

Essays in Empirical Industrial Economics

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Abstract

This thesis consists of two parts, which are connected by an introduction on auction and oligopoly markets and a short discussion about the obtained results at the end. The first part provides a literature review on auctions and analyzes bidders' behavior in Austrian cattle auctions. The aim is to investigate whether there are differences among bidders and whether bidders take the possibility of buying later into account when bidding for objects. The second part analyzes firms' strategies in the semiconductor industry. In particular, the strategic effects of learning by doing and spillovers are considered. Further, the consequences of aggregating firms' pricing behavior to an industry level pricing equation are empirically investigated. In both parts emphasis is put on the question, whether neglecting asymmetries across market participants and/or neglecting dynamic effects influences the estimated parameters.

Keywords:

Auctions, oligopoly, applied econometrics, applied game theory

Zusammenfassung

Diese Dissertation besteht aus zwei Teilen, die durch eine Einleitung zu Auktions- und Oligopolmärkten und durch eine kurze Diskussion über die erzielten Resultate am Ende der Arbeit miteinander verbunden sind. Der erste Teil diskutiert die Literatur zu Auktionen und analysiert das Verhalten von Bieter in österreichischen Rinderauktionen. Das Ziel der Untersuchung ist es zu bestimmen, ob es Unterschiede im Verhalten der Bieter gibt und ob diese die Möglichkeit eines späteren Kaufes in Betracht ziehen. Der zweite Teil beschäftigt sich mit den Strategien von Firmen in der Halbleiterindustrie. Im besonderen werden die strategischen Effekte von “learning-by-doing” und “spillovers” betrachtet. Des weiteren werden die Konsequenzen der Aggregation von firmenspezifischen Preisverhalten zu einer industriespezifischen Preisgleichung empirisch untersucht. In beiden Teilen wird schwerpunktmäßig auf der Frage eingegangen, ob das Vernachlässigen von Asymmetrien unter den Marktteilnehmern und/oder das Vernachlässigen dynamischer Effekte die geschätzten Parameter beeinflusst.

Schlagwörter:

Auktionen, Oligopol, Angewandte Ökonometrie, Angewandte Spieltheorie

To my daughter Lisa and my parents

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Chapter 1

Introduction

The field of industrial economics includes the analysis of market structure and firms behavior in the market. Most real markets are imperfectly competitive markets. The interest of economists lies in exploring these kind of markets, as they are unlikely to maximize social welfare. Modern industrial organization has been influenced by non-cooperative game theory in an essential way. Formal theories offer precise and therefore testable characterizations of firms' behavior supporting the non-competitive outcome. Further, empirical work making use of game theory has been developed in the study of oligopolistic markets over last decades. Researchers derive testable implications from game theoretic models by concentrating on reduced form econometric models to test certain implications of theory. One concern of this approach is the possibility that other models of behavior may have the same reduced-form predictions. Others have been led to more and more structural models. These models rely on the hypothesis that the observed data are the equilibrium strategies of an underlying game-theoretic model, which can be used to estimate the characteristics of the market.

Besides oligopolistic markets auctions are another example of imperfectly competitive markets. In both areas empirical work testing theory has made large progress the last two decades. However, testing theory is one part of empirical work. The other important strand is to infer relations between economic variables out of the real world data and to establish stylized facts. Theoretical models take these relations and facts then into account.

In this thesis I follow a structural approach and analyze the semiconductor industry as an example of an oligopolistic market and cattle auctions in Austria as an example of an auction market. Firms' strategies in the semiconductor industry form one point of interest. Bidding behavior in auctions the other. In both markets dynamic effects and asymmetries among players seem to matter. In the semiconductor industry learning-by-doing and spillovers are prevalent. Whether firms take the strategic effects of learning-by-doing and learning spillovers actually into account when choosing their output strategies is answered empirically. Austrian cattle auctions are conducted in a sequence of objects. The aim is to investigate whether there are differences among bidders and whether bidders take the possibility of buying later into account when bidding for objects. In both cases the consequences on the estimated parameters (e.g. learning-by-doing) are investigated.

Does it matter, when asymmetries and dynamic effects are taken into account or is the difference between the estimates rather small?

1.1 Auction markets

Auctions are one of the oldest forms to determine transaction prices. Historical sources tell us about various auctions taking place in Greece, the Roman Empire, China, and Japan. Not only history is witness of this economic institution, but also nowadays auctions are used in a remarkable range of situations. There are auctions for livestock, flowers, antiques, artwork, stamps, wine, real estate, publishing rights, timber rights, used cars, contracts and land, and for equipment and supplies of bankrupt firms and farms. Auctions are of special interest to economists because they are explicit mechanisms, which describe how prices are formed. The continuing popularity of auctions makes one wonder about the reasons why. Following Milgrom (1987) some explanations can be given: One explanation is that auctions often yield outcomes that are efficient and stable. A second explanation might be that a seller in a relatively weak bargaining position, consider the case where the seller is the owner of a nearly bankrupt firm, can do as well as a strong bargainer by conducting an auction. However, she then can not use strategic policies like imposing a reserve price or charging entry fees. Even a seller in a strong bargaining position will decide to sell via auction, if it is optimal in relation to other exchange games. These three partly complementary explanations provide a cogent set of reasons for a seller to use an auction when selling an indivisible object.

In bidding for an object a bidder faces an uncertainty about the value of the auctioned object, a strategic uncertainty relative to other players' strategies and relative to other players' characteristics. Thus in auction markets we find ourselves in the class of games with incomplete information. Through the use of the Bayesian Nash equilibrium concept by Harsanyi (1967) the theory of auctions has provided the necessary developments. The three most prominent auctions models are the independent private value model due to Vickrey (1961), the symmetric common value model due to Rothkopf (1969) and Wilson ((1969) and (1977)) and the asymmetric model due to Wilson ((1967) and (1969)). Milgrom and Weber (1982a) developed a model of competitive bidding in which the winning bidder's payoff may depend upon his personal preferences, the preferences of others, and the intrinsic qualities of the object being sold. They introduced the concept of affiliated values and showed that the three above mentioned models are special cases of the affiliated value paradigm.

A lot of the theoretical models investigate one shot games only. However, the same commodities are often sold in sequential auctions. Ashenfelter (1989) noticed a so called declining price anomaly in wine and art auctions: winning prices decrease during the day. One theoretical model of sequential auctions is due to Weber (1983). With independent private values, symmetry, and bidders desiring at most one unit of the auctioned commodity, he showed that winning bids in sequential auctions should follow a martingale process. With affiliated values, the sequence of winning prices displays an upward lift (Weber (1983), Milgrom and Weber (1982b)). McAfee and Vincent (1993) showed how

risk aversion of bidders may explain declining prices.

Auctions are analyzed by assuming that the characteristics of the bidders are drawn by Nature from probability distributions which are common knowledge to all bidders. The key explanatory variables of bidding behavior are these distributions. In experiments one can control for these distributions and can analyze the strategic behavior of bidders. The role of experiments is to test the behavioral predictions of the game theoretic analysis.¹ When using field data the distributions of bidders are not known to the researcher and are one subject of interest.

However, auctions are an interesting subject to analyze empirically, as on the one hand the rules of associated games are usually well defined and many constraints are available to define the structural model. Further, the data of auctions are usually quite rich and more readily available than data from other markets. Therefore it seems to be promising to empirically test game theoretic models in the context of auctions. Some authors concentrate on reduced form econometric models to test certain implications of auction theory, with the observed bids as dependent variables. Explanatory variables might then be the reservation price, the number of bidders, and some characteristics of the auctioned object. A second approach, the structural approach, relies on the hypothesis that the observed bids are the equilibrium bids of the considered auction model. As the optimal strategy is a function of private values or signals, depending on the model (private vs. common), the equilibrium strategy gained from the theoretical model can be used to estimate the characteristics of the distribution of private values or signals, respectively. The first moment of the distribution is of particular interest, as it characterizes the expected gain for the seller.

The main difficulty of the structural approach lies in the typically highly nonlinear equilibrium bid function and in the complex density of the winning bids. Laffont, Ossard and Vuong (1995) developed a simulated non-linear least squares estimator that can handle a broad class of distributions. This is in contrast to other methods, which require that the joint distribution belongs to particular families of distributions (see e.g. Donald and Paarsch (1993)). Nevertheless a specific distributional assumption must still be made. To avoid the distributional assumptions Elyakime, Laffont, Loisel, and Vuong (1994) have proposed nonparametric methods for estimating the probability law of valuations. However, in contrast to parametric methods, this approach requires knowledge of all bids, not just the winning bids. Parametric models provide a test of the joint hypothesis that the distribution of valuations belongs to the assumed family of distributions and that potential buyers bid according to theory.

Most of the literature on empirical estimation of auctions assumes a static setting. On the contrary there is little empirical work on sequential auction games. Beggs and Graddy (1997) study the order of sale in art auctions and found that the final (winning) bid relative to the auctioneer's estimated price declines throughout the course of an auction. Engelbrecht-Wiggans and Kahn (1999) examined dairy cattle auctions on different days and found that prices decline over the course of an auction day, with the main decline occurring towards the end of the day. Jofre-Bonet and Pesendorfer (1999) consider bidding

¹Kagel (1995) gives a very detailed survey of results in experimental auctions.

behavior in a repeated procurement auction setting. Considering a dynamic bidding model and using data for highway construction procurement in the state of California, they assess the importance of intertemporal constraints. Donald, Paarsch and Robert (1997) consider a model in which a finite number of objects are sold in a sequence of ascending-price auctions. They allow bidders to desire more than one unit and estimate the model using data on the sales of Siberian timber-exports permits. Laffont, Loisel and Robert (1997) consider finitely repeated first-price auctions in which at each stage an identical object is sold. They set up a model that generates an inverse U-shaped intra-day dynamics and confirmed it with data on eggplant auctions.

Chapter 2 reviews parts of the literature on auction theory in more detail. In particular, I primarily concentrate on empirical issues. For this purpose I first start with describing the most prominent auction models and give then some further issues with respect to relaxing the major assumptions of these models. The other part concerns the econometrics of auctions. Issues on experiments on auctions are left out. Chapter 3 provides then an empirical analysis of cattle auctions taking place in Amstetten, Austria. These auctions are held as sequential English auctions. In this market the bidders are either some traders, who visit the auctions on a regular basis, or farmers with single-unit demand. The aim is to investigate whether there is a difference in the valuations of large traders and small bidders. The second question concerns intertemporal effects. Do bidders take the possibility of buying later into account when bidding for objects? By analyzing I follow a structural approach and estimate the characteristics of the distribution of bidders' values. In particular, I concentrate on the first moment of the distribution of the bids, as it characterizes the expected gain for the seller.

The contribution of the analysis of Austrian cattle auctions to the literature lies in specifying an empirical sequential auction model and to investigate whether bidders' valuations are asymmetric and whether bidders take the possibility of buying later into account. The analysis of Austrian cattle auctions shows asymmetries among bidders and a significant effect of the sequential bidding game. A further point of interest deals then with the question, how the estimation results compared to the estimation results of a static symmetric model, which I defined as the benchmark model. In general, the findings show that neglecting asymmetries has a great impact on the estimation results, whereas neglecting the sequential effect does not really change the estimation results.

1.2 Oligopoly markets

The analysis of market structure, firm conduct, and market performance in oligopolistic markets are the main theoretical and empirical concerns of contemporary industrial economics. The central question is about firm and industry conduct: the aim is to estimate the parameters that measure the degree of competition. To measure market power and market conduct with a structural model relies on the hypothesis that the observed prices and output are the equilibrium prices and equilibrium output of the considered game-theoretic model. A system of demand and supply relations is typically estimated. Under the assumption that the market is in equilibrium, the focus lies on the estimation of

market conduct with regard to other market determinants, like e.g. economies of scale, learning-by-doing and/or spillover effects. The supply relations are derived from the first order conditions of firms' maximization problems and specify the behavioral response of firms in a given market. The demand equation represents consumers maximizing their utility.

In studying repeated games strategies are considered in which past play influences current and future strategies. Usually economists focus their attention on equilibria in a smaller class of Markov state-space or feedback strategies. In this case the past influences the current play only through its effect on a state variable that summarizes the direct effect of the past on the current environment (Fudenberg and Tirole (1983)). There are further information concepts. Firms either pre-commit themselves to their production plans or they consider the effect of learning-by-doing and spillovers on their rivals' output decision. Or differently spoken firms use either open-loop or closed-loop (no memory) strategies². Each of these information structures has different implications on the equilibrium outcomes. In an open-loop equilibrium players commit to entire paths of history. In a closed-loop perfect information structure players can condition their play at time t on the history of the game until that date. In a memoryless perfect state information structure the past influences the current play only through its effect on a state variable like in the feedback information pattern but also on the initial value of the state, which is known a priori. With all information structures firms can play their strategies simultaneously or sequentially. In both cases we talk about Nash equilibria.

The dynamic structure in a market can arise from the fact of learning-by-doing within firms and/or learning spillovers among firms in an industry. In learning models firms learn either from their own experience, from the experience of other firms, or both. Learning-by-doing introduces an intertemporal component to firms decisions. Current production adds to the firm's stock of experience and increases in the firm's stock of experience reduce firm's unit costs in future periods. Theoretical research demonstrate that learning can have sizable impact on cost and strategic decisions and market performance (e.g. Spence (1983), Fudenberg and Tirole (1983)).

Most empirical studies of the DRAM market investigate, whether learning-by-doing and spillovers are prevalent in that industry and when yes, how large these effects are. The different setups vary to a certain degree. Baldwin and Krugman (1988), and Flamm (1993) completed simulation studies for different generations of DRAMs. These papers deal with calibrating theoretical models and they were the first to incorporate learning economies into a stylized empirical model of the semiconductor industry. Another part of the semiconductor literature considers econometric models. Gruber (1992), (1996a) estimated reduced form relationships assuming constant price-cost margins and found economies of scale rather than learning-by-doing effects for various generations of DRAMs. Irwin and Klenow (1994) implemented a recursive dynamic specification. They assumed constant returns to scale, Cournot behavior and fixed elasticities of demand. Their results imply learning-by-doing within and learning spillovers across firms, but no spillovers across generations. Brist and Wilson (1997) estimated both a demand and a pricing relation for

²For a mathematical treatment of dynamic games see e.g. Basar and Olsder (1991))

a dynamic game with an open-loop information structure. Neglecting learning spillovers among firms they showed learning-by-doing to be smaller in the presence of economies of scale and estimated markups. Siebert (1999) used a dynamic model and investigated the influence of a multi-product specification on the estimated parameters. He found that multiproduct firms behave as if in perfect competition.

Most of the literature about the semiconductor industry has considered learning-by-doing extensively, but has not considered the dynamic strategic implications. Jarmin (1994) investigated these dynamic effects for the early rayon industry. His results show that firms take their rivals' reactions into account when choosing their strategies. Karp and Perloff (1989) estimated a dynamic oligopoly model and the degree of competition for the rice export market. Their model nests various market structures with firms that either pre-commit themselves to a production plan or that consider the strategic effect of their own output on their rivals' future output decision. However, their model does not take learning-by-doing or spillover effects into account.

The aim of Chapter 4 is to test whether firms in an dynamic oligopolistic industry pre-commit themselves to a production plan or whether they consider the effect of learning-by-doing and spillovers on their rivals' output decision. I apply the same dynamic oligopoly model to the DRAM industry that Jarmin applied to the early rayon industry. The empirical framework for examining the dynamic effects of learning-by-doing and spillovers, and market power is an intra industry study described in Bresnahan (1989). Further I analyze the impact of a dynamic specification on the estimated parameters of learning-by-doing, learning spillovers, economies of scale and price-cost margins. In a conceptual analogous way Röller and Sickles (1900) showed for the airline industry that market conduct in a two-stage set-up of a game in capacity and prices is significantly less collusive than in a one-stage set-up.

The industry under investigation is the semiconductor industry, in particular the Dynamic Random Access Memory (DRAM) market. DRAMs are memory components (chips) and are classified into generation. From a descriptive analysis of the DRAM market one can conclude dynamic elements like learning-by-doing within firms and learning spillovers among firms to matter. The implication of learning by doing in production technology for market conduct and performance can be modelled within a dynamic oligopoly game. Thus the consequences of firms' using experience as a strategic variable can be considered.

Departing from a dynamic oligopoly game the first order conditions for the open-loop and the closed-loop no memory equilibrium are derived in order to implement an econometric model. The closed-loop specification then enables me to evaluate the effect of firm's strategy on the objective function of other firms in future periods. I assume a single product market. The structural econometric approach is used for evaluating market power, learning-by-doing, learning spillovers, economies of scale and strategic behavior. The methodology involves a specification of demand and marginal cost functions and hypotheses about the strategic interactions of the participants. Different behavioral assumption about firms in the DRAM market are tested and the parameters for the demand and the cost functions, including the parameters for market power, learning-by-doing ef-

fects, learning spillovers, economies of scales and strategic behavior are estimated. The empirical results show that firms behave strategically in a dynamic sense and that a possible estimation bias is evident in the DRAM industry. In particular, firms' market power could be wrongly estimated, if one does not consider firms to act strategically over time and that leads to an incorrect assessment of the market under consideration.

For the analysis of market structure, firm conduct, and market performance in an oligopolistic market very often only industry level data is available. Theoretical models of oligopoly are at the firm level and provide the researcher with firm level equilibrium pricing relations. The general objective of chapter 5 concerns the aggregation of firm level pricing equations to an industry level pricing equation. The point of interest lies in comparing two specifications of the industry level pricing relation. The first assumes that the market consists of firms with equal market shares. Actually, the assumption of symmetry is not given for the 256K DRAM market. Thus with a second specification I want to correct for the asymmetry. The two specifications are estimated with quarterly data of the 256K generation at the industry level. For each specification I estimate a structural dynamic model of demand and pricing relations. Under the assumption that the market is in equilibrium, I focus on the estimation of economies of scale, learning-by-doing, the effects of input prices and the intertemporal strategic effect. Given the estimation results of the two specifications a potential aggregation bias can be calculated.

Part I
Auction markets

Chapter 2

Literature review on auctions¹

2.1 Introduction to auction theory

There are a wide range of how auctions are conducted. The four most prominent types of auctions are first-price, second-price, English and Dutch auctions. The first-price auction is a sealed bid auction in which the buyer with the highest bid claims the object and pays the amount she has bid. Whereas in the second-price auction the item still goes to the bidder with the highest bid, but she pays only the amount of the second highest bid. This arrangement does not necessarily mean a loss of revenue for the seller, as in this form of auction the buyers will generally bid higher than in the first-price auction. The second-price auction is also known as a “Vickreyäuction. The Dutch auction, also called descending auction, is conducted by an auctioneer who initially calls for a very high price and then continuously lowers the price until some bidder stops the auction and claims the good for that price. This kind of auction is frequently used in the agricultural sector. There are several variants of the English auction. In one, the participants themselves are calling out the bids and when nobody is willing to raise a bid anymore the auction ends. Another possibility is that the auctioneer calls the bids and the participants indicate their assents by a slight gesture. In yet another form of English auction, the price is posted using an electronic display and is raised continuously. A bidder who is active at the current price presses a button. The moment she releases the button she withdraws from the auction. This particular variant is used in Japan. These are three quite different forms of English auction with three quite different corresponding games.

Differences among the bidders’ valuations of the auctioned object can have two possible causes: differences in the bidders’ tastes or the bidders have access to different information. To be more explicit, suppose that each bidder knows exactly how highly she values the item to be sold. Further she knows nothing about the other bidders valuations, she perceives any other bidder’s valuation as a draw from some probability distribution and she is aware that the other bidders regard her valuation to be drawn from some probability distribution as well. These probability distributions are common knowledge and the valuations of the bidders are statistically independent. In general this is called the *independent private value*

¹The main part of this chapter draw on Böheim and Zulehner [Böheim and Zulehner \(1996\)](#).

model. Now consider the case where the auctioned object has a value known to everyone. Namely the amount of this item on the market. However nobody knows the true value, but has some information about the item. And the bidders' perceived values are conditional on the unobserved value independent draws from some probability distribution. This is called the *common value model* or the *mineral rights model*. The first situation applies, for example, to an auction of an antique, where the bidders buy for their own use and will not resale it. Whereas in the latter situation an auction for an antique that is being bid for by dealers who intend to resell it is described. The independent private value model and the common value model describe two extremes. In reality one might find auction situations lying between these two cases. A general model that allows for correlation among the bidders' valuations and that takes into consideration the two above described special cases, was developed by Milgrom and Weber (1982a). To go back to the example given above, an auction of an antique cannot be fully described in either of the two extreme cases. As the dealers may be guessing about the ultimate market value of the object, but they may differ in their selling abilities, so that the market value depends on which dealer wins the bidding. This argument suggests the need for a more general model.

2.1.1 The independent private value model

Much of the existing literature on auction theory deals with the independent private value paradigm in a risk neutral setting. In this section we now want to list the results and conclusions emerging from the independent private value model. As described above, in that model a single indivisible good is to be sold to one of n bidders. Any of the bidders knows the value of the item to herself, and nothing about the values of the other bidders. The values are then modelled to be independent draws from some continuous probability distribution. As the bidders are assumed to behave competitively, i.e. there is no collusion, the auction can be treated as a noncooperative game. There are several important results for this game (see among others Milgrom and Weber (1982a)):

Result 1: The Dutch and the first-price auctions are strategically equivalent.

Result 2: In the context of the private value model, English and second price auctions are equivalent as well, although in a somewhat weaker sense than the "strategic equivalence" of the Dutch and second-price auctions, i.e., in the latter case no assumptions about the values to the bidders of various outcomes is required. In particular, the bidder does not need to know the value of the item to herself.

Result 3: The outcome of the English and second-price auctions is Pareto optimal. In symmetric models the Dutch and first-price auctions also yield Pareto optimal allocations.

Result 4: The expected revenue generated for the seller by a given mechanism is precisely the expected value of the object to the second-highest evaluator.

Result 5: All four auctions, i.e. first-price, second-price, Dutch, and English, lead to identical expected revenues for the seller (Vickrey (1961), Riley and Samuelson (1981)). This is the so-called revenue-equivalence result.

Result 6: For many common sample distributions - including the normal, exponential and uniform distributions - the four standard auction forms with suitably chosen reserve

prices or entry fees are optimal auctions (Myerson (1981), Riley and Samuelson (1981)).

Result 7: In case of either a risk-averse buyer or risk-averse seller the seller will strictly prefer the Dutch or first-price to the English or second-price auction.

The theory of optimal auction design addresses the question which auction maximizes the expected revenue of the seller, given a single object to sell. The decision which kind of auction is the best is a problem of decision in the face of uncertainty. I.e. the seller does not know the value of the item to be sold to the bidders. Otherwise she would announce a nonnegotiable price at or just below the highest bidder's valuation. However, as the seller does not know the bidder's true valuations she is forced to choose among auction mechanism which are almost surely going to give her less than this perfect information optimum (Myerson (1981)).

The tool to answer this question is the Revelation Principle. It shows that the seller can restrict herself to the class of direct and incentive-compatible mechanisms. In a direct mechanism each bidder is asked simply to report her true valuation. Whereas in an incentive-compatible mechanism the bidder finds it in her own interest to report her valuation honestly. The direct revelation game has one equilibrium that leads to the same allocation as the original equilibrium. But this equilibrium need not be unique (see also Fudenberg and Tirole (1991)). The optimal direct mechanism is found as the solution to a mathematical programming problem with two constraints: First, incentive-compatibility or self-selection constraints, which state that the bidders cannot gain by not truthfully reporting their valuations and second, individual-rationality or free-exit constraints, which guarantee that the bidders are not better off if they refuse to take part.

In most of the literature on optimal auction design the independent private value assumption is made. In this setup following results have been shown: The auction that maximizes the expected price has the following characteristics: (i) The seller optimally sets a reserve price and does not sell the item if all bidders' valuations are too low. (ii) Otherwise she sells to the bidder with the highest valuation (Myerson (1981), Riley and Samuelson (1981), Milgrom (1987)). (iii) Any of the English, Dutch, first-price, and second-price auctions is the optimal selling mechanism provided it is supplemented by the optimally set reserve price (Myerson (1981), Riley and Samuelson (1981)).

Bulow and Roberts (1989) have shown that the seller's problem in devising an optimal auction is virtually identical to the monopolist's problem in third-degree price discrimination. The question whether a public auction or an optimally structured negotiation is more profitable to sell a company was answered by Bulow and Klemperer (1994). They found out that under standard assumptions, like risk-neutrality, independence of signals, or increasing bid functions, the public auction is always preferable. The result holds for the independent private value and the common value, as well.

Myerson (1981) has shown an optimal auction mechanism for an example with dependent bidders' values. The optimal auction includes side-bets, which are not possible in the independent case. In the general non-independent case we can expect side-bets more commonly. With carefully designed side-bets the seller can counterbalance the bidders' incentive to lie to buy the object at a lower price.

2.1.2 The common value model

In the common value auction we assume that the bidders make (conditionally) independent estimates of the common value of the item to be sold. The bidder making the largest estimate will give the highest bid. A consequence of this bidding strategy is that the winner will find that she overestimated on average the value of the item she has won, even if all other bidders are making unbiased estimates as well. This phenomenon is known as the *winner's curse*. It was first described by Capen, Clapp, and Campbell (1971), who claimed that this phenomenon is the reason for the low profits earned by oil companies on offshore tracts in the 1960's in the US. In the case of first-price auctions the equilibrium of this model has been studied extensively. Those results dealing with the relations between information, prices, and bidder profits are the more interesting ones. For example, Milgrom (1979) and Wilson (1977) showed that - under certain regularity assumptions - the equilibrium price in a first-price auction is a consistent estimator of the true value. I.e., that although no bidder knows the true value of the item, the seller will receive that value as the sale price. In a common value auction the price can therefore be effective in aggregating private information. Further, the bidder's expected profits depend more on the privacy than on the accuracy of the information about the common value of the good (Milgrom (1981), Milgrom and Weber (1982a)).

2.1.3 The general model of Milgrom and Weber

In Milgrom and Weber's paper (1982a) a general model for risk neutral bidders is developed. In the sense that there is space for cases like the independent private value model and the common value model, as well as a range of intermediate models. Consider an auction in which a single object is to be sold and in which risk neutral bidders compete for the possession of that object. Each of these bidders has some information about the object. Milgrom and Weber (1982a) then introduce the concept of affiliation² and assume bidders' valuations to be affiliated. Roughly speaking, this means that large values for some of the variables make the other variables more likely to be large rather than small (see Milgrom and Weber (1982a), p.1098). Generally it can be said, that when bidders' valuations are affiliated, the English auction yields a higher expected revenue than the first-price, the second-price, or the Dutch auction. Additionally it is true that the second-price auction leads to higher expected revenue than the first-price auction, which yields the same revenue as the Dutch auction. In the standard auction forms the seller can raise her expected revenue by having a reporting policy of revealing any information she has about the item's true value. If one bidder's information is available to another bidder, her expected surplus is zero (see Milgrom (1981), Milgrom and Weber (1982a)). This result implies that the privacy of information is of more importance than its accuracy.

²A general definition can be found in the Appendix of Milgrom and Weber (1982a). For variables with densities, the following simpler definition of (1982a) will suffice. Let z and z' be points in R^{m+n} . Let $z \vee z'$ denote the component-wise maximum of z and z' , and let $z \wedge z'$ denote the component-wise minimum of z and z' . The variables z and z' are affiliated, if for all z and z' , $f(z \vee z')f(z \wedge z') \geq f(z)f(z')$.

2.2 Some further issues in auction theory

2.2.1 Asymmetric Bidders

The revenue-equivalence theorem for auctions predicts that expected seller revenue is independent of the bidding rules, as long as equilibrium has the properties that the buyer with the highest reservation price wins and any buyer with the lowest possible reservation price has zero expected surplus. Following McAfee and McMillan (1987) we now assume that the bidders fall into separate groups. Therefore we do not have one distribution of private values anymore, but two. Bidders of every type still draw their valuations independently from their specific probability distribution. In this setting the English auction operates much as in the private value model. The bidder with the highest valuation wins and therefore the outcome is efficient. As the first-price auction yields a different price than the English auction does, revenue equivalence breaks down. Vickrey (1961) among others constructed examples in which the price in the English auction could on average be higher or lower than the price in the first-price auction. In the special case where the two distributions are only distinguishable by their mean, i.e. the shapes of the distribution are the same, only the means differ, the class of bidders with the lower average valuation are favored in the optimal auction (see McAfee and McMillan (1987)). The benefit from such a policy is that the bidders with the higher average valuation are forced to bid higher than they otherwise would. Thus the price is driven up on average. Maskin and Riley (2000) drop the symmetry assumption in a formal analysis and they show, that “strong” buyers prefer English auctions, whereas “weak” buyers prefer first-price auctions.

2.2.2 Sequential auctions

Under the usual assumptions of risk neutral bidders, private and independent values, symmetry, and bidders desiring at most one unit of the auctioned commodity, it is well known that winning bids in sequential auctions should follow a martingale process, both for first-price and second-price auctions (see Weber (1983)). Weber proved that, with affiliated values, the sequence of winning prices displays an upward lift. In the symmetric affiliated model, Milgrom and Weber (1982b) showed that the sequential first price yields greater expected revenues than the discriminatory auction and that the sequence of winning bids displays an upward lift. McAfee and Vincent (1993) have shown how risk aversion of bidders may explain declining prices. In a general symmetric setting with two stages, which includes the private and the common value setting as special cases, Hausch (1988) showed, that bidders’ optimal strategy for the first object is to shade the bid in contrast to the one-stage game. This result holds for the first-price and the second-price auction. However, assuming independent private values the term of shading in a second-price auction is equal to zero. Katzman (1999) explores the features of a two stage sequential auction with multi-unit demand. Working within the independent private values paradigm, he examines a sequence of two second price auctions where individual bidders have diminishing marginal valuations. When information is complete, allocations can be inefficient and price sequences constant or decreasing. However, when information is incomplete

and symmetric, equilibrium behavior produces efficient outcomes and an expectation of increasing prices. These divergent findings are reconciled using an argument based on ex ante bidder asymmetry that can also explain the declining price anomaly.

Another issue in this context is strategic jump bidding. Avery (1998) solves for equilibria in sequential bid (or English) auctions with affiliated values when jump bidding strategies may be employed to intimidate one's opponents. In these equilibria, jump bids serve as correlating devices which select asymmetric bidding functions to be played subsequently. Each possibility of jump bidding provides a Pareto improvement for the bidders from the symmetric equilibrium of a sealed bid, second-price auction. The expanded set of equilibria can approximate either first- or second-price outcomes and produce exactly the set of expected prices between those two bounds. These results contrast with standard conclusions that equate English and second-price auctions.

2.3 Econometrics of auctions

Many recent papers in auction literature are concerned with the possibility of formulating and testing hypotheses. In empirical auction theory two approaches have emerged: structural and non-structural models. For a review of the existing literature on empirical work concerning auctions see Hendricks and Paarsch (1995) and Laffont (1997). One aim of recent work in auction theory is to identify the probability law behind the valuations of potential bidders. This is essential if one wants to implement an optimal auction mechanism. Bayesian Nash Equilibrium behavior imposes restrictions upon the relationships amongst bidders (e.g between informed and uninformed bidders) which do not depend on the functional form of the probability law for the valuations. If one assumes that there is no unobserved heterogeneity the actual knowledge of this probability law is unnecessary to test these restrictions (therefore "non-structural or reduced form approach"). When concentrating on reduced form econometric models one can test certain implications of auction theory, with the observed bids as explained variables. Explanatory variables might then be the reservation price, the number of bidders, and some characteristics of the auctioned object. One concern of this approach is the possibility that other models of behavior may have the same reduced-form predictions. In contrast to the former approach, some authors use the entire structure of the auction to derive the data generating process. Heterogeneity, observed and unobserved, is recognized in this approach (the "structural approach"). It relies on the hypothesis that the observed bids are the equilibrium bids of the considered auction model. As the optimal strategy is a function of private values or signals, depending on the model (private vs. common), the equilibrium strategy gained from the theoretical model can be used to estimate the characteristics of the distribution of private values or signals, respectively. The main difficulty with this approach is the typically highly nonlinear equilibrium bid function. In some cases, there exists no closed form solutions for the equilibrium bid functions. Another difficulty arise from the complex density of the winning bids. Laffont, Ossard and Vuong (1995) have developed a simulated non-linear least squares estimator, which is based on simulations following McFadden (1989) and Pakes and Pollard (1989). It can handle a broad class of distributions.

This is in contrast to other methods, which require that the joint distribution belongs to particular families of distributions (see e.g. Donald and Paarsch (1993)). Nevertheless a specific distributional assumption must still be made. To avoid these distributional assumptions Elyakime, Laffont, Loisel, and Vuong (1994) have proposed nonparametric methods for estimating the probability law of valuations. However, in contrast to parametric methods, this approach requires knowledge of all bids, not just the winning bid. Parametric models provide a test of the joint hypothesis that the distribution of valuations belongs to the assumed family of distributions and that potential buyers bid according to theory.

2.3.1 The non-structural approach

The sale of drainage leases was described as following a common value auction with a first-price sealed-bid mechanism. Hendricks and Porter (1992) imposed affiliation on the joint distribution of values, signals, and reserve price. Following this approach Hendricks and Porter (1992) derived three restrictions governing the behavior of informed and uninformed bidders in the Outer Continental Shelf (OCS) auctions. First, a lower participation rate of non-neighboring firms; second, few non-neighboring bids below some de facto reserve price; third, distributional equivalence above some level (where bids are almost never rejected, a de facto acceptance price). They report tests on these restrictions and the empirical distributions of bids produced “remarkable strong support” for the theory. However, there are two caveats: firstly, the distribution of data was truncated, but that can be accommodated in that there is a condition on the first order stochastic dominance. Second, the assumption of independent distributions might not be fulfilled and for this reason the asymptotic distribution of the test statistic is almost surely not standard (and up to some computational difficulties).

McAfee and Vincent (1992) use data from Hendricks and Porter for OCS auctions, and extend the generalized mineral-rights model to allow for stochastic endogenous participation. In this model we have nature as a player that determines the number of possible bidders, n , with some probability q_n . Out of these a subset of the potential bidders is drawn at random. The true value is v and the bidders receive some signal, x_i , which is independently distributed. A theorem is derived that provides a distribution-free test of whether participation is optimal. The auction is attracting inefficiently few bidders whenever net revenues exceed the values of tracts that attracted two or more bids.

2.3.2 The structural approach

English auctions

Under the private value paradigm the setup of the English auction the simplest to test auction theory is to estimate the joint distribution function on the bidders’ valuations. This is because of two important assumptions: first, the independence of valuations, and, second, the failure to distinguish between buyers. This means, that the marginal distributions of the joint distributions are identical. If the task is to estimate the cumulative

distribution function, this can be accomplished by recovering the entire joint distribution for the buyers' valuations. From this understanding a parametric formulation can be derived, a likelihood-function calculated and the unknown values of the distribution function estimated (see e.g. Hendricks and Paarsch (1995) for a formal derivation).

First-price sealed bid auctions

The winning bid in a first-price sealed bid auction, under independent private values, is a function of the set of bidders' valuations. As in the previous section a parametric specification for each auction can be derived. The difficulty with this framework is the fact that the upper bound of the support of the winning bid depends on the parameters of interest. This violates the asymptotic consistency of the maximum-likelihood estimator. Donald, Paarsch and Robert (1997) have used this framework for the timber auctions in British Columbia. The results showed variation in the distribution function depending on the use of English auctions or first-price sealed bid auctions. The bidding behavior differed in that the winning bid was more often the reserve price with English auctions than with first-price sealed bid auctions. Moreover, the amount of rent accruing to the government was negative.

Simulated non-linear least squares

One further drawback with the last estimation method is its computational complexity. In general the involved functions will not have an analytic solution and have to be solved numerically. The proposed alternative of Laffont, Ossard and Vuong(1995) is related to the method of simulated moments (McFadden (1989) and Pakes and Pollard (1989)). The simulated non-linear least squares estimator can be derived by minimizing an adjusted non-linear least squares objective function. The parameters that determine the mean and/or the variance of the distribution function are estimated using a simulated estimate for the expected winning bid. Laffont, Ossard and Vuong(1995) have shown that the asymptotic distribution is normal.

Non-parametric estimation

The main criticism of the maximum likelihood method or the simulated non-linear least squares is that an explicit assumption concerning the density functions is needed. The non-parametric approach, however, has to use all of the bids, not just the winning bid, which the above methods used. The assumptions that are made is that each potential buyer is bidding optimally against the opponent's bidding strategy, potential buyers are using the same strategy, and this strategy is increasing in bidders' valuations. The procedure consists of two steps. The first step involves the estimation of the conditional density in a non-parametric way. The estimation of the "hazard rate" is then used to estimate the bidding-strategy and the conditional density of valuations. This provides a test of the behavioral hypothesis, which is carried out in Elyakime et al. (1994) for timber sales. The auction is interesting in that the seller's reserve price is not announced until the bids

have been submitted. Theoretically, from the point of the buyers, the seller is another buyer, but with a different pay-off function. This implies an additional bidding strategy.

Private vs. common values

Paarsch (1992) uses auctions of tree planting contracts in British Columbia, Canada, from 1985 to 1988, to find out whether these auctions fall within the private or common value paradigm framework. The contracts are awarded to the lowest bid, which is typically the cost per tree planted, in a sealed bid first-price auction. Differences in bidding behavior can be a result of two different (and opposing) paradigms. In the first case, the cost of planting a tree is unknown to all, but the same to all bidders. If this is true, then a sealed-bid framework offers no additional help in finding out the most efficient since all are equally efficient. If, on the other hand, there are differences in the planting costs then the use of the sealed-bid framework will induce the bidder with the lowest cost to submit the lowest bid.

Which paradigm applies will be reflected in the bidders' bidding functions and in the winning bids. For common value auctions, the bid functions will increase in the number of bidders, n , where in auctions within the private value setting the bids will decrease monotonically. The expected value of the winning bid will have no relationship with the number of bidders in a common value setting, in private value auctions it will fall in n . The distribution of the winning bids do not provide enough information to decide between the models. Neither the shape nor the mean of the data allows discrimination. Employing several empirical specifications (proportional bids, cost additive bid functions, nonlinear functions of cost) all versions of the private value paradigm are rejected and there is consistency between the data and the common value paradigm.

Collusion

Empirical papers on collusion can be divided into two groups. The first one tries to distinguish between competitive and collusive behavior. Baldwin, Marshall and Richard (1997) examine bidding behavior in Forest Service timber sales in the Pacific Northwest of the US. Allegations of bidder collusion were common in the 1970s. They formulated an empirical model that allows both bidder collusion and supply effects. They compared various empirical models and found that a model of collusion outperformed noncooperative behavior in which a single unit is sold. Supply effects are dominated by collusion in determining the winning bids in the market. Porter and Zona (1997) examine the institutional details of the school milk procurement process, bidding data, statement of dairy executives, and supply characteristics in Ohio during the 1980s. By comparing the bidding behavior of a group of firms to a control group they found the behavior of each of these firms differs from that of the control group and is consistent with collusion.

In the second group of papers collusive behavior can be assumed as it has been e.g. proved by court. These papers investigate the different kinds of collusive behavior. Pendorfer (2000) examines the bidding for school milk contracts in Florida and Texas during the 1980s. In both states firms were convicted of bid-rigging. The cartel in one

state divides the market among members, while the other cartel also uses side payments to compensate members for refraining from bidding. With a sufficiently large number of contracts he can show that both forms of cartel agreements are almost optimal. Further the data support the predicted equilibrium bidding behavior in asymmetric auctions in accordance with optimal cartels.

Sequential auctions

The literature on empirical estimation of auctions assumes mostly a static auction setting. There is little empirical work on sequential auction games. Ashenfelter (1989) noticed a so called declining price anomaly in wine and art auctions: winning prices decrease during the day. Beggs and Graddy (1997) study the order of sale in art auctions. The final bid relative to the auctioneer's estimated price declines throughout the course of an auction. They show within a theoretical model, that in an auction ordered by declining valuation, even in the presence of risk-neutral bidders, the price received relative to the estimate for later items in an auction should be less than the price relative to the estimate for earlier items. Furthermore, ordering heterogeneous items by value maximizes revenue for the auctioneer. Engelbrecht-Wiggans and Kahn (1999) examined dairy cattle auctions on different days and found that prices decline over the course of an auction day, with the main decline occurring towards the end of the day. Jofre-Bonet and Pesendorfer (1999) consider bidding behavior in a repeated procurement auction setting. They consider a dynamic bidding model that takes into account bidder asymmetry and the presence of intertemporal effects such as capacity constraints. They study bid data for highway construction procurement in the state of California, estimate the model and assess the importance of intertemporal constraints. Donald, Paarsch and Robert (1997) consider a model in which a finite number of objects are sold in a sequence of ascending-price auctions. They estimate the model using data on the sales of Sibirian timber-exports permit. Laffont, Loisel and Robert (1997) consider a finitely repeated first-price auctions in which at each stage an identical object is sold. Their model generates intra-day dynamics which are applied to data on eggplant auctions.

Chapter 3

Bidding behavior in Austrian cattle auctions

3.1 Introduction

Auctions are an interesting subject to analyze econometrically. The rules of associated games are usually well defined and many constraints are available to define a structural model. On the other hand, the data of auctions are usually quite rich and more readily available than data from other markets. Therefore it seems to be promising to empirically test game theoretic models. Most of the literature on empirical estimation of auctions assumes a static auction setting. On the contrary there is little empirical work on sequential auction games.

In this chapter I analyze cattle auctions taking place in Amstetten, Austria. Each of these auctions is conducted as an English auction. On those days, on which auctions take place, roughly 200 objects are offered sequentially. Such a sequence of auctions is held every month. Various issues are relevant and interesting in these auctions: There are some traders, who visit the auctions on a regular basis. Two of them represent a regional trade firm each. The others work for local trade firms. All the other bidders are usually farmers from the (near) neighborhood. These bidders buy usually one animal on one auction day, whereas the traders buy sometimes up to 55 animals per auction day.

Summarizing the relevant facts of these cattle auctions suggests to implement a theoretical model of sequential auctions with asymmetric bidders empirically. The aim is to investigate whether there is a difference in the bidding behavior of large traders and small bidders. The second question concerns intertemporal effects. Do bidders take the possibility of buying later into account when bidding for objects?

I follow a structural approach. As a benchmark model I analyze an English auction, considering this type of auction in the independent private value paradigm and in a static environment. Bidders' valuations are assumed to be symmetric. By also implementing a model with affiliated values I test for and confirm the independent private value assumption. The static model with independent private values is then contrasted with a model where bidders' valuations are asymmetric. This gives the possibility to distinguish

between the groups of bidders and to test for a difference in their bidding behavior. As a next step I consider a sequential bidding model with symmetric and asymmetric bidders. These models are implemented econometrically and are brought to data. The characteristics of the distribution of bidders' values are estimated and the heterogeneity of the auctioned objects is taken into account. In particular, I concentrate on the first moment of the distribution of bids, as it characterizes the expected gain for the seller.

The focus of the analysis of Austrian cattle auctions lies in specifying an empirical sequential auction model and to investigate whether bidders' valuations are asymmetric and whether bidders take the possibility of buying later into account. The results show asymmetries among bidders and a significant effect of the sequential bidding game. A further point of interest deals then with the question, how the estimation results compared to the estimation results of a static symmetric model, which I define as the benchmark model. The findings show that neglecting asymmetries has more impact on the estimation results than neglecting the sequential effect.

The chapter is organized as follows: In Section 3.2 I give a description of cattle auctions in Amstetten, Lower Austria and of the data I use for estimation. Some (summary) statistics and a preliminary analysis of the winning bids is also presented. The employed theoretical models are introduced in Sections 3.3.1 and 3.3.2. Section 3.4 analyzes the applied estimation method and then gives the empirical results. Section 3.6 concludes.

3.2 Cattle auction in Amstetten, Austria

In this section I describe the auction market under investigation. As we will see from this description the relevant issues of cattle auctions in Amstetten, Austria, are asymmetries among bidders and the fact of sequential auctions. Given the detailed literature review from the section before, the contribution of the analysis of Austrian cattle auctions to the literature lies in specifying an empirical sequential auction model and to investigate whether bidders' valuations are asymmetric and whether bidders take the possibility of buying later into account.

3.2.1 Description

Ascending price auctions are frequently used to sell cattle, pigs, or other animals. The particular auction we focus on is a cattle auction that takes place in Amstetten, Austria. Most of the cattle auctioned are (dairy) cows and stock bulls. In this market the sellers are farmers and the buyers are farmers or representatives of two resale trade firms. From January to April 1996 these two large traders bought on average 22% of all the auctioned cattle. Auctions take place eleven times a year. Each auction lasts for two days. On the first day the cattle are displayed to give interested persons the opportunity to view the animals. A catalog with a detailed description of every animal is available at a price of ATS 20.¹ Description of the cattle includes various quality criteria like milk production,

¹ATS=Austrian Schilling.

milk components, the owner of the animal, its date of birth, the parents and grandparents as well as some of the quality criteria of the parents and grandparents. Further, medical checks are carried out during the animals' stay in the auction stable and the results are published in the morning of the second day. On this day also the auctions take place. In 1994, on average, 340 animals have been sold per auction day (1994).

The auction is held by an auctioneer who announces the prices. The auctioneer is paid by the Chamber for Agriculture in Lower Austria. Neither the sellers nor the bidders have to pay anything for the auction house unlike at privately organized auctions (e.g. by Sotheby's).² The auctioneer starts the auction at a fixed price and raises the price in fixed step sizes. The bidders have so-called "Winkers". They look like small traffic signs with number on them, with which they indicate to accept the bid. Everyone who wants to bid has to pay a fee for a "Winker". The auction lasts until nobody is willing to accept the next highest bid. When the bidding stops the object for sale is hammered down, but not necessarily sold as the seller has the possibility to reject the price. During the auction the respective seller represents his or her cattle in front of the bidders. If nobody is willing to accept the starting price the auctioneer lowers the price like in a Dutch or descending auction until somebody accepts that price. Then the auctioneer starts to raise the price with the same fixed step size again and the procedure continues as described above.

3.2.2 Data

The data are from auctions which took place on January 24th, February 21st, March 20th and April 24th 1996. On average at each auction day about 230 heads of cattle have been sold. For each animal the winning bid, the weight, the breed, two quality criteria, the auction day, the number of the "Winker" and the number of order on the specific auction day is known. Further we know the total number of "Winkers" given out for each auction.

The cattle are divided into four categories, namely bulls, female calves, young female calves and cows. For reasons of simplicity the bulls are not considered for estimation. The cattle are of two different breeds: "Fleckvieh" or "Braunvieh". The first quality criteria has six different classifications, 1A to 3B. For cows and female calves this quality criteria gives the minimum requirements for the output and the structure (fat, protein) of their milk. In case of young female calves it gives the minimum requirements of their mother's milk. However, a cattle of the highest classification, 1A, was not sold on one of these four auction days. The second quality criteria has three classifications, 1 to 3. As everybody, who wants to bid, has at least one "Winker", the seller can be identified in an anonymous way. Usually bidders have different numbers on their "Winkers" at different days. However, the large traders always get the same number. Therefore they can be identified throughout the four auction days. This is helpful to determine possible asymmetries among bidders (valuations). The number of potential bidders is the total number of given out "Winkers". But this is not the number of bidders actually participating at each auction round, since people are not staying at the auction the whole day as they

²However, every Austrian farmer has to be member of the Chamber for Agriculture and has to pay a membership fee.

might not be interested in every animal.

3.2.3 Winning Bids

The average sale price for all auctions is ATS 19839 with a standard deviation of ATS 4136 (see also Table 3.1). The highest winning bid is ATS 33200 and the lowest is ATS 7800. The variation of the average winning bid across the four auction days is substantial. The difference between the average sale prices on February 21st and April 24th is ATS 2273, which is about 11% of the overall mean. The variation of the average winning bid is also given across other subgroups like the milk quality criteria. The mean selling price in the classification 1B is ATS 26709, whereas in the lowest classification 3B it is only ATS 11203.

3.2.4 Who are the large traders?

The large traders are identified by the number of objects they have won. Most of the bidders, namely 89%, bought one or two objects. On January 24th, 1996 190 objects were sold (Table 3.2): 114 bidders bought one animal each. 17 bidders bought two animals. The other 5 bidders purchased 3, 4, 8, 11 and 16 animals, respectively. In Table 3.2 the exact frequencies are also shown for the other auction days. The overall picture is the same for all four auction days. In Table 3.3 the descriptive statistics of selected large traders and that of the remaining small bidders are given. The bidders T30 and T200³ are the same bidders, respectively, throughout all auction days. This need not be true for the other bidders (e.g. T70). Those who have bought more than 2 objects I define as large. In particular, the difference in the average winning bid between the small bidders and the traders T30 and T200 is significant, using a Mann-Whitney test. As I do not control here for other variables like quality or category, the reason for this difference is a-priori not clear. One possibility could be that these two groups of bidders bid for different kinds of cattle or there could be some other kind of asymmetry between bidders. If one takes a look at the kernel density of the bids of these two large traders and compares that to the densities of the bids of the small bidders, one recognizes a difference in the distributions (see Figures 3.1 and 3.2, respectively). The large traders can be considered as agents of retail sellers who have placed orders at specific prices before the opening of the market. These prices are the valuations of the traders in the auction (see also Laffont, Ossard and Vuong (1995)). Thus they also do not have budget constraints, whereas small bidders seem to have them.

3.2.5 Summary

This cattle auction is as a first step modelled within the independent private value paradigm. The assumption of private values can be justified by the available information about the cattle. As almost every detail of the cattle's quality is known to all bidders

³T30 and T200 are the bidders with the "Winker" number 30 and 200, respectively.

there is hardly any uncertainty about the common value of the cattle. Therefore none of the bidders should have private information about the cattle's characteristics. Besides, in cattle auctions bidders tend to agree on the various characteristics of the animals (Engelbrecht-Wiggans and Kahn (1999)). As a consequence the bidders preferences are of pure private nature. Every bidder ranks the different characteristics in another order depending on breeding program goals. The second source of common values is the possibility of resale. However, as transportation and resale costs in this market are high it is unlikely that short term speculation plays a significant role. Shortterm speculation is also ruled out by the fact, that the auctioned animals have to be in possession of the owner for at least six months. This fact itself does not prevent resale, but the cows can at least not be sold at the next auctions.

As noted above on one auction day many animals are auctioned in a sequence. These cattle auctions are probably most similar to the sequential auctions considered in Laffont, Loisel and Vuong (1997) or Donald, Paarsch and Robert (1997), where identical units of a good or identical lots of a given commodity are auctioned off (e.g. wine, flowers, fish, tobacco). Laffont, Loisel and Vuong (1997) find that winning bids of descending or Dutch auctions for eggplants exhibit a regular inverse U-shape in the course of one day. In his description of wine auctions, Ashenfelter (1989) noticed a so called declining price anomaly: winning prices decrease during the day. The winning bids of Austrian cattle auctions do not obviously exhibit any pattern. In Figure 3.3 the price of the winning bids in the order of how the objects were auctioned is shown.

The fact of an existing secret reservation price, as the seller has the possibility to reject the hammered down price, has to be ignored because of the unavailability of appropriate data for these cases.

3.3 The theoretical models

3.3.1 The independent private value model

In order to introduce the notation and the empirically implemented models I now briefly review a model of English auctions in the independent private value model, which is equivalent to the second-price auction (Vickrey (1961)). In the independent private value setting a single indivisible good is to be sold to one of n risk neutral bidders. Each of the bidders knows the value of the item herself, and nothing about the values of the other bidders. The values are modelled as independent draws from some continuous probability distribution. The bidders are assumed to behave competitively, i.e. there is no collusion, and thus the auction can be treated as a non-cooperative game. Assuming symmetry among bidders implies that the independent draws are from the same distribution. In case of asymmetry, bidders' valuations would be from different distributions. The bidders are also supposed to be risk neutral. In this setting the English or ascending auction is equivalent to the second-price auction. The dominant strategy in a second-price auction is to bid one's own valuation, regardless of others. These results do not depend on the symmetry of the model (Vickrey (1961)).

Let $X = (X_1, \dots, X_n)$ be a vector. The components of this vector are real-valued *signals* observed by the individual bidders. Let X_i denote the actual value of the object to bidder i . The variables X_1, \dots, X_n are independent. And let $Y_{i,1}, \dots, Y_{i,n-1}$ denote the largest, \dots , smallest estimates from among $X_j, j \neq i$. Further let $f(x)$ denote the joint probability density of the random elements of the model, which is symmetric in its arguments. The expectation $E[X_i]$ is assumed to exist. The bidders' valuations are in monetary units and the bidders are risk neutral. Therefore, bidder i 's payoff is $X_i - b$, if she receives the auctioned object and pays the amount b . A strategy for bidder i is a function mapping her value estimate x_i into a bid $b = b_i \geq 0$. Supposing bidders $j \neq i$ adopt strategy b_j then the highest bid among them will be $W = \max_{j \neq i} b_j(x_j)$. Bidder i will win the auction if her bid exceeds W , which will also be the price bidder i has to pay. The decision problem bidder i is facing is to choose a bid b that maximizes the expected actual value minus the price, ignoring the cases where her bid is not the highest, conditional on her signal. It can be shown that the dominant equilibrium strategy in a second-price auction is to bid

$$b_i^*(x_i) = x_i \tag{3.1}$$

for every player i and this fact does not depend on symmetry (Vickrey (1961)). As the bidder with the highest valuation will stop raising her bid after the bidder with the second highest valuation has left the auction, the observable winning bid is

$$b^w = x_{[2]}, \tag{3.2}$$

where $x_{[2]}$ denotes the second highest of n independent draws of the distribution function F . The winning bids therefore follow the second order statistic, which has a certain distribution and density function. Thus the characteristics of this distribution function can be estimated (see Section 3.4 below). With asymmetry among bidders the characteristics of two or more distribution functions are estimated. For each group of bidders the private values are drawn from different distribution functions. The expected selling price is the expected price of bidder i conditional on bidder i winning the auction: $R = E[Y_{i,1} | X_i > Y_{i,1}] = E[X_{[2]}]$, where $X_{[2]}$ denotes the second-order statistic.

3.3.2 A sequential auction model with two objects

The one-shot independent private value model from above does not really capture the features of Austrian cattle auctions. As the cattle are auctioned in a sequence the theoretical model should not ignore dynamic considerations. Taking the description of Austrian cattle auctions (see Section 3.2) into account the model has to incorporate an auction with n asymmetric bidders with multi-unit demand and T objects. There are two possible asymmetries: One reason for asymmetry lies in different bidders, which can be expressed by different distribution functions of bidders private valuations. In a first step I concentrate on the case of n symmetric bidders with multi-unit demand and two objects auctioned in a sequence. Bidders are assumed to have no budget constraints. The independent private value paradigm still holds and bidders are again assumed to be risk neutral.

The bidding procedure corresponds to a model of two sequential English auctions. The time horizon spans $t = 1, 2$. At each of these points in time an English auction takes

place. I assume the independent private value model. In this setting an English auction is equivalent to a second-price auction. Bidders $i = 1, \dots, n$ are risk neutral, symmetric and have multi-unit demand.

Each period t bidder i learns the value x_{it} of the object.⁴ Each of the bidders knows the value of the item herself, and nothing about the values of the other bidders. Bidders do not adjust their valuations even upon learning how others feel about the good. The values x_{it} are modelled as independent draws from some continuous probability distribution F . We find independence among bidders, but it can be assumed that bidder i 's valuation for the two objects will not be independent.

The priors of other bidders and the buyer about the value of bidders are identical and are represented by a continuous distribution function $F(x_{it}|o_t)$ with o_t measuring the characteristics of the object. o_t is assumed to be observable to all bidders. The distribution of values has a continuous density function $f(x|o(t))$ and support $T = [0, V]$. The characteristics of the auctioned objects are known from the beginning. These characteristics include quality, category and breed.

Bidders may bid for every object and the bidder with the highest bid wins the object. The realization of the object characteristics is independent of the characteristics of past objects.⁵

Each bidder i choose b_{it} to maximize intertemporal profits defined as

$$\text{Max}_{b_i} \quad W_i(b_{it}, b_{-it}) = \sum_{t=1}^2 E\{(b_{it} - \max(b_{j \neq it})) \cdot \text{Prob}(i \text{ wins} \mid b_{it}, o_t)\} \quad (3.3)$$

A bidding strategy $b_{it} = b_t(x_{it}, x_{-it}, o_t)$ for bidder i is a function of bidder i 's value x_{it} , of bidders $j \neq i$ valuations x_{-it} , and of the object o_t .

It can be shown that the equilibrium strategy in a two-period second-price auction with independent private values is to bid the valuation of the relevant objects (see e.g. Milgrom and Weber (1982b), Weber (1983), Hausch (1988))

$$b_i^*(x_{i1}, x_{i2}) = (x_{i1}, x_{i2} | x_1) \quad (3.4)$$

for every player i and this fact does not depend on symmetry. As the bidder with the highest valuation will stop raising her bid after the bidder with the second highest valuation has left the auction, the observable winning bid is

$$b^w = (x_{[2]1}, x_{[2]2} | x_1), \quad (3.5)$$

where $x_{[2]1}$ denotes the second highest of n_1 independent draws of the distribution function F , and $x_{[2]2} | x_1$ denotes the second highest of n_2 independent draws of the distribution function F given x_1 . The winning bids therefore follow the second order statistics, which

⁴Due to the information given in the catalogue bidders could know their private values of the objects at the beginning of the auction day. However, when the animal is actually auctioned, the owner of the animal shows it to the audience and goes around with it. And that usually gives the last piece of information to the bidders. Therefore the above assumption seems plausible.

⁵This is in contrast to empirical results concerning art auctions (see Beggs and Graddy (1997)). In these kinds of auctions the auctioneer uses the order of the objects to be sold as a strategic device. However, in Austrian cattle auctions the order of the objects is random.

have a certain distribution and density function. Thus the characteristics of this distribution function can be estimated (see Section 3.4 below). With asymmetry among bidders the characteristics of two or more distribution functions are estimated. For each group of bidders the private values are drawn from different distribution functions.

3.3.3 English auctions with affiliated values

In Milgrom and Weber's paper [Milgrom and Weber \(1982a\)](#) a general model for risk neutral bidders was developed. In the sense that there is space for cases like the independent private value model and the common value model, as well as a range of intermediate models. For reason of comparison I use the same kind of notation as Milgrom and Weber, which I will introduce first. As next step I will repeat the equilibrium strategies of the static symmetric game of an English auction.

Consider now an auction in which a single object is to be sold and in which n risk neutral bidders compete for the possession of that object. Each of these bidders has some information about the object.

Let $X = (X_1, \dots, X_n)$ be a vector. The components of this vector are real-valued *signals* observed by the individual bidders. And let Y_1, \dots, Y_{n-1} denote the largest, \dots , smallest estimates from among X_2, \dots, X_n . Let $S = (S_1, \dots, S_m)$ be a vector of additional real-valued variables which influence the value of the object to the bidders. The seller might observe some of the components of S . Let $V_i = u_i(S, X)$ denote the actual value of the object to bidder i . Further let $f(s, x)$ denote the joint probability density of the random elements of the model. Following assumptions are made:

Assumption 1: \exists function u on R^{m+n} such that $\forall i, u_i(S, X) = u(S, X_i, \{X_j\}_{j \neq i})$. I.e., that all of the bidders' valuations depend on S in the same manner and that each bidder's valuation is a symmetric function of the other bidders' signals.

Assumption 2: u is nonnegative, continuous, and nondecreasing in its variables.

Assumption 3: For each i , $E[V_i] < \infty$.

Assumption 4: The bidders' valuations are in monetary units and the bidders are risk neutral. Therefore, bidder i 's payoff is $V_i - b$, if she receives the auctioned object and pays the amount b .

Assumption 5: f is symmetric in its last n arguments.

Assumption 6: The variables $S_1, \dots, S_m, X_1, \dots, X_n$ are affiliated. More precisely, let x and x' represent a pair of $(m+n)$ vectors, and let $f(x)$ denote the joint probability density of the random variables x , and further let $x \vee x'$ and $x \wedge x'$ denote the component-wise maximum and minimum of x and x' , respectively. Then the variables are defined to be affiliated if, $\forall x, x'$,

$$f(x \vee x')f(x \wedge x') \geq f(x)f(x'). \quad (3.6)$$

Roughly speaking, this condition means that large values for some of the variables make the other variables more likely to be large rather than small (see [Milgrom and Weber \(1982a\)](#), p.1098). We refer to (3.6) as the "affiliation-inequality".

In this general setting both the independent private value paradigm and the common value paradigm can be treated. In the first case $m = 0$ and each $V_i = X_i$. Therefore the

only random variables are X_1, \dots, X_n . They are statistically independent and fulfill (3.6) with equality, i.e. independent variables are always affiliated. In the second case $m = 1$ and each $V_i = S_1$. Let $g(x_i|s)$, $h(s)$ and $f(s, x) = h(s)g(x_1|s) \dots g(x_n|s)$ denote the conditional density of any X_i given the common value S , the marginal density of S and the joint density of any X_i and S , respectively. Assuming that the density g fulfills the monotone likelihood ratio property⁶. Therefore g also fulfills (3.6) and by applying Theorem 1 of Milgrom and Weber (1982a) it follows that f fulfills (3.6) as well. As a consequence the common value model meets the the formulation of the general model, if the density g has the monotone likelihood ratio property. Milgrom and Weber showed further that the function $E[V_i|X_1 = x, Y_{i,1} = y_1, \dots, Y_{i,n-1} = y_{n-1}]$ is nondecreasing in x .

There are several variants of the English auction. Milgrom and Weber developed a game model which corresponds most closely to the Japanese, so called press-button, auction: In the very beginning all bidders are active at price of zero. The auctioneer raises the price and the bidders drop out one by one and can not become active anymore. Furthermore all other bidders know the price at which someone has quit the auction. A strategy for bidder i specifies whether, at any price level p , she will stay in the auction or not, as a function of her signal, the number of bidders having already quit, and the price levels at which they quit. Let $k \in [1, K]$ and $p_1 \leq \dots \leq p_k$ denote the number of bidders who have quit and the levels at which they leave, respectively. Then bidder i 's strategy can be described by a function $b_{ik}(x_i | p_1, \dots, p_k)$ which specify the price at which bidder i will quit if, at that point, k other bidders have left at the prices p_1, \dots, p_k . Naturally $b_{ik}(x_i | p_1, \dots, p_k)$ is required to be at least p_k .

Milgrom and Weber showed that there exists a symmetric equilibrium point in this setup. The optimal bidding strategy $b^* = (b_{i,0}^*, \dots, b_{i,k}^*)$ for bidder i is defined iteratively

$$\begin{aligned} b_{i,0}^*(s, x) &= E[V_i | X_i = x, Y_{i,1} = x, \dots, Y_{i,n-1} = x], \\ &\dots \\ b_{i,k}^*(s, x | p_1, \dots, p_k) &= E[V_i | X_i = x, Y_{i,1} = x, \dots, Y_{i,n-1} = x, \\ &\quad b_{i,k-1}^*(Y_{i,n-k} | p_1, \dots, p_{k-1}) = p_k, \dots, b_{i,0}^*(Y_{i,n-1}) = p_1]. \end{aligned} \quad (3.7)$$

The winning bid is then

$$\begin{aligned} b^w &= b^w(s, x) = e(V_{[2]}, p_{K-2}, \dots, p_1) \\ &= E[V_{[2]} | X_K = x, Y_{K,1} = x, p_{K-2}, \dots, p_1] \end{aligned} \quad (3.8)$$

with $V_{[2]}$ denoting the second-order statistic of n bidders. Further can be shown that the expected price in the English auction is not less than in the second-price auction. In effect, the English auction can be divided into two parts: First, the $n - 2$ bidders with the lowest estimates reveal their signal publicly through their bidding behavior. The last two players are then engaged in a second-price auction.

The expected selling price is the expected price of bidder i conditional on bidder i winning the auction:

$$R = E [E [V_{[2]} | X_K = x, Y_{K,1} = x, p_{K-2}, \dots, p_1]]$$

⁶If for all $s' > s$ and $x' > x$, $g(x | s)/g(x | s') \geq g(x' | s)/g(x' | s')$, the density g has the monotone likelihood ratio property. This definition is equivalent to the affiliation inequality.

$$= E [V_{[2]}] \tag{3.9}$$

3.4 Econometric implementation

There are five theoretical models to implement econometrically. Three static models with symmetric and asymmetric bidders, and two sequential models with symmetric and asymmetric bidders. One static model does not assume independent private values, but affiliated values. I consider this model to test for affiliated values, which can be rejected as we later see. Therefore I do not consider the models with affiliated values further in the context of asymmetry or sequential auctions. In the case of private values the symmetric models are nested in the asymmetric models, whereas the static models are nested in the sequential models. The winning bids present the following predictions for empirical testing. The difference between symmetric and asymmetric bidders results in different distribution functions among bidders. I assume the distribution functions to be from the same family and the differences to lie in the characteristics of the distributions.

The winning bid in the static games is the second-order statistic of bidders' valuations, whereas the winning bid in the sequential model is a sequence of second-order statistics. However, the distribution functions are different. For simplicity I assume that only the next period matters. Thus the difference between static and sequential winning bids can be attributed to an additional term, which is essentially the winning bid of the period before. This term takes the sequential aspect of the auction into account. If the parameter estimate of this variable is significantly different from zero, we can conclude that bidders use sequential strategies and take the intertemporal effect into account.

In the next sections I first specify the functional form of the distribution of private values. Then I describe the estimation method and give the results.

3.4.1 Functional specification

I assume private values⁷ to follow a log-normal distribution. This distribution depends on various characteristics concerning the auction day, the breed, the category, the quality and the weight of the cattle. In particular, I assume that the expectation of the private values follows a linear function of fourteen exogenous variables:

$$\begin{aligned} E[\ln(x_t)] = & \theta_1 + \theta_2 \text{Date1}_t + \theta_3 \text{Date2}_t + \theta_4 \text{Date3}_t + \theta_5 \text{Breed}_t + \theta_6 \text{Cate1}_t + \\ & \theta_7 \text{Cate2}_t + \theta_8 \text{Qual11}_t + \theta_9 \text{Qual12}_t + \theta_{10} \text{Qual13}_t + \theta_{11} \text{Qual14}_t + \\ & \theta_{12} \text{Qual21}_t + \theta_{13} \text{Qual22}_t + \theta_{14} \text{Weight}_t, \end{aligned} \tag{3.10}$$

where $t = 1, \dots, T$ and T denotes the overall number of auctions. The variance $\sigma = \text{Var}[\ln(x_t)]$ is assumed to be constant. The reason for the latter assumption is that the estimations cause fewer convergence problems.

⁷Affiliated values are also assumed to follow a log-normal distribution, but the expressions for the expectation is not displayed.

Depending on the day, on which the different objects have been auctioned, the dummy variables Date1-Date3 have been introduced. The variable Date1 (Date2, Date3) is equal to one for items sold on January 24th (February 21st, March 20th) and zero otherwise. The dummy variable Breed is equal to one for “Fleckvieh” and zero for “Braunvieh”. There are three different categories: female calves, young female calves and cows. They are introduced by two dummy variables. The dummy variable Cate1 is assigned the value one for female calves and zero otherwise, while Cate2 takes the value one for young female calves and zero otherwise. There are two quality criteria, Qual1 and Qual2. Qual1 has five different classifications (see Section 3.2.2) and Qual2 has three classifications. In the data set there were no cattle out of the highest classification of Qual1. Therefore I construct out of both classifications six dummy variables, which are equal to one, when the particular classification is met and zero else.

Using (3.10) implies that the distribution F is equal for all bidders. Asymmetry can introduce different distributions among bidders’ valuations. For simplicity I assume the distribution functions to be from the same family of distribution functions. However, the characteristics, in particular the means, differ among bidders. The difference I model via bidder specific variables. This yields the following equation for various groups of bidders:

$$\begin{aligned} E[\ln(x_{it})] = & \theta_{i1} + \theta_{i2}\text{Date1}_{it} + \theta_{i3}\text{Date2}_{it} + \theta_{i4}\text{Date3}_{it} + \theta_{i5}\text{Breed}_{it} + \\ & \theta_{i6}\text{Cate1}_{it} + \theta_{i7}\text{Cate2}_{it} + \theta_{i8}\text{Qual11}_{it} + \theta_{i9}\text{Qual12}_{it} + \theta_{i10}\text{Qual13}_{it} + \\ & \theta_{i11}\text{Qual14}_{it} + \theta_{i12}\text{Qual21}_{it} + \theta_{i13}\text{Qual22}_{it} + \theta_{i14}\text{Weight}_{it}, \end{aligned} \quad (3.11)$$

with i = small bidders, large traders, T30 and T200. The expectation of the private values follows a linear function of the same fourteen exogenous variables as before. But for each bidder group the expectation of private values is allowed to be different. One group are the small bidders who bought only one or two objects. The other bidders are defined as large traders (see Section 3.2.4). Two of the large traders bought a lot more animals than the other traders did. Thus and because they could be identified through the number of their “Winker” for all four auction days, I assume that each of these two traders, T30 and T200, form a group of their own. Asymmetry among bidders is expressed by differences in the expectation of the distribution. Thus I do not allow bidders’ private values to be different in a more general way like assuming different probability distributions. The variance $\sigma_i = \text{Var}[\ln(x_{it})]$ is assumed to be constant within each of the four groups of bidders.

In the sequential models the private values at $t = 2, \dots, T$ follow a log-normal distribution conditional on the private values at $t - 1$.

$$\begin{aligned} E[\ln(x_{it})|x_{t-1}] = & \theta_{i1} + \theta_{i2}\text{Date1}_{it} + \theta_{i3}\text{Date2}_{it} + \theta_{i4}\text{Date3}_{it} + \theta_{i5}\text{Breed}_{it} + \\ & \theta_{i6}\text{Cate1}_{it} + \theta_{i7}\text{Cate2}_{it} + \theta_{i8}\text{Qual11}_{it} + \theta_{i9}\text{Qual12}_{it} + \theta_{i10}\text{Qual13}_{it} + \\ & \theta_{i11}\text{Qual14}_{it} + \theta_{i12}\text{Qual21}_{it} + \theta_{i13}\text{Qual22}_{it} + \theta_{i14}\text{Weight}_{it} + \theta_{i15}x_{t-1}, \end{aligned} \quad (3.12)$$

with i = all bidders or i = small bidders, large traders, T30 and T200. The functional form of the expectation of the private values can be expressed in an analogous way as in (3.10) and (3.11). Bidder’s optimal strategy (3.4) in a sequential auction at t is to bid

one's own valuation conditional on the bidders' valuation at $t - 1$. As the data covers winning bids only, we do not observe x_{t-1} , but $x_{[2]t-1}$. For simplicity I assume that the conditional expectation (3.12) is a linear function of the winning bid at $t - 1$. The variance $\sigma_i = Var[\ln(x_{it})]$ is again assumed to be constant within each of the four groups of bidders.

3.4.2 Estimation method for the models with private values

The main problem in empirical auction theory is that the valuations of the bidders are unobservable. In contrast to that, bids can be observed. As the optimal strategy is a function of private values the equilibrium strategy implied by the theoretical model can be used to estimate the moments of the distribution of private values. Especially, the first moment is of interest, as it characterizes the expected gain for the seller. Implicitly we assume bidders bid according to the equilibrium function of the underlying game. However, due to experimental evidence this assumption offers no restriction. In English clock auctions in an independent private value setting market prices rapidly converge to the dominant strategy price (Kagel (1995)).

In general, the auctioned objects are not identical. Therefore we have to take into account possible heterogeneity. That means that the distribution of private values for the t th auction may depend on some characteristics of the t th object to be sold. Hereafter, T denotes the total number of auctions and subscript t denotes all relevant quantities concerning the t th auction. We assume that z_t is fully observed. In the static specification I have further to assume mutual independence among observed auctions.

Adopting a parametric formulation means that $F_t = F(\cdot, z_t, \theta)$ for all $t = 1, \dots, T$, where $\theta \in \Theta \subset R^k$ and $F(\cdot, z_t, \theta)$ is a chosen distribution function. For the static models I now consider the winning bid (3.2) of the model described in Section 3.3.1. The density h of the winning bids can be expressed as

$$h(b_t^w) = n \cdot (n - 1) \cdot F_t^{n-2}(x_t) \cdot (1 - F_t(x_t)) \cdot f_t(x_t),$$

where F and f denote the distribution and the density function of the private values (see e.g. Poirier (1995)). To obtain an estimator for θ one has to calculate the likelihood function and to maximize it with respect to θ .

For the sequential models I consider the winning bid (3.5). The density h of the winning bid can be expressed as

$$h(b_t^w) = n \cdot (n - 1) \cdot F_t^{n-2}(x_t|x_{t-1}) \cdot (1 - F_t(x_t|x_{t-1})) \cdot f_t(x_t|x_{t-1}),$$

assuming the valuations occurring at $t + 2$ to be independent. F and f denote the distribution and the density function of the private values (see e.g. Poirier (1995)).

To obtain an estimator for θ and σ in the static models one has to calculate the likelihood function and to maximize it with respect to θ and σ . In the symmetric models θ follows (3.10) meaning that the distribution F is identical for all bidders. Asymmetry introduces different distributions among bidders' valuations and θ_i follows (3.11). That means that the distribution functions are from the same family of distribution functions. However,

the characteristics, in particular the means, differ among bidders. In the sequential models one also has to maximize the likelihood function with θ_i following either (3.12).

3.4.3 Estimation method for the model with affiliated values

We consider now the winning bid (3.8). Its density h can be expressed as

$$\begin{aligned} h(b_t^w(s, x)) &= h(e(V_{[2]}, p_{K-2}, \dots, p_1)), \\ &= f(e^{-1}(V_{[2]}, p_{K-2}, \dots, p_1)) \cdot \frac{\partial e^{-1}}{\partial b_t^w} \end{aligned} \quad (3.13)$$

according to the transformation rule for densities (integrals) and f denotes the distribution and the density function of the s, x values (see section 3.3.3).

One way to obtain an estimator for θ is to calculate the likelihood function and to maximize it with respect to θ . However, the inverse of the equilibrium function or respectively of the winning bid, which is necessary to calculate the density of the winning bid, is not analytic, but can only be evaluated numerically. Thus I estimate the parameters of the underlying distribution with a simulated nonlinear least square estimator, which has been proposed by Laffont, Ossard and Vuong [Laffont et al. \(1995\)](#) to circumvent above described obstacles. Another possibility would be to use a so-called piecewise maximum likelihood estimator, which has been developed by Donald and Paarsch [Donald and Paarsch \(1993\)](#). However, this estimator requires all the exogenous variables z to be discrete.

Let now $E[b_t^w] \equiv R_t(\theta) \equiv R(z_t, \theta)$ denote the conditional expectation of the winning bid b_t^w given n , which is now assumed to be constant for simplicity, and z_t . The usual non-linear least square (NLLS) estimator minimizes the objective function

$$Q_T(\theta) = (1/T) \sum_{t=1}^T (b_t^w - R_t(\theta))^2 \quad (3.14)$$

with respect to θ . As the expected winning bid is equal to the expected selling price (3.9), and because (3.9) is not readily available, it is one way to replace $R_t(\theta)$ by an unbiased simulator $\bar{X}_t(\theta)$.

Equation (3.9) can be viewed as an integral with respect to the density of $V_{[2]}$. Then (3.9) becomes

$$\begin{aligned} R &= \int_L u_{[2]} f(u) du \\ &= \int_L u_{[2]} \frac{f(u)}{g(u)} \cdot g(u) du, \end{aligned} \quad (3.15)$$

where g is an arbitrary chosen density with support L , called the importance function (see e.g. Rubinstein [Rubinstein \(1981\)](#)). Now, for every $t = 1, \dots, T$, we draw S samples, each of size n , denoted by $u_{1,t}^s, \dots, u_{n,t}^s$, where $u_{i,t}^s$ are affiliated draws from the distribution with density $g(\cdot)$ for $s = 1, \dots, S$. Then, for every t , $E[b_t^w]$ can be approximated by the sample mean

$$\bar{X}_t(\theta) = \frac{1}{S} \sum_{s=1}^S X_{s,t}(\theta) \quad \text{where}$$

$$X_{s,t} = u_{[2],t}^s \frac{f(u_{1,t}^s, \dots, u_{n,t}^s)}{g(u_{1,t}^s, \dots, u_{n,t}^s)}, \quad (3.16)$$

and $u_{[2],t}^s$ denotes the second highest element of each random sample with respect to the number of bidders, for each $s = 1, \dots, S$ and each $t = 1, \dots, T$. But now the objective function (3.14) produces an inconsistent estimator for any fixed number of simulations S as T increases to infinity.

Laffont, Ossard and Vuong Laffont et al. (1995) have shown, that the “simulatednon-linear least square (SNLLS) objective function

$$Q_{S,T}^* = \frac{1}{T} \sum_{t=1}^T [(b_t^w - \bar{X}_t(\theta))^2 - \frac{1}{S(S-1)} \sum_{s=1}^S (X_{s,t}(\theta) - \bar{X}_t(\theta))^2] \quad (3.17)$$

minimized over θ gives a consistent and \sqrt{T} -asymptotically normal estimator $\hat{\theta}$ for fixed S as $T \rightarrow \infty$. Further, it can be shown that the SNLLS estimator is as efficient as the NLLS of θ as S increases to infinity.

The affiliated values are assumed to come from a log-normal distribution. This distribution depends on various characteristics concerning the auction day, the breed, the category, the quality and the weight of the cattle. In particular, I assume that the expectation $E[\ln(v_t)]$ follows a linear function of fourteen exogenous variables according to equation 3.10, where $t = 1, \dots, T$ and T denotes the overall number of auctions. The variance $Var[\ln(v_t)]$ is assumed to be constant. The reason for the latter assumption is that the estimations cause fewer convergence problems.

3.5 Estimation results

3.5.1 Static model with symmetric bidders

By maximizing the likelihood we now get estimates for the structural model derived from the theoretical model, that is described in Section 3.3.1 and the parameters of (3.10) are then estimated. The parameter estimates and their standard errors for the symmetric static model are given in the first two columns of Table 3.4 as well as the value of the likelihood function. All estimates are significantly different from zero at a 95% significance level. For the value of the likelihood function I get 720.24.

Given the choice of the log-normal distribution and the parameterization (3.10), each parameter estimate of Table 3.4 can be interpreted as the percentage change of the expected value of the auctioned item. That means for instance in the case of the dummy variables “Qual11 to “Qual14”, that quality 1B, which is the highest quality class, quality 2A, 2B and 3A are 51.9%, 47.3%, 37.4% and 12.7% more valuable than the fifth quality 3B.

The other parameters shown in Table 3.4 have also the expected signs. The parameter estimates of the dummy variables for the three first auction days Date1 to Date3, with values of 11.5%, , are significant and reflect the market situation in comparison to the last auction day. Thus the bids on the first (second, third) auction day were on average 11.5%

(12.8%, 9.5%) higher than on the last auction day. Thus it seems that some exogenous shock happened before the fourth auction day.

The sign of the breed parameter with a value of 4.8% specifies that the breed “Fleckvieh” yields a higher expected average selling price than “Braunvieh”, after controlling for other variables like quality or category. The dummy variable *Cate1* is significantly positive indicating that female calves are most valuable in comparison to young female calves and cows. Female calves are worth 25.8% more than cows, whereas cows are more valuable than young female calves, as the negative sign and a value of 8.5% for the dummy variable *Cate2* shows. The signs and the orders of magnitude for the first set of quality dummies agree with common beliefs as noted above. The same is true for the second quality criteria. The parameter values for *Qual21* and *Qual22*, respectively, indicate that these two classification are worth 14.3% and 6.3% more than *Qual23*. The significantly positive coefficient of 78.7% for the weight also coincides with conventional wisdom, that weight has an positive impact on prices.

3.5.2 Static model with affiliated values

By minimizing the objective function (3.17) we get estimates for the structural model with affiliated values described in section 3.3.3. I use 100 simulations per auction. For the choice of the importance function g I follow Laffont, Ossard, and Vuong (1995), who suggested g to be a log-normal density with mean given by equation (3.10), where θ is equal to some preliminary consistent estimate $\tilde{\theta}^8$, and a standard deviation equal to 0.10. The function f in equation (3.16) is also chosen to be the density of a log-normal distribution (see section 3.4.1) with mean given by equation (3.10). A starting value θ_0 close to $\tilde{\theta}$ is selected and the parameters of equation (3.10) are then estimated. The estimation results are given in columns three and four of table 3.4. The parameter estimates do not differ a lot from those assuming independent private values. Actually, a Cox-Hausmann specification test shows that the hypothesis of independent private values cannot be rejected. The test statistic is distributed according to a χ^2 distribution function with 14 degrees of freedom and its value is equal to 3.730.

3.5.3 Static model with asymmetric bidders

In the columns one to eight of table 3.5 the results for the static model with asymmetric bidders are displayed. The estimations were run separately for the group of small bidders, the group of large traders⁹, for the trader with the “Winker” number 30 (T30) and for the trader with the “Winker” number 200 (T200). The values of the four likelihood functions are 460.63, 131.39, 121.88 and 106.14, respectively. Compared with the value of the likelihood for the static model with symmetric bidders this means one has to prefer the model with asymmetries, as the sum of the four values of the separated estimations is

⁸How to obtain this preliminary estimator for θ is described in more detail in Laffont, Ossard, and Vuong (1995).

⁹The group of large traders do not include the traders T30 and T200.

with a value of 819.14 greater than 720.24. In general the estimation results are analogous to those in the static model. The signs and the orders of magnitude for e.g. the first set of quality dummies (Qual11 - Qual14) show the same qualitative pattern as in the symmetric model. This is also true for the other parameters. However, the magnitudes of the estimated parameters are different in the sequential auction model. Again most of the parameters are significantly different from zero at a 95% significance level. There are only a few exceptions.

From a close look at the magnitudes of the parameters it comes apparent that there are differences among bidders. The bidders do not value the attributes of the animals in the same way. Small bidders have a higher willingness to pay for e.g. animals of Qual12 than the large traders and trader T200 have.¹⁰ In the first case the parameter estimate is 58.7%, which is significantly different from the values 46.1% and 42.0% for Qual13 in the other cases.¹¹ A similar pattern is found for the variables Qual13, Qual21 and Qual22.

In general, small bidders value the characteristics coming along with quality more than the large traders, including T30 and T200, do. One exception is the variable Qual14, for which trader T200's willingness to pay is equal to 20.0% and highest among all bidders. As quality is primarily defined with respect to milk production and milk components of the animals, small bidders, most of them farmers, value milk cows higher than traders do. On the other side large traders, also T30 and T200, value weight more than the small bidders. The value estimate for Weight among small bidders is equal to 0.5301, but it is equal to 1.2556 (1.0796, 1.3755) for large traders (T30, T200). The traders, representing whole sale firms, prefer to buy meat cows.

For the parameter estimates of the quality criteria Qual12 and Qual13 and for weight a dividing line between small bidders on the one side and large traders, including T30 and T200, on the other side can be drawn. That is not true for all parameter estimates. As already mentioned, one example is Qual14. Another example concerns the category. Female calves are most valuable in comparison to young female calves and cows. The estimate of the dummy variable Cate1 is equal to 30.3% in the group of small bidders and has a value of 21.3% in the group of large traders. Female calves are worth 17.0% more than cows for bidder T30, but are worth 37.8% more for bidder T200.

The parameter estimates of the dummy variables for the three first auction days Date1 to Date3 are significant for the four groups of bidders and reflect the market situation in comparison to the last auction day. They are also different across the bidder groups. However, the general pattern, that the prices of the first three auction days are significantly higher than on the last day, is valid for all bidder groups. Therefore the suspicion of some exogenous shock does not seem to be wrong.

The conclusion that can be drawn from the estimations for the four bidder groups are twofold: First, asymmetries among bidders matter even in this rather small cattle auction market. Second, the results that are significantly different across bidder groups indicate a

¹⁰None of the large traders, trader T30 or trader T200 bought an animal of Qual11. Trader T30 also did not bought any animal of Qual12.

¹¹The t-tests with unknown variances are equal to 14.976 (small bidders vs. large traders) and to 17.287 (small bidders vs. T200).

rather large difference across the estimates. The first moment of the distribution of bids characterizes the expected gain for the seller. Thus the significantly different estimates for various groups of bidders yield substantial changes in the seller's expected gain.

3.5.4 Sequential models

In the third two columns of tables 3.4 and in table 3.6 the results for the sequential models are described. The first table gives the estimates of the model that assumes symmetry among bidders, the other table gives the results for the model with asymmetry. In that case the estimations were again run separately for the group of small bidders, the group of large traders, T30 and T200. For all five estimations the parameter estimate of the lagged winning price is significantly different from zero. Thus we can conclude that bidders take the sequential effect into account. Although, as the sometimes positive and sometimes negative sign shows, bidders respond to that effect differently. And again we see, that asymmetries are prevalent. Bidders react differently to the sequential aspect of the auction.

The bidders as one group respond to the price of the before auctioned object negatively. A high price one period before results in a low winning bid now and the other way round. However, in the case of small bidders the sign of the price of the auctioned object one point in time before is positive. That indicates that small bidders bid high, when the price before was high. The same is true for trader T30. Contrarily, the large traders and the trader T200 rather win with a lower bid, when the price of the object before was high.

The other estimates with respect to quality, breed and so on are nearly the same as in the static models.¹² That it true for all five estimations. Thus neglecting the sequential effect does not have such an impact on the expected gain for the seller as neglecting asymmetries has.

3.6 Conclusions

In this chapter I described the econometrics of English auctions in the independent private value model. Further I set up a sequential bidding model and applied both to field data. For this purpose I used data of cattle auctions in Amstetten, Austria. The data cover four auction days from January to April 1996 with a total number of observations of 900. In this market the sellers are usually farmers and the buyers are either farmers as well or resale trade firms. A further characteristic of this market are some large bidders, each representing a resale trade firm. The auction is carried out by an auctioneer provided by the chamber of agriculture in Lower Austria. A catalogue with detailed information about the milk production, milk components, the owner, date of birth, the parents and grandparents of the cattle can be bought. As all important characteristics of the cattle are known the independent private value model is adopted.

In analyzing I followed a structural approach. First I focused on English auctions, considering this type of auction in the private value paradigm and in an static environment.

¹²Differences concern the third digit after the comma.

As a next step I considered a simple sequential bidding model with asymmetric bidders. These models were implemented econometrically and were brought to data. By also implementing a model with affiliated values I test for and confirm the independent private value assumption. I estimated the characteristics of the distribution of bidders' values and took the heterogeneity of the auctioned objects into account. In particular, I concentrated on the first moment of the distribution of bids, as it characterized the expected gain for the seller.

The most important conclusions that can be drawn from the estimations among bidder groups are twofold: First, asymmetries among bidders matter even in this rather small cattle auction market. Bidders' valuations are different. Second, the significantly different results across bidder groups show a rather large difference across the estimates.

Further we can conclude that bidders take the sequential effect into account. Although, as the sometimes positive and sometimes negative sign shows, bidders respond to that effect differently. And again we see, that asymmetries are prevalent. Bidders react differently to the sequential aspect of the auction.

The analysis of Austrian cattle auctions shows asymmetries among bidders and a significant effect of the sequential bidding game. A further point of interest deals then with the question, how the estimation results compared to the estimation results of a static symmetric model, which I defined as the benchmark model. In general, the findings show that neglecting asymmetries has a great impact on the estimation results, whereas neglecting the sequential effect does not really change the estimation results.

3.7 Appendix: Tables and Figures

Table 3.1: Winning bids for different subgroups

Variable	Name	Number	Mean*	Std. Error	Minimum	Maximum
Date1	January 24th, 1996	190	20.556	4.136	7.800	30.600
Date2	February 21st, 1996	196	21.116	3.400	10.600	30.000
Date3	March 20th, 1996	238	19.371	5.350	8.200	33.200
Date4	April 24th, 1996	276	18.842	4.205	9.500	28.200
Breed1	“Fleckvieh”	804	19.821	4.218	7.800	33.200
Breed2	“Braunvieh”	96	19.988	3.319	12.000	27.000
Cate2	Female Calves	839	20.425	3.556	10.000	33.200
Cate3	Young Female Calves	50	10.824	1.498	7.800	13.400
Cate4	Cows	11	16.091	3.528	9.500	23.400
Qual11	Quality 1B	22	26.709	2.607	23.200	33.200
Qual12	Quality 2A	34	24.571	2.343	18.800	28.200
Qual13	Quality 2B	573	21.178	2.859	12.400	31.200
Qual14	Quality 3A	236	16.546	3.022	8.000	23.600
Qual15	Quality 3B	35	11.203	2.383	7.800	16.800
Qual21	Quality 1	544	20.024	4.753	7.800	33.200
Qual22	Quality 2	270	19.714	2.932	12.000	25.800
Qual23	Quality 3	86	19.063	2.832	13.000	28.400
All Data		900	19.839	4.128	7.800	33.200

*Prices in ATS.

Table 3.2: Frequencies of winning bids

Date	Number of bidders	Number of objects	Total
Jan. 24th, 1996	114	1	
	17	2	
	1	3	
	1	4	
	1	8	
	1	11	
	1	16	190
Feb. 21st, 1996	104	1	
	12	2	
	1	4	
	1	8	
	1	12	
	2	22	196
Mar. 20th, 1996	108	1	
	21	2	
	3	3	
	1	5	
	2	12	
	1	23	
	1	27	238
Apr. 24th, 1996	118	1	
	21	2	
	5	3	
	1	4	
	1	7	
	1	35	
	1	55	276

Table 3.3: Descriptive statistics of winning bids of large traders vs. small bidders

Date	Bidder(s)*	Number	Mean**	Std. Err.	Minimum	Maximum
Jan. 24th, 1996						
	T30	11	15.782	3.050	9.600	19.200
	T50	8	17.325	1.422	14.800	19.200
	T55	4	19.900	2.666	16.000	22.000
	T145	3	25.267	1.677	24.200	27.200
	T200	16	15.588	5.112	7.800	23.200
	Small bidders***	148	21.545	3.482	12.400	30.600
Feb. 21st, 1996						
	T30	22	21.964	2.079	16.400	25.600
	T70	8	16.200	3.997	11.200	21.000
	T120	4	24.975	1.034	24.000	26.400
	T200	22	19.700	3.275	10.600	24.400
	T270	12	18.783	1.237	15.600	20.400
	Small bidders	128	21.619	3.328	12.700	30.000
Mar. 20th, 1996						
	T30	23	18.096	2.882	12.200	23.600
	T163	3	21.867	0.611	21.200	22.400
	T183	5	20.280	0.687	19.600	21.200
	T200	12	20.933	2.281	17.800	27.000
	T201	12	17.817	1.550	15.000	20.000
	T210	3	12.400	0.529	11.800	12.800
	T400	27	10.370	1.425	8.200	13.300
	T408	3	16.200	0.917	15.200	17.000
	Small bidders	150	21.308	3.879	11.600	33.200
Apr. 24th, 1996						
	T30	55	17.040	2.923	10.200	23.800
	T70	3	14.400	2.358	9.500	28.200
	T118	3	18.000	2.000	16.000	20.000
	T157	4	18.350	3.638	15.800	23.600
	T158	3	16.933	1.007	16.000	18.000
	T159	3	18.067	0.306	17.800	18.400
	T200	35	19.146	2.374	15.000	24.000
	T270	7	14.314	0.855	13.000	15.200
	T290	3	14.266	0.462	14.000	14.800
	Small bidders	160	19.841	3.655	9.500	28.200

* Bidders T30 and T200 are the same bidders, respectively, through all auction days.

** Prices in ATS.

*** Small bidders bought one or two objects.

Table 3.4: Estimation results for symmetric models

Variable	Static models				Sequential model	
	Private values		Affiliated values		Private values	
	(1)	(2)	(3)	(4)	(5)	(6)
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	8.3188**	0.0634	8.3399**	0.2822	8.5244**	0.0662
Date1	0.1150**	0.0104	0.1095**	0.0445	0.1186**	0.0045
Date2	0.1279**	0.0102	0.1245**	0.0440	0.1348**	0.0045
Date3	0.0953**	0.0100	0.0941**	0.0450	0.0983**	0.0043
Breed	0.0476**	0.0476	0.0466	0.0525	0.0556**	0.0052
Cate2	0.2583**	0.0342	0.2617**	0.1508	0.2727**	0.0153
Cate3	-0.0852**	0.0410	0.0952	0.1816	-0.0703**	0.0181
Qual11	0.5192**	0.0342	0.5377**	0.1523	0.5196**	0.0146
Qual12	0.4725**	0.0313	0.4690**	0.1407	0.4803**	0.0133
Qual13	0.3736**	0.0257	0.3858**	0.1169	0.3728**	0.0109
Qual14	0.1269**	0.0247	0.1395	0.1137	0.1241**	0.0104
Qual21	0.1437**	0.0139	0.1474**	0.0607	0.1422**	0.0060
Qual22	0.0629**	0.0136	0.0628	0.0593	0.0655**	0.0058
Weight	0.7866**	0.0684	0.7895**	0.2984	0.8245**	0.0296
LnBid(-1)	-	-			-0.0138**	0.0063
Variance	0.2476**	0.0059			0.1080**	-
Obs.	900		900		899	
Max.Lik.:	720.2420		-		-598.2971	
Value of obj.fct.:	-		95.2203		-	

** (*) denotes significance at the 95% (90%) level of confidence.

Table 3.5: Estimation results for asymmetric static models with private values

Variable	Small bidders		Large traders***		T30		T200	
	(1) Coefficient	(2) Std. error	(3) Coefficient	(4) Std. error	(5) Coefficient	(6) Std. error	(7) Coefficient	(8) Std. error
Constant	8.3349**	0.0970	8.1608**	0.1249	8.2968**	0.1575	8.0189**	0.1715
Date1	0.1155**	0.0127	0.1163**	0.0294	0.0635**	0.0322	0.0570**	0.0268
Date2	0.1131**	0.0132	0.1138**	0.0282	0.1793**	0.0213	0.0956**	0.0222
Date3	0.0802**	0.0127	0.1063**	0.0241	0.0921**	0.0202	0.1247**	0.0284
Breed	0.0485**	0.0154	0.1228**	0.0403	0.1025**	0.0445	0.0088	0.1094
Cate2	0.3038**	0.0464	0.2131**	0.0528	0.1695**	0.0811	0.3781**	0.0843
Cate3	-0.0682	0.1208	-0.0880	0.0658	-0.1856**	0.0882	0.0367	0.0192
Qual11	0.6297**	0.0601	-	-	-	-	-	-
Qual12	0.5871**	0.0590	0.4608**	0.0866	-	-	0.4201**	0.0862
Qual13	0.4897**	0.0557	0.2665**	0.0407	0.2303**	0.0282	0.2926**	0.0782
Qual14	0.1635**	0.0566	0.1117**	0.0347	0.1053**	0.0468	0.2002**	0.0740
Qual21	0.1538**	0.0167	0.0770**	0.0355	0.1121**	0.0344	0.0818**	0.0395
Qual22	0.0682**	0.0164	0.0444	0.0314	0.0487	0.0318	0.0352**	0.0342
Weight	0.5301**	0.0909	1.2556**	0.1529	1.0796**	0.1818	1.3755**	0.2010
Variance	0.2520**	0.0074	0.1739**	0.0117	0.1827**	0.0124	0.1569**	0.0122
Obs.	589		115		111		85	
Max.Lik.:	460.6296		131.3888		121.8803		106.1405	

** (*) denotes significance at the 95% (90%) level of confidence.

*** Large traders are without T30 and T200.

Table 3.6: Estimation results for asymmetric sequential models with private values

Variable	Small bidders		Large traders***		T30		T200	
	(1) Coefficient	(2) Std. error	(3) Coefficient	(4) Std. error	(5) Coefficient	(6) Std. error	(7) Coefficient	(8) Std. error
Constant	8.1628 **	0.1157	9.6332**	0.1976	8.1303**	0.1402	8.6943**	0.1634
Date1	0.1158 **	0.0055	0.1918**	0.0143	0.0598**	0.0148	0.0664**	0.0131
Date2	0.1130 **	0.0058	0.2087**	0.0141	0.1847**	0.0098	0.1102**	0.0110
Date3	0.0799 **	0.0056	0.1647**	0.0117	0.0939**	0.0090	0.1329**	0.0136
Breed	0.0577 **	0.0069	0.1223**	0.0232	0.1031**	0.0200	0.0122*	0.0079
Cate2	0.3033 **	0.0201	0.1630**	0.0266	0.1406**	0.0360	0.3966**	0.0494
Cate3	0.1097 **	0.0509	-0.2160**	0.0329	-0.2081**	0.0392	0.0431	0.0675
Qual11	0.6273 **	0.0257	-	-	-	-	-	-
Qual12	0.5879 **	0.0252	0.4542**	0.0434	-	-	0.3969**	0.0397
Qual13	0.4834 **	0.0238	0.2818**	0.0215	0.2147**	0.0240	0.2568**	0.0358
Qual14	0.1468 **	0.0243	0.1147**	0.0182	0.0901**	0.0212	0.1656**	0.0338
Qual21	0.1592 **	0.0073	0.0607**	0.0182	0.1194**	0.0157	0.0848**	0.0191
Qual22	0.0752 **	0.0072	0.0548**	0.0159	0.0459**	0.0144	0.0383**	0.0160
Weight	0.5327 **	0.0401	1.0602**	0.0772	0.9782**	0.0816	1.4090**	0.1058
LnBid(-1)	0.0286 **	0.0114	-0.1306**	0.0201	0.0361**	0.0127	-0.0635**	0.0126
Variance	0.1110	-	0.0900**	-	0.0840	-	0.0750	-
Obs.	588		114		110		84	
Max.Lik.:	-375.3857		-15.0966		0.7723		31.3666	

** (*) denotes significance at the 95% (90%) level of confidence.

*** Large traders are without T30 and T200.

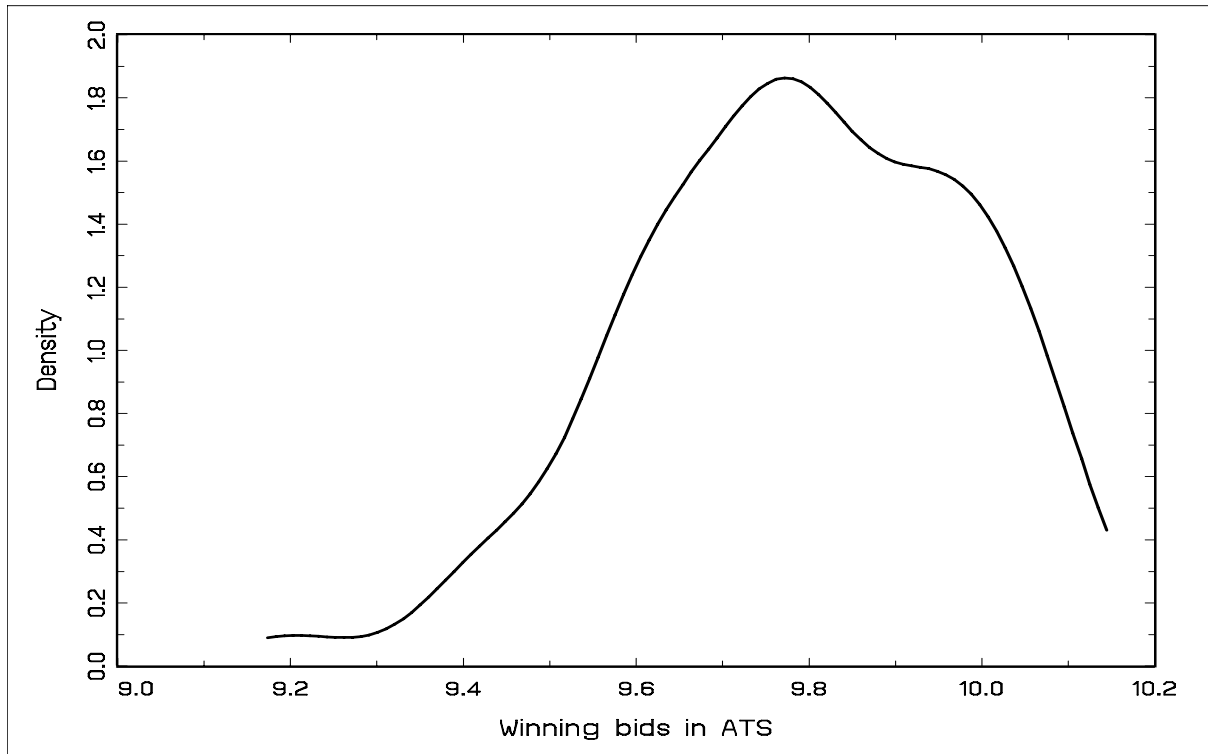


Figure 3.1: Kernel density estimation of winning bids of one large trader

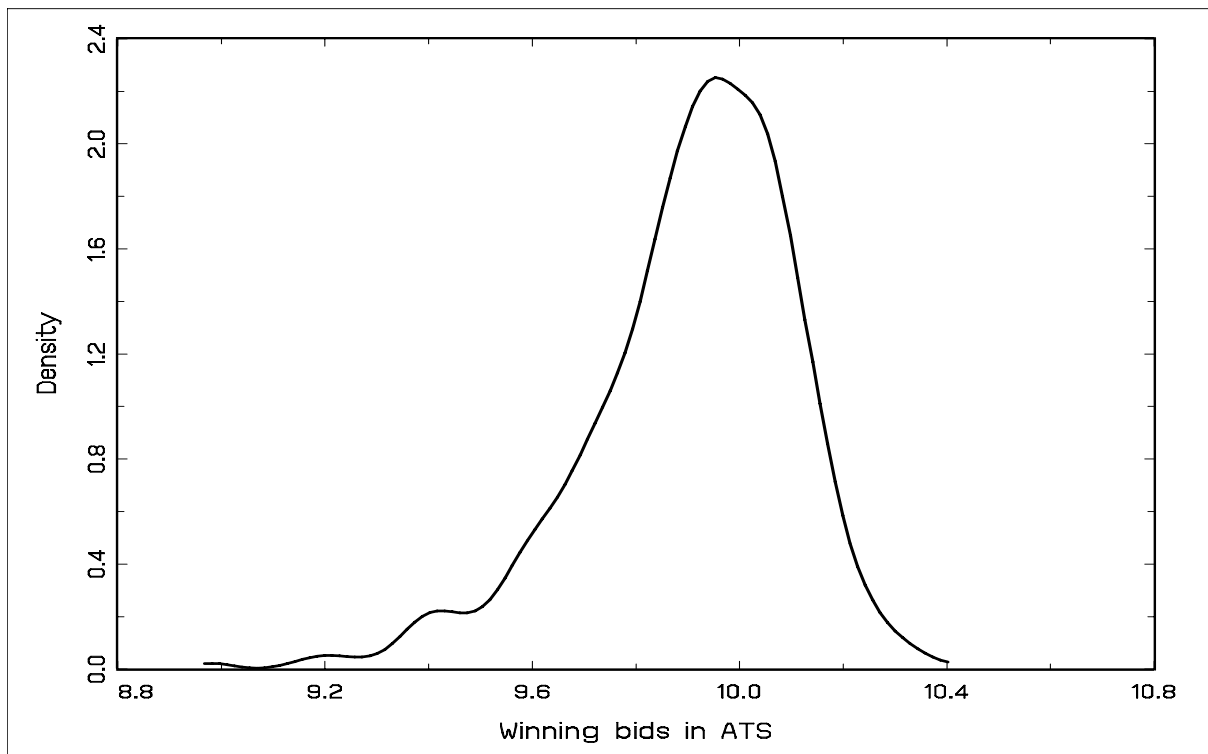


Figure 3.2: Kernel density estimation of winning bids of small bidders

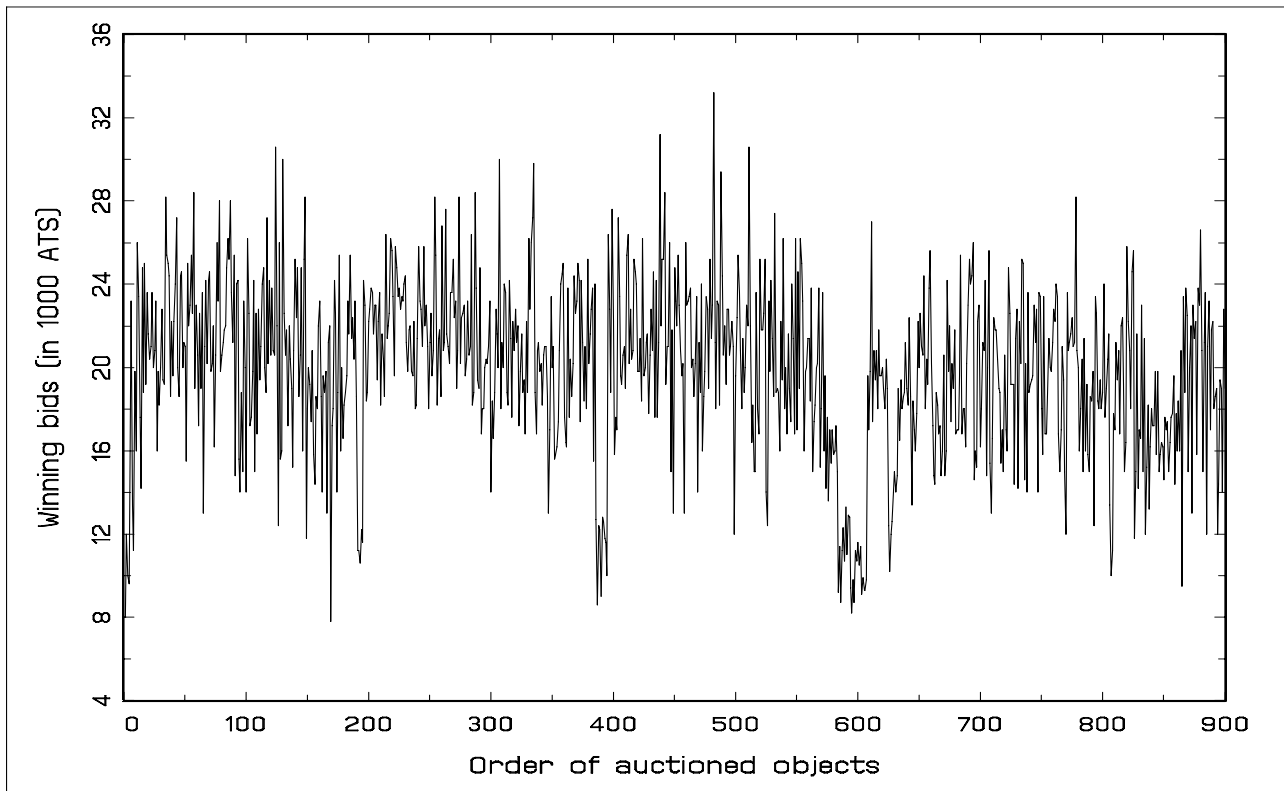


Figure 3.3: Winning bids of all auction days

Part II

Oligopoly markets

Chapter 4

Testing dynamic oligopolistic interaction: Evidence from the semiconductor industry

4.1 Introduction

Learning-by-doing and spillovers are prevalent in the semiconductor industry and in particular in the Dynamic Random Access Memory (DRAM) market.¹ Firms in this market deal with a production process that yields cost reductions the more output has been fabricated in the past. This adds an intertemporal component to firms' output decisions. But do firms take their rivals' future reactions into account when they choose their output strategies today? Jarmin (1994) already asked this question for the early rayon industry and found empirical evidence of dynamic strategic behavior.

The objective of this paper is to test whether firms in an dynamic oligopolistic industry like the DRAM industry pre-commit themselves to a production plan or whether they consider the strategic effect of learning-by-doing and spillovers on their rivals' future output decision. I empirically investigate whether firms act strategically in a dynamic sense, when they formulate their output strategies. And if they do, what is the sign of this strategic effect. Do firms consider the future output of other firms as strategic substitutes or as strategic complements. The second objective of the paper is to analyze how the estimated parameters in a structural model of dynamic quantity competition change when the dynamic strategic effect is not accounted for. My main point of interest lies then on the price-cost margins. The industry, I concentrate on, is the semiconductor industry and there the DRAM market. DRAMs are memory components (chips) and are classified into generations. As we find learning-by-doing and spillovers in this market it seems to be appropriate to investigate above described issues. Another aspect of this particular industry is, that semiconductors are an important input to several high-technology industries and that DRAMs are usually thought of as technology drivers.

¹See, for example, Irwin and Klenow (1994), Gruber (1996a), Brist and Wilson (1997) and Siebert (1999).

In learning-by-doing models firms learn either from their own experience, from the experience of other firms, or both. Learning-by-doing introduces an intertemporal component to firms decisions. Under the assumption that an appropriate measure of experience is past cumulative output, current production adds to the firm's stock of experience. Increases in the firm's stock of experience reduce its unit costs in future periods. Theoretical research demonstrate that learning can have sizable impact on cost and strategic decisions and market performance (e.g. Spence (1983), Fudenberg and Tirole (1983)). If the firm's experience is completely proprietary, its optimal strategy is to overproduce in early periods as an investment in future cost reduction. Incumbent firms can exploit the learning curve and thereby have an absolute cost advantage over potential entrants. Thus entry barriers can be erected. However, if there are spillovers among firms the incentives for overproducing diminish (Fudenberg and Tirole (1983)).

There exist a lot of empirical studies about the DRAM market. Most investigate, whether learning-by-doing and spillovers are prevalent in that industry and when yes, how large these effects are. The different setups vary to a certain degree. Baldwin and Krugman (1988) did a simulation study for the 16K generation. This was the pioneering attempt to incorporate learning economies into a stylized empirical model of the semiconductor industry. Flamm (1993) also completed a simulation study, but on the 1MB generation. Further he used a different theoretical model where firms first compete in capacity and then in output. However, his simulations were extremely sensitive to the specification of some parameters. These two papers deal with calibrating theoretical models. Another part of the semiconductor literature considers econometric models. Gruber (1992), (1996a) estimated a reduced form relationship assuming constant cost-price margins and found economies of scale rather than learning-by-doing effects for various generations of DRAMs. Irwin and Klenow (1994) implemented a recursive dynamic specification. They assumed constant returns to scale, Cournot behavior and fixed elasticities of demand. Their results imply learning-by-doing within and learning spillovers across firms, but no spillovers across generations. Brist and Wilson (1997) estimated both a demand and a pricing relation for a dynamic game with open-loop strategies. Neglecting learning spillovers among firms they showed learning-by-doing to be smaller in the presence of economies of scale and estimated markups. Siebert (1999) used a dynamic model and investigated the influence of a multi-product specification on the estimated parameters. He found that multiproduct firms behave as if in perfect competition.

Most of the literature about the semiconductor industry has considered learning-by-doing extensively, but has not considered the dynamic strategic implications. Jarmin (1994) investigated these dynamic effects for the early rayon industry. His results show that firms take their rivals' reactions into account when choosing their strategies. Karp and Perloff (1989) estimated a dynamic oligopoly model and the degree of competition for the rice export market. Their model nests various market structures with firms that either pre-commit themselves to a production plan or that consider the strategic effect of their own output on their rivals' future output decision. However, in this market learning-by-doing or spillover do not matter. Therefore their model does not take these effects into account. Slade (1995) developed a dynamic model for a market in which firms compete

in prices and advertising intensity. In contrast to these papers Steen and Salvanes (1999) proposed a dynamic oligopoly model in an error correcting framework. Using data of the French market for fresh salmon they separated the long-run effects from the short-run effects. Their results suggest a competitive market in the long run, but indicate that the largest producer has some market power in the short run.

In this paper I apply the same dynamic oligopoly model to the DRAM industry that Jarmin applied to the early rayon industry. The empirical framework for examining the dynamic effects of learning-by-doing and spillovers, and market power is an intra industry study described in Bresnahan (1989). The contribution of this paper is to investigate whether firms take the strategic effect of learning-by-doing and spillovers on their rivals' future output decision into account, and thus to test a closed-loop specification for the DRAM industry. Further I compare the estimated parameters with the estimated parameters of the pre-commitment specification and investigate the influence of the assumption of one equilibrium concept on learning-by-doing, learning spillovers, economies of scale and price-cost margins. In a conceptual analogous way Röller and Sickles (1900) showed for the airline industry that market conduct in a two-stage set-up of a game in capacity and prices is significantly less collusive than in a one-stage set-up.

The implication of learning by doing in production technology for market power and performance can be modelled within a dynamic oligopoly game. Thus the consequences of firms' using experience as a strategic variable can be considered. Departing from a dynamic oligopoly game the first order conditions for the pre-commitment and the closed-loop equilibrium are derived to implement an econometric model. The closed-loop specification then enables me to evaluate the effect of a firm's strategy on the objective function of other firms in future periods. I assume a single product market. A structural econometric approach is used for evaluating market power, learning-by-doing, learning spillovers, economies of scale and strategic behavior. The methodology involves a specification of demand and marginal cost functions and hypotheses about the strategic interactions of the participants. Different behavioral assumptions about firms in the DRAM market are tested.

Section 4.2 contains a description of the DRAM market. In Section 4.3 I set up the theoretical model allowing firms in an dynamic oligopolistic industry either to pre-commit themselves to a production plan or to consider the effect of learning-by-doing and spillovers on their rivals' output decision. The implemented econometric model is given in Section 4.3.2. In Section 4.4 the data and the estimation procedure are discussed. Estimation results for three different DRAM generations are also provided in this section. Conclusions are given in Section 4.5.

4.2 The DRAM industry

In this section I give a short description of the DRAM industry. More detailed descriptions can be found in Gruber ((1996c), (1996b)), Irwin and Klenow (1994) and Flamm (1993). DRAMs are memory components (chips) designed for storage and retrieval of information in a binary form. One characteristic of DRAMs is that they lose memory

once they are switched off and they are therefore used when memory storage need not be permanent. They are classified into 'generations' according to their storage capacity in terms of binary information units. DRAMs are part of semiconductors, which are a key input for electronic goods. The main segments are computers, consumer electronics, communications equipment, industrial applications and cars (Gruber (1996b)).

Memory chips, like DRAMs, are produced in batches on silicon wafers. The production of semiconductors requires a complex sequence of photolithographic transfer of circuit patterns from photo masks onto the wafer and of etching processes. The manufacturing process has to be very precise in terms of many physical determinants (for example, temperature, dust, vibration levels). The wafer, once processed, is cut and the single chips are then assembled. The wafer processing stage is the most critical and also the most costly. The main cost determinant of a chip is the silicon material. Learning-by-doing takes place over the entire product cycle. In the beginning of the chip production a large proportion of the output is usually defective and has to be discarded. The yield rate, which is measured by the ratio of usable chips to the total number of chips on the wafer, is very low at that time. Later, the yield rate increases as firms learn. The necessary amount of silicon and firms' costs decreases at the same time. Therefore the use of the traditional measure of learning, namely cumulative output, fits this pattern very well. Part of the semiconductor production knowledge can be viewed as plant specific, because of the difficulty of transferring the created knowledge even within one firm. However, there are several research and development, and production joint ventures among firms. This shows the importance of spillovers in this industry. Furthermore, as capital expenditures for a state of the art production facility are very high, a firm's concern is to take advantage of the benefits of economies of scale.

Life cycles of different semiconductor industries and generations are comparable and short-lived, fitting the standard product cycles. The time between introduction of a new chip and the peak in output is relatively short compared to other products. Different generations overlap from one generation to the other. Further, the price decline at the beginning of a new generation is very extreme. Within the first year the price, for example, the 256K (1MB) generation fell about 60% (70%).

In the 1980s there was an extensive policy debate going on in the US about the pricing behavior of Japanese semiconductor firms. The general allegation was price dumping. Late in 1985, the US government started investigations. Japanese producers of 64K and 256K DRAMs were asked to file a quarterly estimate of their full cost data. Japanese 64K DRAM producers were found guilty of charging prices below their current fair market value or cost of production. The dumping case against Japanese 256K DRAM producers was suspended (see, for example, Nye (1996)). If learning-by-doing is present in an industry as in the DRAM industry, firms may have an incentive to sell products even below their static marginal costs during the early periods of the product cycle. Dick (1991) rejected the dumping hypothesis for the DRAM industry on the basis of this incentive.

However, do firms take this incentive actually into account? This paper tries to find an answer to this question and further, empirically investigates price-cost margins in the presence of learning-by-doing and spillovers, which introduce an intertemporal component

to firms' decisions. Firms use their current output to build up experience and thereby affect the behavior of their rivals in the future. In contrast, if firms precommit themselves to an output path, the intertemporal component does not play a role and firms should not sell below their static marginal cost. In the case firms take the intertemporal strategic effect of learning-by-doing and spillovers into account, we are interested to quantify the magnitude of this effect and the change in price-cost margins. Also the consequences on market power and competition policy should be considered.

4.3 The model

In this section I present the model, the implications of the theoretical model for the estimations, and the econometric implementation.

In studying repeated games strategies are considered in which past play influences current and future strategies. Usually economists focus their attention on equilibria in a smaller class of Markov state-space or feedback strategies. In this case the past influences the current play only through its effect on a state variable that summarizes the direct effect of the past on the current environment (Fudenberg and Tirole (1983)). There are further information concepts. Firms either pre-commit themselves to their productions plan or they consider the effect of learning-by-doing and spillovers on their rivals' output decision. Or differently spoken firms use either open-loop or closed-loop (no memory) strategies. The terms open-loop and closed-loop (no memory) are used to distinguish between different information structures in multi-stage games.

Open-loop strategies are functions of calendar time only. In an open-loop equilibrium players simultaneously commit to entire paths of history. Thus the open-loop equilibria are really static, in that there is only one decision point for each player. The open-loop (pre-commitment) equilibria are just like Cournot-Nash equilibria, but with a larger strategy space (Fudenberg and Tirole (1986)). Open-loop strategies are not perfect, as they ignore deviations by subsets of positive measure (Fudenberg and Tirole (1983)).

In a closed-loop information structure players can condition their play at time t on the history of the game until that date. The term closed-loop equilibrium usually means perfect equilibrium of the game, where players can observe and respond to their opponents' actions at the end of each period. Another information structure are above mentioned Markov state-space or feedback strategies. These strategies are closed-loop strategies, but do not depend on the initial value of the state-space variable as closed-loop strategies do (see e.g. Feichtinger and Hartl (1986)). In a memoryless perfect state information structure the past influences the current play only through its effect on a state variable like in the feedback information pattern and also on the initial value of the state, which is known a priori.

In the theoretical model firms are assumed to maximize their profits over the product cycle. The model considers the case of learning-by-doing within each firm and allows firms not only to learn from their own experience, but also from learning spillovers from other firms. Therefore the law of motion for the state variable describes the industry experience vector (i.e. cumulative output vector). The model is solved for equilibria in open-loop

(pre-commitment) and closed-loop² strategies, respectively. It is a T -period extension of Fudenberg and Tirole (1983)'s two period game and it is the same model Jarmin (1994) applied to the early rayon industry.³ Fudenberg and Tirole showed that firms consider the effect of their learning-by-doing on the actions of their rivals. These strategic incentives can induce firms to choose decreasing output paths. Further little learning spillovers across firms increase output if firms use open-loop strategies, but decrease output if firms play strategically. Fudenberg and Tirole derived analytical output paths under the assumption of a linear demand. The theoretical model is solved in open-loop and closed-loop strategies.

Like Jarmin (1994) I do not derive analytical output paths but rather first order conditions, which are empirically implemented later on. A particular drawback of the use of quantity competition to study learning-by-doing arises according to Fudenberg and Tirole (1986) by neglecting of another strategic aspect. Firms cannot only reduce their future costs by producing more, but can also increase their opponents' future cost by reducing their current market share and preventing them from learning. In a model with price competition this strategic aspect would be reflected. However, with quantity competition the opponents' current output is fixed. The reason why firms might set quantities rather than prices lies in the fact that in the DRAM industry reducing one's own cost through learning-by-doing is the crucial element. Firms set up state of the art factories at high fixed cost, start production and try to be as fast as possible to reduce their own costs and to use their full capacity.

4.3.1 A model with learning-by-doing and spillovers

Competition in an industry characterized by learning-by-doing and learning spillovers can be modelled as a dynamic game, as learning-by-doing introduces an intertemporal component to a firm's decisions. This model incorporates not only propriety learning but also learning spillovers across firms. It is the same model that Jarmin (1994) applied to the early rayon industry. Firms are modelled to maximize their profit over the product cycle. Assume there are $i = 1, \dots, n$ firms and $t = 1, \dots, T$ discrete time periods. At the beginning of each period, firms choose quantities of a homogeneous output, q_{it} . Firm i 's cost in period t , $C_{it} := C(q_{it}, X_t, W_{it})$, are a function of current output, input prices, firm i 's experience and the experience of all firms other than i . X_t is the vector of cumulative output of each firm i , representing the experience gain due to learning-by-doing within the own firm and among other firms in the industry. Experience is assumed to be measured by past cumulative output. Thus, firm i 's stock of experience is $x_{it} := \sum_{s=1}^{t-1} q_{is}$. Output choices play an additional role as investment into experience. The more output is produced today, the lower unit costs will be tomorrow. Each firm i choose q_{it} in order to maximize

²I use the term closed-loop strategies in the sense of closed-loop no memory strategies (Basar and Olsder (1991)).

³However, the empirical implementation is different in the sense that I allow for an estimated conduct parameter, whereas Jarmin does not.

intertemporal profits defined as

$$\begin{aligned} \text{Max}_{q_{it}} \Pi_i &= \sum_{t=1}^T \delta^{t-1} \{P_t q_{it} - C(q_{it}, X_t, W_{it})\} \\ \text{s.t. } X_t &= X_{t-1} + Q_{t-1} \quad \text{and} \quad X_0 = 0 \end{aligned} \quad (4.1)$$

where δ is the discount rate, $q_t := \sum_{i=1}^n q_{it}$ is industry output, Q_t is the vector of firm specific output, and $P_t := P(q_t)$ is the inverse market demand function for a given generation.

The necessary conditions for a open-loop Nash equilibrium⁴ of (4.1) are

$$P_t + \frac{\partial P_t}{\partial q_t} \frac{\partial q_t}{\partial q_{it}} q_{it} = \frac{\partial C_{it}}{\partial q_{it}} + \sum_{s=t+1}^T \delta^{s-t} \sum_{j=1}^n \frac{\partial C_{is}}{\partial x_{js}} \frac{\partial x_{js}}{\partial q_{it}} \quad (4.2)$$

for all $i = 1, \dots, n$ and $t = 1, \dots, T$. The left-hand side term of equation (4.2) is the standard Cournot marginal revenue. The first term of the right-hand side is the contemporaneous effect of output on marginal cost, the standard marginal cost without learning-by-doing and learning spillovers. The second term is the discounted future cost saving of learning-by-doing and learning spillovers gained through the contemporaneous output decision. In case of learning-by-doing and/or learning spillovers effects, this term should be negative. Both terms together denote dynamic marginal cost. Firms set marginal revenue equal to dynamic marginal costs, which lie below static marginal cost and increase output in order to benefit from learning-by-doing and learning spillovers reduce future costs.

The necessary conditions for a closed-loop (no memory) Nash equilibrium⁵ of (4.1) are

$$\begin{aligned} P_t + \frac{\partial P_t}{\partial q_t} \frac{\partial q_t}{\partial q_{it}} q_{it} &= \frac{\partial C_{it}}{\partial q_{it}} + \sum_{s=t+1}^T \delta^{s-t} \sum_{j=1}^n \frac{\partial C_{is}}{\partial x_{js}} \frac{\partial x_{js}}{\partial q_{it}} \\ &\quad - \sum_{s=t+1}^T \delta^{s-t} \frac{\partial P_s}{\partial q_s} q_{is} \sum_{j=1}^n \frac{\partial q_s}{\partial q_{js}} \frac{\partial q_{js}}{\partial x_{is}} \frac{\partial x_{is}}{\partial q_{it}} \end{aligned} \quad (4.3)$$

for all $i = 1, \dots, n$ and $t = 1, \dots, T$.⁶ The first terms of (4.3) are the standard first order condition from the static Cournot problem without learning-by-doing and without learning spillovers. With closed-loop strategies learning-by-doing and learning spillovers create an explicit intertemporal link between strategies firms employ today and the competitive environment in which firms find themselves tomorrow (Jarmin (1994)). Firms anticipate correctly that future profits will be simultaneously determined by the current

⁴The existence of a Nash equilibrium in an infinite game with an open-loop information structure is guaranteed, when the objective function is continuously differentiable and the state equation is convex and continuously differentiable. For further details see Basar and Olsder (1991).

⁵The existence of a Nash equilibrium in an infinite game with a no memory closed-loop information structure is guaranteed, when the objective function is continuously differentiable and the state equation is convex and continuously differentiable. For further details see Basar and Olsder (1991).

⁶The necessary conditions for an open-loop Nash equilibrium of (4.1) are the same as those for a closed-loop Nash equilibrium only without the last term in (4.3).

and future output decisions of all firms. The last term in the first line of (4.3) is the discounted future cost saving of learning-by-doing and learning spillovers gained through firm's contemporaneous output decision. This effect is the direct effect of the firm's output choices on its payoffs. In case of learning-by-doing and learning spillovers, this term should be negative. Both terms together denote dynamic marginal cost. The terms in the second line show the intertemporal strategic effect due to learning-by-doing and learning spillovers. A change in firm i 's strategy at time t affects firm $j \neq i$'s objective function in period $s = t + 1, \dots, T$ through x_{is} . When there is learning-by-doing, but no spillovers, incumbent firms may, by overinvesting in experience, erect entry barriers (Spence (1983), Fudenberg and Tirole (1983)). The ability of incumbents to deter entry by accumulating experience can be reduced by spillovers. In case of learning-by-doing and no or small spillovers q_{it} and q_{js} will be strategic substitutes. If spillovers are large enough q_{it} and q_{js} will be strategic complements.

4.3.2 The econometric implementation

The empirical model of the DRAM industry consists of a demand equation and two pricing relations for each firm based on equations (4.2) and (4.3). This gives two systems of equations, one for open-loop strategies and one for closed-loop strategies. For estimation, structure has to be placed on the demand and on the cost functions, as demand and cost parameters enter the pricing relations.

Inverse demand equation

The elasticity of demand plays an important role in the pricing relations. The inverse demand function is specified as

$$\begin{aligned} \ln(P_t) = & \beta_0 + \beta_1 \ln(q_t) + \beta_2 \ln(q_t^{S_1}) + \beta_3 \ln(q_t^{S_2}) + \beta_4 \ln(Y_t) \\ & + \beta_5 \text{time} + \lambda \text{AR}(1) + \mu_t, \end{aligned} \quad (4.4)$$

where $\beta_i, i = 1, \dots, 5$, and λ are the parameters to be estimated. P_t is the average selling price of a chip at time t , q_t is the output of the chip at time t , $q_t^{S_1}$ and $q_t^{S_2}$ are the respective quantities of substitute semiconductors, Y_t is a vector of other nonprice demand shifters and t is a time trend. The parameters to be estimated reflect the own inverse elasticity of demand, cross elasticities of demand, the effect of demand shifters on a DRAM generation, a trend that captures the effect of the time that a particular generation has been on the market and the effect of the lagged price of the relevant DRAM. As substitute semiconductors I take the preceding and the following generation of DRAMs. Because I estimate an inverse demand function with an autoregressive term $\beta_1^S = \beta_1$ denotes the inverse short-run elasticity of demand. The short-run elasticity of demand is denoted by $\epsilon^S = \frac{1}{\beta_1^S}$. Whereas $\epsilon_1^L = \frac{\epsilon^S}{1-\lambda}$ is the long-run elasticity of demand.

Pricing relations

The empirical models of pricing are the generalized first order conditions (4.3) and its counterpart in open-loop strategies (4.2) which allow market structure to be estimated rather than imposed. The econometric implementation of the open-loop equilibrium is in line with Brist and Wilson (1997). However, they do not consider learning spillovers and do not use input prices. I additionally set up the first-order conditions in closed-loop strategies. The closed-loop pricing relation is formed in an analogous way and nests the open-loop pricing relation. I compare the two estimated parameter sets and test the two specifications.

Intertemporal strategic parameter The model in closed-loop strategies would be overparameterized if all terms that measure dynamic strategic effects were to be estimated. Thus I define the intertemporal strategic parameter one period ahead only. I define the term

$$\theta_{ij} := \frac{\partial q_{jt+1}}{\partial x_{it+1}} \frac{\partial x_{it+1}}{\partial q_{it}} \quad (4.5)$$

as the intertemporal strategic parameter.⁷ It varies over firms and measures how a change in firm i 's output at time t changes firm j 's output at time $t+1$. If firm i 's experience is proprietary and it behaves rationally, the expected sign of the strategic parameter is negative. q_{it} and q_{jt+1} are then strategic substitutes. If firm i 's experience benefits no one, the estimate of this parameter should be zero. The expected sign of the strategic parameter when i 's rival benefits from its experience is ambiguous. If learning spillovers are strong enough, the strategic parameter could be positive. And if this strategic parameter is positive, then q_{it} and q_{jt+1} are strategic complements.

The first order conditions can give the following advice for empirical testing. The difference between open-loop and closed-loop first order conditions can be pinned down by the intertemporal strategic parameter θ_{ij} . If this term is not equal to zero, we can conclude that firms use closed-loop strategies. On other hand if this term equals zero, nothing can be said. The situations where firms use either open-loop strategies or closed-loop strategies without a strategic impact cannot be distinguished. If there is strategic interaction, two possibilities emerge: i) $\theta_{ij} < 0$, i.e. q_{it} and q_{jt+1} are strategic substitutes. There is either only learning-by-doing or learning-by-doing and not large enough learning spillovers. That means the learning-by-doing effect still exceeds the learning spillovers. ii) $\theta_{ij} > 0$, i.e. q_{it} and q_{jt+1} are strategic complements. Here we have learning-by-doing and large learning spillovers. The learning spillovers are larger than learning-by-doing effects. The sign and the significance of θ_{ij} can be tested. I again assume symmetry in the sense that firm i reacts in the same way to different firms $j, \forall j \neq i$ and that all firms i are symmetric in their reaction to the other firms. Thus θ captures the average effect of firm i 's strategy on the objective function of all other firms in the next period.

⁷See also Jarmin (1994) for a discussion on that parameter.

Further dynamic effects Like Roberts and Samuelson (1988) and Jarmin (1994), I capture all dynamic effects that occur two or more periods into the future via a firm specific constant and define them in the following way

$$\alpha_i := \sum_{s=t+2}^T \delta^{s-t} \frac{\partial P_s}{\partial q_s} q_{is} \sum_{j=1}^n \frac{\partial q_s}{\partial q_{js}} \frac{\partial q_{js}}{\partial x_{is}} \frac{\partial x_{is}}{\partial q_{it}} \quad (4.6)$$

The terms α_i are relevant only for the closed-loop specification, as there are no future dynamic effects in the open-loop specification.

Specification of the marginal cost function The pricing relations require expressions for marginal cost and for future cumulative marginal cost. These expressions include parameters that measure learning-by-doing and learning spillovers. The marginal cost function I approximate with a log-linear function assuming that the cost function $C_{it} = f(q_{it}, x_{it}, x_{-it}, W_{it})$ itself is also of log-linear form. Marginal cost $MC_{it} = \frac{\partial C_{it}}{\partial q_{it}}$ then look like

$$MC_{it} = \gamma_{1i} + \gamma_2 \ln(q_{it}) + \gamma_3 \ln(x_{it}) + \gamma_4 \ln(x_{-it}) + \gamma_5 \ln(MAT_{it}) + \gamma_6 \ln(ENE_{it}) + \gamma_7 \ln(LAB_{it}) + \gamma_8 \ln(CAP_{it}) + \gamma_9 \ln(INP_{it}) \quad (4.7)$$

for $i = 1, \dots, n$ and $t = 1, \dots, T$. The marginal cost functions varies for firm i through a firm-specific intercept. Like Brist and Wilson (1997) I allow for nonconstant returns to scale in the marginal cost function. Learning-by-doing is measured by cumulative past output $x_{it} := \sum_{s=1}^{t-1} q_{is}$. Learning spillovers are assumed to be symmetric and are defined by the sum of all past cumulative output of other firms $x_{-it} := \sum_{j \neq i} \sum_{s=0}^{t-1} q_{js}$. The last five variables are input prices: MAT denotes the price of silicon, ENE the price of energy, LAB the price of wages, CAP the price of capital, and INP the price for other inputs. The terms of future marginal cost are captured via a firm-specific variable

$$\gamma_{0i} := \sum_{s=t+1}^T \delta^{s-t} \sum_{j=1}^n \frac{\partial C_{it+1}}{\partial x_{jt+1}} \frac{\partial x_{jt+1}}{\partial q_{it}} \quad (4.8)$$

for $i = 1, \dots, n$ and $t = 1, \dots, T$.

Firm-specific fixed effects For the open-loop equilibrium relation the firm-specific constants are now given by

$$\gamma_i = \gamma_{0i} + \gamma_{1i}. \quad (4.9)$$

These are firm-specific future marginal cost (4.8) and the firm-specific intercepts from the marginal cost function (4.7). For the closed-loop equilibrium relation the firm-specific constants are defined as follows

$$\gamma_i = \gamma_{0i} + \gamma_{1i} + \alpha_i. \quad (4.10)$$

In this case the firm-specific constants additionally include the future dynamic effects (4.6). Thus firm specific fixed effects are different in the two equilibrium settings, respectively.

Equilibrium relation Incorporating all definitions made before leads to the following econometric models of the pricing relations. Using (4.13), (4.7) and (4.8) we get for the open-loop equilibrium

$$P_t = \gamma_i + \gamma_2 \ln(q_{it}) + \gamma_3 \ln(x_{it}) + \gamma_4 \ln(x_{-it}) + \gamma_5 \ln(MAT_{it}) + \gamma_6 \ln(ENE_{it}) \\ + \gamma_7 \ln(LAB_{it}) + \gamma_8 \ln(CAP_{it}) + \gamma_9 \ln(INP_{it}) - \beta_1 P_t s_{it} + \mu_{it} \quad (4.11)$$

Using (4.13) - (4.8) we get for the closed-loop equilibrium

$$P_t = \gamma_i + \gamma_2 \ln(q_{it}) + \gamma_3 \ln(x_{it}) + \gamma_4 \ln(x_{-it}) + \gamma_5 \ln(MAT_{it}) + \gamma_6 \ln(ENE_{it}) \\ + \gamma_7 \ln(LAB_{it}) + \gamma_8 \ln(CAP_{it}) + \gamma_9 \ln(INP_{it}) - \beta_1 P_t s_{it} \\ - \beta_1 \theta P_{t+1} s_{it+1} + \mu_{it} \quad (4.12)$$

for $i, j = 1, \dots, n$ and $t = 1, \dots, T$ and where $s_{it} = \frac{q_{it}}{q_t}$. The econometric pricing relation for open-loop strategies is nested in (4.12) without the term including θ . In these equations the price for DRAMs is a function of dynamical marginal costs, of the elasticity of demand and in the closed-loop setting also of future strategic behavior measured by the intertemporal strategic parameter θ .

I then test the effect of a firm's strategy on the objective functions of other firms in future periods by testing the significance of θ . The implications on the estimates of various parameters can be explored, when the true strategies are closed-loop but one estimates the open-loop specification. How do the price-cost margins change? Another question I want to address, how dynamic marginal costs change in a closed-loop equilibrium compared to an open-loop equilibrium? Further, the implications for the estimation of economies of scale, learning-by-doing and spillovers are studied. How do estimated economies of scale, learning-by-doing or spillovers change in the case of strategic substitutes (complements).

These questions can be answered by calculating the potential omitted variable bias and its sign. One can easily show, that if q_{it} and q_{it+1} are strategic substitutes (complements) and the closed-loop specification is the true specification, then in an open-loop specification the estimated learning-by-doing would be overestimated (underestimated). Another possibility of an omitted variable bias concerns economies of scale and spillovers which would be overestimated (underestimated) in case of strategic substitutes (complements). This gives empirically testable hypotheses, which are derived from the theoretical model.

Price-cost margins

The degree of market power of firms in an oligopoly market is measured by the extent to which firms can hold price above marginal cost. In a dynamic context there has also the intertemporal strategic effects to be considered. Thus the price-cost margins can be defined as follows:

$$\frac{P_t - MC_{it} - \gamma_{0i}}{P_t} := -\beta_1 s_{it} - \theta \beta_1 s_{it+1} \frac{P_{t+1}}{P_t} - \frac{\alpha_i}{P_t}. \quad (4.13)$$

The price-cost margins are calculated with respect to dynamic marginal cost, as γ_{0i} , representing future cost savings (4.8), is included. Further, the intertemporal strategic

effects θ and α_i emerge on the righthand side of (4.13). In the open-loop setting these effects are equal to zero. Thus in this case the price-cost margins are equal to the static ones.⁸ In the closed-loop setting price-cost margins are the sum of the open-loop price-cost margins and the intertemporal strategic effects.

In the estimated pricing relations (4.12) the measure of future cost savings γ_{0i} and α_i , measuring intertemporal strategic effects occurring $t + 2$ onwards, are not identified separately. Therefore it is not possible to calculate the exact price-cost margins in the closed-loop case. However, an approximation can be given. For that purpose I find it more convenient to reformulate (4.13). This gives

$$\frac{P_t - MC_{it} - \gamma_{0i} + \alpha_i + \theta\beta_1 s_{it+1} P_{t+1}}{P_t} = -\beta_1 s_{it}, \quad (4.14)$$

where the sum of price-cost margins and the intertemporal strategic effects together measure market power.

If the strategic parameter θ is, for example, negative and q_{it} and q_{jt+1} are strategic substitutes, then the price-cost margins are lower in the strategic dynamic setting than in the pre-commitment setting. Or equally, price-cost margins would be overestimated in the later setting. However, to state this claim, one has to be more precise: It is not only necessary that θ is negative, but it is also necessary that, although (empirically) not identifiable, α_i corresponds to strategic substitutability or, if (the negative) θ and α_i are of opposite strategic interaction, that the size effect of α_i is not larger than that of θ .⁹ In this second case the intertemporal strategic effect between t and $t + 1$ should be larger than the intertemporal strategic effects between t and $t + 2, \dots, T$. If the size effect of α_i is larger, then it is also possible that the price-cost margins in the closed-loop setting are larger than those in the open-loop setting. As already mentioned, α_i is not identifiable. Thus empirically, no absolute answer can be given. However, to assume that either θ and α_i exhibit the same intertemporal strategic behavior or that, if this behavior changes over time, the effect between t and $t + 1$ is the largest in absolute terms and outweighs all other future effects, that correspond to strategic complementarity, is not implausible. Otherwise effects occurring later in the future have more weight than those in the more immediate future.

One has also to consider that the estimated dynamic marginal cost can change due to the omitted variable bias. The parameters in the marginal cost functions MC_{it} and the

⁸In the static case the righthand side of (4.13) is often multiplied with a conduct parameter. This parameter indexes the competitiveness of oligopoly conduct (Bresnahan (1989)). In a competitive market a change in firm i 's output would not have any consequences on prices. Firms price according to their marginal costs. Thus the conduct parameter and the price-cost markup would be both equal to zero. In a Cournot game a change in firm i 's output has impact on prices. Firms price higher than their marginal costs and the conduct parameter would be one, the price-cost markup equal to $\frac{1}{\beta_1}$. If firms maximize joint profits, the conduct parameter would be equal to the number of firms in the industry and the resulting price-cost markup also that times higher. For the open-loop and the closed-loop specifications the conduct parameter is equal to one. If firms collude or they are price takers, then the pre-commitment model and the closed-loop model are equal (see, for example, Karp and Perloff (1989)).

⁹One has to keep in mind, that α_i is equal to (4.6), which combines future strategic effects and the elasticity of demand.

γ_{0i} 's are different contingent on the equilibrium concept. Although this is most likely, the above made claims concerning the price-cost margins are independent of a change in the parameter estimates, as long as the stated necessary conditions are fulfilled.

4.4 Data and estimation results

The data are firms producing DRAMs and are compiled by Dataquest Inc. The data cover firms' units shipped from the 4K generation to the 64MB generation and the average selling price. These generations span a time period from January 1974 to December 1996. The data are available on a quarterly basis. From the firm-level output data I construct three variables. Namely, current output, own past cumulative output and other firms' past cumulative output. Current output serves as measure for economies of scale. The own cumulative output variable represents learning-by-doing. The cumulative past output of all other firms proxies learning spillovers. Further I use price data for four important inputs - price of silicon, energy cost, wages for production and user cost of capital. For the material cost I use the world market price of silicon compiled by Metal Bulletin. Energy costs and wages of production are compiled in the following way: according to each firms production location the energy prices and the industry wages (ISIC 3825) of the concerned location (country) are used¹⁰. User cost of capital is constructed for each firm and year by exploiting the firms' annual reports. As a nonprice demand shifter I use a proportion of GNP directly attributed to electronic and electrical equipment from the OECD (1998). Table 4.2 gives some summary statistics.

In the empirical analysis of the DRAM industry I analyze whether firms take the intertemporal strategic effect of learning-by-doing and spillovers into account, i.e. I test whether the estimate of θ in (4.12) is significantly different from zero. And if firms do consider the effect of their own output decision in t on their rivals output decision in $t + 1$, what is the sign of the intertemporal effect? When there is learning-by-doing and no spillovers, θ will be negative and q_{it} and q_{jt+1} will be strategic substitutes. With small spillovers θ will be still negative. If on the other hand spillovers are large enough to offset the effects of learning-by-doing, θ will be positive and q_{it} and q_{jt+1} will be strategic complements. The second part of the analysis takes a closer look at the consequences of a possible misspecification by ignoring a significant intertemporal strategic effect. In particular, I concentrate on the estimated economies of scale, learning-by-doing and spillovers and investigate the differences between the estimates of the closed-loop and the open-loop specification.

For this purpose two systems of equations are estimated: equations (4.4) and (4.12) for the closed-loop equilibrium. For the open-loop specification I also use equations (4.4) and (4.12) with θ set equal to zero. I run the estimations for three different generations of DRAMs, namely the 64K, the 256K, and the 1MB generation. This selection relies primarily on the fact that not all generations of DRAMS were in the market for a long period of time. Thus I do not consider generations, which give relatively fewer data points.

¹⁰The source for energy prices is OECD/IEA (1998), that for industry wages OECD (1998)

The generations 64K and 256K are of particular interest as these generations were under dumping investigations by the US Commerce Department and the International Trade Commission (see e.g. Flamm (1993)).

For estimating the demand relations for three different generations I use single equation techniques, in particular instrumental variable estimations. The estimations are done in Eviews (1999) with the generalized method of moments (see e.g. Davidson and MacKinnon (1993)). The instruments in the inverse demand equation consist of the exogenous variables in the demand equation and summary measures from the supply side, like average market share, number of firms in the industry, and cumulative world output. For the 64K and the 1MB generation I also include lagged quantities as instruments. I corrected for first order autocorrelation by specifying the demand equation (4.4) and further the GMM estimates are robust to heteroskedasticity and autocorrelation of unknown form. For the pricing relation I use exogenous variables in the specification, the age of the generation, the nonprice demand shifter, and lagged (input) prices as instruments.

The estimates of the demand equation with their respective standard errors are reported in Table (4.3) for three different generations of DRAMs.¹¹ For estimation 67, 56 and 45 observations are used. All three estimations have very good fits. The adjusted R-squares are 0.960 and higher.

The coefficient of the autoregressive process of order one is significant for all three generations. Each generation's own demand elasticity is negative and significant, indicating that higher industry output decreases prices. The estimates across generations with respect to their own inverse demand elasticity range from 0.354 to 0.298 and 0.433 for 64K, 256K and 1MB, respectively. The values correspond to short-run elasticities of demand of 2.824, 3.580 and 2.309 and are in line with the previous literature (Flamm (1993) or Brist and Wilson (1997)). The estimates of long-run elasticities of demand can be calculated with the help of the first-order autoregressive terms λ : $\epsilon^L = \frac{\epsilon^S}{1-\lambda}$ with $\epsilon^S = \frac{1}{\beta_1}$. Using this formula we get values of 8.508, 8.791 and 6.469 for the long run elasticities of demand for the three generations of DRAMs. For all three generations the long run elasticities are greater than the short run ones.

The cross elasticity to the previous generation is positive but not and significant for the 64K generation. There seems to be no cross price effect between the 16K and 64K generation of DRAMs. In the case of the 256K generation the cross elasticity of demand to the previous generation is positive and significant. For the 1MB generation this effect is negative, but not significant. The cross elasticity with respect to the following generations is not significant for neither generation of DRAMs. The nonprice demand shifter has the correct sign and is significant for the 256K and the 1MB generation. The remaining demand determinant, the time trend, should be negative, suggesting that buyers substitute away from the generation as time elapses. The estimations results show that for all generations.

¹¹The time series in the demand equation are tested for a Unit root. By using (Augmented) Dickey Fuller tests I can reject the Null hypothesis of a unit root at a significance level of 5% for prices and outputs of the 64K, the 256K and the 1MB generation. However the general demand shifter, the logarithm of GDP attributed to electronic and electrical equipment, has a unit root. I therefore use the once differentiated time series, which has no unit root.

For estimating the pricing relations I again use single equation techniques. The estimations are done with linear 2SLS. The instruments in the pricing equations consist of exogenous variables in the demand equation and summary measures from the supply side, like average market shares, number of firms in the industry, and cumulative world output. I estimate two specifications: The first assumes nonconstant returns to scale, learning-by-doing, and spillovers, corresponding the open-loop equilibrium. The other specification has an additional intertemporal strategic parameter and reflects the closed-loop equilibrium relation. Afterwards I also calculate price-cost margins and compare the two specifications.

As the open-loop equation is nested in the closed-loop specification the significance of the intertemporal strategic parameter θ can be used for model selection. If θ is significant, the open-loop specification can be rejected.¹² Because of the panel data structure I estimate a fixed-effects model with instrumental variables and estimate the equations with the statistical software package STATA (2000).

Tables 4.4 and 4.5 contain the parameter estimates for the closed-loop and the open-loop pricing relations for the estimated generations 64K, 256K and 1MB. For estimation 607, 739 and 641 observations are used. The fit of the three estimations is not as good as the fit for the demand equations with adjusted R-squares ranging from 0.287 to 0.682. The coefficient of the intertemporal strategic parameter θ ¹³ is significantly negative for all estimated generations, suggesting that firms react strategically on the objective function of other firms in the next period (see Table 4.4). The Null hypothesis of an open-loop equilibrium can be rejected for the three estimated generations. The adjusted R-squared model selection criterion favors the closed-loop specification for the 64K and the 1MB generations. However, in the case of the 256K generation one should decide for the open-loop specification according to this model selection criterium.

The negative sign of θ suggests q_{it} and q_{js} to be intertemporal strategic substitutes. Firms view the future production of their rivals as a strategic substitute. As there are both significant learning-by-doing and spillovers, this further indicates that the spillovers are not large enough relative to proprietary learning-by-doing to bring about intertemporal strategic complements. The consequence of neglecting the intertemporal strategic interaction can be an omitted variable bias as the following description of the estimates show.

Economies of scale¹⁴ are measured by the logarithm of current output. The coefficients of this variable are negative and significant for all DRAM generations under consideration and in both specifications indicating increasing returns to scale. Economies of scale are overestimated (in absolute values) in the open-loop specification compared to the closed-loop specification and the differences between the estimates of the two specifications are

¹²The Null hypothesis is open-loop, the alternative hypothesis is closed-loop.

¹³In fact, I estimated rather $\delta\theta$ than θ . However, as the discount factor δ is strictly positive, a significant negative (positive) sign of the estimate means that θ has to be negative (positive) and significantly different from zero.

¹⁴The estimates for economies of scale, learning-by-doing and spillovers in Table 4.4 and Table 4.5 are expressed as elasticities evaluated at the sample mean.

significant for all the 256K and the 1MB generations using a t-test.¹⁵

Now consider the parameter that measures learning-by-doing. The parameter is always negative and significant in both the open-loop and the closed-loop settings. Firms learn through their own past output. Comparing the estimates of the two specifications shows an overestimation of learning-by-doing in the case of the open-loop set-up. Learning rates can be derived by $1 - 2^{\gamma_3}$ (see, for example, Berndt (1991)). Using this formula results in learning rates of 32% (10% and 13%) for the 64K (256K and 1MB) generation in the closed-loop specification. The respective learning rates in the pre-commitment specification have values of 25%, 5% and 12%. Thus the estimates of the learning rates are underestimated in the pre-commitment specification. Further, the differences are significantly different from zero for the 64K and the 256K generations.¹⁶

Spillovers are negative and significant for the 64K, and the 256K in the closed-loop specification, indicating that firms also learn through spillovers from other firms. In the case of these two generations this is also true in open-loop specification. The spillover estimates are overestimated in the pre-commitment specification, but the differences are only significantly different from zero for the 256K generation.¹⁷ Only for the 1MB generation, spillovers do not matter. In this case the estimate of spillovers are not significantly different from zero.

The results for the input prices are not clear across different generations and specifications. However, their influence in the pricing equations seems to be given as their significance levels show. There are no differences in the signs between the estimates of the input prices in the two specifications for all generations. However, there are differences in magnitudes. In the case of the 64K generation the prices of silicon, labor, and capital have a significant positive effect on marginal cost, whereas the price of energy influence marginal cost negatively. The price of other inputs has no significant effect. Marginal cost of the firms producing the 256K generation is positively effected by the price of energy and wages, but negatively by the price of the material and other inputs. For these two generations user cost of capital has no effect on marginal cost, as the insignificant estimates show. The price of the most important input material has a significant positive effect on marginal cost of the 1MB DRAM. The higher the price of silicon the higher marginal cost. The same is true for the price of energy, whereas the influence of capital and other inputs is not significantly different from zero. Unexpectedly, the price of labor has a significantly negative effect on marginal cost. This indicates a high degree of factor substitution.

In terms of policy and antitrust, the results concerning the price-cost margins are the most interesting ones. To be able to judge the difference between closed-loop and open-loop price-cost margins, an assumption on the future dynamic effects α_i has to be made: Either θ and α_i exhibit the same intertemporal strategic behavior or, if this behavior changes over time, the effect between t and $t + 1$ is the largest and outweighs all other future effects, that exhibit strategic complementarity (see also Section 23). Under these

¹⁵The t-tests with unknown variances are equal to 0.247 (64K), to 9.000 (256K), and to 8.196 (1MB).

¹⁶The t-tests with unknown variances are equal to 2.059 (64K), to 2.248 (256K), and to 1.098 (1MB).

¹⁷The t-tests with unknown variances are equal to 0.810 (64K), and to 4.550 (256K).

conditions, the price-cost margins in the closed-loop setting are always smaller than in the open-loop setting. Price-cost margins (including the strategic effects) are calculated according to (4.14) and are equal to 13% for the 64K generation, 7% for the 256K generation and equal to 6% for the 1MB generation. The estimated mark-ups are highest for the 64K generation and become gradually lower with more generations out into the market. Competition among firms strengthens over generations of DRAMs. These values are respective upper bounds for the true price-cost margins in the presence of a significant negative intertemporal strategic parameter θ . The true mark-ups over marginal cost are supposed to lie beneath these values. However, these values cannot be calculated.

Because of the significant intertemporal strategic effect, I consider the estimation results of the closed-loop specification as the relevant ones. Ignoring that firms consider the intertemporal strategic effect of their today's output decision on their rivals' output decision tomorrow leads to an incorrect assessment of a market. Actually, market power is lower in the case of a closed-loop information structure, where firms can react in every point of time.

4.5 Conclusions

In this chapter, I estimated an dynamic oligopoly model that incorporates the strategic implications of learning-by-doing and spillovers. I derived a structural model from the theoretical game for estimation. The first order conditions were set up in closed-loop strategies and in open-loop strategies. The contribution of this chapter was then to test the dynamic closed-loop specification and to compare the estimated parameters with those of the open-loop specification and to investigate the influence of the equilibrium concept on learning-by-doing, spillovers, economies of scale and price-cost margins. The two models were estimated using firm-level data from the DRAM semiconductor industry. The difference between these two specifications could be described by the intertemporal strategic parameter. As the open-loop equation was nested in the closed-loop specification the (in)significance of the intertemporal strategic parameter could be used for model selection.

The estimation results supported learning-by-doing and spillovers. The significant coefficient of the intertemporal strategic parameter indicated that firms reacted strategically on the objective function of other firms in the next period. The Null hypothesis of an open-loop equilibrium could be rejected. The negative sign of the intertemporal strategic parameter suggested that firms viewed the future production of their rivals as an intertemporal strategic substitute. It further indicated that the spillovers were not large enough relative to proprietary learning to bring about strategic complements. The consequences of this intertemporal strategic interaction could be that some of the parameters were under- or overestimated due to an omitted variable bias. The estimation results showed that this bias was evident in the DRAM industry. The inferred structural parameters, such as economies of scale, learning-by-doing and price-cost margins were significantly affected by the equilibrium concept. In particular, price-cost margins were significantly overestimated, if one did not consider firms to act strategically over time. This implied

that market power was actually lower in a dynamic context than in a more static framework such as the open-loop equilibrium.

4.6 Appendix: Tables and Figures

Table 4.1: Generations of DRAMs in the market over time

Year	4K	16K	64K	256K	1MB	2MB	4MB	8MB	16MB	64MB
1974	x	-	-	-	-	-	-	-	-	-
1975	x	-	-	-	-	-	-	-	-	-
1976	x	x	-	-	-	-	-	-	-	-
1977	x	x	-	-	-	-	-	-	-	-
1978	x	x	-	-	-	-	-	-	-	-
1979	x	x	x	-	-	-	-	-	-	-
1980	x	x	x	-	-	-	-	-	-	-
1981	x	x	x	-	-	-	-	-	-	-
1982	x	x	x	x	-	-	-	-	-	-
1983	x	x	x	x	-	-	-	-	-	-
1984	x	x	x	x	-	-	-	-	-	-
1985	x	x	x	x	-	-	-	-	-	-
1986	-	-	x	x	x	-	-	-	-	-
1987	-	-	x	x	x	-	-	-	-	-
1988	-	-	x	x	x	-	x	-	-	-
1989	-	-	x	x	x	-	x	-	-	-
1990	-	-	x	x	x	-	x	-	-	-
1991	-	-	x	x	x	-	x	-	x	-
1992	-	-	x	x	x	x	x	-	x	-
1993	-	-	x	x	x	x	x	-	x	-
1994	-	-	x	x	x	x	x	-	x	-
1995	-	-	x	x	x	x	x	-	x	x
1996	-	-	-	x	x	x	x	x	x	x

Table 4.2: Summary statistics for the 64k, 256K, and 1MB generation

Variable	64K	256K	1MB
Industry price			
Mean	13.0212	11.8362	14.5490
Std. dev.	30.7383	27.2328	22.0765
Min.	0.750	1.624	3.132
Max.	135.000	150.000	110.000
Nobs	68	57	46
Industry output			
Mean	38717563	88039188	103296567
Std. dev.	60386120	83457093	6357646
Min.	3000	10000	11000
Max.	264395000	242412000	215632700
Nobs	68	57	46
Firm output			
Mean	3799125	5734476	6692453
Std. dev.	5855855	7726461	6357646
Min.	1000	3000	1000
Max.	31525000	39000000	31500000
Nobs	693	817	710

Table 4.3: Estimation results for the inverse demand equation

Variable	64K		256K		1MB	
	Coefficient	Std. error	Coefficient	Std. error	Coefficient	Std. error
Constant	10.925**	0.749	8.528**	1.081	-274.295*	162.375
Log(Own Output)	-0.354**	0.029	-0.279**	0.051	-0.433**	0.137
Log(Output of previous generation)	0.002	0.002	0.004**	0.001	-0.206	0.508
Log(Output of following generation)	0.003	0.002	-0.004	0.004	0.002	0.002
Log(Growth of GDP)	0.473	2.943	22.213**	6.382	17.774*	10.141
TIME	-0.281**	0.027	-0.150**	0.025	-0.562**	0.218
AR(1)	0.668**	0.167	0.593**	0.259	0.643**	0.120
adj. R ²	0.987		0.981		0.960	
Obs.	67		56		45	

** (*) denotes significance at the 95% (90%) level of confidence.

Table 4.4: Estimation results for the pricing relation of the closed-loop model

Variable	64K		256K		1MB	
	Coefficient	Std. err.	Coefficient	Std. err.	Coefficient	Std. err.
Log(Output) ^{***}	-0.325**	0.021	-0.102**	0.014	-0.054**	0.012
Learning	-0.567**	0.053	-0.148**	0.028	-0.207**	0.017
Spillovers	-0.355**	0.058	-0.103**	0.037	0.012	0.022
θ	-0.647**	0.149	-3.845**	0.896	-4.965**	0.696
Material	12.062**	2.465	-1.820*	0.998	4.700**	1.147
Energy	-25.608**	4.121	2.594*	1.522	11.259**	1.194
Wages	11.121**	4.362	5.781**	2.150	-11.402**	1.518
Capital	3.344*	1.825	1.434	0.914	-1.076	0.716
Other inputs	0.079	4.906	-6.989**	2.505	-2.481	2.350
Constant	-112.160**	57.664	-62.583**	29.612	149.783**	22.139
R ²	0.529		0.470		0.682	
Obs.	607		738		710	

** (*) denotes significance at the 95% (90%) level of confidence.

*** The estimates for economies of scale, learning-by-doing and spillovers are expressed as elasticities evaluated at the sample mean.

Table 4.5: Estimation results for the pricing relation of the open-loop model

Variable	64K		256K		1MB	
	Coefficient	Std. err.	Coefficient	Std. err.	Coefficient	Std. err.
Log(Output) ^{***}	-0.332**	0.019	-0.307**	0.018	-0.199**	0.013
Learning	-0.417**	0.050	-0.059**	0.028	-0.179**	0.019
Spillovers	-0.417**	0.050	-0.386**	0.050	-0.015	0.025
Material	14.635**	2.435	-1.422	1.155	2.250*	1.277
Energy	-17.200**	4.078	-3.811**	1.842	7.936**	1.370
Wages	13.937**	4.380	6.792**	2.479	-9.787**	1.683
Capital	2.679	1.837	1.747*	1.059	-2.042**	0.780
Other inputs	-13.051**	4.770	-2.305	2.892	2.643	2.571
Constant	-162.762**	57.759	-30.828	34.387	171.918**	23.615
R ²	0.524		0.287		0.610	
Obs.	624		738		640	

** (*) denotes significance at the 95% (90%) level of confidence.

*** The estimates for economies of scale, learning-by-doing and spillovers are expressed as elasticities evaluated at the sample mean.

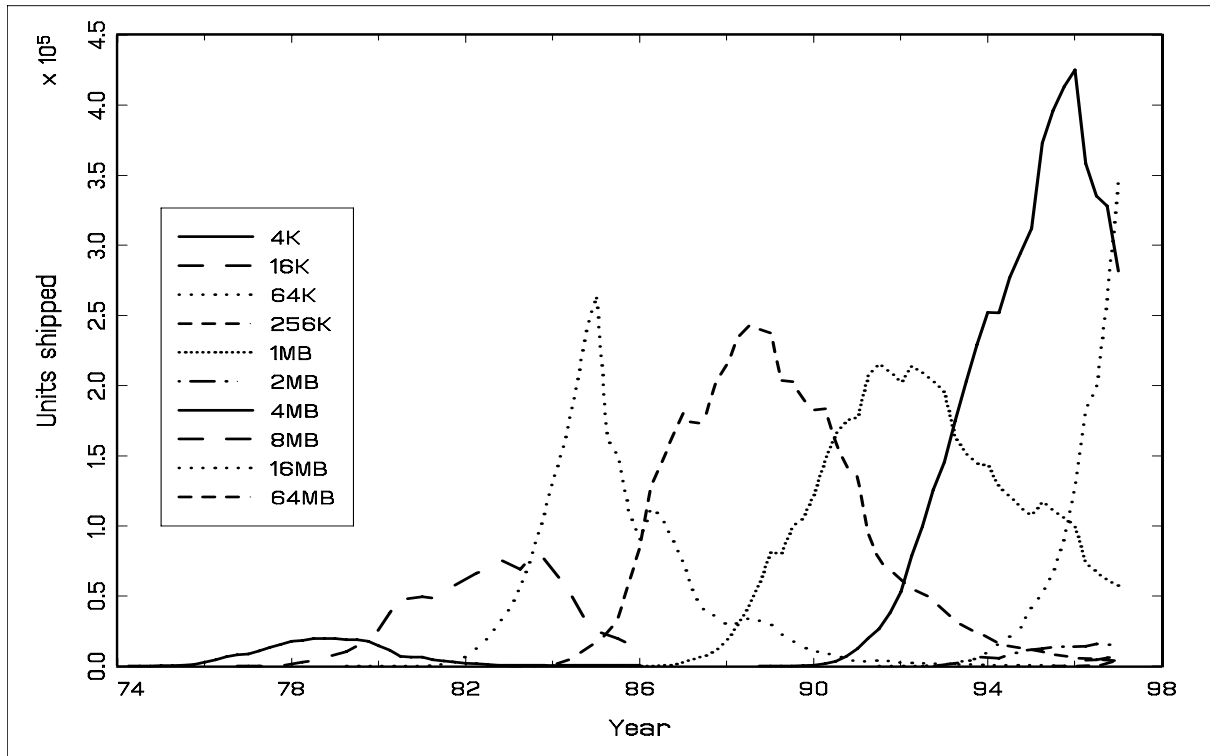


Figure 4.1: Industry units shipped for different generations of DRAMs

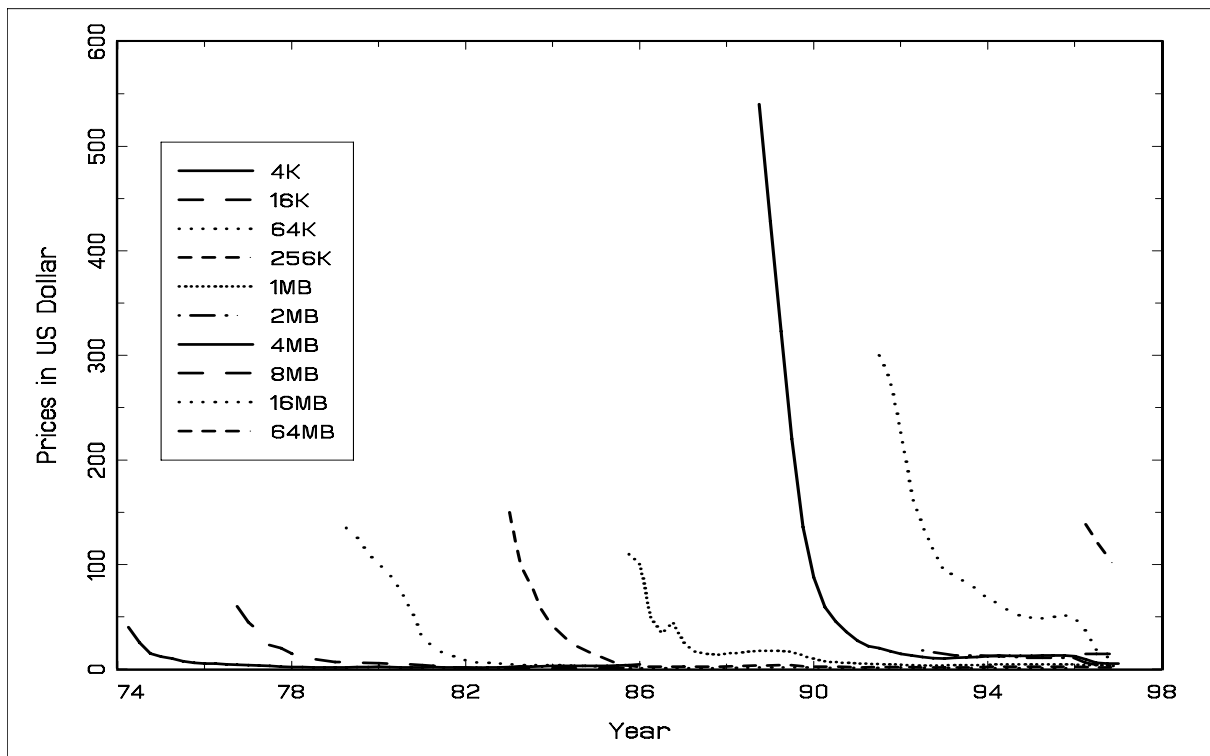


Figure 4.2: Average selling prices in USD for different generations of DRAMs

Chapter 5

Aggregation of dynamic oligopoly models

5.1 Introduction

For the analysis of market structure, firm conduct, and market performance in an oligopolistic market very often only industry level data is available. Theoretical models of oligopoly are at the firm level and provide the researcher with firm level equilibrium pricing relations. The general objective of this study concerns the aggregation of firm level pricing equations to an industry level pricing equation. In the case, in that all firms in a market have the same cost structure and the same market shares, the aggregation does not yield any particularities or difficulties. In the case of different cost structure across firms and different market shares, the representative firm is a weighted mean of all firms and not the unweighted mean of all firm. If the researcher only has industry level data, he/she has to make an assumption whether the market is symmetric or asymmetric when the industry level pricing equation is set up and estimated to infer market structure. I want to investigate, whether the assumption on (a)symmetry is crucial or not with respect to the relevant parameter estimates, and if yes, how large the differences between the estimates are.

For this purpose I set up an aggregated dynamic oligopoly model, which is derived from a model with learning-by-doing and spillovers. The individual first order conditions of firms' dynamic maximization problems are aggregated over firms and implemented for estimations. The aggregated model is estimated for the DRAM industry, in particular for the 256K generation. The point of interest lies in comparing two specifications of the industry level pricing relation. The first assumes that the market consists of firms with equal market shares. Actually, the assumption of symmetry is not given for the 256K DRAM market. Thus with a second specification I want to correct for the asymmetry. The full data set for the 256K DRAM industry includes firm-level data. Therefore it is possible to correct for asymmetries and to calculate the possible aggregation bias with this data set. A system of demand and supply relations is estimated. Under the assumption that the market is in equilibrium, I focus on the estimation of economies of scale, learning-

by-doing, the effects of input prices and an intertemporal strategic effect. This effect arises as firms consider the strategic effect of learning-by-doing and spillovers on their rivals' future output decision. The supply function is derived from the aggregated first order conditions of firms dynamic maximization problems, and specifies the behavioral response of firms in the market.

Learning-by-doing and spillovers introduce a dynamic dimension into a static oligopoly game. Learning-by-doing measured by past cumulative output influences firms' current and future decisions. Closed-loop equilibria in dynamic oligopolistic models¹ are characterized by a set of prices and outputs chosen by firms conditional on exogenous parameters and on future outputs. The exogenous parameters are costs, demand and conjectures about the behavior of firms' rivals in the market. Firms react strategically at every point in time and consider the strategic effect of learning-by-doing and spillovers on their rivals' future output decision. In an open-loop setting firms pre-commit themselves to a certain path at the beginning of the game, i.e. to a certain production plan.

In chapter 4 an empirical comparison between open-loop and closed-loop equilibria suggested that firms take the intertemporal strategic effect on their rivals' future output decision into account. Therefore I now only consider firms using closed-loop strategies. However, it is still possible to test for this kind of behavior at the industry level. Firms follow a dynamic production strategy to earn positive profits over the entire life cycle. Their optimal strategy is to overproduce (in a static sense) in order to invest in future cost reductions. This induces firms to make their optimal output decisions not on the basis of current period costs but rather on their lower shadow costs of production (see eg. Fudenberg and Tirole (1983), Spence (1983)).

The remainder of the chapter is organized as follows. In section 5.2, I consider some theoretical aspects and the econometric implementation of the aggregated dynamic model. The results are presented in section 5.3. Conclusions are given in section 5.4.

5.2 An aggregated model of dynamic oligopoly

5.2.1 The basic model

The basic theoretical model is the same as was described in section 4.3. In this section only the main features are repeated and some aspects concerning the aggregation of firm level to industry level pricing equations are considered. Firms are modelled to maximize their profit over the product cycle. Assume there are $i = 1, \dots, n$ firms and $t = 1, \dots, T$ discrete time periods. At the beginning of each period, firms choose quantities of a homogeneous output, q_{it} . Firm i 's cost in period t , $C_{it} := C(q_{it}, X_t, W_{it})$, are a function of current output, input prices, firm i 's experience and the experience of all firms other than i . X_t is the vector of cumulative output of each firm i , representing the experience gain due to learning-by-doing within the own firm and among other firms in the industry. Experience is assumed to be measured by past cumulative output. Thus, firm i 's stock of experience is $x_{it} := \sum_{s=1}^{t-1} q_{is}$. Output choices play an additional role as investment into

¹For a mathematical treatment of dynamic games see Basar and Olsder (1991).

experience. The more output is produced today, the lower unit costs will be tomorrow. Each firm i choose q_{it} in order to maximize intertemporal profits defined as

$$\begin{aligned} \text{Max}_{q_{it}} \Pi_i &= \sum_{t=1}^T \delta^{t-1} \{P_t q_{it} - C(q_{it}, X_t, W_{it})\} \\ \text{s.t. } X_t &= X_{t-1} + Q_{t-1} \quad \text{and} \quad X_0 = 0 \end{aligned} \quad (5.1)$$

where δ is the discount rate, $q_t := \sum_{i=1}^n q_{it}$ is industry output, Q_t is the vector of firm specific output, and $P_t := P(q_t)$ is the inverse market demand function for a given generation of DRAMs.

The necessary conditions for a closed-loop Nash equilibrium of (5.1) are

$$\begin{aligned} P_t + \frac{\partial P_t}{\partial q_t} \frac{\partial q_t}{\partial q_{it}} q_{it} &= \frac{\partial C_{it}}{\partial q_{it}} + \sum_{s=t+1}^T \delta^{s-t} \sum_{j=1}^n \frac{\partial C_{is}}{\partial x_{js}} \frac{\partial x_{js}}{\partial q_{it}} \\ &\quad - \sum_{s=t+1}^T \delta^{s-t} \frac{\partial P_s}{\partial q_s} q_{is} \sum_{j=1}^n \frac{\partial q_s}{\partial q_{js}} \frac{\partial q_{js}}{\partial x_{is}} \frac{\partial x_{is}}{\partial q_{it}} \end{aligned} \quad (5.2)$$

for all $i = 1, \dots, n$ and $t = 1, \dots, T$. The first three terms of (5.2) are the standard first order conditions from the static Cournot problem without learning-by-doing and without learning spillovers. The last term of the first line reflects future cost savings due to learning-by-doing and spillovers. The last line is the intertemporal strategic effect.

A derived empirical firm level pricing equation² is given by

$$P_t = MC_{it} + \gamma_{0i} + \alpha_i - \beta'_1 \theta_1 q_{it} - \beta'_1 \theta_1 \theta_2 q_{it+1} + \mu_{it} \quad (5.3)$$

for $i = 1, \dots, n$ and $t = 1, \dots, T$. Firm specific marginal cost is denoted by MC_{it} . Future cost savings are modelled by firm specific dummy variables γ_{0i} . The term $\beta'_1 = \frac{\partial P_t}{\partial q_t}$ represents the partial derivative of output on price. The term θ_1 defines the conduct parameter in an industry (see e.g. Bresnahan (1989)). The intertemporal strategic parameter θ_2 measures the effect of firms output decision today on their rivals output decision tomorrow. The α_i 's capture the intertemporal strategic effects occurring from $t+2$ onwards (see equation (4.6)). In equation (5.3) the price for DRAMs is a function of dynamical marginal costs, of the inverse effect on demand and of future strategic behavior measured by the intertemporal strategic parameter θ_2 . An econometric pricing relation for an open-loop information structure would be nested in (5.3) with the intertemporal strategic term θ_2 and the α_i 's equal to zero.

Now, aggregating (5.3) and dividing by n yields

$$\begin{aligned} P_t &= \frac{1}{n} \sum_{i=1}^n MC_{it} + \frac{1}{n} \sum_{i=1}^n \gamma_{0i} + \frac{1}{n} \sum_{i=1}^n \alpha_i - \beta'_1 \theta_1 \frac{1}{n} \sum_{i=1}^n q_{it} - \beta'_1 \theta_1 \theta_2 \frac{1}{n} \sum_{i=1}^n q_{it+1} \\ P_t &= \overline{MC}_t + \gamma_0 + \alpha - \beta'_1 \theta_1 \frac{q_t}{n} - \beta'_1 \theta_1 \theta_2 \frac{q_{t+1}}{n} \end{aligned} \quad (5.4)$$

This gives the equation to be estimated. The relevant parameters at the industry level will be determined. We are now able to test dynamic strategic behavior at the industry

²For a detailed derivation of the empirical pricing relation see section 4.3.

level. The aggregated first order conditions give the following advice for empirical testing. A difference between open-loop and closed-loop strategies can be pinned down by the intertemporal strategic parameter θ_2 . If this term is not equal to zero, we can conclude that firms use closed-loop strategies.

θ_1 is interpreted as the average of the conduct parameters of the firms. In a competitive market a change in firm i 's output would not have any consequences on prices. Firms price according to their marginal costs. Thus the conduct parameter θ_1 and the price-cost markup would be both equal to zero. In a Cournot game a change in firm i 's output has an impact on prices. Firms price higher than their marginal costs and the conduct parameter would be equal to one over the number of firms in the industry. If firms maximize joint profits, the conduct parameter would be equal to one. For closed-loop specifications the parameter θ_1 is equal to one over the number of firms.

The terms θ_1 and θ_2 are not identified at the same time. I fix θ_1 assuming firms to set quantities according to the first-order condition (5.2). A significant intertemporal strategic parameter θ_2 would confirm that firms use closed-loop strategies. The term $\beta'_1 = \frac{\partial P_t}{\partial q_t}$ plays an important role in the pricing relations and for identification of θ_2 an estimate of β'_1 is needed. For this purpose I define an inverse log-linear demand function, which is specified in section 4.3.2. To derive an estimate for β'_1 I multiply β_1 , defined in equation 4.4, with $\frac{\bar{P}_t}{\bar{q}_t}$. \bar{P}_t , and \bar{q}_t denote the sample means of industry price and industry output, respectively.

5.2.2 Aggregation of marginal cost

Estimation of the pricing relations at the industry level, requires expressions for marginal cost. These expressions include parameters that measure learning-by-doing and learning spillovers. The marginal cost function I approximate with a second-order Taylor series

$$MC_{it} = \gamma_{1i} + \gamma_2 q_{it} + \gamma_3 q_{it}^2 + \gamma_4 x_{it} + \gamma_5 MAT_{it} + \gamma_6 ENE_{it} + \gamma_7 LAB_{it} + \gamma_8 CAP_{it} + \gamma_9 INP_{it} \quad (5.5)$$

with q_{it} to be firm level output, x_{it} firm level learning-by-doing and the other variables MAT , ENE , LAB , CAP and INP to be the input prices of material, energy, labor, capital and other input prices, respectively. In contrast to chapter 4 I define marginal cost without spillovers, as after aggregation we can not distinguish between learning-by-doing and spillovers at the industry level. Aggregation of firm level marginal cost (5.5) and dividing by n yields³

$$\overline{MC}_t = \frac{1}{n} \sum_{i=1}^n \gamma_{1i} + \gamma_2 \frac{1}{n} \sum_{i=1}^n q_{it} + \gamma_3 \frac{1}{n} \sum_{i=1}^n q_{it}^2 + \gamma_4 \frac{1}{n} \sum_{i=1}^n x_{it} + \gamma_5 \frac{1}{n} \sum_{i=1}^n MAT_{it} + \gamma_6 \frac{1}{n} \sum_{i=1}^n ENE_{it} + \gamma_7 \frac{1}{n} \sum_{i=1}^n LAB_{it} + \gamma_8 \frac{1}{n} \sum_{i=1}^n CAP_{it} + \gamma_9 \frac{1}{n} \sum_{i=1}^n INP_{it} \quad (5.6)$$

³Neven and Röller (1999) applied an aggregated structural model of competition to the European banking industry. They use data at the industry level and refer to potential biases due to misspecification of aggregated marginal cost. By aggregating marginal cost I follow their procedure.

To able to estimate average marginal cost (5.6) the quadratic term $\frac{1}{n} \sum_{i=1}^n q_{it}^2$ has to be rewritten. For all other terms it is possible to exchange summation and division. Using the definition of the Herfindahl index $HI = \frac{1}{n} \sum_{i=1}^n s_{it}^2$ with market share s_{it} of firm i and by defining m to be the number of symmetric firms corresponding to the Herfindahl index we can now manipulate equation (5.7)⁴ to get

$$\begin{aligned} \overline{MC}_t = & \gamma_1 + \gamma_2 \frac{q_t}{n} + \gamma_3 \frac{q_t^2}{n * m} + \gamma_4 \frac{x_t}{n} + \gamma_5 \frac{MAT_t}{n} + \gamma_6 \frac{ENE_t}{n} + \gamma_7 \frac{LAB_t}{n} \\ & + \gamma_8 \frac{CAP_t}{n} + \gamma_9 \frac{INP_t}{n} \end{aligned} \quad (5.7)$$

This equation also enables us to infer a possible misspecification due to neglecting an asymmetric market structure. In the case we have a symmetric market structure $m = n$. The more asymmetric a market is the smaller m in comparison to n . If then marginal cost are convex ($\gamma_3 > 0$) and using n instead of m yields a downward bias in marginal cost (Neven and Röller (1999)).

The firm specific effects of equation (5.3) also include firm-specific future marginal cost (4.8), the firm-specific intercepts from the marginal cost function (4.7) and the future dynamic effects (4.6). Aggregating these effects gives

$$\gamma = \gamma_0 + \gamma_1 + \alpha. \quad (5.8)$$

5.2.3 Empirical pricing relations

Incorporating all definitions made before leads to the following econometric models of industry level pricing relations. Using (5.4), (5.7) and (5.8) we get

$$\begin{aligned} P_t = & \gamma + (\gamma_2 - \beta'_1) \frac{q_t}{n} + \gamma_3 \frac{q_t^2}{n * m} + \gamma_4 \frac{x_t}{n} + \gamma_5 \frac{MAT_t}{n} + \gamma_6 \frac{ENE_t}{n} \\ & + \gamma_7 \frac{LAB_t}{n} + \gamma_8 \frac{CAP_t}{n} + \gamma_9 \frac{INP_t}{n} - \beta'_1 \theta_2 \frac{q_{t+1}}{n} + \mu_{it} \end{aligned} \quad (5.9)$$

In these equations the price for DRAMs is a function of aggregated dynamical marginal costs, of the inverse elasticity of demand and of future strategic behavior measured by the intertemporal strategic parameter θ_2 .

5.3 Estimation results

For the industry level pricing relation I estimate a specification that assumes nonconstant returns to scale, learning by doing and an intertemporal strategic parameter. Further the impact of input prices on marginal cost is determined. A system of equations is estimated: equation (4.4)⁵ and equation (5.9) are estimated for the 256K DRAM generation. Table

⁴For marginal cost I assume a rather simple functional form. In the case of e.g. a log-linear function, the aggregation of firm level marginal cost functions is not that easy to achieve. Then the Herfindahl index can not be used for aggregation of non linear terms.

⁵The estimation results of the inverse demand equation are displayed in table 4.3 of chapter 4.

5.1 shows firms' market shares for this product. It is obvious that this market is not symmetric. The average Herfindahl index is 0.201 and shows that the corresponding number of symmetric firms in the 256K DRAM market would be five. This number is not constant over time indicating that the asymmetries change over the product cycle. Further the number of firms is not constant over time. In the beginning and in the ending of the product cycle there less firms in the market then in between.

Therefore I estimate equation (5.9) in two specifications. The first specification takes price, output, past cumulative output and input prices at the industry level by assuming symmetry among firms and by holding the number of firms constant over time. I mimic the case that the researcher only has industry level data, and also has no information about the Herfindahl index. For the second specification the industry level data are generated from firm level data by accounting for asymmetries in the market and by using the actual number of firms in the market.

Thus the estimations of the two specifications of the aggregated pricing relation enable us to test whether an aggregation bias is given and if there is one, how large is it. The two specifications are estimated with 2SLS⁶ with the statistical software package STATA (2000). The instruments in the pricing equations consist of the exogenous variables in the demand equation and summary measures from the supply side, like cumulative world output.

The estimates are shown in Table 5.2. Panel A covers the results of the specification assuming symmetry among firms, panel B those accounting for asymmetry. For the estimations 56 observations are used. The values of the R-square are equal to 0.6435 and 0.8718, respectively. This model selection criterion suggests that the preferred specification is the one that controls for asymmetry. It indicates that this specification generates the more reliable model. By comparing the results from the two specification displayed in panel A and panel B we also see the differences in the various estimates. In the following I describe the estimates of the two specifications and the differences between them. Further I calculate the aggregation bias for the point estimates of economies of scale, learning-by-doing, and the intertemporal strategic effect.

In illustrating the estimation results from panels A and B of table 5.2, I describe the estimation results of the second specification as the reference results. I begin with the parameter estimates of contemporaneous output and contemporaneous output squared. Given the specification of equation (5.9) actually $\gamma_2 - \beta_1'$ has been estimated in both specifications. With some algebra we get -0.00001097 for γ_2 indicating decreasing marginal cost. Evaluated at the sample means a value of -0.263 for the elasticity follows. This result is roughly in line with the firm specific estimation results in chapter 4. The additional insignificant estimate for contemporaneous output squared indicates that the marginal cost function is linear. The difference in the estimates for economies of scale is significantly different from zero at the 5% level using a t-test with unknown variances, which is equal to 3.087.

The estimate of the learning-by-doing parameter is highly significant. This provides ev-

⁶I also estimated the demand and the pricing relations with 3SLS. The results do not change very much.

idence that a higher degree of past experience reduces marginal cost at the industry level. Further a learning-by-doing rate of 12% supports the reliability of the model specification. In the case of learning-by-doing a t-test with unknown variances of 5.486 indicates the difference in the estimates learning-by-doing of the two specifications.

The estimate for the strategic intertemporal parameter, shown by θ_2 , is significantly negative for both specifications, indicating that firms react strategically on the objective function of other firms in the next period. The negative sign of this parameter suggests that firms consider their rivals' output tomorrow to be a strategic substitute. Although there is no difference between learning-by-doing and spillovers at the industry level, this still indicates that the learning spillovers are not large enough relative to proprietary learning-by-doing to bring about intertemporal strategic complements. Firms price according to their dynamic marginal costs, which lie below static marginal costs.

Turning to the parameter estimates for the factor prices we see that the estimations results of the two specification differ a lot more. Concerning economies of scale, learning-by-doing and the intertemporal strategic parameter the results were qualitatively the same, but differ in magnitude. However, the estimates for factor prices also show different signs between the two specification. In the first specification only the price of labor is significantly positive, the prices of energy and capital are insignificant, and the prices of material and other inputs are significantly negative. In contrast, the second specification gives more plausible results. The prices of material (silicon) and labor are significantly positive, indicating that higher factor prices raise firms marginal costs. The price of the most important input material has a significant positive effect on marginal cost of the 256K DRAM. The higher the price of silicon the higher marginal cost. The price of capital has a negative influence on marginal cost. Energy and other input prices, are not significantly different from zero, indicating that those factor prices have no significant impact on marginal costs.

The coefficients for economies of scale and learning-by-doing are overestimated when symmetry is assumed. The reason for this lies in a wrong assumption about firms' market shares. If the market is completely symmetric, the estimation results would be the same. However, if firms actual market shares cannot be taken into account because of a lack of data, one has to be aware of a potential aggregation bias.

5.4 Conclusions

In this chapter I set up an aggregated dynamic oligopoly model. The individual first order conditions of firms' dynamic maximization problems were aggregated over firms and then estimated with data of the DRAM industry. I considered two specifications. First I assumed that the market consists of firms with equal market shares. Actually, the assumption of symmetry was not given. Thus with a second specification I corrected for the asymmetry. Thus the second point of interest lied then in comparing the estimates of the two specifications. Given the estimation results the aggregation bias could be calculated and it was found to be noticeable.

5.5 Appendix: Tables

Table 5.1: Market shares of the 256K generation

Firm	256K
AT&T Microelectronics	0.75
Fujitsu	9.08
Hitachi	10.53
Hyundai	2.54
Inmos	0.19
Intel	0.78
LG Semicon	1.10
Matsushita	2.22
Micron	5.76
Mitsubishi	8.27
Mosel Vitalic	1.35
Mostek	0.01
Motorola	1.58
National Semiconductor	0.00
NEC	16.20
Nippon Steel	3.28
OKI	6.35
Samsung	7.36
Sanyo	0.40
Sharp	2.22
Siemens	1.63
Texas Instruments	12.28
Toshiba	5.76
Total	100.00

Table 5.2: Estimation results for the aggregated 256K pricing relation

Variable	Coefficient	Std. error	t-value	p-value	95% Conf. Interval	
Panel A						
Output	6.55e-07	2.80e-07	2.34	0.024	9.22e-08 1.22e-06	
Output ²	-1.38e-27	1.21e-27	-1.14	0.254	-3.74e-27 9.88e-28	
Learning	-1.26e-08	3.72e-09	-3.39	0.001	-2.01e-08 -5.12e-09	
θ_2	-5.03e-07	2.92e-07	-1.72	0.092	-1.09e-06 8.47e-08	
Material	-.0546584	.0194329	-2.81	0.007	-.0937748 -.015542	
Energy	-.0075857	.0053656	-1.41	0.164	-.0183861 .0032147	
Wages	4.14e-08	4.98e-08	0.83	0.410	-5.89e-08 1.42e-07	
Capital	.0784862	.0394535	1.99	0.053	-.0009295 .1579019	
Other inputs	-1.368912	.774766	-1.77	0.084	-2.928435 .1906107	
Constant	301.658	75.49892	4.00	0.000	149.6866 453.6295	
adj. R ²	0.6435					
Panel B						
Output	.0000175	5.96e-06	2.94	0.005	5.51e-06 .0000295	
Output ²	-2.82e-13	1.77e-13	-1.59	0.111	-6.28e-13 6.46e-14	
Learning	-1.73e-07	3.17e-08	-5.45	0.000	-2.37e-07 -1.09e-07	
θ_2	-.0000185	6.14e-06	-3.01	0.004	-.0000308 -6.10e-06	
Material	.0119663	.0039051	3.06	0.004	.0041057 .0198269	
Energy	.0014249	.0029307	0.49	0.629	-.0044743 .0073242	
Wages	3.79e-08	1.93e-08	1.97	0.055	-8.64e-10 7.68e-08	
Capital	-.0111146	.0167383	-0.66	0.510	-.0448069 .0225778	
Other inputs	-.3964863	.2330472	-1.70	0.096	-.865586 .0726135	
Constant	31.98526	6.594428	4.85	0.000	18.71137 45.25916	
adj. R ²	0.8718					
Obs.	56					

Chapter 6

Conclusions

This thesis explored two imperfectly competitive markets and illustrated these two markets by one example each. The emphasis of this thesis lied in a structural empirical analysis of these markets. In particular, dynamic effects and asymmetries were explored. A structural econometric approach relies on the hypothesis that the observed data in a market are the equilibrium strategies (bids, prices, output) of the considered game-theoretic model. The equilibrium strategy gained from the theoretical model can be used to estimate the characteristics of the market.

Chapter 3 investigated auctions markets and analyzed cattle auctions taking place in Amstetten, Austria. The econometrics of English auctions in the independent private value model were described. Further a static and a sequential specification of the independent private value model was explored. Both specifications were investigated with symmetric and asymmetric bidders. These four different models were implemented econometrically and were brought to data. By also implementing a model with affiliated values I tested for and confirmed the independent private value assumption. I estimated the characteristics of the distribution of bidders' values and took the heterogeneity of the auctioned objects into account. The empirical results showed asymmetries among bidders and a significant effect of the sequential bidding game.

In Chapter 4 I estimated a dynamic oligopoly model that incorporated the strategic implications of learning by doing and learning spillovers. The first order conditions of this dynamic game were set up in open-loop strategies and in closed-loop strategies. The contribution of this chapter was then to test the dynamic closed-loop specification and to compare the estimated parameters with those of the open-loop specification and to investigate the influence of the equilibrium concept on learning-by-doing, learning spillovers, economies of scale and the conduct parameter. The two models were estimated using firm-level data from the DRAM semiconductor industry. The difference between these two specifications could be described by the intertemporal strategic parameter. The estimation results supported learning by doing and learning spillovers. The significant coefficient of the intertemporal strategic parameter indicated that firms reacted strategically on the objective function of other firms in the next period.

In Chapter 5 I set up an aggregated dynamic oligopoly model. The individual first order conditions of firms' dynamic maximization problems were aggregated over firms. This

was then implemented for estimations with data of the DRAM industry. I considered two specifications. First I assumed that the market consists of firms with equal market shares. Actually, the assumption of symmetry was not given. Thus with a second specification I corrected for the asymmetry. Thus the second point of interest lied then in comparing the estimates of the two specifications. Given the estimation results the aggregation bias could be calculated and it was noticeable.

Summing up the empirical results of above described chapters I conclude, that dynamic strategic behavior among firms or bidders takes place and that further, asymmetries among players independent of the markets under consideration exist and have consequences on the parameter estimates of interest. The questions I raised can be summarized as follows: Do we find strategic dynamic behavior among firms/bidders? Are there differences among players in the respective markets? Both questions I could answer positively with empirical evidence for two different markets.

Bibliography

- Ashenfelter, O. (1989). How auctions work for wine and art, *Journal of Economic Perspectives* **3**: 39–64.
- Avery, C. (1998). Strategic jump bidding in english auctions, *Review of Economic Studies* **65**(2): 185–210.
- Baldwin, L. H., Marshall, R. C. and Francois Richard, J. (1997). Bidder collusion at forest service timber sales, *Journal of Political Economy* **105**(4): 657–697.
- Baldwin, R. E. and Krugman, P. R. (1988). Market access and international competition: A simulation study of 16k Random Access Memories, in Robert C. Feenstra, ed.: *Empirical Methods for International Trade*, Cambridge: MIT Press pp. 171–97.
- Basar, T. and Olsder, G. J. (1991). *Dynamic Noncooperative Game Theory*, Academic Press, London. Second edition.
- Beggs, A. and Graddy, K. (1997). Declining values and the afternoon effect: evidence from art auctions, *RAND Journal of Economics* **28**(3): 544–565.
- Berndt, E. R. (1991). *The Practice of Econometrics*, Addison Wesley, Reading Massachusetts.
- Böheim, R. and Zulehner, C. (1996). Auctions - a survey, *IAS Working Paper Economics Series 39*.
- Bresnahan, T. F. (1989). Empirical studies of industries with market power, in R. Schmalensee and R. D. Willig, eds.: *Handbook of Industrial Economics, Volume II*, North-Holland, Amsterdam pp. 1011–1057.
- Brist, L. E. and Wilson, W. W. (1997). Economies of scale, markups and learning by doing in DRAM markets. mimeo.
- Bulow, J. and Klemperer, P. (1994). Auctions vs. negotiations, *NBER Working Paper* **4608**.
- Bulow, J. and Roberts, J. (1989). The simple economics of optimal auctions, *Journal of Political Economy* **97**: 1060–1090.

- Capen, E., Clapp, R. and Campbell, W. (1971). Competitive bidding in high-risk situations, *Journal of Petroleum Technology* **23**: 641–653. quoted in: Milgrom and Weber [Milgrom and Weber \(1982a\)](#).
- Davidson, R. and MacKinnon, J. G. (1993). *Estimation and Inference in Econometrics*, Oxford University Press, New York.
- der Niederösterreichischen Rinderzüchter, V. (1994). *Rinderzucht in Niederösterreich*, Verband nö. Rinderzüchter et al., Wien.
- Dick, A. R. (1991). Learning-by-doing and dumping in the semiconductor industry, *Journal of Law and Economics* **34**: 133–159.
- Donald, S. D. and Paarsch, H. J. (1993). Piecewise maximum likelihood estimation in empirical models of auctions, *International Economic Review* **34**: 121–148.
- Donald, S. D., Paarsch, H. J. and Robert, J. (1997). Identification, estimation and testing in empirical models of sequential, ascending-price auctions with multi-unit demand: An application to siberian timber-export permits. Typescript, Department of Economics, University of Iowa.
- Elyakime, B., Laffont, J.-J., Ossard, H. and Vuong, Q. (1994). First-price sealed-bid auctions with secret reservation prices, *Annales d'Economie et de Statistique* **34**: 115–141.
- Engelbrecht-Wiggans, R. and Kahn, C. M. (1999). Calibration of a model of declining prices in cattle auctions, *Quarterly Review of Economics and Finance* **39**(1): 113–28.
- Feichtinger, G. and Hartl, R. F. (1986). *Optimal Kontrolle ökonomischer Prozesse*, de Gruyter, Berlin.
- Flamm, K. (1993). Semiconductor dependency and strategic trade policy, *Brooking Papers: Microeconomics 1993* pp. 249–333.
- Fudenberg, D. and Tirole, J. (1983). Learning-by-doing and market performance, *The BELL Journal of Economics* **14**: 522–530.
- Fudenberg, D. and Tirole, J. (1986). *Dynamic Models of Oligopoly*, Harwood, London.
- Fudenberg, D. and Tirole, J. (1991). *Game Theory*, MIT Press, Cambridge Massachusetts.
- Gruber, H. (1992). The learning curve in the production of semiconductor memory chips, *Applied economics* **24**: 885–894.
- Gruber, H. (1996a). Learning by doing and spillovers: further evidence for the semiconductor industry. mimeo.
- Gruber, H. (1996b). *The Semiconductor Industry: Review of the Sector and Financing Opportunities*, European Investmentbank, Luxembourg.

- Gruber, H. (1996c). Trade policy and learning-by-doing: The case of semiconductor, *Research policy* **25**: 723–739.
- Harsanyi, J. (1967). Games with incomplete information played by bayesian players, *Management Science* **614**: 159–182,320–334,486–502.
- Hausch, D. B. (1988). A model of sequential auctions, *Economic Letters* **26**: 227–233.
- Hendricks, K. and Paarsch, H. J. (1995). A survey of recent empirical work concerning auctions, *Canadian Journal of Economics* **28**(2): 403–426.
- Hendricks, K. and Porter, R. (1992). Joint bidding in osc drainage auctions, *American Economic Review (Papers and Proceedings)* **82**: 506–511.
- Irwin, D. A. and Klenow, P. J. (1994). Learning-by-doing in the semiconductor industry, *Journal of Political Economy* **102**(6): 1200–1227.
- Jarmin, R. S. (1994). Learning by doing and competition in the early rayon industry, *The RAND Journal of Economics* **25**(3): 441–454.
- Jofre-Bonet, M. and Pesendorfer, M. (1999). Bidding behavior in a repeated procurement auction. mimeo, Yale University.
- Kagel, J. H. (1995). Auctions: A survey of experimental research, in Kagel, John H. and A.E. Roth, eds.: *The Handbook of Experimental Economics*, Princeton University Press, Princeton, New Jersey pp. 501–580.
- Karp, L. and Perloff, J. (1989). Dynamic oligopoly in the rice export market, *Review of Economics and Statistics* **71**: 462–470.
- Katzman, B. (1999). A two stage sequential auction with multi-unit demand, *Journal of Economic Theory* **86**: 77–99.
- Laffont, J.-J. (1997). Game theory and empirical economics: The case of auction data, *European Economic Review* **41**: 1–35.
- Laffont, J.-J., Loisel, P. and Robert, J. (1997). Intra-day dynamics in sequential auctions: Theory and estimation. mimeo, IDEI Toulouse.
- Laffont, J.-J., Ossard, H. and Vuong, Q. (1995). Econometrics of first-price auctions, *Econometrica* **63**: 953–980.
- Maskin, E. and Riley, J. (2000). Asymmetric auctions, *Review of Economic Studies* **67**: 413–438.
- McAfee, R. and McMillan, J. (1987). Auctions and biddings, *Journal of Economic Literature* **25**: 708–747.

- McAfee, R. P. and Vincent, D. (1992). Updating the reserve price in common-value auctions, *American Economic Review (Papers and Proceedings)* **82**: 512–518.
- McAfee, R. and Vincent, D. (1993). The declining price anomaly, *Journal of Economic Theory* **60**: 191–212.
- McFadden, D. (1989). A method of simulated moments for estimation of discrete response models, *Econometrica* **57**: 995–1026.
- Milgrom, P. R. (1979). A convergence theorem for competitive bidding with differential information, *Econometrica* **47**: 679–688.
- Milgrom, P. R. (1981). Rational expectations, information acquisition, and competitive bidding, *Econometrica* **49**: 921–943.
- Milgrom, P. R. (1987). Auction theory, in *Advances in Economic Theory*, edited by T. Bewley. Cambridge: Cambridge University Press .
- Milgrom, P. R. and Weber, R. J. (1982a). A theory of auctions and competitive bidding, *Econometrica* **50**: 1089–1122.
- Milgrom, P. R. and Weber, R. J. (1982b). A theory of auctions and competitive bidding, partii, unpublished manuscript, in the meantime published in Paul Klemperer (Ed.): *The Economic Theory of Auctions*, Edgar Elgar, 2000 .
- Myerson, R. (1981). Optimal auction design, *Mathematics of Operation Research* **6**: 58–73.
- Neven, D. J. and Röller, L.-H. (1999). An aggregated model of competition in the european banking industry, *International Journal of Industrial Organization* **17**: 1059–1074.
- Nye, W. W. (1996). Firm-specific learning-by-doing in semiconductor production: Some evidence from the 1996 trade agreement, *Review of Industrial Organization* **11**: 383–394.
- OECD (1998). *STAN Database*, OECD, Paris.
- OECD/IEA (1998). *Energy Prices and Taxes: First Quarter to Fourth Quarter, 1984-1998*, OECD, Paris.
- Paarsch, H. (1992). Deciding between the common and private value paradigms in empirical models of auctions, *Journal of Econometrics* **51**: 192–215.
- Pakes, A. and Pollard, D. (1989). Simulation and the asymptotics of optimization estimators, *Econometrica* **57**: 1027–1057.
- Pesendorfer, M. (2000). A study of collusion in first-price auctions, *Review of Economic Studies* **67**: 381–411.
- Poirier, D. J. (1995). *Intermediate Statistics and Econometrics*, MIT Press, Cambridge Massachusetts.

- Porter, R. H. and Zona, J. D. (1997). Ohio school milk markets: An analysis of bidding, *NBER Working paper* **6037**.
- Quantitative Micro Software (1999). *Eviews 3.1*.
- Riley, J. and Samuelson, W. (1981). Optimal auctions, *American Economic Review* **71**: 381–392.
- Roberts, M. J. and Samuelson, L. (1988). An empirical analysis of dynamic, nonprice competition in an oligopolistic industry, *The RAND Journal of Economics* **19**(2): 201–220.
- Röller, L.-H. and Sickles, R. C. (1990). Capacity and product market competition: measuring market power in a ‘puppy dog’ industry, *International Journal of Industrial Organization* **18**: 845–865.
- Rothkopf, M. (1969). A model of rational competitive bidding, *Management Science* **15**: 774–777.
- Rubinstein, R. Y. (1981). *Simulation and Monte Carlo Method*, John Wiley and Sons, New York.
- Siebert, R. (1999). Multiproduct competition and learning-by-doing over the product life cycle: Evidence from the dram industry, *WZB Discussion Paper Series* **FS-IV 99-21**.
- Slade, M. E. (1995). Product rivalry with multiple strategic weapons: An analysis of price and advertising competition, *Journal of Economics and Management Strategy* **4**(3): 445–476.
- Spence, A. M. (1983). The learning curve and competition, *The BELL Journal of Economics* **12**: 49–70.
- Stata Corporation (2000). *Intercooled Stata 7.0 for Windows 95/98/NT*, College Station, Texas.
- Steen, F. and Salvanes, K. G. (1999). Testing for market power using a dynamic oligopoly model, *International Journal of Industrial Organization* **17**: 147–177.
- Vickrey, W. (1961). Counterspeculation, auctions and competitive sealed tenders, *Journal of Finance* **16**: 8–37.
- Weber, R. J. (1983). Multiple-object auctions, in *Auctions, Bidding, and Contracting: Uses and Theory*, edited by Richard Engelbrecht-Wiggans, Martin Shubik, and Robert M. Stark, New York University Press, New York pp. 165–191.
- Wilson, R. (1967). Competitive bidding with asymmetric information, *Management Science* **13**: 816–820.

Wilson, R. (1969). Competitive bidding with disparate information, *Management Science* **15**: 446–448.

Wilson, R. (1977). A bidding model of perfect competition, *Review of Economics Studies* **4**: 511–518.

Appendix: Data description

Auction data

The data are from auctions which took place on January 24th, February 21st, March 20th and April 24th 1996. On average at each auction day about 230 heads of cattle have been sold. For each animal the winning bid, the weight, the breed, two quality criteria, the auction day, the number of the “Winker” and the number of order on the specific auction day is known. Further we know the total number of given out “Winkers” for each auction. The cattle are divided into four categories, namely bulls, female calves, young female calves and cows. The cattle are of two different breeds: “Fleckvieh” or “Braunvieh”. The first quality criteria has six different classifications, 1A to 3B. For cows and female calves this quality criteria gives the minimum requirements for the output and the structure (fat, protein) of their milk. In case of young female calves it gives the minimum requirements of their mother’s milk. However, a cattle of the highest classification, 1A, was not sold on one of these four auction days. The second quality criteria has three classifications, 1 to 3. As everybody, who wants to bid, has at least one “Winker”, the seller can be identified in an anonymous way. Usually bidders have different numbers on their “Winkers” at different days. However, the large traders always get the same number. Therefore they can be identified throughout the four auction days. The number of potential bidders is the total number of given out “Winkers”. But this is not the number of bidders actually participating at each auction round, since people are not staying at the auction the whole day as they might be not interested in every cattle.

DRAM data

The data used for estimating represent firms producing DRAMs and are compiled by Dataquest Inc. The data covers firms' units shipped from the 4K generation to the 64MB generation and the average selling price. These generations span a time period from January 1974 to December 1996. The data are available at a quarterly basis. Table 4.1 shows in which year which generation of DRAMs were in the market. The very first generation of DRAMs, namely the 4K generation, emerged in 1974 and stayed in the market until 1985. Two years after the start off of the 4K generation the 16K generation was on the market. On average two to three years after one generation has emerged the following generations goes on market. The last generation - 64MB - went on the market in 1995 and is still at the beginning of its product cycle. Two exceptions are the 2MB and the 8MB generations. These are byproducts and do not follow the general pattern. From the firm-level output data I construct three variables. Namely, current output, own past cumulative output and other firms' past cumulative output. Current output serves as measure for economies of scale. The own cumulative output variable represents learning-by-doing. The cumulative past output of all other firms proxies learning spillovers. Further I use price data for four important inputs - price of silicon, energy cost, wages for production and user cost of capital. For the material cost I use the world market price of silicon compiled by Metal Bulletin. Energy costs and wages of production are compiled in the following way: according to each firms production location the energy prices and the industry wages (ISIC 3825) of the concerned location (country) is used. The source for energy prices is OECD/IEA OECD/IEA (1998), that for industry wages OECD OECD (1998). User cost of capital is constructed for each firm and year by exploiting firms annual reports. As a nonprice demand shifter I use a proportion of GNP directly attributed to electronic and electrical equipment from the OECD OECD (1998). A time variable also enters the demand equation as a proxy for the incremental changes in a generation over the life cycle. As substitutes for one generation I assume its proceeding and following generation.

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Selbständigkeitserklärung

Hiermit erkläre ich, dass ich außer der im Literaturverzeichnis angeführten Literatur keine weiteren Hilfsmittel benutzt habe. Außer von den unter 'Acknowledgements' genannten Personen habe ich keine weitere Hilfe erhalten. Des weiteren ist diese Dissertation noch nie einer Begutachtung unterzogen worden. Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

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