Bonet and Pesendorfer (2006) who have already shown that for sequential auctions with only two service providers the second-price auction leads to lower procurement cost in comparison to the first-price auction, if the services are complements. It might be interesting to study if these results also hold for more than two service providers. A confirmation would provide interesting insights: While under the newsvendor auction (see Chapter 3) it was beneficial for the retailer to implement a maybe more complicated first-price auction instead of a second-price auction in order to minimize the procurement cost, this would not be the case for the procurement of complements, where it is better to implement the simple second-price auction.

Appendix A

Proofs

A.1 Proof of Proposition 1

Since $q_R(w)$ decreases in w, the proof follows the same lines as in Hansen (1988) and we omit it here.

■

A.2 Proof of Lemma 1

According to the revenue equivalence theorem (see Myerson, 1981, which we adapted for the reverse auction), every auction where risk-neutral bidders sell a single unit yields the same expected prices and revenues, if i) the bidders' costs are independently drawn from a common, strictly-increasing atomless distribution, ii) the bidder with the lowest signal always wins, and iii) the bidder with the highest-feasible signal expects zero surplus.

i) $E(C(c)) = cq_S(c) + z\int_{q_S(c)}^{\infty}(x - q_S(c))\phi(x)dx$ gives the expected cost in case of winning (see 24). $\frac{dE(C(c))}{dc} > 0$ and since c is drawn from a strictly-increasing atomless distribution, the total expected costs follow a strictly-increasing atomless distribution, being the same for all suppliers. From (24), $\frac{dq_S(c)}{db(c)} = 0$, i.e. the quantity for a given demand distribution is independent from the bid and only depends on the private costs. Therefore, $\frac{E(\Pi_S^{f,Pull}(b(c_i)))}{db(c)} = \mu$. Thus, the supplier's profit is linear in the resulting wholesale price and can be analyzed as a single-product auction with risk-neutral preferences.

ii) It is sufficient to show that in both, first- and second-price auction, the bids increase in cost as in both auction formats the lowest bid wins. Since the optimal bid in the second-price auction is to bid the expected average cost per unit, $\frac{db^s(c)}{dc} = \frac{d\frac{E(C(c))}{\mu}}{dc} > 0$. For the first-price auction, we know from (25) (together with (26) and (28)) that $\frac{db^f(c)}{dc} > 0\ \forall c < \bar{c}$

iii) $b^s(\bar{c}) = b^f(\bar{c}) = \frac{E(C(\bar{c}))}{\mu}$: Any bidder with the highest cost expects zero surplus.

Thus, the expected prices for the first- and the second-price pull auction are the same.

Consider now the expected retailer profit. Under a pull contract, the quantity sold is equal to the realized demand. Therefore, the retailer's expected profit is equal the expected demand multiplied by the market price minus wholesale price: $E(\Pi_R^{Pull}) = E(x \cdot (p - w))$. Since the realization of demand and wholesale price do not depend on each other, $E(x \cdot (p-w)) = \mu \cdot (p - E(w))$. Thus, the expected profit under a pull contract is linear in the wholesale price and is therefore the same for two different auction formats as long as the expected wholesale price is the same. The equivalence of $E(w)$ for both pull auctions has been shown above. Therefore, both auctions lead to the same expected profits for the retailer, even though the distributions of the bids in the first- and second-price auction differ. Since production quantities do not depend on the wholesale price either, revenue equivalence also holds for the expected profits of a supplier and for the profits of the whole supply chain.

■

A.3 Proof of the Convexity of Equation 19

Differentiate at the optimal point ($q_R(w) = q_R^*(w) = \Phi^{-1}[(z-w)/z]$) with respect to w using the envelope theorem:

$$\frac{E(\Pi_R^{Push^*}(w))}{dw} = \frac{E(\Pi_R^{Push^*}(w))}{\partial w} = -q_R^*(w) = -\Phi^{-1}[(z-w)/z]. \tag{83}$$

Since $E(\Pi_R^{Push^*}(0)) = \mu p$ we get:

$$E(\Pi_R^{Push^*}(w)) = \mu p - \int_0^w \Phi^{-1}[(z-x)/z]dx. \tag{84}$$

Therefore,

$$E(\Pi_R^{Push^*}(w))' = -q_R^*(w), E(\Pi_R^{Push^*}(w))'' = q_R^*(w)' \tag{85}$$

Since the optimal order quantity is decreasing in w, $E(\Pi_R^{Push^*}(w))' \leq 0$ and $E(\Pi_R^{Push^*}(w))'' \geq 0$. Thus, the retailer's optimized profit under a push contract is a decreasing convex function of w.

■

A.4 Proof of Lemma 2

The proof follows from a comparison of expected retailer profit under the pull contract (27) with (23). Both expressions are equal because $q_S(c) = q_R(c)$. The revenue equivalence of the first- and second-price pull auction has been shown in Lemma 1, what completes the proof.

■

A.5 Proof of Corollary 1

Consider the push contract and let $b(c)_n$ denote the bidding strategy when marginal cost is c and there are n bidders.

$$\frac{dE(\Pi_R^{Push})}{dw} = -q_R(w) = -\Phi^{-1}[(z-w)/z] < 0 \tag{86}$$

and since $\frac{d\Phi^{-1}[(z-w)/z]}{dw} < 0$, $E(\Pi_R^{Push})$ is a decreasing convex function of w. Consider the first-price push contract. Using (21),

$$\begin{aligned}\left(\frac{db}{dc}\right)_{n+1} &= \frac{f(c)(n)(b_{n+1}(c)-c)q(b_{n+1}(c))}{(1-F(c))(q(b_{n+1}(c))+(b_{n+1}(c)-c)\frac{dq}{db})} \\ &> \frac{f(c)(n-1)(b_n(c)-c)q(b_n(c))}{(1-F(c))(q(b_n(c))+(b_n(c)-c)\frac{dq}{db})} = \left(\frac{db}{dc}\right)_n\end{aligned} \tag{87}$$

as long as $dq/db < 0$ which is valid for all $q > 0$. Therefore, $b(c)_{n+1} < b(c)_n$ for $c < \overline{c}$ and $b(\overline{c})_{n+1} = b(\overline{c})_n$. Considering the cost of the lowest bidder c_I with the probability density of the lowest cost bidder given as $f_{I:n}(c) = n(1-F(c))^{n-1}f(c)$ (see Arnold et al., 1993), then $\frac{f_{I:n}(c)}{f_{I:n+1}(c)} = \frac{n}{(n+1)(1-F(c))}$ increases in c. $c_{I:n}$ therefore third-order stochastically dominates $c_{I:n+1}$ and c_I stochastically decreases with n. Thus, the expected retailer profit increases in n under first-price push contracts. In the second-price push contract, the cost c_{II} of the second-lowest bidder with probability density $f_{II:n}(c) = n(n-1)F(c)(1-F(c))^{n-2}f(c)$ determines the resulting wholesale price. It is therefore sufficient to show that c_{II} stochastically decreases with n. This always holds since $\frac{f_{II:n}(c)}{f_{II:n+1}(c)} = \frac{n-1}{(n+1)(1-F(c))}$ is increasing in c and thus $c_{II:n}$ third-order stochastically dominates $c_{II:n+1}$. Since the pull contracts lead to the same expected retailer profit, it is also proven that the expected retailer profit under a pull contract increases in n. From the total supply chain profits under a push contract $E(\Pi_{SC}^{Push}) = -cq_R(w(c)) + p\mu - z\int_{q_R(w(c))}^{\infty}(x - q_R(w(c)))\phi(x)dx$ we get $\frac{dE(\Pi_{SC}^{Push})}{dc} = -q_R(w(c)) = -\Phi^{-1}[(z-w(c))/z] < 0$. Because $\frac{d\Phi^{-1}[(z-w)/z]}{dw} < 0$, $E(\Pi_{SC}^{Push})$ is a decreasing convex function of w. Since the wholesale prices in the first- and second-price push auction stochastically decrease in n, the proof is completed for push contracts.

For the pull contract, it is sufficient to show that $E(\Pi_{SC}^{Pull})$ is a decreasing convex function of c. From $E(\Pi_{SC}^{Pull}) = -cq_S(c)+p\mu-z\int_{q_S(c)}^{\infty}(x-q_S(c))\phi(x)dx$, we get $\frac{dE(\Pi_{SC}^{Pull})}{dc} = -q_S(c) = -\Phi^{-1}[(z-c)/z] < 0$ and since $\frac{d\Phi^{-1}[(z-c)/z]}{dc} < 0$, the proof is completed.

■

A.6 Proof of Theorem 1

i) Waehrer et al. (1998) show that in a reverse single-unit auction with a risk-averse buyer the auctioneer prefers the first-price over the second-price auction. Since under the pull contract the order quantities do not depend on the price, this contract is equivalent to a single-unit auction and the retailer prefers the first-price pull to the second-price pull contract.

ii) Define risk aversion by the Arrow-Pratt measure $r(z) = -u''(z)/u'(z)$ (or more generally an increase in risk aversion as a concave transformation of the utility function, see e.g. Eeckhoudt et al. (1995)). It is sufficient to consider the extreme cases with $r = 0$ and $r \to \infty$. For $r = 0$ we have the case of risk neutrality where the retailer prefers the push to the pull auction. For $r \to \infty$, Eeckhoudt et al. (1995) show that $\frac{dq_R^{push}}{dr} < 0$ and since demand is continuous on $[0, T]$ and $p \geq z \geq \overline{c}$ it holds that $\lim_{r\to\infty} q_R^{push} = 0$, because the wholesale price will always be greater than $c > \underline{c}$. Since $w^{pull} < z$, we then get:

$$\lim_{r\to\infty} H_R^{Push} = \int_0^T u[(p-z)x]\phi(x)dx < \lim_{r\to\infty} H_R^{Pull} = \int_0^T u[(p-w^{pull})x]\phi(x)dx \quad (88)$$

Further, since under any incentive compatible push contract with a risk-neutral supplier, where the $Q^*(c)$ is strictly decreasing on $[\underline{c}, c_*]$, the retailer's total payment $W^*(c)$ to the winning supplier with cost c is given by: $W^*(c) = cQ^*(c) + \frac{\int_c^{c^*} Q^*(z)(1-F(z))^{n-1}dz}{(1-F(c))^{n-1}}$ (compare e.g. Chen, 2007, for the risk-neutral retailer)). Thus, the average per unit procurement cost is always greater than $c > \underline{c}$ and it holds that $H_R(W^*(c)) < H_R(c \cdot q(c))$ with $q(c)$ chosen according to equation (30). Therefore, Theorem 1 also holds for an optimally chosen push contract and any other incentive compatible push contract.

iii) Under DARA preferences, the optimal order quantity (strictly) decreases in the wholesale price (see Eeckhoudt et al., 1995) and thus Proposition 1 holds.

■

A.7 Proof of Lemma 3

The suppliers' expected utility in the push contract is

$$E(U(c, b(c))) = (1 - F(c))^{n-1}u[(q(b(c))(b(c) - c)]. \quad (89)$$

The optimal bidding strategy for the first-price auction is given by

$$\frac{db(c)}{dc} = \frac{f(c)(n-1)u((b(c)-c)q(b(c)))}{u'((b(c)-c)q(b(c)))(1-F(c))(q(b(c))+(b(c)-c)\frac{dq(b(c))}{db(c)})}. \tag{90}$$

Comparing with the risk-neutral bidder by using (21) and given that the seller with the highest possible cost $\overline{c}$ has zero expected profit $b(\overline{c}) = \overline{c}$, it follows

$$\left(\frac{db(c)}{dc}\right)_{riskneutral} = \frac{f(c)(n-1)(b(c)-c)q(b(c))}{(1-F(c))(q(b(c))+(b(c)-c)\frac{dq(b(c))}{db(c)})} < \frac{db(c)}{dc}$$

whenever $\frac{u(z)}{u'(z)} > z$ which is fulfilled for all strictly concave functions with $u(0) = 0$ and $z > 0$. The risk-averse bid is always lower than the one by the risk-neutral bidder for all $c \in [\underline{c}, \overline{c})$. The retailer has a higher expected profit with a risk-averse bidder than with a risk-neutral bidder.

■

A.8 Proof of Theorem 2

Since the second-price push contract is not affected by the suppliers' risk-aversion but risk-aversion in the second-price pull contract results in an inefficient production quantity, the retailer prefers the push contract. As proof of the second part, consider the extreme cases of the first-price auction. Since $\lim_{r(z)\to\infty} b^{pull}(c) = z$, the retailer prefers the second-price push contract to the first-price pull contract, provided risk-aversion exceeds a certain threshold level. In the case without demand uncertainty, the push and pull contracts lead to the same results and only in the first-price auction the risk-averse bidder bids more aggressively and the retailer always prefers the first-price auction (see also Lemma 3).

■

A.9 Proof of Theorem 3

Define $E[i]$ as the future expected payoffs if the service provider is in state i. Assume that an auction occurs. The provider's optimization problem is to maximize the expected payoff from the auction, as well as to incorporate the future expected payoffs. Define $E(\pi_i)$ as the expected profit of a provider who is in state i and facing an occurring auction (in contrast to $E(\Pi)$ from (35), the long-term equilibrium). If the provider wins, he gets the payoff and moves from state i to state $i-1$, otherwise he remains in state i. We get the following functional equation:

$$E(\pi_i) = P(b(c)_i) \cdot [b(c)_i - c + E[i-1]] + (1 - P(b(c)_i)) \cdot E[i] \tag{91}$$

Maximizing $E(\pi_i)$ over $b(c)$ we get:

$$\frac{dE(\pi_i)}{dc} = \frac{P(b(c)_i)}{dc} \cdot [b(c)_i - c + E[i-1] - E[i]] + P(b(c)_i) \cdot \frac{db(c)_i}{dc} = 0 \tag{92}$$

(For the proof it only matters if $E[i-1] - E[i]$ is positive or negative, since we only rank the bids, given the specific properties of future payoffs. Thus c_r only holds for the single decision and has no influence on $E[i]$ or $E[i-1]$ and therefore $\frac{dE[i]}{dc_r} = 0$). In equilibrium, the provider follows the bidding strategy and reports truthfully. We can replace c_r with c and rearrange equation (92) to

$$\frac{db(c)_i}{dc} = \frac{-\frac{P(b(c)_i)}{dc} \cdot [b(c)_i - c + E[i-1] - E[i]]}{P(b(c)_i)} \tag{93}$$

While for the bid $b(c)_{nr}$ in a non-repeated auction it holds that:

$$\frac{db(c)_{nr}}{dc} = \frac{-\frac{P(b(c)_i)}{dc} \cdot [b(c)_{nr} - c]}{P(b(c)_i)} \tag{94}$$

Since in both auctions the provider with the highest possible cost expects zero surplus, in equilibrium we have $b(\overline{c}) = \overline{c}$, and $\frac{db(c)_i}{dc} < \frac{db(c)_{nr}}{dc} \forall c < \overline{c}$ if $E[i-1] < E[i]$ and $\frac{db(c)_i}{dc} > \frac{db(c)_{nr}}{dc} \forall c < \overline{c}$ if $E[i-1] > E[i]$. Consequently, the bid in the repeated game at state i is higher than the one in the non-repeated game whenever $E[i-1] < E[i]$ and vice versa.

To now compare $E[i]$ for different states, we start comparing $E[0]$ with $E[1]$. At state 0, the provider cannot participate in an occurring auction and has to wait until he moves to state 1 before he can participate again. In state 1, a movement to state 0 implies a payment of $b(c)_i - c > 0 \forall c < \overline{c}$. Since $E[i] \geq 0 \; \forall i$ (a provider never bids under his cost), $E[0] < E[1]$ and thus $b(c)_1 > b(c)_{nr}$. At state 2, winning an auction implies a payment of $b(c)_2 - c$ and a movement to state 1. Since $P(b(c)_n r) \cdot [b(c)_n r - c] > P(b(c)_1) \cdot [b(c)_1 - c] > 0$, $E[1] - E[0] > E[2] - E[1] > 0$ and therefore $b(c)_1 > b(c)_2 > b(c)_{nr}$ as long as $E[i-1] \leq E[i] \forall i > 2$. This holds for all $i \geq$. To show that $E[i-1] \leq E[i]$, consider the other end of the chain and compare $E[K-1]$ and $E[K]$. To show that $E[K-1] < E[K]$, let us first assume the opposite. Assume that $E[K-1] > E[K]$. In this case we would have $b(c)_K < b(c)_{nr}$. Since the provider in K always has the option to bid the non-repeated bid (the bid that maximizes $P(b(c)) \cdot [b(c) - c]$), $E[K-1]$ can only be higher than $E[K]$ if either state $K-1$ or one of the previous states generates a higher expected profit from the next occurring auction (given as $P(b(c)) \cdot [b(c) - c]$) than the one in the non-repeated auction. But since $b(c)_{nr}$ maximizes $P(b(c)) \cdot [b(c) - c]$, this cannot be the case. Thus $E[K-1] \leq E[K]$. Since we have already shown that $E[0] < E[1]$, we even get that

$E[K-1] < E[K]$. We can apply the argumentation from state K to every state, and thus it holds that $E[i-1] < E[i]$ and therefore, $b(c)_{i-1} > b(c)_i > b(c)_{nr}$. Thus, the bid in the repeated auction is equal to a bid in a non-repeated auction plus a mark-up that depends on the opportunity cost, while the higher the level of free capacity, the lower the bid, but it will always be higher than the bid in the non-repeated-auction.

■

A.10 Proof of Theorem 4

Since $K = 1$ and thus bidding is only possible in State 1, the bidding strategy only depends on the cost, rather than on the state. Thus, in equilibrium, the probability of winning an auction is equal to the probability of having the lowest cost of all competing providers (the number of providers that have a free capacity level). Assume that the provider reports his cost as c_r. The expected profit and deviation for his real cost are:

$$\Pi(c_r, c) = \frac{(b(c_r) - c) \cdot (1 - F(c_r))^{n-1}}{\lambda + (1 - F(c_r))^{n-1} \cdot \rho}, \Pi'(c) = -\frac{(1 - F(c_r))^{n-1}}{\lambda + (1 - F(c_r))^{n-1} \cdot \rho} \tag{95}$$

In an equilibrium, sellers choose honest revelation and $\Pi(x, c) = \Pi(c, c)$. Thus

$$\Pi(c, c) = \frac{(b(c) - c) \cdot (1 - F(c))^{n-1}}{\lambda + (1 - F(c))^{n-1} \cdot \rho}, \Pi'(c) = -\frac{(1 - F(c))^{n-1}}{\lambda + (1 - F(c))^{n-1} \cdot \rho} \tag{96}$$

Since it has to hold that $\Pi(\overline{c}) = \Pi(\overline{c}, \overline{c}) = 0$ we have

$$\Pi(c) = \int_{\overline{c}}^{c} \Pi'(z) dz = \int_{c}^{\overline{c}} \frac{(1 - F(z))^{n-1}}{\lambda + (1 - F(z))^{n-1} \cdot \rho} dz \tag{97}$$

Since in equilibrium it has to hold that $\Pi(c, c) = \Pi(c)$ we get

$$\frac{(b(c) - c) \cdot (1 - F(c))^{n-1}}{\lambda + (1 - F(c))^{n-1} \cdot \rho} = \int_{c}^{\overline{c}} \frac{(1 - F(z))^{n-1}}{\lambda + (1 - F(z))^{n-1} \cdot \rho} dz \tag{98}$$

Therefore,

$$b(c) = c + \frac{(\frac{\lambda}{\rho} + (1 - F(c))^{n-1}) \cdot \int_{c}^{\overline{c}} \frac{(1-F(z))^{n-1}}{\frac{\lambda}{\rho} + (1-F(z))^{n-1}} dz}{(1 - F(c))^{n-1}} \tag{99}$$

■

A.11 Proof of Theorem 5

To proof Theorem 5, we show that if future profits are not influenced by the choice of the current auction format, then the first- and second-price auction are revenue equivalent.

Therefore, consider a service provider who faces an auction and has the choice between the first- and second-price auctions, while for all subsequent strategy a first-price auction will be conducted (alternatively one might assume that a second-price format is chosen for all subsequent auctions).

$E(\Pi)_{future}(c)$ is the expected future profit, without the payment of the current auction, but depending on whether or not the provider wins the auction he faces now. $E(\Pi)_{future}(c)$ only depends on the state the provider will be in after the auction, thus whether the provider wins the current auction or not, but not on the payment of the current auction. Therefore, if for a given cost and state the probability of winning an auction is the same for two auction formats, $E(\Pi)_{future}(c)$ is also the same for both formats.

Determine $\Pi^w_{future}(c)$ as the future profits if the provider wins the auctions and $E(\Pi)^l_{future}(c)$ as the ones if he looses. We can now consider the actual bidding problem as a single unit bidding problem with total cost $c_t = c + E(\Pi)^l_{future}(c) - E(\Pi)^w_{future}(c)$ where $E(\Pi)^l_{future}(c) - E(\Pi)^w_{future}(c)$ are the opportunity costs of winning the auction (c_t is increasing in c for any incentive compatible auction). c_t depends on c, as well as on the actual state of the provider, but ex ante all providers hold the same beliefs on the distribution of c_t for the other providers. Thus, the provider is faced with a single auction decision, where in equilibrium the provider with the lowest bid submitted wins and the provider with the highest feasible bid expects zero surplus. Since further costs are independently drawn from a common, strictly-increasing atomless distribution, the bids of the auction will hold the same expected revenue for both the first- and second-price auction (see Myerson, 1981, which we adapted for the reverse auction). This comparison can be applied for all future auctions. Thus, whenever the provider faces an auction, he is indifferent between the first- and second-price auction. This proof also holds for other standard auctions like the English or the Dutch auction.

■

A.12 Proof of Theorem 6

For the proof we refer to *Lemma 2* and *Proposition 3* in Grimm (2007) and their proof.

■

A.13 Proof of Theorem 7

Consider the expected profits in the second of the two sequential auctions. Since the winner of the first auction always wins the second auction it holds that $(E(\Pi(c_1, c_2))^{won} = E[C_{d_2}(x_1^{-1})] - E[C_{d_1+d_2}(c_1, x) - C_{d_1}(c_1)]$ and $E(\Pi(C_1, x))^{lost}) = 0$. Thus the extra value of winning the first auction is the difference between the expected cost of the winner in the second auction and the expected lowest cost of the remaining service providers in the second auction. This is equal to the expected payment $E(P_2)$ in the second auction minus the expected cost of the winner and we get

$$b(c_1) = E[C_{d_2}(x_1^{-1})] - E[C_{d_1+d_2}(c_1, x) - C_{d_1}(c_1)] \tag{100}$$

which leads to

$$E(P_1) = \int_{\underline{c_1}}^{\overline{c_1}} \left(C_{d_1}(c_1) + \int_{\underline{c_2}}^{\overline{c_2}} (C_{d_1+d_2}(c_1, c_2) - C_{d_1}(c_1) - E[P_2]) f(c_2) dc_2 \right) g^{II}(c_1) dc_1 \tag{101}$$

We then get

$$E(P_1) + E(P_2) = \int_{\underline{c_1}}^{\overline{c_1}} \left(C_{d_1}(c_1) + \int_{\underline{c_2}}^{\overline{c_2}} (C_{d_1+d_2}(c_1, c_2) - C_{d_1}(c_1) - E[P_2]) f(c_2) dc_2 \right) + E[P_2] g^{II}(c_1) dc_1 \tag{102}$$

and since $E(P_2)$ does not depend on the cost of the winner, we can eliminate $E(P_2)$

$$E(P_1) + E(P_2) = \int_{\underline{c_1}}^{\overline{c_1}} \left(C_{d_1}(c_1) + \int_{\underline{c_2}}^{\overline{c_2}} (C_{d_1+d_2}(c_1, c_2) - C_{d_1}(c_1)) f(c_2) dc_2 \right) g^{II}(c_1) dc_1 \tag{103}$$

and further simplify to

$$E(P_1) + E(P_2) = \int_{\underline{c_1}}^{\overline{c_1}} \left(\int_{\underline{c_2}}^{\overline{c_2}} (C_{d_1+d_2}(c_1, c_2)) f(c_2) dc_2 \right) g^{II}(c_1) dc_1 \tag{104}$$

which is equal to the expected cost in the bundle auction (compare equation (61)).

■

A.14 Proof of Corollary 2

The first part follows directly from Theorem 6. Further, since $E[X_C]$ do not change in the number of bidders, while $E[X_{(2)}^{-1}]$ and $E[X_{(1)}^{-C}]$ decrease in n, the second part also follows from Theorem 6.

■

A.15 Proof of Theorem 8

For the proof we refer to Lemma 2 and Lemma 3 in Grimm (2007) and her proof. Modifying for marginal cost in the second period to be distributed on $[\underline{c_2}, \overline{c_2}]$, using the density function for the lowest cost service provider defined as: $f_{I:n}(c) = n(1-F(x))^{n-1}f(x)$ (see e.g. Arnold et al., 1993) and not allowing providers of only one service, we get Theorem 8.

■

A.16 Proof of Proposition 2

We refer to the proof of *Proposition 1* from Van Mieghem (1998), since we just provide a simply modified version of that Proposition.

■

Appendix B

Derivations

We here derive the of closed-form expressions for the different auction formats presented in Section 3

B.1 First-price push contract

Since $b^{f,Push}(c) = \frac{1}{1+n} + \frac{n}{1+n}c$ it follows

$$E(w^{f,Push}) = \frac{1}{1+n} + \int_0^1 n(1-c)^{n-1} c \frac{n}{1+n} dc = \frac{1}{1+n} + \frac{n}{(1+n)^2}$$

$$\begin{aligned} E(\Pi_R^{f,Push}) &= \frac{p}{2} - \int_0^1 n(1-c)^{n-1} \left[\frac{(1-c)n}{1+n} \frac{1+nc}{n+1} + \int_{\frac{(1-c)n}{1+n}}^1 \theta - (\frac{(1-c)n}{1+n}) d\theta \right] dc \\ &= \frac{1}{2} \left(p - \frac{4n^2+5n+2}{(n+1)^2(n+2)} \right) \end{aligned}$$

$$\begin{aligned} E(\Pi_{SC}^{f,Push}) &= \int_0^1 n(1-c)^{n-1} \left(\frac{1}{1+n} + \frac{n}{1+n} c - c \right) \frac{(1-c)n}{1+n} dc + \frac{1}{2} \left(p - \frac{4n^2+5n+2}{(n+1)^2(n+2)} \right) \\ &= \frac{n^2}{(n+1)^2(n+2)} + \frac{1}{2} \left(p - \frac{4n^2+5n+2}{(n+1)^2(n+2)} \right) = \frac{p}{2} - \frac{2n+1}{2(n+1)^2} \end{aligned}$$

B.2 Second-price push contract

$$E(w^{s,Push}) = \int_0^1 n(n-1)c(1-c)^{n-2} c dc = \frac{2}{n+1}$$

$$\begin{aligned} E(\Pi_R^{s,Push}) &= \frac{p}{2} - \int_0^1 n(n-1)c(1-c)^{n-2}[c(1-c) + \int_{1-c}^1 \theta - (1-c)d\theta]dc \\ &= \frac{1}{2}\left(p - \frac{4n+2}{(n+1)(n+2)}\right) \end{aligned}$$

$$\begin{aligned} E(\Pi_{SC}^{s,Push}) &= \int_0^1 n(1-c)^{n-1}(\frac{1}{1-c}\int_c^1 (n-1)\left(\frac{1-c_2}{1-c}\right)^{n-2}((c_2-c)(1-c_2)dc_2)dc \\ &+ \quad E(\Pi_R^{s,Push}) = \frac{p}{2} - \frac{1}{n+1} \end{aligned}$$

B.3 Pull contract

$$E(w^{s,Pull}) = \int_0^1 n(n-1)c(1-c)^{n-2}c(2-c)dc = \frac{4n+2}{(n+1)(n+2)}$$

$$E(\Pi_R^{s,Pull}) = \frac{1}{2}\left(p - \frac{4n+2}{(n+1)(n+2)}\right)$$

$$E(\Pi_{SC}^{s,Pull}) = \frac{p}{2} - \int_0^1 (n(1-c)^{n-1}\left[c(1-c) + \int_{1-c}^1 (\theta - (1-c))d\theta)\right] dc = \frac{p}{2} - \frac{1}{n+2}$$

B.4 English Auction

Since the ideal price in the monopoly case is $\frac{1+c}{2}$,

$$\begin{aligned} E(w^{e,Push}) &= \int_0^{\frac{1}{2}} cn(n-1)c(1-c)^{n-2}dc \\ &+ \int_{\frac{1}{2}}^1 \frac{1}{c}\left(\int_0^{2c-1} \frac{1+x}{2}dx + \int_{2c-1}^c cdx\right) n(n-1)c(1-c)^{n-2}dc \\ &= \frac{2-2^{-n}}{1+n} \end{aligned}$$

$$E(\Pi_R^{e,Push}) = \frac{p}{2} - \int_0^{\frac{1}{2}} n(n-1)c(1-c)^{n-2}[c(1-c) + \int_{1-c}^1 \theta - (1-c)d\theta]dc$$

$$
\begin{aligned}
&- \int_{\frac{1}{2}}^{1} \left(\int_{0}^{2c-1} [\frac{1-x^2}{4} + \int_{\frac{1-x}{2}}^{1} \theta - (\frac{1-x}{2}) d\theta] dx \right) n(n-1)(1-c)^{n-2} dc \\
&- \int_{\frac{1}{2}}^{1} \left(\int_{2c-1}^{c} [c(1-c) + \int_{1-c}^{1} \theta - (1-c) d\theta] \, dx \right) n(n-1)(1-c)^{n-2} dc \\
&= \frac{p}{2} - \frac{1 + 2n - 2^{-(1+n)} n}{2 + 3n + n^2}
\end{aligned}
$$

$$
\begin{aligned}
E(\Pi_{SC}^{e,Push}) &= E(\Pi_{R}^{e,Push}) + \int_{0}^{\frac{1}{2}} n(n-1)c(1-c)^{n-2} \left[(1-c)(c - \frac{1}{c} \int_{0}^{c} x dx) \right] dc \\
&\quad + \int_{\frac{1}{2}}^{1} \left(\int_{0}^{2c-1} \frac{(1-x)^2}{4} dx + \int_{2c-1}^{c} (c-x)(1-c) dx \right) n(n-1)(1-c)^{n-2} dc \\
&= \frac{p}{2} - \frac{1 - 2^{-(1+n)}}{1+n}
\end{aligned}
$$

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