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Agnes Pesau

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Betreuerin:	Dr. Christine Zulehner

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Abstract

This study poses the questions if Static Random Access Memory (SRAM) producing firms have market power, how high price-cost margins are and if market power is higher in the early periods of the product life cycle of an SRAM chip. For this purpose, the method of the New Empirical Industrial Organization (NEIO) is applied and a model related to the work of Genesove and Mullin (1998) is set up. The model consists of a demand function and a pricing relation, which are estimated for four SRAM generations. Different marginal cost specificatons lead to different pricing relations. The (industry-level) SRAM data are from Gartner, Inc, the price of silicon (the main cost factor) stems from Metall Bulletin Ltd. Reasonable estimates for marginal costs and market conduct were only found for two generations. According to these outcomes, firms operate in an oligopolistic market and have thus, some market power to raise price above marginal cost. The market of the 64KB SRAM chip is more competitive than of the 256KB SRAM chip. But these results should be watched critically, since results of other generations are dissatisfying and thus, the model cannot be adapted to the whole SRAM industry. The positive relationship of prices and Lerner indices suggests that market power is high when prices are high, which is the case in the year after market introduction. But the estimates of the model indicate, that the opposite is the case. A concrete answer cannot be given.

Contents

1 Introduction

Identifying price-cost margins and market conduct are interesting fields of economic research. The purpose is to get measures or estimates of market conduct, i.e. if firms (a) collude within the market (cartel), if they (b) operate in an oligopoly market or if they (c) behave like competitors. Market conduct and price-cost margins are connected to each other through market power. The definition of market power says that it is is “the ability of a firm to profitably raise price above marginal cost”[1]. Firms that operate as mentioned in (a) have high market power and as a consequence a high price-costs margin. Oligopolists – (b) – have still market power and prices are therefore still higher than marginal cost. In (c), which presents an industry with perfect competition, firms have no market power and thus, prices equal marginal costs.

Empirical studies on this issue are worked out from the 1940s on. A method, which was established in the early periods, is called the “structure-conduct-performance paradigm” (SCPP) and concentrates on cross-section samples. It searches for observable structural characteristics of a market to see how firms behave in the market and get measures for price-cost margins (market performance). So, this approach is less theoretical, but focusses on measurable facts and characterictics.[2] Since not everybody believed, that price-cost margins can be directly observed from accounting data, another method – the “new empirical industrial organization” (NEIO) approach – was developed. This method is based on the fact that firms usually do not reveal complete information about the structure of their production process, about (marginal) cost of production and their mark-up. Only prices and the number of sold units are really available. Thus, I can only estimate price-cost margins with an econometrical model. In the next chapter, I give a short summary of some papers that deal with the NEIO method. For my work, I also used the NEIO approach and applied it on the semiconductor industry – or, to be more precise, on the Static Random Access Memory (SRAM) industry.

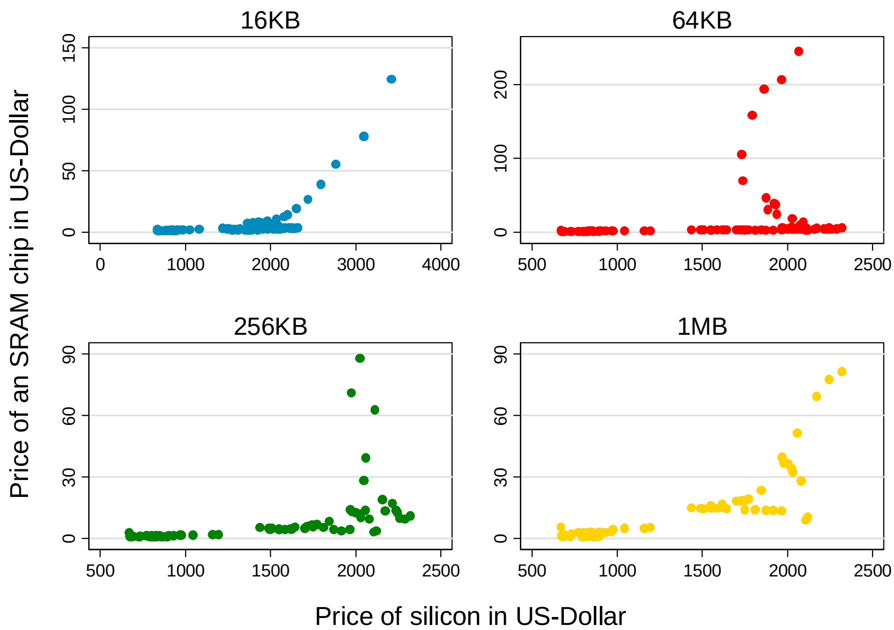
The semiconductor industry is an interesting field for economic research, because semiconductors are an important input to several high-technology industries. Since various papers have already been written on the Dynamic Random Access Memory (DRAM) market,

[1] Church (2000), p. 29
[2] Martin (2002)

I chose to concentrate on the related SRAM market. Another fact that argues for analyzing this market is, that the structure of the production process seems simple and clear: the main cost factor in producing SRAM chips is the price of silicon. SRAM chips are grouped in different generations, which reflect the memory capacity in kilobyte (KB) or megabyte (MB).

Figure 1 shows the positive impact of the price of silicon on the price of an SRAM chip of four selected generations. Taking a look on the prices close to 0, this statement is still true. For higher SRAM prices, which appear in the first period of the product life cycle of SRAM chips, it seems that there have to be other influence factors too (especially for the 64KB and the 256KB generation). This may be an indicator for some market power in the industry.

Figure 1: Comparison of the price of silicon and the price of an SRAM-chip in US-Dollar, for 4 selected generations



Notes: Prices are in constant US-Dollar. The data are from Gartner, Inc. and Metall Bulletin Ltd.

The method, that is adequate for my thesis comes from the work of Genesove and Mullin (1998). In their paper, they “test” the NEIO approach by comparing the estimates, which they received by applying the NEIO method, with measures from the U.S. East Coast cane sugar refining industry in the years 1890-1914. Such measures are available for that industry since the production process is simple. So they can be quite sure about the strucural form of marginal cost. They have also the prices of raw and refined sugar and very good estimates of labor and other costs at their disposal, and can therefore directly measure marginal cost and a price-cost margin. The authors conclude that the NEIO method performs reasonably well.

The sugar refining industry mentioned above is in a way comparable with the SRAM industry (which is my field of interest - details of market and data in the chapter 3) as the structure of the production process is transparent too. The main factor of production is silicon (comparable with raw sugar in the sugar refining industry), which is transformed at a fixed coefficient into SRAM chips (refined sugar in the sugar industry). Therefore I deduced that the methodology used by Genesove and Mullin (1998) would also work well if it is adapted to the SRAM market.

First of all, a linear demand equation is estimated. With the derived demand elasticity and a marginal cost function, that includes the price of silicon, I set up a pricing relation. The regression of this equation produces estimates of market conduct and of the parameters of the cost function. The data that I can make use of are on an industry level. Therefore, my estimates of price-cost margins and market conduct give an average of all firms in the industry.

My diploma thesis can be summarized by saying that cost, demand and firm conduct of the SRAM industry are (in contrast to industry price and quantity) unknown and getting estimates of them is the goal.[3]

The questions I pose in my diploma thesis are:

- Do firms engaging in the production of SRAM chips have market power, and to what extent can they raise price above marginal cost?
- Is market power higher in the early periods of the product life cycle?

In the next chapter, I summarize some papers that concentrate on the implementation of the NEIO approach on different industries. Chapter 3 describes the term “SRAM”, the production process and the properties of an SRAM chip. Furthermore, the data that will be analyzed is presented. In Chapter 4 I set up the model, divided into demand and supply model, and write about the estimation method I apply on the demand model (two stages least squares estimation). Chapter 5 gives the required test statistics and lists the results of the demand and supply relation. This paper ends with a conclusion in Chapter 6.

[3] Bresnahan (1989)

2 Literature review

There exist many papers following the NEIO issue, but this approach can be used in different ways. Most of the authors concentrate in deriving a parameter for market conduct to check if the industry is dominated by collusive, oligopolistic or competitive behaviour.

Bresnahan (1982) solves the identification problem by adding an interaction term between price and a demand-side exogenous variable (e.g. the price of a substitute good) in the demand equation. The demand function is now able to capture changes of the demand slope and not only up- and down-shifts of the intercept. Therefore, one can distinguish if the equilibrium comes from the marginal cost function either of a monopolist or of a competitor and the parameter indexing the degree of market power is identified. Lau (1982) figures out – based on the work of Bresnahan (1982) – the conditions under which the parameter for market conduct can be identified. As a result, he gets an impossibility theorem, that states under which assumptions the parameter cannot be identified.

The underlying article for many of the papers, that deal with the identification of market conduct and firm behavior in a market is that of Porter (1983). Porter concentrates here on the Joint Executive Committee railroad cartel from 1880 to 1886, which controlled eastbound freight shipments from Chicago to the Atlantic seaboard. He tests whether significant switches between Cournot and collusive output levels occur and tries to identify the periods in which they took place. He concludes that the changes in price and quantity are not only due to exogenous changes in demand and structural conditions, but arise from switches in firm behavior.

An extension to the model of Porter (1983) is the paper of Mariuzzo and Walsh (2006). They can now make use of weekly transportation prices of grain over the Great Lakes and Canals. Furthermore, they estimate the mark-up (price-cost margin/unobservable term) by using “semi-parametric techniques”. Compared to Porter’s (1983) model, Mariuzzo’s and Walsh’s (2006) model explains 77 % of pricing instead of just 36 %. Moreover, they demonstrate that mark-ups were higher in the weeks before lakes closing than in the weeks before lakes opening. In other words, the variable ‘number of weeks to lakes closing’ induces the mark-up to rise, whereas the ‘number of weeks to lakes opening’ lets the mark-up decrease.

Panzar and Rosse (1987) set up a test to check if a firm acts like a profit maximizing monopolist. They find out that "[t]he sum of the factor price elasticities of a monopolist's reduced form revenue equation must be nonpositive."[4] This method has the advantage, that it captures changes in costs even if the cost data is unavailable (which is mostly the case). For the sum being positive, they broaden their concept to test for monopolistically competitive, oligopolistic and perfectly competitive markets.

Bresnahan (1987) gives an explanation for the increase in the American automobile production in 1955. He claims that there was a supply shock in the form of a change in the industry conduct in such a way that the industry gets more competitive. Thus, the author tests the hypothesis, that the price war in 1955 is attended by the situation that collusive conduct switches over to competitive conduct only in 1955, with industry data. He can reject the hypothesis, that this is not the case.

A work, which uses firm-level data, is that of Zulehner (2003). She deals with learning-by-doing effects and spillovers in the dynamic random access memory (DRAM) market. DRAM chips can to some extent be compared with SRAM (static random access memory) chips, as the more has been produced in the past, the cheaper is the production process per unit in the present. Thus, she poses the question, whether firms precommit themselves to a production plan or whether they care for the effect, that learning-by-doing and spillovers have on the future output decision of their competitors. Therefore, she sets up two specifications, the closed-loop no memory and the open-loop equilibrium relation. Thereafter, she tests whether the intertemporal strategic parameters (which describe the difference between the two specifications) are jointly significant, and rejects the open-loop specification if this is the case. Later in the paper, she analyzes the trend of the estimated intertemporal strategic effects and compares the price-cost margins of the two specifications. She concludes, that firms take the strategic effect, that their output decision has on their rivals' future output decision, into account. Thus, she can reject the open-loop specification.

[4] Panzar and Rosse (1987), p. 445.

3 Industry facts and data

3.1 Description of the SRAM industry

SRAM is the abbreviation for Static Random Access Memory. So it is a type of semiconductor memory. “The term ‘semiconductor’ refers to a class of material with electrical properties between conductors and insulators.”[5]

SRAM chips are, like other semiconductors, produced in batches on silicon wafers. The production is a complex photolithographic sequence, which includes many different processes of manufacturing. The rooms, in which production takes place, have to be very clean, because even a tiny dust particle on the wafer leads to a defective chip. Since it is not possible to have a perfect raw silicon wafer, some chips are always faulty, but this part can be reduced to a very small percentage rate. The last stage of production is to cut the wafer, test and assemble the chips. The wafer processing stage is the most critical and also the most costly since the silicon material is the main cost factor in the production of a chip.[6]

SRAM holds data as long as power is supplied to the circuit. In contrast to DRAM (dynamic random access memory), it does not have to be periodically refreshed to retain its data. Other advantages are that it provides faster memory access times and can in some applications need less power than DRAM. But SRAM needs more space (because it uses more than one transistor) than DRAM and is more expensive in production for the same reason.[7]

SRAM is used in automotive electronics, digital cameras, cell phones, synthesizers, but also in personal computers, routers and other electronic devices.[8] The important semiconductor companies are situated in the U.S.A. and in Japan, such as Intel, Texas Instruments, Nippon Electric Corporation (NEC), Toshiba, etc. European semiconductor companies are Philips or Siemens.

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[5] Kumar and Krenner (2002), p. 229
[6] Gruber (1999)
[7] http://www.pctechguide.com/glossary/WordFind.php?wordInput=SRAM (2010-02-08)
http://www.pctechguide.com/14Memory_L1_cache.htm (2010-02-08)
[8] http://en.wikipedia.org/wiki/Static_random_access_memory (2010-02-08)

3.2 Description of the data set

The data for 21 generations of SRAM chips stem from Gartner, Inc[9]. The observations are on a quarterly basis for the years 1974 to 2004 and cover data for SRAM chips from the 4KB generation to the 64MB generation. The data set includes industry-level data about units shipped, average selling prices and the number of firms producing particular SRAM generations. The price of silicon, which is the main cost factor in the production of SRAM chips, is compiled by Metall Bulletin Ltd[10].

For my analysis, I only chose the four SRAM generations (16KB, 64KB, 256KB and 1MB) with the most observations. These generations were on the market for a longer period of time in comparison to other generations, so there exist 64-91 observations for each of them. Estimation for generations with less than 60 observations may not be reasonable.

Table 1: Summary Statistics, 1980-2004

Variable	**16K**	**64K**	**256K**	**1MB**
Price				
Mean	6.80	15.81	8.68	14.80
Std.Dev.	16.50	43.87	15.14	17.75
Median	2.74	2.71	4.48	13.58
Minimum	0.65	0.65	0.70	0.85
Maximum	124.49	245.72	87.78	81.48
Output				
Sum	1,765,568	3,259,202	5,421,165	3,383,168
Mean	19,191	37,036	73,259	52,862
Std.Dev.	18,303	27,111	46,844	43,339
Median	12,566	32,753	70,165	48,060
Minimum	7	10	15	365
Maximum	59,254	84,998	190,930	133,630
Price of Silicon				
Mean	1,679.30	1,551.49	1,481.45	1,379.02
Std.Dev.	588.75	536.54	556.16	527.12
Observations	91	88	74	64

Notes: Prices are in constant US-Dollar. The data are from Gartner, Inc. and Metall Bulletin Ltd.

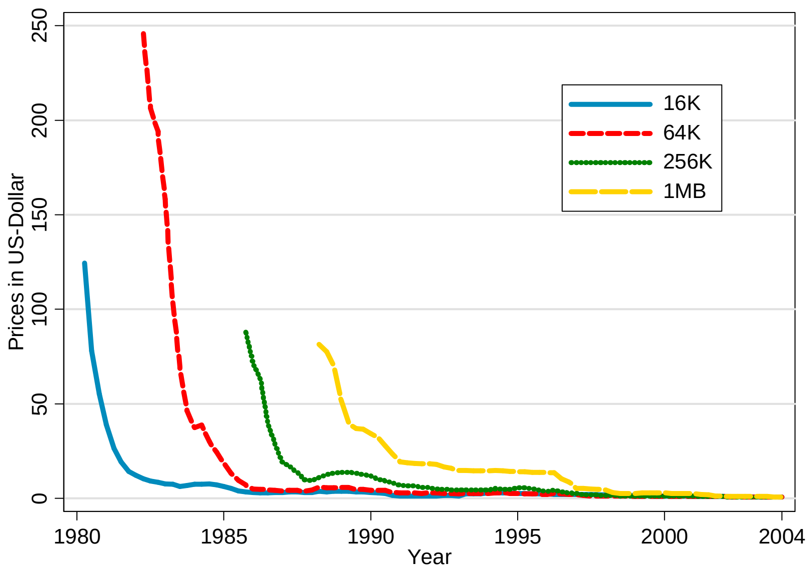
To give an overview of the data, Table 1 provides some summary statistics of industry prices and output and the price of silicon for the chosen SRAM generations. Comparing the 16KB, the 64KB, the 256KB and the 1MB generation I find out that the 64KB SRAM chip has the

[9] a consulting firm in Stamford, U.S.A.
[10] a consulting firm in London, Great Britain

highest price on average (15.81 $), whereas the 16KB chip has the lowest average price (6.80 $). Every quarter 73,259 units of the 256KB generation were sold on average. On the other side there is the lowest average number of 19,191 units shipped of the 16KB generation. The highest number of sold units (190,930) was reached by the 256KB generation in the last quarter of 1995. Until 2004, the most successful generation was the 256KB generation; from 1985 to 2004 5,421,165 units of chips were sold. The price of silicon per kilogram is decreasing with every new generation; an average price of 1,679.30 $ for the 16KB generation falls to 1,379.02 $ for the 1MB generation. There should also be mentioned, that the product life cycles of the 64KB, the 256KB and the 1MB generation have not ended in 2004 and that, unfortunately, the number of observations for the four chosen generations is still relatively small.

Figure 2 states the prices of the four SRAM generations between 1980 and 2004. What stands out immediately is, that for each generation prices fall extremely only shortly after the introduction on the market. The reasons are, that firms learn very quickly and more and more companies enter the market. For example, the average selling price of the 64KB generation dropped by nearly 60 % within the first year, the price of the 256KB generation by almost 70 % and the 16KB generation faces a price decline of roughly 80 % within the first 12 months. I found it also interesting to remark that the 64KB generation has a significantly higher introduction price than the other generations.

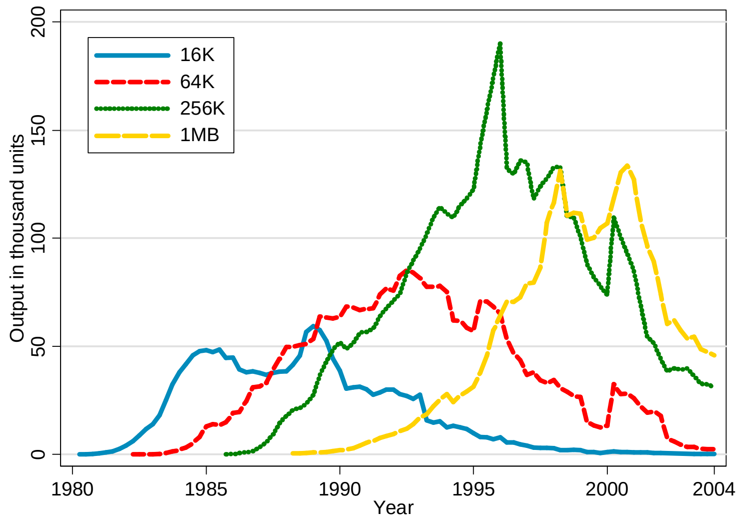
Figure 2: Average selling prices in US-Dollar, 1980-2004



Notes: Prices are in constant US-Dollar. The dataset is from Gartner, Inc.

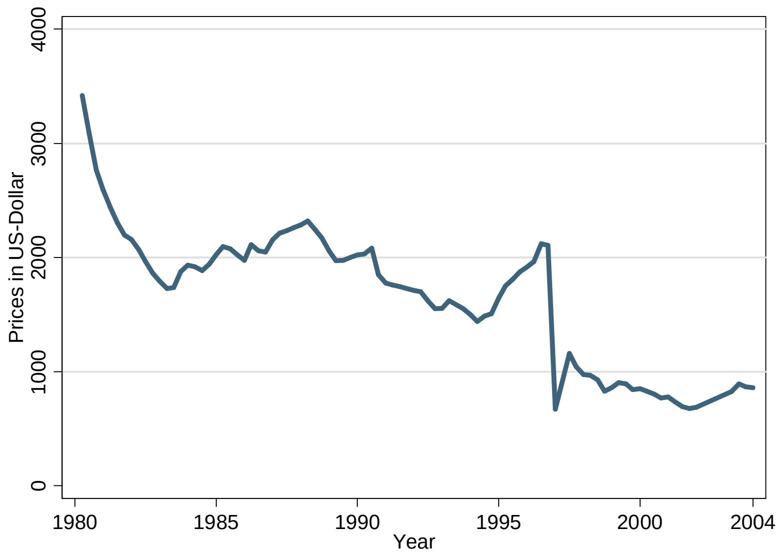
Figure 3 shows the number of units sold between 1980 and 2004. It is a fact that the life cylces of different generations are in a way similar and that different generations overlap. Each starts with a very small output since only one firm has introduced the particular SRAM generation. A peak is reached relatively soon (compared with other products)[11]. One can observe that some generations have a second peak a few years after the first. It is also noticeable that in 1999 the number of sold units goes down for the 64KB, the 256KB and the 1MB SRAM chip.

Figure 3: Number of sold units, 1980-2004



Notes: Prices are in constant US-Dollar. The dataset is from Gartner, Inc.

Figure 4: Price of silicon per kilogram in US-Dollar, 1980-2004

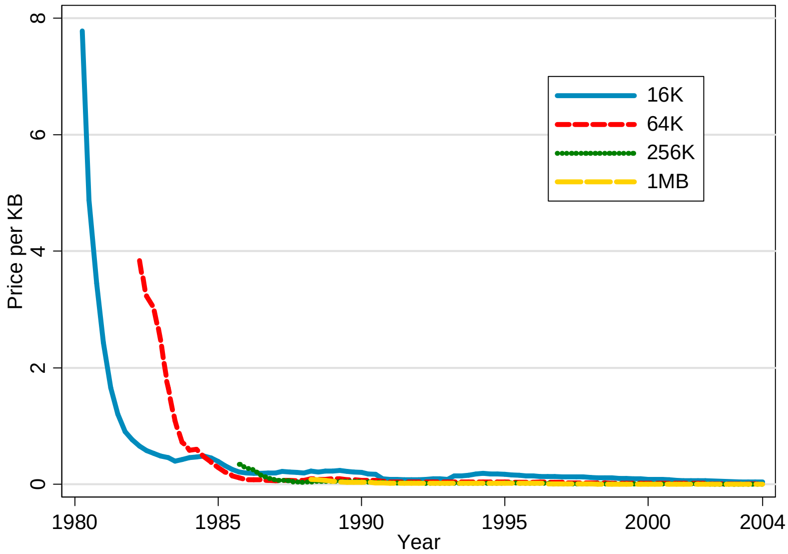


Notes: Prices are in constant US-Dollar. The dataset is from Metall Bulletin Ltd.

[11] Irwin and Klenow (1994)

The price of silicon per kilogram (relative to the consumer price index) is decreasing in the long-run, as displayed in Figure 4 (only the years 1980 to 2004 are shown, that correspond to the four chosen SRAM generations). The highest price was 3419.97 $ and was reached in the first quarter of 1980. The lowest was 671.61 $, at the end of 1996, which was caused by a remarkable price fall after an increase in the price of silicon from 1994 on.

Figure 5: Average selling prices per KB in US-Dollar, 1980-2004



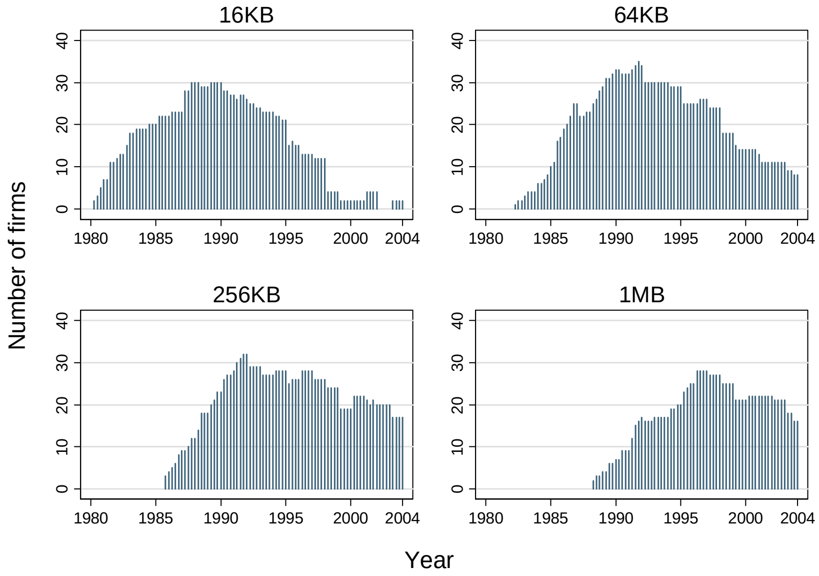
Notes: Prices are in constant US-Dollar. The dataset is from Gartner, Inc.

I also calculated a price index (Figure 5) for each generation at each point in time, which represents the price per KB and is given by $PI_{it}^{a} = \frac{p_{it}}{KB_i}$, where p_{it} is the price of the SRAM chip of generation *i* at time *t* and KB_i is the number of kilobyte, that a chip of generation *i* can store. The pattern of these curves is similar to those of the absolute price, but for the 256KB and the 1MB generation the “start point” is already relatively low in comparison to the absolute introduction price. It can be observed that the index decreases steadily for each generation with just a few fluctuations. The maximum of this price index is 7.78 $ and refers to the 16KB SRAM chip in the first quarter of 1980, whereas the minimum is 0.085 $-Cent and relates to the 1MB chip at the end of 2003. So one can assume a further fall in the price index. If the view is broadened and also other generations are considered, I found out that the index for the 64MB chip is with 0.008 $-Cent at the end of 2003 even lower.

I assume that one or only a few firms start producing a new generation of SRAM chips, but other firms are following very quickly; and the data shows that this assumption is right (Figure

6). Within a short period of time a peak of roughly 30 firms is reached and the number of firms declines nearly as rapidely as it rose.

Figure 6: Number of firms in the SRAM industry, 1980-2004



Notes: The dataset is from Gartner, Inc.

4 The model

The model I use in my diploma thesis determines market price and quantity by the intersection of a demand function and a supply relation.[12]

In this chapter I present the demand model and the supply model, the theoretical aspects and the econometric implementation. At the end of this part, I describe the Instrumental Variable and the Two Stages Least Squares estimation method, which I will apply on the model in chapter 5.

Genesove and Mullin (1998) – as mentioned before – engage in the sugar industry, where they set up the marginal cost function of refining sugar

$$c = c_0 + k \times p_{RAW} \tag{1}$$

where c stands for the marginal cost of producing 100 pounds of refined sugar, c_0 are all variable costs other than the cost of raw sugar itself, p_{RAW} represents the price for raw sugar, and k is the (fixed) parameter, that explains, how many pounds of raw sugar are needed for the production of one pound of refined sugar. The authors get a precise estimate for k (k=1.075) by working out that only 96 % of raw sugar are sucrose and that there is also some loss of sugar in the refining process. As a measure for c_0 they use 26 ¢ per hundred pounds, which is made up of taxes, packages, wages, fuel, etc and reduced by the value of by-products such as syrup. With this information they derive the conduct parameter θ, which is equal to the elasticity-adjusted Lerner index, L_η:

$$\theta = \eta(P)\frac{P-c}{P} \equiv L_\eta \tag{2}$$

where $\eta(P)$ represents the demand elasticity. Comparing the derived θ with their estimated $\hat{\theta}$ they conclude that the method performs reasonably well. In the following I will describe my modification of this model.

[12] "Supply functions" are only defined in a perfectly competitve market. Therefore the literature uses the term "supply relations" for industries, where firms have some market power.

4.1 Demand model

Generally, the demand function takes the form

$$Q = \beta(\alpha - P)^{\gamma} \tag{3}$$

where Q is the quantity of SRAM chips demanded, P is the price of one unit of an SRAM chip, β is a measure for the size of market demand, γ is an index of convexity and α stands for the maximum willingness to pay (when γ is positive).

In the rest of the paper I will specialize in the linear demand function (where $\gamma = 1$), which looks as follows:

$$Q = \beta(\alpha - P) + \varepsilon_d \tag{4}$$

Here, ε_d represents the error term of the demand function and includes proportional shifts in demand.

In my work on the SRAM industry I estimate the linear demand equation

$$output_t = \alpha_0 + \alpha_1 pricec_t + \varepsilon_{dt} \tag{5}$$

for $t = 1, ..., T$, where α_0 and α_1 are the parameters to be estimated, $pricec_t$ is the average selling price of an SRAM chip at time t, $output_t$ are the chips sold at time t.

The analysis of the estimated parameters should give a negative sign for $\hat{\alpha}_1$, which represents the marginal effect of *pricec* on *output*. Comparing with equation (4) one recognizes that $\hat{\alpha}_0 = \hat{\beta}\hat{\alpha}$ and $\hat{\alpha}_1 = -\hat{\beta}$, which leads me to $\hat{\alpha} = -\frac{\hat{\alpha}_0}{\hat{\alpha}_1}$. $\hat{\alpha}$ is required for estimating the pricing rule later on.

4.2 Supply model

The SRAM market is an oligopoly with a few firms producing these chips, as Figure 6 proved. Each firm should have some market power, so that it could raise the price for an SRAM chip above its marginal cost. To which extent a single firm may do this depends on how much its market power is limited by supply side substitution and/or demand side substitution. Supply side substitution explains the fact, that there are other suppliers who produce the same good. This description applies to the SRAM industry since the chips are homogenous and produced by a few firms. Demand side substitution means that consumers may switch to other products if they see them as acceptable substitutes. In the SRAM industry SRAM chips of other generations or even DRAM chips may be used as substitutes, respectively.

My aim in this part of my thesis is to get an equation that shows how price depends on (marginal) cost. Therefore, I maximize the profit function of a firm *i* with respect to Q_i[13]:

$$\max_{Q_i} \pi(Q_i) = R(Q_i) - C_i(Q_i) \tag{6}$$

where $R(Q_i)$ is the revenue function and $C_i(Q_i)$ the cost function for firm *i*, and get as a result

$$MR(Q_i^*) = c_i(Q_i^*) \tag{7}$$

where $MR(Q_i^*)$ and $c_i(Q_i^*)$ are marginal revenue and marginal cost at the profit-maximizing output level for firm *i* Q_i^*, respectively.

If the firm is operating under perfect competition, it acts as a price taker and has therefore the revenue function

$$R(Q_i) = PQ_i \tag{8}$$

Thus, $MR(q_i)=P$. Substituting this into (7) leads me to the profit-maximizing rule for a firm in a perfectly competitive market

$$P = c_i(Q_i) \tag{9}$$

[13] For simplicity, I omit here and in following equations other variables that may influence the revenue or the cost function and therefore the profit.

On the other hand side, if the firm is a monopolist or some firms form a cartel, it/they can set the price herself/themselves and changes in the price P lead to changes in units sold Q_i. The sum of the units sold of each firm gives a total output $Q = \sum_{i=1}^{n} Q_i$ for n firms in the market. I insert the new revenue function $R(Q_i)=P(Q)Q_i$ into the the profit function and the maximization problem is now

$$\max_{Q_i} \pi(Q_i) = P(Q)Q_i - C_i(Q_i) \tag{10}$$

The first difference gives

$$P(Q) + \frac{\partial P(Q)}{\partial Q} Q_i - c_i(Q_i) = 0 \tag{11}$$

Thus, the profit-maximizing condition for a monopolist or a firm in a cartel turns out to be

$$P(Q) + \frac{\partial P(Q)}{\partial Q} Q_i = c_i(Q_i) \tag{12}$$

Comparing the conditions for markets characterized by perfect competition – (9) – and by monopoly/cartel – (12) –, one can write a general supply relation:[14]

$$P(Q) + \theta \frac{\partial P(Q)}{\partial Q} Q_i = c_i(Q_i) \tag{13}$$

where θ is a parameter indexing the competitiveness of industry conduct, $\theta = 0$ indicates perfect competition, from $\theta = 1$ I conclude that the industry is a monopoly or perfect cartel, and θ between 0 and 1 describes another oligopoly solution – for example $\theta = 1/n$ for Cournot equilibrium (where n is the number of firms in the industry). θ is taken to be constant over time and equal for all firms in the market. Thus, the parameter can be interpreted as average conduct in the industry.[15]

[14] Church and Ware (2000)
[15] Cowling and Waterson (1976)

From equations (13) and (3) the pricing rule

$$P(c)=\frac{\theta\alpha+\gamma c}{\gamma+\theta} \tag{14}$$

is derived (see Appendix). Since I specialize in the linear demand function (where γ = 1), the pricing rule can be written as

$$P(c)=\frac{\theta\alpha+c}{1+\theta} \tag{15}$$

Genesove and Mullin (1998) specify the linear marginal cost function mentioned in (1). Their pricing rule looks as follows:

$$P(c)=\frac{\theta\alpha+c_0+k\times p_{RAW}}{1+\theta} \tag{16}$$

In my model, p_{RAW} is replaced by *sil1c*, which is the main cost factor in the production of memory chips. Thus, I set up the following marginal cost (MC) functions, which I will make use of in the course of this paper:

$$\begin{array}{ll}
\text{(c1)} & c=c_0+k\times sil1c \\
\text{(c2)} & c=c_0+k\times sil1c+j\times output \\
\text{(c3)} & c=c_0+k\times sil1c+m\times outputcum_1 \\
\text{(c4)} & c=c_0+k\times sil1c+j\times output+m\times outputcum_1 \\
\text{(c5)} & c=\exp(c_0+k\times sil1c) \\
\text{(c6)} & c=\exp(c_0+k\times sil1c+j\times output) \\
\text{(c7)} & c=\exp(c_0+k\times sil1c+m\times outputcum_1) \\
\text{(c8)} & c=\exp(c_0+k\times sil1c+j\times output+m\times outputcum_1) \\
\text{(c9)} & c=(c_0+k\times sil1c)^2 \\
\text{(c10)} & c=(c_0+k\times sil1c+j\times output)^2 \\
\text{(c11)} & c=(c_0+k\times sil1c+m\times outputcum_1)^2 \\
\text{(c12)} & c=(c_0+k\times sil1c+j\times output+m\times outputcum_1)^2
\end{array} \tag{17}$$

where functions (c1) – (c4) are linear, (c5) – (c8) are exponential and (c9) – (c12) are quadratic MC functions. I made use of exponential and quadratic MC functions, because I thought they would represent the shape of the true MC curve better. Equations (c2), (c6), (c10) include *output* and functions (c3), (c7), (c11) *outputcum_1* (which is *output* accumulated until *t-1*) as factors that influence marginal cost. In (c4), (c8) and (c12) both *output* and *outputcum_1* are used. The variable *output* may influence marginal cost, since the more is produced the lower the costs for an additional SRAM chip are. The impact of lagged accumulated output *outputcum_1* on MC has to do with learning-by-doing. More cumulative output means more production experience. Thus, precision in production can be improved, the percentage of defective chips is minimized and costs for producing one additional unit decrease.[16]

Substituting the particular marginal cost function – from (c1) to (c12) – in (15) yields the pricing rules for estimation:

(P1) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{c_0}{1+\theta} + \frac{k}{1+\theta} sil1c_t + \varepsilon_{st}$$

(P2) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{c_0}{1+\theta} + \frac{k}{1+\theta} sil1c_t + \frac{j}{1+\theta} output_t + \varepsilon_{st}$$

(P3) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{c_0}{1+\theta} + \frac{k}{1+\theta} sil1c_t + \frac{m}{1+\theta} outputcum\_1_t + \varepsilon_{st}$$

(P4) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{c_0}{1+\theta} + \frac{k}{1+\theta} sil1c_t + \frac{j}{1+\theta} output_t + \frac{m}{1+\theta} outputcum\_1_t + \varepsilon$$

(P5) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{\exp(c_0 + k \times sil1c_t)}{1+\theta} + \varepsilon_{st}$$

(P6) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{\exp(c_0 + k \times sil1c_t + j \times output_t)}{1+\theta} + \varepsilon_{st} \qquad (18)$$

(P7) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{\exp(c_0 + k \times sil1c_t + m \times outputcum\_1_t)}{1+\theta} + \varepsilon_{st}$$

(P8) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{\exp(c_0 + k \times sil1c_t + j \times output_t + m \times outputcum\_1_t)}{1+\theta} + \varepsilon_{st}$$

(P9) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{(c_0 + k \times sil1c_t)^2}{1+\theta} + \varepsilon_{st}$$

(P10) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{(c_0 + k \times sil1c_t + j \times output_t)^2}{1+\theta} + \varepsilon_{st}$$

[16] Irwin and Klenow (1994)

(P11) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{(c_0 + k \times sil1c_t + m \times outputcum\_1_t)^2}{1+\theta} + \varepsilon_{st}$$

(P12) $$pricec_t = \frac{\theta}{1+\theta}\hat{\alpha}_t + \frac{(c_0 + k \times sil1c_t + j \times output_t + m \times outputcum\_1_t)^2}{1+\theta} + \varepsilon_{st}$$

for $t = 1, ..., T$, where θ, c_0, k, j and m are the parameters to be estimated, $pricec_t$ is the average selling price of an SRAM chip at time t, $\hat{\alpha}_t$ is the parameter at time t, which I get by estimating the demand function (5), $sil1c_t$ is the price of silicon at time t, $output_t$ is the number of sold SRAM chips at time t, $outputcum\_1_t$ is *output* accumulated until time *t-1* and ε_{st} represents the error term of the supply relation at time t.

For the estimated $\hat{\theta}$ I expect a value between 0 and 1, $\hat{c}_0$ and $\hat{k}$ should have a positive sign and $\hat{j}$ and $\hat{m}$ are supposed to have a negative influence on marginal cost and, as a consequence, on price.

To answer my second question, I calculate the Lerner index, which is a measure of market power, as one can find out from (2). Another method to calculate this index is

$$L_\eta = \frac{1}{\eta(P) \times nof} \tag{19}$$

where $\eta(P)$ is the price elasticity of demand and *nof* is the number of firms in the industry for each particular generation. High values of the Lerner index are an indicator for high market power of the firms.

4.3 Estimation Method[17]

For estimating the demand function I use two-stage least square estimation (2SLS). In the following I will explain the instrumental variable (IV) estimation method, which can be seen as the base of 2SLS, and, of course, the 2SLS estimation method.

[17] cf. Wooldridge (2005), p. 510ff.

4.3.1 Instrumental variable estimation

Instrumental variable estimation is a method that can be used if assumption MLR.4 – according to Wooldridge (2005) – of the OLS model is violated. This assumption says that

> „[T]he error u has an expected value of zero given any values of the independent variables. In other words,
>
> $E(u \mid x_1, x_2, ..., x_k) = 0$ “.[18] (20)

This implies that the model looks as follows:

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k + u, \tag{21}$$

where y is the dependent variable, x_i are the explanatory variables, β_i are the unknown parameters and u is the error term (i=1,...,k).

The above mentioned assumption may not be fulfilled if there is an unobserved variable in the error term u (unobserved heterogeneity), such that e.g. the explanatory variable x_1 is correlated with u, (i.e. $E(u|x_1) \neq 0$). As a consequence all of the estimators would be biased and inconsistent if I would estimate (21) by OLS. One could deal with this problem by replacing the unobserved variable with a proxy variable, but it may be not easy or even impossible to find a suitable one.

The instrumental variable estimation technique is another approach. It searches for an instrument z_1, that is,

(i) uncorrelated with u, i.e. $E(u|z_1) = 0$; and
(ii) correlated with x_1, i.e. $Cov(z_1,x_1) \neq 0$.

The first condition states that z_1 has to be exogenous. It can only be effectively tested if there is more than one instrumental variable. The second condition means that z_1 and x_1 must be (positively or negatively) linked to each other. This assumption can be tested by estimating the linear function

[18] Wooldridge (2005), p. 87

$$x_1 = \pi_0 + \pi_1 z_1 + \pi_2 x_2 + ... + \pi_k x_k + v_1 \quad (22)$$

which consists of the endogenous explanatory variable x_1 on the left-hand side and the exogenous variables and an error term on the right-hand side; π_j are unknown parameters.

Therefore, the required condition to ratify that z_1 and x_1 are correlated is that

$$\pi_1 \neq 0. \quad (23)$$

So, equation (22) is estimated by OLS and a t-test that should reject the null hypothesis

$$H_0: \pi_1 = 0 \quad (24)$$

against the alternative hypothesis

$$H_A: \pi_1 \neq 0 \quad (25)$$

is carried out.

Thus, if the conditions (i) and (ii) are true, z_1 is a valid instrumental variable for x_1.

4.3.2 Two stage least squares estimation

Two stage least squares estimation is similar to instrumental variable estimation. The main difference is simply, that there can be more than one instrumental variable for the endogenous explanatory variable x_1; but also, that there exists more than one endogenous explanatory variable.

Let me consider firstly the case, where there is only one endogenous explanatory variable x_1 but more than one instrumental variable. The model looks as in equation (21), but now there is more than one exogenous variable excluded from it (here named z_l, l = 1, ... m). Clearly, these variables are uncorrelated with the error term u. Hence, any linear combination of all exogenous variables is also uncorrelated with u and can therefore be a valid instrument for x_1. To get the linear combination that is most highly correlated with x_1, the reduced form equation for x_1 is estimated:

$$x_1 = \pi_0 + \pi_1 z_1 + \ldots + \pi_m z_m + \pi_{m+1} x_2 + \ldots + \pi_{m+k-1} x_k + v_2 \tag{26}$$

Now, an F-test, where I test the null hypothesis

$$H_0 \colon \pi_2 = \pi_3 = 0 \tag{27}$$

against the alternative hypothesis

$$H_A : \pi_2 \neq 0 \text{ or } \pi_3 \neq 0, \tag{28}$$

can be used to check, if the linear combination

$$\hat{x}_1 = \hat{\pi}_0 + \hat{\pi}_1 z_1 + \ldots + \hat{\pi}_m z_m + \hat{\pi}_{m+1} x_2 + \ldots + \hat{\pi}_{m+k-1} x_k \tag{29}$$

is a proper instrumental variable for x_1.

Thus, the two stage least squares estimation method has two steps: In the first stage, equation (29) has to be estimated, where the fitted values $\hat{x}_1$ are obtained which have to serve as the instrument. In the second stage, I regress y on $\hat{x}_1$ and z_1 by OLS.

Now, I assume that there is not only one, but there are multiple endogenous explanatory variables. To estimate (21) I need at least as many exogenous variables, that are not included in (21), as endogenous explanatory variables. This (necessary) condition is called the order condition and easy to check. The rank condition is not as easy to verify, but sufficient for identification.

5 Results

The equation system, which consists of the demand equation (5) and the particular pricing rule – from (P1) to (P12) –, is now estimated, using the data described in chapter 3.2. Since for some SRAM generations there are relatively few data points, I select only four generations, namely the 16KB, the 64KB, the 256KB and the 1MB generation, for estimation.

5.1 Demand side

The demand equation given in (5) has to be estimated using 2SLS. The two stages least squares estimation method is necessary, because both variables *output* and *pricec* are assumed to be endogenous, so they are correlated with the error term ε_{dt} . That means for *pricec* that it is correlated with an unobserved variable included in the error term. Since using 2SLS is less efficient than OLS if all explanatory variables are exogenous, I have to make sure, that *pricec* is really endogenous. This can be checked by using the Hausman (1978) test, which compares the OLS and 2SLS estimates to find out whether the differences are statistically significant. If this is the case, *pricec* must be endogenous.

Table 2: Hausman (1978) test - chi-square statistic

H_0: difference in coefficients is not systematic
H_A: difference in coefficients is systematic

	1st quarter	2nd quarter	3rd quarter	4th quarter
16KB	2.76	3.28	3.64	1.74
64KB	4.79 **	4.69 **	4.35 **	3.86 **
256KB	3.29 *	1.90	3.66 *	3.60 *
1MB	4.98 **	5.00 **	5.16 **	4.20 **

Notes: */**/*** indicate, that the result is significant at a 90-/95-/99-%-level. The data are from Gartner, Inc. and Metall Bulletin Ltd.

From Table 2, which shows the results of the Hausman test, I can conclude that *pricec* is endogenous. Since most of the chi-square statistics of the different generations and quarters indicate that the null hypothesis can be rejected, it is reasonable to use the 2SLS estimation method.

When a demand function is estimated, the unobserved variable indicates shocks on the supply side. Thus, the estimates would be biased and inconsistent if I would use OLS, so I search for at least one instrument that is exogenous and correlated with *pricec*. Instruments for shocks on the supply side can be, for example, input prices, the number of firms in the market, lagged prices or world prices (if only a small market is examined, that could not influence the world prices). In my work, I use the price of silicon, *sil1c*, and the number of firms in the SRAM market, *nof*, as instruments for *pricec*. To justify this decision, an F-test, which checks for the joint significance of the instruments, is necessary (as described in chapter 4.3 – equations (26) to (28) have to be considered). By applying this test on the first stage of regression, I obtain F-statistics that support my choice of instruments, since the p-values are all below 0.01.

Table 3 presents the first stage of the estimation results of the demand equation. The important point in this table is that the variables (instruments) are jointly significant (as discussed above) and that R^2 has a high value. R^2 has good values for the 16KB and the 1MB generation (between 0.72 and 0.82), is acceptable for the 256KB generation (values between 0.54 and 0.71), but is relatively low for the 64KB generation (values between 0.38 and 0.51). This means that for the 16KB and the 1MB generation up to 82 % of the variation of *pricec* in the sample is explained by the given explanatory variables, whereas for the 64KB generation only up to 51 % of the variation of *pricec* is explained.

The coefficients of the first stage show, what I expected in advance: The coefficient of *nof* is negative, since more firms in the industry lead to more competition, price wars and thus, lower prices. The effect is highest in the first quarter of the 64KB generation, where one additional firm in the market lets the price decrease by 3.83 $; the lowest coefficient is found in the fourth quarter of the 16KB generation, with a price fall of 0.67 $ if another firm enters the market. The coefficient of *sil1c* gives a positive sign. Clearly, a rise of an input price causes the price of an SRAM chip to increase. There is hardly a difference between the coefficients of the different generations. For the 256KB and the 1MB generation it ranges between 0.01 and 0.02, which means that a 1 $ increase in the price of silicon raises the price of an SRAM chip by 0.01 $ or 0.02 $, respectively. The effect for the 16KB generation lies between 0.01 in the third and fourth quarter and 0.04 in the first quarter. For the 64KB generation the coefficient is with 0.05 in the first quarter the highest one in the sample.

Table 3: Demand for SRAM chips: Estimation results of the first stage, separately by generation and quarter

Dependent variable: *pricec*				
Explanatory variables	**1st quarter**	**2nd quarter**	**3rd quarter**	**4th quarter**
16KB				
time1	0.19	-0.05	-0.11	-0.11
	(0.19)	(0.12)	(0.10)	(0.08)
nof	-1.62	-1.17	-0.89	-0.67
	(0.29)	(0.20)	(0.17)	(0.13)
sil1c	0.04	0.02	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.00)
Intercept	-53.93	-10.09	3.70	8.27
	(27.50)	(17.42)	(13.88)	(10.88)
R^2	0.80	0.77	0.72	0.72
64KB				
nof	-3.83	-3.28	-2.74	-2.12
	(0.93)	(0.81)	(0.78)	(0.67)
sil1c	0.05	0.04	0.03	0.02
	(0.02)	(0.01)	(0.01)	(0.01)
Intercept	21.23	18.36	17.69	19.44
	(29.47)	(24.22)	(23.36)	(19.18)
R^2	0.51	0.49	0.42	0.38
256KB				
nof	-1.21	-0.81	-1.73	-1.26
	(0.34)	(0.19)	(0.43)	(0.38)
sil1c	0.01	0.01	0.01	0.01
	(0.00)	(0.00)	(0.01)	(0.00)
Intercept	18.73	11.09	30.70	23.44
	(10.74)	(5.76)	(13.96)	(12.49)
R^2	0.61	0.71	0.60	0.54
1MB				
nof	-1.40	-1.62	-1.43	-0.88
	(0.40)	(0.39)	(0.33)	(0.32)
sil1c	0.02	0.02	0.01	0.01
	(0.01)	(0.01)	(0.00)	(0.00)
Intercept	15.79	23.81	20.10	10.29
	(13.84)	(12.88)	(10.75)	(10.64)
R^2	0.82	0.81	0.81	0.82

Notes: Standard errors are in parentheses. The regression of the 16KB generation includes a time trend, otherwise the coefficients would be insignificant in the second stage. The data are from Gartner, Inc. and Metall Bulletin Ltd.

Table 4: Demand for SRAM chips: Estimation results of the second stage, separately by generation and quarter

Dependent variable: *output* Explanatory variable		1st quarter	2nd quarter	3rd quarter	4th quarter
16KB					
pricec	-919	-547	-1001	-1625	-2168
	(290)	(222)	(393)	(653)	(785)
time1	-588	-519	-613	-705	-737
	(65)	(134)	(121)	(115)	(119)
Intercept	67046	59926	69112	78938	83220
	(6311)	(12442)	(11445)	(11148)	(12013)
64KB					
pricec	-659	-516	-644	-741	-896
	(182)	(262)	(348)	(435)	(527)
Intercept	47459	47634	47537	47749	47700
	(3155)	(6330)	(6715)	(6682)	(6394)
256KB					
pricec	-2864	-2891	-3712	-2258	-3050
	(709)	(1328)	(1288)	(1089)	(1544)
Intercept	98134	98448	99882	95670	99892
	(5881)	(11547)	(12104)	(11319)	(12968)
1MB					
pricec	-2348	-2078	-2134	-2443	-2981
	(402)	(738)	(767)	(852)	(818)
Intercept	87611	85916	84683	89385	91996
	(5703)	(12097)	(11199)	(12025)	(11631)

Notes: Standard errors are in parentheses and heteroskedasticity-robust. The regression of the 16KB generation includes a time trend, otherwise the variables would be insignificant. The data are from Gartner, Inc. and Metall Bulletin Ltd.

Table 4 reports the demand estimates, separately by generation and quarter. The table states the coefficients and their standard errors, which are heteroskedasticity-robust. As expected, the demand curve is downward sloping in all quarters and generations. The time trend for the 16KB generation is negative, which is reasonable since it indicates a price fall over time. *pricec* has the highest coefficient in the 256KB generation: -2864.12 means that a price increase of 1 $ leads to a decrease in units sold of 2864.12 units on average. The coefficient is even higher in the second quarter of the 256KB generation (-3712.07). On the other hand side, a price increase of 1 $ causes only a decrease of 659.42 units of output in the 64KB generation on average. I found the lowest coefficient in the first quarter of the 64KB generation (-516.01). Another fact that seems interesting is, that – except for the 256KB generation – the coefficients rise (in absolute values) from quarter to quarter. Thus, in the fourth quarter output reacts mostly more sensitive in an increase of the price of an SRAM chip than in other parts of the year.

5.2 Supply side

As described in the previous chapters, I can now generate $\hat{\alpha}$ from the coefficient of *pricec* and the intercept of demand equation (5) ($\hat{\alpha} = -\frac{\hat{\alpha}_0}{\hat{\alpha}_1}$). Now I am able to estimate the pricing rules (P1) to (P12) as mentioned in (18).

Column (1) of Table 5 presents the results of estimating (P1), but they differ to some extent from what I expected. $\hat{\theta}$ takes on values between 0.034 and 0.039 for the 16KB and 1MB generation on the one hand, but values between 0.22 and 0.245 for the 64KB and 256KB generation on the other hand. It seems that for the 16KB and 1MB generation the market is more competitive, whereas the sale of the 64KB and 256KB generation takes place in an oligopoly market. However, I have serious doubts about the accuracy of these outcomes, since the estimated parameter $\hat{c}_0$ is negative for all four generations.

Changing the marginal cost function may solve this problem. Until now, I assumed that marginal costs have a linear shape, so that the appropriate specification is (c1). In the following I will make use of other marginal cost functions (c2) to (c12) – as mentioned in (17) – to get reasonable results.

The analysis of Table 5 shows, that the coefficients of columns (1) to (4), that correspond to the linear MC specification, give no acceptable results. The problem is either, that the estimates for θ are negative (θ is a parameter for market conduct and should lie between 0 and 1), or, that the regression produces values below 0 for the fixed factor of MC $\hat{c}_0$. The outcomes of the quadratic MC functions – columns (9) to (12) – are also not satisfying, since most of the coefficients again have the wrong sign or are insignificant, respectively. Adequate results can only be found for the 64KB and the 256KB generation. Columns (6) to (8), which refer to the exponential MC specification, give reasonable and significant results for the 64KB generation. The coefficients of the exponential MC function including *output* – column (6) – have also the right signs, but $\hat{c}_0$ is insignificant. Nevertheless, I will use the MC specification (c6) for further analysis of the 64KB and the 256KB SRAM chip.

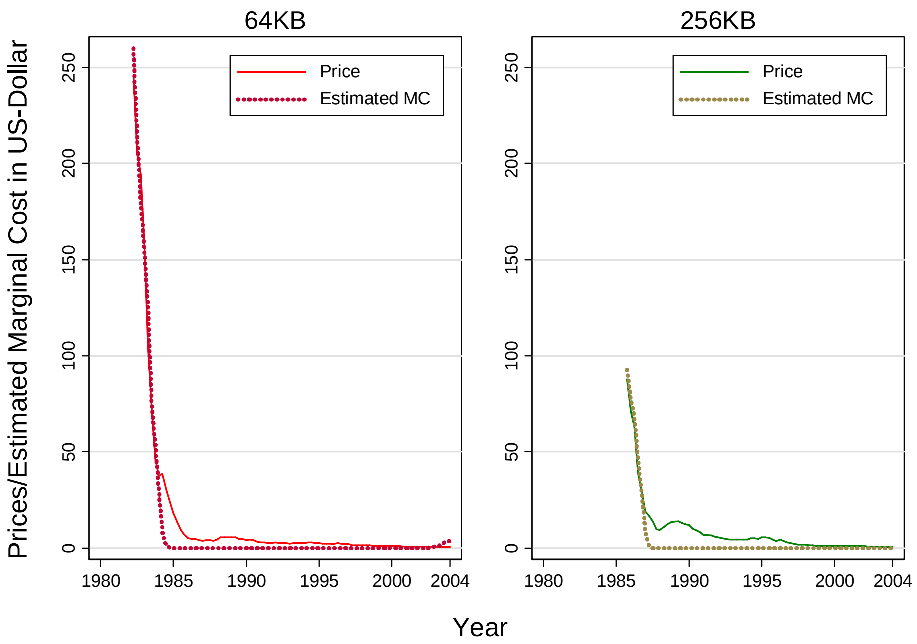
Table 5: Pricing Rule for SRAM chips - Estimated Parameters

Dependent variable: *pricec*												
	linear MC function				**exponential MC function**				**quadratic MC function**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
16KB												
$\hat{\theta}$	0.039	0.019	-0.019	-0.021	-0.019	-0.010	0.020	0.015	-0.057	-0.006	-0.042	-0.006
	(0.058)	(0.044)	(0.035)	(0.027)	(0.011)	(0.008)	(0.004)	(0.004)	(0.010)	(0.009)	(0.009)	(0.007)
$\hat{c}_0$	-22.758	-23.746	2.455	0.566	-2.049	-0.737	-1.144	-0.815	-6.769	-5.763	-3.779	-3.439
	(6.420)	(5.001)	(6.334)	(4.857)	(0.278)	(0.174)	(0.140)	(0.158)	(0.280)	(0.294)	(0.574)	(0.455)
$\hat{k}$	0.016	0.024	0.006	0.012	0.002	0.002	0.002	0.002	0.005	0.005	0.004	0.004
	(0.003)	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\hat{j}$		-0.001		0.000		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
$\hat{m}$			0.000	0.000			0.000	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
64KB												
$\hat{\theta}$	0.220	0.177	-0.017	-0.030	-0.026	0.053	0.061	0.055	0.013	-0.107	-0.137	-0.096
	(0.478)	(0.387)	(0.233)	(0.216)	(0.286)	(0.011)	(0.013)	(0.011)	(0.304)	(0.049)	(0.051)	(0.044)
$\hat{c}_0$	-31.228	-15.598	116.336	77.320	1.426	2.233	1.643	1.758	0.180	1.928	-23.940	14.767
	(42.733)	(31.339)	(29.835)	(28.519)	(3.121)	(0.266)	(0.534)	(0.414)	(6.955)	(1.577)	(2.043)	(2.946)
$\hat{k}$	0.023	0.037	-0.038	-0.012	0.001	0.002	0.002	0.002	0.002	0.004	0.008	-0.003
	(0.013)	(0.015)	(0.016)	(0.015)	(0.001)	(0.000)	(0.000)	(0.000)	(0.003)	(0.001)	(0.001)	(0.002)
$\hat{j}$		-0.001		0.000		-0.001		-0.001		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
$\hat{m}$			0.000	0.000			-0.001	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
256KB												
$\hat{\theta}$	0.245	0.230	-0.068	-0.055	-0.051	0.164	0.090	0.071	0.036	0.001	-0.029	-0.048
	(0.438)	(0.386)	(0.189)	(0.177)	(0.169)	(0.021)	(0.023)	(0.026)	(0.086)	(0.049)	(0.048)	(0.041)
$\hat{c}_0$	-21.405	-4.048	13.530	16.772	0.110	1.253	14.896	12.830	-2.339	3.496	3.882	12.175
	(20.285)	(13.567)	(11.142)	(10.104)	(2.129)	(1.726)	(1.278)	(1.342)	(2.793)	(1.104)	(2.380)	(1.746)
$\hat{k}$	0.016	0.013	0.002	0.002	0.001	0.002	-0.005	-0.004	0.003	0.001	0.000	-0.003
	(0.007)	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\hat{j}$		0.000		0.000		-0.001		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
$\hat{m}$			0.000	0.000			0.000	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)
1MB												
$\hat{\theta}$	0.034	0.080	-0.116	-0.081	0.080	0.081	0.091	0.090	0.025	-0.060	-0.046	-0.027
	(0.385)	(0.415)	(0.251)	(0.265)	(0.055)	(0.026)	(0.025)	(0.026)	(0.046)	(0.031)	(0.048)	(0.028)
$\hat{c}_0$	-23.025	-13.058	-14.471	-4.436	-2.720	-1.146	-1.621	-1.451	-5.984	-2.791	-1.808	-2.795
	(22.369)	(20.282)	(15.959)	(14.711)	(0.816)	(0.335)	(0.396)	(0.531)	(0.934)	(0.725)	(1.151)	(0.810)
$\hat{k}$	0.027	0.022	0.022	0.018	0.003	0.002	0.003	0.003	0.006	0.005	0.004	0.005
	(0.010)	(0.009)	(0.007)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
$\hat{j}$		0.000		0.000		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
$\hat{m}$			0.000	0.000			0.000	0.000			0.000	0.000
			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)

Notes: Standard errors are in parentheses. I included a time trend as an explanatory variable in the regressions of the 16KB generation, since the results would be insignificant otherwise. Column (1) refers to marginal cost function (c1), column (2) to MC function (c2) etc. The data are from Gartner, Inc. and Metall Bulletin Ltd.

The estimates for θ are 0.053 and 0.164 for the two mentioned generations, respectively, which means that the market for the 64KB SRAM chip is more competitive than the market for the 256KB chip. The Cournot solution is $\theta = {}^{1}\!/_{nof}$, which implies for both generations an average value of roughly 0.05 (the number of firms ranges from 1 to 35 for the 64KB generation and from 3 to 32 for the 256KB generation). Thus, I conclude that the suppliers of the two observed SRAM generations are oligopolists and have still some market power to raise price above marginal costs. $\hat{c}_0$ takes on values of 2.233 and 1.253, respectively and $\hat{k}$ values of 0.002 for both generations, which shows a positive impact of the price of silicon *sil1c* on the price of an SRAM chip. The number of units sold, *output*, has – as expected – a small negative effect on marginal costs and on the price.

Figure 7: Comparison of Prices and Estimated Marginal Costs - according to specification (c6) - in US-Dollar for the SRAM generations 64KB and 256KB, 1980-2004

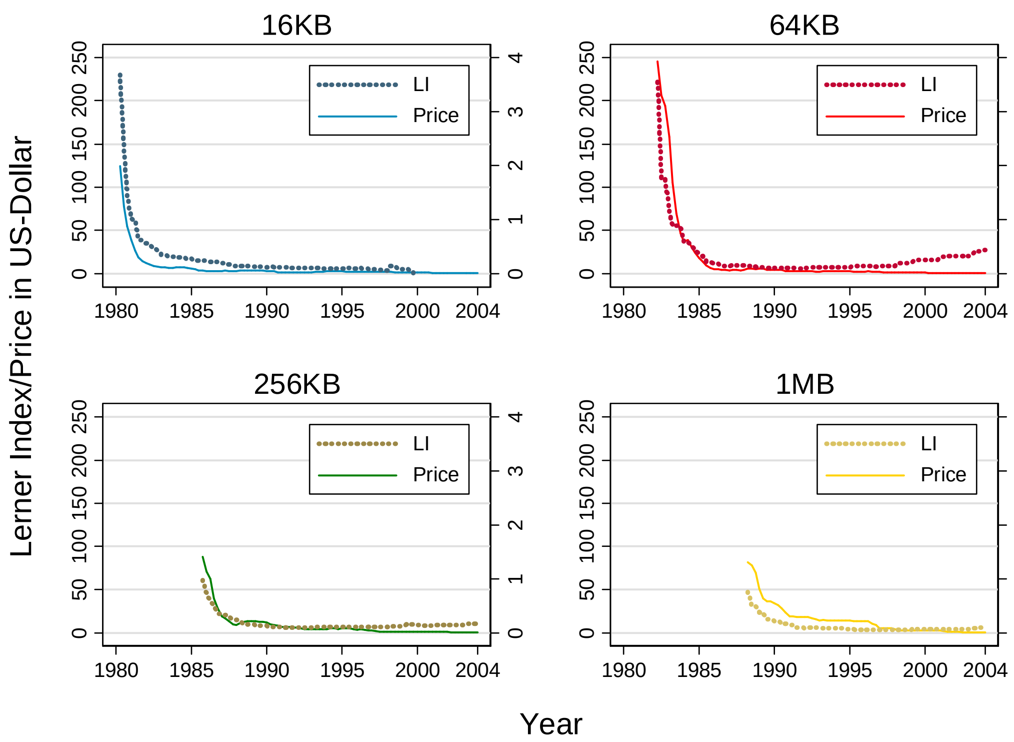


Notes: The data are from Gartner, Inc. and Metall Bulletin Ltd.

Figure 7 shows the results of column (6) of Table 5 graphically. Estimated marginal costs (MC) are compared with the price of an SRAM chip of the 64KB and the 256KB generation. Examining the shape of the estimated MC curves, one notices that they are (like the prices) very high when introducing the chip on the market. This fact is easy to explain, since many chips are defective in the beginning of the production process, but the percentage of useable chips increases little by little with production experience. After market launch, estimated MC exceed prices for one to two years. This situation is found in many industries, where learning-by-doing is present (like the SRAM industry), after the introduction on the market.[19] For the 64KB generation I found out, that from the end of 1983 on, MC fall below price and the estimated values are close to 0 until the end of 2002, where price is again lower than MC. The MC curve of the 256KB generation is above the price curve from mid 1985 to mid 1986. From this time on, estimated MC decrease until they reach almost 0 and stay on such a low level for the whole observation period.

Although the chosen MC curve lies above 0 in the whole time period (in contrast to other MC specification), I am not sure if I should trust these results. Analyzing the exact values of the estimated MC of the 256KB generation I found out that the curve lies on the 0-line from 1994 to 1998. Thus, I think that my model doesn't work well, since in reality, there exist at least very low costs for producing one additional unit of a memory chip. Furthermore, a reason, why the method works for two but not for all four selected generations, is not apparent to me.

Figure 8: Comparison of Lerner Index and Price of an SRAM chip in the time period of 1980 to 2004 for the 16KB, 64KB, 256KB and 1MB generation



Notes: Lerner Index restricted to ≥0. The data are from Gartner, Inc. and Metall Bulletin Ltd.

Figure 8 tries to solve the second question of my thesis, which asks if market power is higher for higher prices. High prices of an SRAM chip are found mainly in the first year of the product life cycle. Figure 1 suggests, that higher prices are not only due to high prices of

[19] Zulehner (2003)

silicon, but that other factors have an impact on the price of an SRAM chip. Figure 8 supports this statement, since it shows that the Lerner index (an indicator for market power) is generally higher for the high prices at market launch of the different generations. Although the Lerner index for all generations (except for the 16KB SRAM) rises again slightly in the last observed years, Figure 8 indicates, that market power is highest in the year after the introduction of an SRAM chip on the market (when prices are very high) and thus, prices can in this time period be raised above MC. Unfortunately, this is the opposite of what Figure 7 suggests, where MC exceed prices in the first periods of the life cycle. Since evidence in industries, where learning-by-doing is an issue, shows, that MC are often higher than prices in the introduction phase, I am not sure in which outcome to believe.

6 Conclusion

The SRAM (Static Random Access Memory) industry is, like the semiconductor industry in common, a quite young industry. SRAM chips are not as often used as DRAM chips. The product life cycle of memory chips is relatively short. Since the number of transistors per wafer is increased steadily, new generations are invented within short periods of time. These are all reasons for few observations per SRAM generation. In my work, I chose to analyze the four most successful generations – which had the most observations over time – from 21 available generations. The selected generations – 16KB, 64KB, 256KB and 1MB – had 91, 88, 74 and 64 observations, respectively.

The goal of my diploma thesis is to get estimates for demand, marginal cost and market conduct, although I only have data for price and sold units of SRAM chips, price of silicon (the main cost factor in the production of semiconductors) and the number of firms in the SRAM industry at my disposal. In the course of the paper, I described these chosen data sets and set up a model, that consists of a simple linear demand function and a supply relation and is based on the NEIO (New Empirical Industrial Organization) approch and particularly, on the model of Genesove and Mullin (1998).

The supply relation contains a parameter for market conduct, θ, and a marginal cost function c. θ should take on values between 0 and 1, where 0 stands for a market with perfect competition, 1 for a monopoly or cartel situation in the industry and a value in between for an oligopoly situation on the market. The demand function has to be estimated using the 2SLS (two stages least squares) estimation method, because the variables *pricec* and *output* are assumed to be both endogenous and thus, correlated with the error term. A Hausman (1978) test verifies this decision. As assumed, a higher price leads to fewer units of SRAM chips being sold. This effect is highest for the 256KB generation and lowest for the 64KB generation.

Since estimation with a linear marginal cost funcion doesn't produce any reasonable results, I tried a few other marginal cost specifications (exponential or quadratic form, including output and/or lagged cumulative output) to solve the first question of my diploma thesis. The results were satisfying only for the 64KB and the 256KB generation and the exponential specification. The other outcomes were unrealistic because of the wrong signs of the coefficients. According to my model, the market for the 64KB SRAM chip is more competitive than for the 256KB chip. Suppliers of both generations may operate in an oligopolistic market, so they have some market power to raise price above marginal costs. Thus, in the early periods of the product life cycle marginal costs exceed prices. After one to two years until the end of the observation period marginal costs are very close to 0 and below prices.

Nevertheless, I am not sure if I should rely on these results. The model gives useable results only for two of the selected four generations, so it cannot be adapted to the whole SRAM industry. I tried different marginal cost functions to meet the shape of the true marginal cost curve and added different factors which may have an impact on marginal costs. For another estimation (that is not displayed in this paper) I used the price per KB instead of the absolute price together with the constructed marginal cost functions. But all the outcomes were not satisfying.

The reasons why the model is not able to produce reasonable results for all generations can hardly be explained. The main problem may be that there do not exist enough observations for the chosen generations. Another factor to mention is, that for the 64KB, the 256KB and the 1MB generation the product life cycle has not ended in 2004, but data was not available for the years after. Furthermore, the extreme price fall in the first year after introduction may have distorted the results, since in my model price-cost margins (and thus market conduct) of each generation are assumed to be constant in the whole observation period. In reality, there may be changes in competition throughout the product life cycle. Probably, I would also have to take other factors into account, which may influence marginal costs but were not considered in my thesis. Therefore, the marginal cost function and – as a consequence – the pricing rule may not fit to the real situation in the SRAM industry.

The second point of my thesis deals with the question, if market power is higher in the early periods of the product life cycle. Unfortunately, a concrete answer to this question cannot be given. The calculation of the Lerner index gives high values for high prices of SRAM chips, which are prevalent in the first year of the life cycle of a chip. This indicates, that market conduct is more likely a collusive oligopoly in the beginning of the life cycle of an SRAM generation than one or two years after, and firms can raise prices above marginal costs. The estimation of the chosen pricing rule tells the opposite (as mentioned above): marginal costs exceed prices in the first time of the product life cycle. Thus, further research can be done on this topic to find out how SRAM producing firms behave.

Summarizing my diploma thesis, I can say that the problem of identifying price-cost-margins in the SRAM industry is not yet solved. Although I was able to produce estimates of market conduct and marginal costs for the 64KB and the 256KB generation of SRAM chips, I have to put these results in question, since the model in this form cannot be adapted to other generations. Moreover, no concrete answer was found for the second question about higher market power in the first periods of the product life cycle of SRAM chips.

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A Appendix

A.1 Derivation of the pricing rule

Given the general supply relation in (13) and the general demand function in (3), a pricing rule can be formed, which depends on marginal cost c, the conduct parameter θ, and the parameters of the demand function α and γ.

Since I know that

$$\frac{\partial P(Q)}{\partial Q} = \left(\frac{\partial Q(P)}{\partial P}\right)^{-1}, \tag{30}$$

I can differentiate the demand function (3) with respect to P and get

$$\frac{\partial P(Q)}{\partial Q} = \left(\frac{\partial Q(P)}{\partial P}\right)^{-1} = \left(-\gamma\beta(\alpha - P)^{\gamma-1}\right)^{-1} \tag{31}$$

which I plug together with the demand function (3) into the supply relation (13) to receive

$$P - \theta\beta(\alpha - P)^{\gamma} \frac{1}{\gamma\beta(\alpha - P)^{\gamma-1}} = c \tag{32}$$

(32) is now reduced to

$$P - \theta \frac{\alpha - P}{\gamma} = c \tag{33}$$

and formed to

$$P - \frac{\theta\alpha - \theta P}{\gamma} = c \tag{34}$$

and

$$P+\frac{\theta P}{\gamma}=c+\frac{\theta\alpha}{\gamma} \tag{35}$$

Another way to write this equation is

$$P\left(1+\frac{\theta}{\gamma}\right)=\frac{\theta\alpha+\gamma c}{\gamma} \tag{36}$$

So, finally I get the general pricing rule

$$P(c)=\frac{\theta\alpha+\gamma c}{\gamma+\theta} \tag{37}$$

A.2 List of abbreviations and variables

DRAM	Dynamic Random Access Memory
IV	Instrumental variable
KB	Kilobyte
MB	Megabyte
MC	Marginal cost
NEIO	New Empirical Industrial Organization
SCPP	Structure-conduct-performance paradigm
SRAM	Static Random Access Memory
2SLS	Two stages least squares

pricec or P	Price of an SRAM chip in constant US-Dollar
output or Q	Sold units of SRAM chips
sil1c	Price of silicon in constant US-Dollar
nof	Number of firms in the SRAM industry
time1	Time trend
outputcum_1	Sold units of SRAM chips accumulated until time t-1
θ	Parameter for market conduct
c	Marginal cost function
PI	Price index/price per KB in constant US-Dollar
L_η	Lerner index

A.3 List of Tables

A.4 List of Figures

A.5 Zusammenfassung

Kosten-Preis-Spannen sind im Allgemeinen nicht messbar, da Unternehmen keine Daten über Grenzkosten preisgeben. Die „New Empirical Industrial Organization“ (NEIO) Methode versucht, diese Kosten und auch das Marktverhalten eines Unternehmens zu schätzen. Auch die vorliegende Diplomarbeit baut auf diesem Ansatz auf und konzentriert sich dabei auf die Static Random Access Memory (SRAM) Industrie. Die Daten dafür stammen von Gartner, Inc, der Silizium-Preis (Hauptkostenfaktor bei der Produktion von Halbleitern) von Metall Bulletin Ltd. Die Analyse findet auf der Industrie-weiten Ebene statt, die Ergebnisse müssen deshalb als Durchschnitt aller Unternehmen gesehen werden.

Die Fragen, die in dieser Arbeit untersucht werden sind, ob SRAM-produzierende Unternehmen über Marktmacht verfügen, wie hoch Kosten-Preis-Spannen sind und ob die Marktmacht im ersten Jahr ab der Markteinführung der SRAM-Chips größer ist.

Für das Modell, das aus einer Nachfragefunktion und einer Preisrelation besteht, werden verschiedene Spezifikationen von Grenzkostenfunktionen (lineare, exponentielle, quadratische) verwendet und auf vier Generationen von SRAM-Chips (16KB, 64KB, 256KB, 1MB) angewandt. Als Grundlage dient dabei die Arbeit von Genesove und Mullin (1998), die den NEIO-Ansatz an der US-amerikanischen Zuckerindustrie testen.

Die Ergebnisse, die nur für die 64KB und die 256KB Generation sinnvoll und interpretierbar sind, lassen auf eine oligopolistische Marktstruktur schließen. Unternehmen verfügen also über Marktmacht um den Preis über die Grenzkosten setzen zu können. Jedoch müssen die Resultate dieser Schätzungen angezweifelt werden, da das Modell nicht auf alle vier ausgewählten Generationen angewandt werden kann und nur wenige Beobachtungen pro Generation existieren.

Der Vermutung, dass die Marktmacht in der Einführungsphase des Produktlebenszyklus (die auch von sehr hohen Preisen geprägt ist) größer ist, kann nicht wirklich zugestimmt werden. Ein Vergleich des errechneten Lerner Index mit dem Preis der SRAM-Chips bestätigt zwar, dass höhere Preise mit höheren Werten des Lerner Index und deshalb mit größerer Marktmacht zur Markteinführung der Chips einher gehen. Die Modell-Schätzungen brachten jedoch gegensätzliche Ergebnisse: In der Anfangsphase der SRAM-Produktion seien die Grenzkosten höher als die Marktpreise. Die Tatsache, dass das Marktverhalten der Unternehmen innerhalb des Produktlebenszyklus nicht konstant bleibt (wie die Annahme des

Modells voraussetzt), könnte ein Grund für die zweifelhaften und unterschiedlichen Resultate sein.

A.6 Curriculum Vitae

Agnes Pesau

Contact

Adress	Prager Straße 5/10
	1210 Vienna
	Austria
E-mail	agnes_pesau@hotmail.com

Personal Data

Date of birth	19th July 1986
Place of birth	Mistelbach, Austria
Nationality	Austria

Education

2005 – 2011	Study of Economics, University of Vienna
2000 – 2005	Handelsakademie Mistelbach, Austria

Professional Experience in the field of economics

09/2010 – 12/2010	Internship at the Centre for European Economic Research (ZEW) GmbH, Mannheim, Germany
07/2009	Internship at the Financial Department of Raiffeisen-Holding Niederösterreich-Wien, Vienna, Austria

Publications

Rammer, C., Pesau, A., Sellenthin, M.O. (2011), Europäische Dimension der Forschungs- und Innovationspolitik, Studien zum deutschen Innovationssystem Nr. 12-2011, Berlin.

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