Aalto University
School of Business

Economic Approach to Advertising and Consumer Choice - Comparison of Advertising Elasticities in the Smartphone Handset Market between Countries, Media and Advertisers

Economics

Master's thesis

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AALTO UNIVERSITY SCHOOL OF BUSINESS ABSTRACT
Master's Thesis, Economics 4.7.2013

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Economic Approach to Advertising and Consumer Choice – Comparison of Advertising Elasticities in the Smartphone Handset Market between Countries, Media and Advertisers

Purpose of the Study
In my master's thesis I attempt to give the economist's view of advertising and consumer choice. I represent some reasons why economists are interested in researching them. I also do an empirical research to demonstrate the response of sales to advertising. The empirical part of my thesis concentrates on the smartphone handset market which is a typical example of a market with infrequently purchased goods with the frequent introductions of new products. Such market suits well for the discrete choice modeling framework. I concentrate on high-end smartphones the price of which has exceeded €300 at some phase of the life cycle. These are more interesting from the economist's point of view, because they are more differentiated, innovative and less prone to the price competition than the cheaper ones. Non-price competition in the market of differentiated goods can be considered as an umbrella for the paper.

Methodology
The thesis starts with the literature review about economic, both theoretical and empirical, research concerning advertising. I introduce the potential effects of advertising on the market structure and on the utility of a consumer. I cover some consumer choice behavior models and concentrate on logit model which is applied in the empirical part of the paper. In the empirical part of the paper, I compute the advertising elasticities of market share in nine different markets (China, Germany, India, Indonesia, Italy, Russia, Saudi Arabia, United Kingdom, USA), by different media (cinema, online, outdoor, print, tv) and by advertisers (manufacturer, operator/retailer). The model does not fit for computing substitution patterns between goods but it is a simple way of comparison market share responses to advertising between countries, media and advertisers. I use the unbalanced panel data of sales volumes and advertising investments of 20 products representing various brands from January 2011 until November 2012. I run different regressions (pooled OLS, brand fixed effects and product fixed effects) with advertising as a periodical investment and as a depreciating and accumulating stock.

Findings
Advertising elasticities differed somewhat between different regressions, but China and United Kingdom got the highest elasticities in most of the regressions whereas Germany and USA got the lowest. By media, the highest elasticities on the whole sample level got print and tv. That result varied somewhat across countries. Some media got implausible or non-significant coefficients, which is partly explained by the noise and partly by the fact that absolute advertising investments do not capture the advertising exposure as clearly as advertising measured in GRP. The advertising by advertisers yielded neither significant nor plausible results, which is at least partially explained by the measurement error in the data.

Keywords: Smartphone industry, advertising elasticity, consumer choice, non-price competition

AALTO-YLIOPISTON KAUPPAKORKEAKOULU TIIVISTELMÄ
Pro gradu –tutkielma, taloustiede 4.7.2013

Aapo Parkkonen

Taloustieteellinen lähestymistapa mainontaan ja kuluttajan valintaan – Älypuhelinlaitteiden mainontajoustojen vertailu maiden, viestintäkanavien ja mainostajien välillä

Tutkimuksen tarkoitus

Pro gradu –tutkielmassani pyrin esittämään taloustieteilijän näkemyksen mainontaan ja kuluttajan valintakäyttäytymiseen. Esitän syitä miksi taloustieteilijät ovat kiinnostuneita niistä. Teen lisäksi empiirisen tutkimuksen havainnollistaakseni myyntien reaktiota mainontaan. Työni empiirinen osa keskittyy älypuhelinlaitteiden markkinaan, joka on hyvä esimerkki harvoin hankittujen tuotteiden markkinasta, jolle tulee usein uusia tuotteita. Tällainen markkina sopii hyvin diskreetin valinnan mallien viitekehykseen. Keskityn kalliimman hintaluokan älypuhelimiin, joiden hinta on jossain elinkaarensa vaiheessa ylittänyt 300€. Taloustieteilijän näkökulmasta ne ovat mielenkiintoisempia kuin edullisemmat, koska ne ovat enemmän differoituneita, innovatiivisempia ja siksi vähemmän alttiita hintakilpailulle. Yksi työn kattoteemoista onkin ei-hintakilpailu differoiduilla tuotteilla.

Menetelmä

Tutkielma alkaa kirjallisuuskatsauksella taloustieteellisestä sekä teoreettisesta että empiirisestä kirjallisuudesta koskien mainontaa. Esittelin mainonnan potentiaalisia vaikutuksia markkinan rakenteeseen ja kuluttajan hyötyyn. Käsittelen myös kuluttajan valintakäyttäytymisen malleja keskittyen logittimalliin, jota hyödynnetään empiirisessä osuudessa. Empiirisessä osuudessa lasken markkinaosuuden mainontajoustoja yhdeksällä eri markkinalla (Kiina, Saksa, Intia, Indonesia, Italia, Venäjä, Saudi Arabia, Yhdistynyt Kuningaskunta ja Yhdysvallat), eri viestintäkanavittain (elokuvateatteri, online, ulkomainonta, painotuotteet ja tv) sekä mainostajittain (valmistaja, operaattori/jälleenmyyjä). Käytetty malli ei sovellu tuotteiden välisten substituutioiden laskentaan, mutta tarjoaa yksinkertaisen tavan verrata markkinaosuuden reaktioita mainontaan alueiden, mainontakanavien ja mainostajien välillä. Datana käytän kiertävää paneeliaineistoa 20 useita brändejä edustavan tuotteen myyntivolyymeistä ja mainontainvestoinneista tammikuusta 2011 marraskuuhun 2012. Suoritan eri regressioita (yhdistetty PNS, brändin kiinteät vaikutukset ja tuotteen kiinteät vaikutukset), joissa mainontaa käsiteltiin sekä kausikohtaisena investointina että kuluvana ja kasvavana varastona.

Tulokset

Mainontajoustot erosivat jonkin verran eri regressioiden välillä, mutta Kiina ja Yhdistynyt Kuningaskunta saivat suurimmat joustot useimmissa regressioissa, kun taas Saksa ja Yhdysvallat saivat pienimmät. Koko näytteen tasolla viestintäkanavista painotuotteet ja tv saivat korkeimmat joustot. Nämä tulokset vaihtelivat hieman maittain. Jotkut viestintäkanavat saivat epäuskottavia ja ei-merkitseviä kertoimia, mikä selittyy osittain datan häiriöillä ja osittain sillä, että absoluuttiset rahamääräiset mainontainvestoinnit eivät mittaa yhtä hyvin altistumista mainonnalle kuin kattavuusyksikköinä (GRP) mitattu mainonta. Regressio mainostajittain ei tuottanut merkitseviä eikä uskottavia tuloksia, mikä ainakin osittain selittyy datan mittausvirheellä.

Avainsanat: Älypuhelinteollisuus, mainontajousto, kuluttajan valinta, ei-hintakilpailu

Preface

This paper has been done in cooperation with Nokia Corporation in the spring 2013. I take the opportunity to thank the marketing and strategy planning team for providing me with good circumstances to complete my thesis efficiently. Special thanks to D.Sc. Lotta Väänänen for valuable advice in data processing and completing the econometric analysis.

I would like to thank my family, friends and fellow students for supporting me through my studies at Aalto University School of Business in 2008-2013. The journey was hard, but interesting and fun as well and absolutely worth making!

In Helsinki on 4th of July 2013

Aapo Parkkonen

Esipuhe

Tämä tutkielma on tehty yhteistyössä Nokia Oyj:n kanssa keväällä 2013. Käytän hyväkseni tilaisuuden kiittää marketing and strategy planning teamia siitä, että se tarjosi minulle hyvät puitteet tehdä tutkielma tehokkaasti. Erityiskiitokset KTT Lotta Väänäselle arvokkaista neuvoista datan käsittelyssä ja ekonometrisen analyysin teossa.

Haluan kiittää perhettäni, ystäviäni ja opiskelutovereitani kannustamisestani läpi opintojeni Aalto-yliopiston kauppakorkeakoulussa vuosina 2008-2013. Tie oli raskas, mutta mielenkiintoinen ja hauskakin ja ehdottomasti kulkemisen arvoinen!

Helsingissä 4. heinäkuuta 2013

Aapo Parkkonen

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1 Introduction

Advertising is intuitively strongly connected with the marketing. However, marketing has its purpose: to increase sales. Sales have a strong connection with the performance of a company and the performance of companies has a strong impact on the market structure. Thus, the advertising is tightly connected with the economics as well. Bain (1959) has represented structure-conduct-performance paradigm. Advertising is one of the main means of industry conduct besides the price. Advertising can be nowadays the even more important means of conduct than the price, because as Schmalensee (1976 and 1978) has noted, the most important form of the contemporary competition is non-price competition. Therefore advertising investments can become notably high in some industries and the response of sales to them is a good topic to be researched in order to improve the budget allocation decisions.

Advertising and its economic aspects have been researched relatively lot. One of the earliest analyses of the economic aspects of advertising is made by Kaldor (1950-51.) Kaldor contributes the influence of advertising on market structure and has claimed that advertising has led to market concentration which can have both positive and negative consequences. However, also the ban of advertising has been proven to lead to a heavy market concentration (e.g. Eckard, 1991.) Advertising increases consumers' awareness of goods and absence of its can reduce awareness of different alternatives and thus make them choose the same old brands again and again. Same time advertising (especially of persuasive character) can make markets more concentrated as well and create the sunk cost barrier of entry (e.g. Kessides, 1986; Doraszelski and Markovich, 2007.) All this prove that there is no straightforward interpretation of advertising and its influence on the market structure and thus the usefulness or harmfulness of it cannot be justified instantly.

Advertising and its influence on sales is a part of the research of consumer behavior. Nowadays goods are differentiated both horizontally and vertically which relaxes the price competition and makes higher markups possible. Purchase of durable consumer goods is usually a discrete choice. Discrete choice models aim at modeling the population choice behavior from individual choice probabilities. These kinds of models include for example logit and probit models and elimination models (e.g. McFadden. 1984.) One of the main difficulties in this kind of modeling is that all factors which influence the decision are not observed (by the researcher.) These characteristics must be either circumvented or estimated somehow. Evasion can lead to biased results because the unobserved characteristics are usually correlated with prices. Techniques for estimating or computing unobservable characteristics have been developed. Even though the models have many simplifying assumptions, they have captured the choice behavior quite realistically.

Berry Levinsohn and Pakes (1995) modeled market equilibrium prices using U.S. automobile market data. They extended the basic logit approach and applied Hansen's (1982) generalized method of moments in defining unobservable (for econometrician) characteristics on demand and cost sides. Goeree (2008) extended BLP by adding advertising as one of the components of its. She added a term of information technology that defines the probability that a consumer is aware of the product. The main contribution of Goeree is that the limited information makes demand less elastic and markups higher than under the assumption of full information. Barroso and Lloebet (2012) included advertising into the utility function of a consumer. Advertising not only increases the awareness of a consumer but also the utility of a consumer. Thus, the choice probability increases as a result of advertising not only because of the increase in the probability of a consumer being aware of the product but also because she gains utility from advertising. This again takes the modeling closer to the reality, because Kaldor (1950-51) already mentioned that there is demand for advertising itself and thus it can increase the utility of a consumer. The main finding of Barroso and Loebet (2012) was that advertising (especially conducted upfront) accelerates the awareness process of new goods.

In this paper, I concentrate on high-end smartphone handset (the initial price above €300) market between January 2011 and November 2012. The smartphone market is a good subject for discrete choice modeling because they are infrequently purchased durable goods with the frequent launches of new products. I use sales volumes and advertising investments data to uncover the possible connections between the advertising and the market shares by computing advertising elasticities of market share. The advertising elasticity is computed as any elasticity in economics. Albers, Mantrala and Sridhar (2010) determined the advertising elasticity as the ratio of percentage change in output to the corresponding percentage change in the input. In this case, the output is the market share and the input is advertising investment. The applied in this paper method is not sufficiently suitable for computing substitutions between products as will be demonstrated below. Therefore I concentrate on analyzing the effectiveness of advertising between countries, media and advertisers. Probably as a result of measurement error, the elasticities between media and advertiser could not be calculated plausibly. Perhaps one reason for that is as well that the advertising in the data is measured in absolute monetary terms instead of gross rating points (GRP), which are given by the reach and frequency of the advertising in a given time period. The absolute advertising investments are used e.g. in represented in Chapter 3 researches of Goeree (2008) and Barroso and Lloebet (2012.) GRP is applied in a number of researches as well (e.g. Dubé, Hitsch and Manchanda, 2005.) They mentioned that GRP captures more realistically how advertising campaigns impact on consumer behavior as they tell more about the exposure of consumers to the advertising.

The researched markets are the United Kingdom, Germany, Italy, Russia, the USA, Saudi Arabia, India, Indonesia and China. They represent a comprehensive sample of world smartphone sales by including the USA, some developed European markets and some emerging markets of the Middle East and Asia. The elasticities between countries have been researched little especially using the same model and data for all countries. Henningsen, Heuke and Clement (2011, 208) noted in their meta-analysis that based on different researches, the elasticities are higher in Europe than in the USA. My main approach is the basic logit model, because it is nice and simple to compute and has proven to be quite robust despite some intuitively unrealistic background assumptions. Also the elasticities can be conveniently calculated using it. My main findings are that advertising should be treated as a stock and not just as a periodical phenomenon. The advertising investments are the highest for the goods with the highest market shares. The highest advertising market share elasticities are in the United Kingdom and China. I applied different regression techniques (pooled OLS, brand fixed effects and product fixed effects) and all of them yielded somewhat different results. Russia and China got significant coefficients in each regression. Advertising by the channels yielded plausible and significant coefficients for the print and TV. The reason probably is that the most of the investments are spent on these channels.

The structure of current paper is following: Chapter 2 describes the many ways how advertising can be connected with the economics and how it has been researched in such context. Chapter 3 takes a closer look at discrete choice models and their applications in modeling consumer behavior. Chapter 4 gives a brief description of contemporary smartphone industry. In Chapter 5, I conduct my data analysis and in Chapter 6 I discuss about conclusions.

2 Advertising in Economic Process

This paper analyzes the connection between advertising investments and market shares in the smartphone market. A field of economics called industrial organization is examining the structure of and boundaries between firms and market. Industrial organization is according to Journal of Economic Literature (JEL) one in 19 economics' primary categories. Joe Bain (1959) introduced structure-conduct-performance paradigm (SCPP) generated by Harvard School in 1940-ies. According to SCPP, the market structure means e.g. the market size, product differentiation and barriers to the entry of new firms. Market conduct can be interpreted as any means which firms use to compete with others, like advertising, pricing, investments, strategies and other tactics. Performance can be explained by the success of a firm. Profits are one good metrics for that. In the basic supply-demand framework, the price is the main conduct parameter. However, many researches and papers (See Schmalensee 1976 and 1978) have argued that most important form of contemporary competition is non-price competition. Draganska and Klapper (2011, 660) in contrast with the traditional assumptions in economics, state that the increase in sales over time is attributed to increasing awareness of the product and not to decreasing price during its life cycle. Advertising is the main means of accumulating awareness. The main parameters of competition can be considered nowadays advertising and product differentiation.

The concept of product differentiation was represented as a competitive strategy the first time by Chamberlin in 1933. After that, it has been discussed more and more. In addition to the differentiation Smith (1956) represented also the concept of market segmentation, which he found to be quite close to differentiation. Differentiation reduces the pressure of price competition. Differentiation is therefore an essential part of contemporary industrial organization. It can be divided into two components: horizontal differentiation and vertical differentiation. In case of vertical differentiation differences between products are objectively measurable, whereas horizontal differentiation distinctions cannot be easily measured. This can be connected with the concepts of experience and search goods represented by Nelson (1970.) The previous ones are goods the quality of which cannot be objectively measured a prior, but it can be ascertained upon consumption. The latter ones' quality can be objectively measured in advance and thus they are proner to price competition.

In SCP, there are two general competing hypotheses: the traditional SCP hypothesis and efficient market structure hypothesis. (See Shaik et al, 2009.) The previous means that the industry concentration is inversely related to the degree of competition. This means that concentration would lead to collusion. The latter means that the performance of a firm is positively related to its efficiency. The most efficient firms with low cost structure could increase their market share and this way their profitability as well. Taking into account the economies of scale and their possible effect on lowering prices as well as need for capital for new innovations, the concentration cannot be a completely harmful thing: it can make possible lower prices and new innovations.

One interesting question that arises from the industrial organization's point of view is: What is the relationship between the market structure, performance and conduct? In other words: How does market conduct effect on the performance of a firm and the market structure? In older literature, the main means of conduction has been the price. The analysis of Bresnahan (1987) of the US automobile industry and its supply-side shock (also known as price war) in 1955 is a transparent and simple approach to analyze the changes in an industry as the conduct changes.

The year 1955 in the US automobile industry was of special interest, because then the prices fell despite macroeconomic expansion, there was an unanticipated increase in quantities and the share of basic transportation segment in total auto sales increased. The hypothesis of Bresnahan is that the shock was caused by the change of industry conduct from collusive to competitive. In the paper, he tested the hypothesis and got support for it. The conduct of the US automobile industry was competitive in 1955 and collusive in both 1954 and 1956. The competitive conduct cut the profits the most in the small car segment, because there are a lot of close substitutes and thus it is proner to the price competition. Bresnahan (1987, 467) notes as well that the total effect of the change of the industry conduct from collusive to competitive is larger when there are more firms than when there are few of them. That is because in case of fewer firms even in case of competition all the firms have at least some market power to guarantee higher price-cost margins, which are mentioned being a good measure of market power. (Bresnahan 1987, 479.) Thus there is obviously a tight connection between structure, performance and conduct. In the next subchapter, I will move on to discuss advertising as a means of industry conduct.

2.1 Advertising as a Means of Industry Conduct

Besides the price another important means of industry conduct is mentioned already by Bain (1959) and it is advertising. As Schmalensee (1976 and 1978) and Draganska and Klapper (2011) note, it can be nowadays the even more important means of the industry conduct than the price. Advertising and its economic aspects have been researched for quite a long time. As advertising can be connected with the economics and it has been connected in such an early stage, it is reasonable to try to explain the economic impacts of advertising. Tirole (1988, 115) mentioned, that advertising has been for a long time considered manipulative and wasteful. It has many psychological and sociological aspects that go beyond objective inference.

However, the economic aspects of advertising have been recognized and analyzed relatively early. Kaldor (1950-51) has written thoroughly about the economic aspects of advertising. He mentioned that the economic aspects of advertising can be conceived either as an analysis of factors which determine the scale of advertising expenditure in different trades (how much spent on advertising in an industry and the price of advertising) or as an inquiry into the effects of advertising on the distribution of costs and prices (advertising expenditure as given, examining concentrated on the welfare effects of advertising.) He defines the provision of information as the social function of advertising. It gives information about goods, their qualities and prices. In this chapter, I will introduce some aspects of advertising research and its connections to the economic processes. One of the influence channels of advertising is a sunk cost which is unrecoverable. Therefore advertising has been researched as an entry and exit game. In the next subchapter, I will briefly introduce the research.

2.2 Advertising as an Entry and Exit Game

Advertising as a sunk cost has been researched mostly as an entry game. One example of such research is Kessides (1986) paper. That paper simply takes the expected discounted profits of a new entrant as a starting point. The entries to the industry continue until the expected discounted profits approach zero. In the market, according to Kessides, advertising can be considered to be either market power (persuation) school or competition (information) school. In the case of persuation school $\frac{\partial}{\partial \frac{A}{S}}\left(\frac{1-\alpha}{\alpha}\right) < 0$, where A/S is advertising to sales ratio and α is the probability the entrant perceives having a successful entry. This means that advertising increases buyer inertia. In case of information school, when $\frac{\partial}{\partial \frac{A}{S}}\left(\frac{1-\alpha}{\alpha}\right) > 0$, the advertising can be considered prompting to enter.

In the paper Kessides uses as a data net entry between 1972 and 1977 in all U.S. SIC (Standard industrial classification) 4-digit manufacturing industries (altogether 266 industries.) The following equation (1) describes the price-cost margin of the ith industry.

$$\Pi_0 = [VA_0^i - W_0^i - (r + \lambda_M^i)M_0^i - (r + \lambda_B^i)B_0^i - (r + \lambda_A^i)A_0^i]S_0^i \qquad (1)$$

i=1,…,266, VA_0^i =value added, W_0^i=payroll, r= opportunity cost of capital, λ_M^i, λ_B^i, λ_A^i are depreciation rates for, machines, buildings and advertising. M_0^i and B_0^i are fixed depreciable assets (machines and buildings) and A_0^i is advertising expenditures. S_0^i are industry sales. Kessides assumed that his modeling probably overestimates sunk costs of machines and buildings, because they obviously have some resale value. However, sunk costs of advertising are captured quite well. There is made one simplifying assumption that capital-to-sales and advertising-to-sales ratios are same for entrants and incumbents.

With these specifications Kessides tested four hypotheses:

1) For the potential new entrant, the required investment in advertising leads to an unrecoverable entry cost in case of failure – thus, advertising creates a sunk cost barrier to entry.
2)
   a) Advertising is a persuation school (see above)
   b) Advertising is an information school
3) The threat of an aggressive post-entry reaction (such as output expansion) is more credible when incumbents have positive profits to protect and are able to cover transitory losses. Thus,

$$\frac{\partial}{\partial \Pi_0}\left(\frac{1-\alpha}{\alpha}\right) > 0 \tag{2}$$

Π_0 is industry pre-entry level of profits.

4) The threat of an aggressive post-entry reaction is more credible when the free-rider effect in driving the entrant out is smaller. Thus,

$$\frac{\partial}{\partial C_0}\left(\frac{1-\alpha}{\alpha}\right) > 0 \tag{3}$$

C_0 is industry pre-entry level of structural concentration.

Kessides got support for hypotheses 1, 3 and 4. Same time the possible failure of entry is less likely if the advertising costs in an industry are high. This supports the assumption of advertising as an information school rather than as a market power school.

According to Doraszelski and Markovich (2007), the incumbent firm can either accommodate or deter entry by its advertising decision. They modeled entry accommodation and deterrence. In order to explain their model, I must introduce the concept of outside good. It is a good which does not belong to the modeling. The presence of it is necessary in order to keep the choice set mutually exclusive and exhaustive by allowing consumers not to purchase any of the researched products. I will return to the outside good in Chapter 3. The main assumption is that all consumers are aware of the outside good. This is also a realistic assumption because the "outside good" is a somewhat misleading appellation, because it contains all possible alternatives of not purchasing any of the goods of interest. In addition, some consumers are aware of neither firm 1 nor firm 2 $(1-s_i)(1-s_j)$. Some are aware of firm 1, but not of firm 2 $s_i(1-s_j)$, some are aware of firm 2 but not of firm 1 $(1-s_i)s_j$. The last segment is aware of both firms s_is_j. The s denotes the market share of a firm and v-p in the parenthesis denotes the net utility obtained by a consumer from purchasing a product. The probability that a randomly chosen consumer purchases from the firm one is therefore:

$$D_1(p_1, p_2; i, j) = s_i(1 - s_j)\frac{\exp(v - p_1)}{1 + \exp(v - p_1)} + s_i s_j \frac{\exp(v - p_1)}{1 + \exp(v - p_1) + \exp(v - p_2)} \qquad (4)$$

The first term on the RHS can be called a captive segment and the second a competitive segment. The previous ones are not aware of the firm two whereas the latter ones are. In other words, a firm should influence via advertising on the both segments: captive in order to include its product in the choice set of a consumer and on competitive in order to make a consumer choose the product over other products in her choice set.

The decision of entry deterrence or accommodation depends on the incumbent's own stock of goodwill or awareness. The entrant's decision of entering or not depends on the perceived quality of products and entry costs. In case of low perceived quality and moderate entry cost, if the incumbent's stock of goodwill or awareness is sufficiently high, entry will not occur and incumbent's advertising strategy remains unchanged regardless of the entry. If incumbent's goodwill or awareness is sufficiently low, it can accommodate the entry by under-advertising. That is because entrant's captive segment is high in comparison with the competitive segment, which means that an entrant must set a higher price. In case of the so called mid-level stock of goodwill or awareness of the incumbent, the incumbent is likely to deter the entry by over-advertising. In case of high perceived quality and high entry costs the incumbent will deter the entry by over-advertising with the higher stock of goodwill or awareness than in the previous case. An interesting finding of Doraszelski and Markovich is that in this case incumbent over-advertises also in case of entry. This means that incumbent accommodates the entry by over-advertising. This could sound irrational, but Doraszelski and Markovich explain it by the preemption race, that is expected to be ahead in such situations and incumbent is making its positions better by over-advertising.

Doraszelski and Markovich (2007) also take up an exit inducement. As Kaldor (1950-51, 13) mentioned, the adoption of advertising has led to the concentration and made the equilibrium in the industry unstable. In an oligopolistic competition one of the general equilibrium stabilizers can be collusion. In the collusive, market also a smaller factor has an intention to stay in the market. This is demonstrated e.g. by Fershtman and Pakes (2000.) Just as Stigler (1964) stated, price cuttings are more likely to take place when there is a new entrant entering a collusive market. Fershtman and Pakes (2000) noted, that large firm has an incentive to deviate from collusion in order to induce the exit. The incumbent exits, if the scrap value of the capital is higher than expected gains from staying in the market. Doraszelski and Markovich (2007) assumed in their model, that exit is induced through heavy advertising and not through price cuts. Thus a firm willing to induce an exit advertises heavier whenever the competitor's value of remaining in the industry is close to the scrap value.

Kessides (1986) found out that advertising is rather an information school than a persuasion school. His findings support that advertising has two channels of influence: sunk cost and differentiation (e.g. Doraszelski and Markovich 2007, Ackerberg 2001.) However, these channels of influence can sometimes overlap. As Ackerberg (2001) notes, the character of advertising in an industry can effect on easiness or difficulty of entry. If the advertising has prestige (persuasive) character, it can be impossible for entrants to get any position in the market. Then the advertising can be considered influencing through both channels: differentiation and sunk cost. Same time an informative character of advertising in the market can be considered making entry easier, because entrants can make consumers aware of their products more easily and in this case the advertising has an influence mostly through the differentiation channel. In the next subchapter, I will briefly discuss advertising as a source of information and a means of persuasion.

2.3 Advertising as a Source of Information and Means of Persuasion

Advertising is according to Kaldor (1950-1951, 1) a source of market information, just e.g. like a stock exchange. However, advertising differs from other information channels: the advertised goods should be regarded as in joint supply, because the advertiser and the seller of the goods is the same economic unit, the price of advertising to the buyer is nil; the cost of advertising is incorporated in the price of commodities advertised, the advertising expenditure can be varied by varying the amount of information supplied or the coverage of information. The last means that also the elaborateness of advertising can be varied. Here Kaldor (1950-51, 4) notes a distinction between informative and persuasive advertising mentioning that actually all advertising is both informative and persuasive. Persuasive a sense, that information is provided from the seller's point of view and informative in a sense, that it always contains some information, at least the name of a firm or a product.

A good question that arises when considering advertising as a source of information is about the reliability of such information. The advertiser is primarily interested in selling the goods, not providing information. Nelson (1970) represented the concepts of search and experience goods. The quality and characteristics of the previous ones can be verified in advance, whereas those of latter ones can be found out only after purchase. Henningsen et al. (2011, 193) confirm that advertising elasticity is higher for experience goods. Obviously, it is easy to assume that the advertising of search good is more realistic and truthful than the advertising of experience goods. However, it is not that straightforward. As Nelson (1974) notes, the advertiser can have an incentive to conduct untruthful advertising concerning search goods and an incentive not to cheat in the advertising of experience goods. The buyers have transportation costs when acquiring a search good and exaggerating advertising up to that transportation cost can increase sales. Same time credibility and reputational aspects as well as a need for repeated purchases encourage the advertiser to refrain from cheating also when it comes to experience goods. Nelson (ibid) also notes that the most of the goods have both search and experience qualities.

Kaldor (1950-51, 4) states, that advertising cannot be justified in the same way as other commodities meaning that consumers' preferences are the ultimate criterion of all economic activity. The advertising is not supplied in response to consumers' demand. However, Kaldor states that also some demand for advertising exists. If information about goods was not provided for free, consumers would be willing to pay for it. As an example, he takes railway guides, which consumers are willing to buy. However, the information provided by advertising is biased. As mentioned above, the advertising provides information from the seller's point of view only. The press provides quite objective information about plays, films, books or the stock exchange. Such information is much less (if at all) provided about consumer goods. One reason for that could be advertising. However, Kaldor made calculations concerning the cost of information provision. His calculations included education, press, books, libraries, museums etc. and advertising. He found out that advertising is the costliest information channel. Thus, a question arises, what is the social influence of such an expensive and inefficient channel of information provision?

Kaldor answers his own question by listing pros and cons of advertising. Pros are for instance the increase in the efficiency of production and distribution by lowering the cost per unit more than the cost of advertising, the raise of the quality, the increase in employment and activity, the increase in customer satisfaction and shopping convenience and promotion of free and independent press in form of payments of advertising. Cons on the other hand are following: the increase in the power of monopoly, the increase in the instability of economy by increasing the amplitude of fluctuations, the creation of false sense of values and lesser satisfaction and it endangers the freedom and independence of the press. However, before final judgment should be considered the influence of advertising on demand. What the sales would have been without advertising?

Nelson (1974, 741-743) takes into account also the various aspects of demand for advertising. Advertising provides information about consumer goods and such information can be obtained little through other information channels. Thus, consumers can search for the hard facts of informative character about the search qualities of goods. Same time the advertiser might want to conduct advertising of persuasive character in order to accumulate his stock of goodwill and awareness of his brand (See Nerlove and Arrow, 1962.) When Nelson (1974) researched the size of advertisement he noticed that the experience good advertising was much larger and more visible than search good advertising. He reasoned this by a consumer's willingness to see what she wants to see. A consumer searching for hard facts about the search good notices a less visible advertisement whereas the experience good advertisements must catch the attention of an uninterested consumer.

Advertising influences also through differentiation. Doraszelski and Markovich (2007) summarize two components of advertising differentiation: goodwill and awareness. The goodwill can be considered as a part of product characteristics. In this case advertising has a persuasive role in creating differentiation. The goodwill is determined according to Nerlove and Arrow (1962) as a stock that depreciates over time. The goodwill stock is denoted A(t), the constant depreciation rate is δ and the future is discounted at the rate of α. The other parameters introduced in their model are: β (the elasticity of demand w. r. t. goodwill), γ (marginal cost of production), η (the elasticity of demand w.r.t. price), ζ (the elasticity of demand w.r.t. to other demand-shifter variables, like income) and ρ (constant rate of change of a demand-shifter, like income.) The derivative of the current advertising a* w.r.t. α is always negative, which is interpreted that increase in discount rate decreases optimal current advertising level. Same time the sign of the derivative w.r.t. δ depends upon the relationships among all the parameters. However, they derive optimal advertising expenditures as a ratio to sales (A/S) denoted by σ.

$$\sigma = \frac{\beta}{\eta(\alpha + \delta)}(\delta + \frac{\zeta\rho}{1 - \beta}) \tag{5}$$

If σ is negative, the optimal advertising is zero. This can be interpreted that income or any other constant proportional change leads to the optimal strategy of keeping A/S fixed. The effect of change of δ upon σ is positive, which means that increase in depreciation rate yields to increase in optimal A/S. Thus, the goodwill can be proven to be a stock that depreciates and advertising increases the goodwill stock. Advertising can be considered both to generate new goodwill and replace the depreciated goodwill stock.

Advertising has its informative aspect as well. Especially in the market of differentiated goods advertising can increase a potential buyer's information about the good and its characteristics. Doraszelski and Markovich (2007) note that both goodwill and awareness can be considered as a stock that decays over time. This is a process of forgetting. Advertising both generates new goodwill or awareness and replaces the lost stock. However, the processes of forgetting and stock generating are independent and stochastic. Therefore a firm cannot determine the influence of advertising on the size of the stock of awareness or goodwill in advance. In the literature (e.g. Barroso and Lloebet, 2012) the stock is assumed to depend on the stock of the previous period with some carryover coefficient. Dubé et al. (2005)

found out that advertising conducted in pulses yields better sales responses than keeping advertising investments flat. This is partly explained by the diminishing marginal utility of advertising.

So far I have covered advertising as an entry and exit game and the informative and persuasive character of its. The researchers have quite unanimously stated that advertising has both persuasive and informative aspects and they cannot always be distinguished. So far it has become clear that advertising can deter an entry to the market. According to the SCPP market structure and conduct are also tightly connected. In the next subchapter, I will focus on the potential effects of advertising on the market structure.

2.4 Advertising and Market Structure

Advertising can have an effect on either general or selective demand or on both of them. The effect on general demand means an increase in demand for the advertised commodity in general. It increases the market size. The effect on selective demand means an increase in the share of general demand falling to the advertising firm. It increases the market share of the advertiser. The influence on general demand can be low, but the influence on selective demand high. However, if the influence on general demand is high, probably the influence on selective demand is high as well. Thus this must be taken into account in analyzing the economic effects of advertising. The influence on general demand is probably the highest in launching a totally new commodity. The influence of continued advertising is somewhat more ambiguous, but Kaldor (1950-51, 8) mentioned, that probably consumption of some commodities, like patent medicines, health beverages, hair care products etc. might be much lower without advertising. The influence on general demand can be considered as an externality of advertising. This creates a free rider opportunity as well when some advertising investment conducted by one firm could benefit another company. However, the possible influence on general demand is likely mostly through the increase in the demand of the initial advertiser. Nevertheless, such spillovers are hard to research and such research has been conducted very little.

The analysis of the influence of advertising on selective demand is again not the simplest possible case, because usually the connection between sales and advertising is not explicit. Sometimes it can be measured with almost 100% certainty, like in case of mail advertising, if the response is required via mail as well. In the most of the cases, however, the effect can be measured only through time series analysis with the elimination of irrelevant factors affecting sales. In economic analysis of advertising it is usually taken as given that advertising is profitable for the advertiser. One reason for that is that otherwise it would not occur. From the welfare economics point of view the role of advertising is more complex. Some professors (according to Kaldor 1950-51, 13) say that advertising of competing monopolies cancels each other. If all the firms complete similar advertising methods the outcome is the same as none of them had made any effort at all. This is anyway a too straightforward reasoning. Advertising can be compared with new innovation that breaks the existing equilibrium. The advertising expenditure cannot be strictly proportionate to the amount spent on advertising. The effect of larger expenditure must overshadow the smaller ones. This would lead to the economic concentration. The number of firms decrease and/or leading firm will grow. The stability of this new equilibrium depends on the continuance of advertising. Keeping fixed the assumption that the effect of larger expenditure overshadows the smaller, this kind of development could lead to a monopoly, because the advertising expenditure is somewhat proportionate with the sales of a firm. However, a more realistic outcome is some kind of oligopoly rather than a monopoly.

As it was mentioned above, the market concentration cannot be a completely harmful thing. Taking into account the economies of scale and advantages of them, concentration might be a good thing from a consumer's point of view. Nevertheless, concentration created by advertising is probably also harmful from the consumer's point of view. If the market concentration would have occurred as a result of production technology improvements and economies of scale would have shown up, the concentration would have occurred as a result of a price competition. When it has occurred through advertising, there is a stock of goodwill that has accumulated to the market leader. This means that companies can and must charge higher profit margins. That is because of their increased market power and in order to cover the advertising costs. When advertising has become an essential part of the industry, it creates a sunk cost barrier to entry which keeps on increasing the market power of incumbent market leaders and leads to a decrease in consumer surplus. This can be returned to the competing SCP hypotheses: traditional and efficient market. Those who assume that the concentration as a result of advertising is harmful support the traditional SCP hypothesis with negative correlation between concentration and competition. However, it can be assumed that the more efficient firms can afford more advertising as well. Thus, neither the concentration as a result of advertising is a bad thing.

On the other hand, some degree of monopoly is useful in creating new innovations if a large outlay of fixed capital is required. Thus industry structures have converged from the initial idea of the competitive market with hundreds of small firms towards modern oligopoly with a few firms controlling the vast bulk of the market. Most manufactured consumer goods are nowadays produced on the market of this kind. For oligopolies of this kind, also collusion is characteristic. In collusion, the firms agree or tacitly agree prices and outputs. Stigler (1964) states that collusion is often mentioned as a response to antitrust policies. Mergers and cartels can be prohibited and they have high administrative costs. Nevertheless, the collusion might have other economic reasons to occur. One argument supporting that is according to him that collusion has occurred in the USA already before antitrust policies and occurs in countries where have never been any antitrust policies.

Stigler (1964) notes that concentrated market and collusion increase profitability. However, secret violation of collusion can increase the profits of a violator, but when other actors detect the violation, it becomes common knowledge and the advantage vanishes. He does not agree with assumptions that non-price means of violation would be more difficult to detect. Advertising or differentiation is usually more easily noticed than secret price cuts. Collusion at some extent (just like some extent of monopoly power) can be useful both for industry and consumers. The empirical part of Stigler's paper, where he investigated US steel industry in 1937 and 1939, showed that the more concentrated the industry is (according to Herfindahl index[1]) the larger the price reductions from the list price. Thus, the price cuttings could be a result of deviating from collusive behavior. Such price cuttings occur most likely if some collusion participants are deviating from collusion or some new entrants are entering the collusive market. This is in line with the findings of Doraszelski and Markovich (2007), who found out that over-advertising might occur when new entrants are planning to enter or some of the incumbent's value of staying in the market is close to the scrap value. Thus, the companies change the means conduct in order to guarantee or improve their position. The

[1] Herfindahl-Hirschman index of industry concentration: $H = \sum_{i=1}^{N} s_i^2$, where s_i is the market share of the 50 largest firms in the industry or all firms if there are less than 50 firms in the industry.

difference is that the means of conduct in Stigler (1964) is price and in Doraszelski and Markovich (2007) advertising.

Based on their findings (Doraszelski and Markovich, 2007) considering goodwill advertising in a small industry or in an industry where advertising is expensive (M/k ratio is low) the advertising depends on the competitor's stock of goodwill. This kind of market leads easily to the very asymmetric structure of a large and small firm. Small firm has no incentive to advertise and try to grow larger because there are little possibilities to succeed. On the other hand, if there are two large or medium size firms, the industry is likely to converge to a symmetric structure of two large firms. They also calculated advertising elasticities i.e. the elasticity of next period's expected demand with respect to this period's advertising. In case of low M/k, the elasticity is 0,0006 and for the large firm 0,0013 and 0 for the small firm, which will not advertise at all. The elasticity in case of high M/k is 0,016. The correlations between current goodwill and past goodwill in the small market are high, but low in the large market. To summarize, neither one of the rivals has a strategic advantage in the large market under the goodwill advertising.

In case of awareness advertising Doraszelski and Markovich (ibid) noted, that market-size-to-advertising-cost ratio (M/k) plays a lesser role. Therefore they assume a relatively large market (or a low advertising cost.) They keep the perceived quality of products fixed and advertising only increases awareness. In case of low perceived quality both firms advertise despite the strategy of the other until the point of full awareness and after that in order to fend of forgetting. This leads to a symmetric industry structure with two large firms. As the perceived quality increases, the advertising strategy changes crucially. The advertising starts to depend on rival's advertising. The large firm has a strategic advantage of advertising. The smaller firm gives up advertising if it is sufficiently far behind. Thus, the industry is moving towards asymmetric structure in the long run. However, the asymmetries are not as sharp as in case of the goodwill advertising with low M/k. Two large firms can achieve joint market share of 96 percent. The remaining four percent is the market share of the outside good, which I mentioned briefly above and will return to it in Chapter 3. As one firm adds its stock of awareness the other reacts by cutting down the price. This leads to heavier competition, because the consumers become aware of two inside goods and more rarely their choice is the outside good. Therefore it is more optimal for medium sized firm to stay behind instead of trying to grow, if it is facing a large firm.

Taking into account all that has been told above about advertising and its impact on the industry structure and the formation of oligopolistic markets could be thought that without advertising industries would be less concentrated. However, banning advertising also tends to lead to the heavier concentration in an industry. In case of goodwill advertising with two large firms, for instance, the regulation may reduce the symmetric structure and let one firm to dominate the whole industry. There is empirical evidence from cigarette and alcoholic beverages industries. (See Eckard (1991), Sass and Saurman (1995.)) So neither this case is so straightforward.

2.5 Wholesalers', Manufacturers' and Retailers' Domination

Now that the concept of goodwill has been introduced it is worthwhile to consider briefly whose goodwill it is actually all about. As we know there are plenty of factors in the supply chain and in very rare cases the sales to the end users are conducted by the manufacturer. Kaldor states (1950-51, 16) that the most of the goods cannot be so standardized, that reputational aspects could be eliminated. Those reputational aspects have been called goodwill, brand equity etc., but it is all about the same thing. The reputation of a certain good in the eyes of consumers was in the beginning created by wholesalers. Consumers had goodwill towards retailers as they had a good reputation of selling good products. Same time retailers relied on their wholesalers who had an intention to provide their retailers with good merchandise. This kind of situation can be called wholesalers' domination (Hawtrey 1925 via Kaldor 1950-51.) Manufacturers or retailers had little to do to change this; because they had their own business networks i.e. wholesalers. The organized advertising campaigns were manufacturers' attempt to release themselves from the dependence on wholesalers' goodwill. Nowadays in many industries wholesalers and retailers are mostly distributing agents without goodwill of their own. The wholesale and retail prices are often determined by the manufacturers as well. A fixed price is often a part of manufacturer's brand. However, in some industries e.g. textile industry the former wholesalers' domination still exists.

One measure of a firm's monopoly power is (p-c)/p, where p is a price that fails to cover the costs of a potential new entrant and cost of production is c. The difference p-c can be considered as a profit for the firm. In the market with imperfect competition, the difference remains positive but in this kind of market of "non-price competition" always occur selling costs. Determined by Chamberlin (1931), production costs are costs that adapt the product to the demand and selling costs are costs that adapt demand to the product. Selling costs can be divided into two components: competitive expenditures (aiming to increase the market share of a firm) and protective expenditures (aiming to increase the monopoly power of a firm.)

Selling costs can be classified in three groups: manufacturer's selling costs (e.g. sales-promotions and free samples), advertising and selling costs incurred in the wholesale and retail stages of distribution. Kaldor (1950-51, 25-26) makes conclusions that large-scale advertising with high selling costs is connected with manufacturer's brand domination. This has also involved the emergence of a much greater degree of concentration of production and standardization of the products. However, it does not necessarily mean that large scale advertising would have led to the establishment of this kind of organization. Nevertheless, continued advertising in a large scale is necessary for the maintenance of the industry structure of this kind. Kaldor (ibid) finds advantageous that this kind of industry structure can restrict excess competition and guarantee the efficient production possibilities of larger economies of scale.

One interesting point is taken up by Kaldor (1950-51, 26), which could combine the efficiency of oligopoly (or manufacturer's dominance) and lower selling costs of wholesaler's dominance. It is called retailers' dominance. The functions of the wholesalers are controlled by the retailers rather than manufacturers. Chain stores and mail order houses are examples of the potential outcomes of this system. Such large scale retailers conduct their own wholesaling and accumulate their own stock of goodwill by establishing their own brands. Kaldor (ibid) takes up some empirical researches which support the assumption that this kind of organization decreases selling costs and can keep the efficient concentrated production structure.

So far I have represented advertising as a part of the economic process. It can be best connected with the economics through the industrial organization and structure-conduct-performance paradigm. Advertising is an important means of industry conduct. It influences through the sunk cost and differentiation. Differentiation can be divided into information and persuasion i.e. informing consumers about product characteristics and creating goodwill towards the brand. In the next chapter, I will introduce about modeling of consumer choice and research conducted concerning it.

3 Discrete Choice Models and Advertising

Train (2003, 15) determines that discrete choice models describe a situation when a decision maker faces a set of alternatives (choice set) and chooses among them. Such choice should be mutually exclusive from the decision maker's point of view i.e. choosing one alternative means not choosing any other alternatives and the choice set should be exhaustive i.e. contain all possible alternatives. The alternative set should be finite as well. Train (2003, 16) notes that almost any choice set can be expanded to mutually exclusive and exhaustive. If a decision maker should make a decision between alternatives A and B, the set is neither mutually exclusive nor exhaustive. By expanding the set with alternatives: "only A", "only B", "both A and B" and "none of the alternatives" it becomes both mutually exclusive and exhaustive. Thus, the existence of outside good mentioned above becomes justified. Outside good is the option of a consumer not to purchase any of the inside goods in the choice set. The concept of outside good is somewhat misleading, because the consumer does not have to buy any good, say, smartphone. The consumer can refrain from buying anything or buy a substitute. Thus, the assumption that everyone is aware of outside good and outside good is available for everyone becomes justified.

Smartphone purchase decision described above is an example of a discrete choice situation. There is a finite set of alternatives and an acquisition is of rather discrete than continuous character. There is also the option not to purchase a smartphone at all and use the substitutes of them (like tablets, laptops, feature phones, digital cameras etc.) In the market of differentiated products are plenty of factors which impact on the choice. McFadden (1973, 105-106) mentioned the difficulty of modeling such choice behavior because an econometrician cannot detect all the relevant factors. He has made an attempt to estimate unobservable characteristics from the data and construct model of the population choice behavior from distributions of individuals' decision rules. The discrete choice models can be divided in three main categories: (1) logit, (2) probit and (3) elimination models. (McFadden 1984, 1411.) In the next subchapter, I will briefly represent them.

3.1 Different Discrete Choice Models

The idea of discrete choice models is to construct the choice behavior of a population from individual choice probabilities. It has been developed a number of such models. In this subchapter, I will briefly introduce their main categories: logit, probit and elimination models. I concentrate on the multinomial logit model (MNL) which is applied in the empirical part of this paper. It is simple and has a low computational burden and proven to be quite robust. However, it has some unrealistic background assumptions which are introduced in this chapter as well. Therefore I will briefly mention a couple word of such models which are more relaxed of those assumptions.

3.1.1 Logit Model

McFadden (1973) takes as a starting point a simple individual choice probability:

$$P(x|s,B) = \pi[\{h\epsilon H|h(s,B) = x\}] \tag{6}$$

The x denotes sets of available alternatives; S the observed attributes of decision makers and H the distribution of behavior patterns in the population. H can be considered as a set of demand functions which are obtained by maximizing some utility function. The h is a demand function obtained by maximizing a specific utility function. Assuming that an alternative set B belongs to X, the probability that a decision maker chooses alternative x can be denoted: P(x|s,B). If model H truthfully describes the decision patterns in the population the probability π specifies the distribution of behavior rules in the population. From this very simple individual choice probability, he derives the model with the maximum likelihood estimator which maximizes the likelihood of a given sample. The final model obtained by the modeling of McFadden (1974) is the multinomial logit model. In my empirical research in Chapter 5, I will apply logit model and therefore I will represent it more thoroughly than other models.

In multinomial logit model the probability of choosing alternative i from the choice set B can be denoted by function f as follows:

$$f^i(x_B, \theta) = e^{x_i\theta} / \sum_{j \epsilon B} e^{x_j\theta} \tag{7}$$

In this model, B is a choice set and x_i is a column vector of observed attributes and θ is a parameter vector, which describes the probability distribution of a vector of taste weights (α). The summation in the denominator denotes other alternatives in the choice set excluding i. Adding the IIA (the independence of irrelevant alternatives) property to this model gives a useful restriction to the model structure. IIA property means that the odds of i being chosen over j are independent of the availability of other alternatives. Despite the implausibility of such property MNL is relatively robust (McFadden 1984, 1414.) Train (2003, 41) notes that the probability given by the logit model is always between zero and 1, which is necessary for the probability estimation models. The most useful characteristic of IIA is that the probability of choice when alternatives increase or decrease can be simply calculated by deleting or adding terms in the denominator. (McFadden 1984, 1414.) Train (2003, 41) notes that this gives a convenient property for the model that probabilities of various choices always sum to one. Train (2003, 53) takes up one more advantage of IIA property: a researcher can focus on choices among subset of alternatives only instead of among all alternatives. As an example he takes a choice to travel to work by car or by bus. With the presence of IIA property, a researcher can estimate the model with the car and bus only excluding the subsets of the users of other means of transport from the sample.

Train (2003, 61-64) represents derivatives and elasticities as a method providing more information from logit estimations. The probabilities calculated by logit estimations are a function of observed variables. Derivatives give more information on changes in probability when some observed variable changes. Let us denote the probability that a decision maker n chooses alternative i P_{ni}, z_{ni} is an observed factor, V_{ni} is the utility from choosing alternative i. Thus we get the following expression for the derivative

$$\frac{\partial P_{ni}}{\partial z_{ni}} = \frac{\partial(e^{V_{ni}}/\sum_j e^{V_{nj}})}{\partial z_{ni}} = \frac{\partial V_{ni}}{\partial z_{ni}} P_{ni}(1 - P_{ni}) \tag{8}$$

Derivatives can be calculated as well with respect to change (in an example below with respect to increase) in observed variable of another alternative:

$$\frac{\partial P_{ni}}{\partial z_{nj}} = \frac{\partial(e^{V_{ni}}/\sum_k e^{V_{nk}})}{\partial z_{nj}} = -\frac{\partial V_{nj}}{\partial z_{nj}} P_{ni} P_{nj} \tag{9}$$

Train (2003, 63) notes and it obviously follows from the IIA property that the changes in probabilities must sum to 0 as the probabilities must sum to 1. Thus, economists measure the changes rather using elasticities than derivatives Elasticity for the previous case would be:

$$E_{iz_{ni}} = \frac{\partial P_{ni}}{\partial z_{ni}} \frac{z_{ni}}{P_{ni}} = \frac{\partial V_{ni}}{\partial z_{ni}} z_{ni}(1 - P_{ni}) \tag{10}$$

and for the latter case:

$$E_{iz_{nj}} = \frac{\partial P_{ni}}{\partial z_{nj}} \frac{z_{nj}}{P_{ni}} = -\frac{\partial V_{nj}}{\partial z_{nj}} z_{nj} P_{nj} \tag{11}$$

If the parameter is linear in the utility function with the coefficient β, the own elasticity takes a following form:

$$E_{iz_{ni}} = \beta z_{ni}(1 - P_{ni}) \tag{12}$$

In such case the cross elasticity would be:

$$E_{iz_{nj}} = -\beta z_{nj} P_{nj} \tag{13}$$

If the parameter appears in the utility function in the logarithmic form, the own elasticity is:

$$E_{iz_{ni}} = \beta(1 - P_{ni}) \tag{14}$$

The cross elasticity is respectively:

$$E_{iz_{nj}} = -\beta P_{nj} \tag{15}$$

In order to explain the elasticities more comprehensively, let us assume that the utility function is a logit function and the observed variable is a price. If the price is a linear variable in the utility function, the derivative of its is a constant. The choice probability can be assumed to denote the market share of a product. Now we notice that cross elasticities (equation 13) depend only on market shares and prices, but not any other variables. Thus, each product has only one cross elasticity with respect to the other products. The own elasticity is the smaller the larger the market share is. In case of a logarithmic variable in the utility function, say advertising, the elasticity would depend only on the estimated coefficient and the market shares. Assuming market share per product sufficiently small, we can treat the coefficients obtained from the regression as elasticities, which makes the analysis and comparisons easier. The unrealistic substitution patterns between goods can be considered the major pitfall of the logit model caused by the IIA property. The last observation concerning the own elasticity increasing as the input (say price or advertising) increases, however, can be quite realistic if we return this to the market power findings of Kaldor (1950-51) and Bresnahan (1987) which were represented in Chapter 2. The larger advertising investment overshadows the smaller and the firms with higher market power can charge higher markups.

Despite the previous pitfalls, the logit model is a "cheap" and convenient way and good if the focus of interest is the effect of change and not the elasticity matrix. I find this model also suitable for market level analysis i.e. comparing the advertising responses between the countries, media and advertisers. Then the same elasticity for all goods can be assumed. In addition to the simplicity this is the main reason why this model is applied in my research. However, relaxing IIA property can sometimes be necessary. Therefore I will briefly represent the other important categories of the discrete choice models: probit models and elimination models.

3.1.2 Probit Model

Other models represented by McFadden (1984, 1411) are more complex and less convenient to use, but they relax IIA restrictions and therefore I will briefly introduce some of them even though they will not be applied in this paper. Multinomial probit model does not have similar IIA restrictions as multinomial logit has.

$$f^1(x, \beta, \Omega) = P(y_1^* > \max(y_2^*, \max(y_3^*, \dots) \dots)) \tag{16}$$

x denotes observed attributes, β is mean and Ω is covariance matrix of the multivariate normal α_t and represents the taste weights. The multinomial probit model is more complex than multinomial logit model, but it permits the very general patterns of cross elasticities. They can handle random taste variation as well, allow any pattern of substitution and can be applied to panel data with temporally correlated substitution. (McFadden 1984, 1418; Train 2003, 101.) According to Train (2003, 101) the only limitation of probit models is that they require normal distributions for all unobserved components of utility.

3.3.3 Elimination Models

Third model category represented by McFadden (1984) is elimination models. The basic idea of those models is that alternatives are screened from the choice set using various criteria until a single element remains. The model can be described:

$$f^i(C) = \sum_D Q(D|C) f^i(D) \tag{17}$$

The $f^i(C)$ is the probability of choosing i from set C and Q(D|C) is a subset of alternatives. Thus, the model determines the probability of transition from a set of alternatives to any subset Q(D|C). Based on McFadden (1984, 1420) this model has not been applied in economics.

The other more common elimination model is generalized extreme value (GEV) model. The latent variable characterization of this model is ((latent variable is a variable which cannot be observed, but inferred from the other measurable or observable variables):

$$y_i^* = x_i\beta + \varepsilon_i, for\ i\epsilon B = \{1, \ldots, m\}\ with\ (\varepsilon_1, \ldots, \varepsilon_m) \tag{18}$$

The distribution of ε_i is:

$F(\varepsilon_1, \ldots, \varepsilon_m) = exp\{-H(e^{-\varepsilon_1}, \ldots, e^{-\varepsilon_m}\}$ and H is non-negative linear homogenous function of non-negative variables.

The model response probabilities are following:

$$f^i(x, \beta) = \partial lnH(e^{x_1\beta}, \ldots, e^{x_m\beta})/\partial x_i\beta \tag{19}$$

The GEV models allow for correlations over alternatives. The unifying attribute of these models is that the unobserved portions of utility for all alternatives are jointly distributed as a generalized extreme value. When correlations are zero, GEV becomes a standard logit. (Train 2003, 80.) The most commonly used GEV model is nested logit. In it the set of alternatives is divided into subsets and IIA holds within each subset (nest) but not between the nests.

By so far I have described the discrete choice situation and possible ways of modeling it by concentrating in the logit model which will be applied in Chapter 5. In addition to the applying different models, also some extensions to the current models can be done in order to improve them. McFadden (1973, 118) notes that, the maximum likelihood method is practical for problems up to 20 variables and 2000 observations, but is pretty costly for large samples. The same results can be obtained more easily taking into account linear restrictions across equations by applying ordinary (OLS) or weighted (WLS) least squares. Such modeling has been applied widely in empirical research concerning discrete choice situation, like an educational choice, an occupational choice and a consumer choice of differentiated goods.

In addition to the mentioned above pitfall with the large samples, also the situation when the form of the distribution function is unknown prevents the use of the maximum likelihood method. Hansen (1982) introduced the generalized method of moments (GMM) for analyzing such cases. The generalized method of moments aims at replacing theoretical expected value with its empirical analog by minimizing with respect to the GMM estimator. GMM has been applied in computing unobservable demand or cost side parameters as well as instruments for correcting the endogeneity of explanatory variables in the research of discrete choice behavior.

In the first part of this chapter, I have covered discrete choice models generally and in the previous chapters I have considered the market of differentiated goods and advertising as a means of differentiation. In the next parts of this chapter, I will make a brief literature review regarding applications of discrete choice models in the context of differentiated products and advertising.

3.2 Discrete Choice Models in Differentiated Products Context

In case of differentiated goods, the demand for different characteristics of goods plays a more important role than the goods itself. Introducing product differentiation requires application of different substitution patterns. The substitutes can be either gross substitutes or net substitutes. If goods are gross substitutes, the demand for one good decreases as the price of another good decreases. Thus, in theory there would not be any demand for the more expensive good. If the goods are net substitutes, the increase in demand for one good as the price of another good increases requires, that the utility of the consumption of both goods is equal. The differentiated goods are rather net substitutes. However, this is more complex to model. Therefore the gross substitution property (GSP) is assumed by Anderson, Palma and Thisse (1989.) They made an attempt to find linkages between discrete choice modeling in the differentiated goods market. They noted that in order GSP to hold, the demand system needs special requirements on the locations of products. The product characteristics space must be larger than or equal to the number of products minus one. They illustrated their framework for the logit, probit and linear probability models of discrete choice models. If the number of variants of a differentiated product is n, the total demand for variants is N, the standard deviation of consumer tastes is μ and the price of a variant is p, the multinomial logit demand function for variant i would be (Anderson et al. 1989, 27):

$$D_i(p_1 - p_i, \ldots, p_n - p_i) = \frac{N}{1 + \sum_{j=1, j\neq i}^{n} \exp(-\frac{(p_j - p_i)}{\mu})} \tag{20}$$

This provides a slight improvement to the substitution patterns of a logit model as the product characteristics are introduced in the demand equation. In the equation (7) they effect only through the consumer utility parameter θ. This a good approach to correct the substitution patterns in the logit models by including the characteristics approach.

Train (2003, 8) mentioned that he will not cover the branch of empirical industrial organization that involves the estimation of discrete choice models of consumer demand on the market-level data. Berry Levinssohn and Pakes (1995), often referred as BLP in the literature, have analyzed such case and I will briefly consider their work because it fits the topic of current paper. Berry (1994) approached the topic in his paper and noted that by that time the most of the literature on estimation under imperfect competition was tied to homogenous goods' markets. This is obviously not a sufficient approach since we live in the world of differentiated goods as it has been mentioned a number of times in current paper as well.

Berry (1994) took up the problem of unobserved characteristics, which actually is the major problem in discrete choice modeling as mentioned at the beginning of the previous subchapter. Sometimes product characteristics may be not of physical character. They can represent a consumer's perceptions of quality, status etc. The other general problem is the endogeneity of prices. They tend to be correlated with the unobserved demand factors as mentioned above. Ignoring that fact may lead inconsistent results. As Berry (1994, 243) notes, in the homogenous goods case, the presence of unobserved demand characteristics and their correlation with prices can be evaded using traditional instrumental variables that are correlated with the price but not with the error term. However, in discrete choice models of differentiated goods the prices and unobserved product characteristics enter demand equations in a non-linear manner and create a problem of non-linear instrumental variables. Berry's solution is to invert the function defining market shares to uncover the mean utility of various products as specified by the primitives of the model. Under BLP, those primitives are the utility surface that assigns values to different possible product characteristics as a function of consumer characteristics, a cost function which determines the production cost associated with different combinations of product characteristics, a distribution of consumer characteristics and a distribution of product characteristics. (Berry et al. 1995, 885.) By definition the mean utility of product j is denoted by δ_j and the equation gets a following form:

$$\delta_j \equiv x_j\beta - \alpha p_j + \xi_j \tag{21}$$

In the equation x_j denotes observed product characteristics and p_j the price of the good j and ξ_j the mean of consumers' valuations of an unobserved product characteristic (e.g. quality). The distribution of consumer preferences about this mean could be denoted by ϵ_{ij}. In the models with independently and identically distributed consumer tastes only mean utility levels (δ_j, which are the differences between logarithmic market shares as it will be demonstrated below) differentiate the products and thus the pair of products with the same market share would have the same cross-price elasticity with respect to any third product despite product characteristics. (Berry 1994, 246.) This is the major pitfall of the logit model caused by the IIA property which was covered in the previous subchapter. Therefore Berry et al. (1995, 847) have developed the model further into more realistic direction by generating the random coefficients model and decomposed the utility function into mean δ_j and into deviation from than mean μ_{ij}. Then the deviation depends on the interaction between consumer and product characteristics which relaxes the assumption of cross-price elasticities based only on market shares. (Berry et al. 1995, 848.)

Further Berry (1994, 249) denotes the market share function by $s(\delta)$. Plugging this into logit model yields:

$$s(\delta) = e^{\delta_j} \Big/ \left(\sum_{k=0}^{N} e^{\delta_k}\right) \tag{22}$$

Further, if the mean utility of outside good is normalized to zero:

$$\ln(s_j) - \ln(s_0) = \delta_j \equiv x_j\beta - \alpha p_j + \xi_j \tag{23}$$

Thus the simple instrumental variable regression of differences in logarithmic market shares on x_j and p_j is suggested. This is a very simple and convenient way, but according to Berry logit model produces unreasonable solution patterns. Berry (1994, 250) also demonstrated vertical model of product differentiation (represented e.g. by Bresnahan (1987).) In such model consumers agree about the quality but have different valuations for quality. As opposite to the logit model with as many consumer characteristics ϵ_{ij} as there are products, the vertical model of product differentiation has only one consumer characteristic: v_i representing the “taste” for quality. Denoting the quality of product j by φ_j and assuming it to be linear in the observed and unobserved characteristics we get:

$$\delta_j = \varphi_j - p_j \tag{24}$$

In addition to Berry (1994) Berry et al. (1995) developed techniques for analyzing demand and supply in the market of differentiated products and applied these techniques to analyze the equilibrium in the U.S. automobile industry. Estimates from their model can be obtained from the using only widely available product level data and aggregated consumer level data. The estimates they obtained are consistent with the structural model in equilibrium.[2] They obtained cost and demand parameters. On the cost side, the cost is estimated as a function of product characteristics. On the demand side, they estimated own and cross price elasticities and elasticities with respect to vehicle attributes. The distribution of consumer preferences is aggregated into a market level demand system which is combined cost functions and price setting behavior in differentiated products to generate equilibrium prices and quantities.

The problem of endogeneity of prices is not completely solved yet. Producers might be aware of unobserved (by econometrician) characteristics and therefore the prices can be correlated with them. In differentiated goods model the demand of an individual and the market demand become a nonlinear function of demand side unobservables. Berry et al. (1995, 851) assume the orthogonality[3] between observed and unobserved characteristics and therefore the x-vector cannot be used for estimation of unobserved characteristics without transforming the observed quantity, price and characteristic data into a linear function of unobservables. The instruments (z) should be chosen according to Berry et al. (1995, 854) for both demand and pricing equations in such way that they are correlated with the specific functions of the observed data but uncorrelated with disturbances.

In addition to demand side Berry et al. (1995, 853-854) also estimated cost side taking as a starting point the logarithm of the marginal cost of good j and denoted observed cost side parameters by w_j and unobserved by ω_j and parameter to be estimated by γ:

[2] In the reduced form models the equation must be solved for endogenous variables i.e. by placing unknown to the LHS and others to the RHS of the model. In structural models, in turn, the equations are derived from theory. Nowadays according to Chintagunta, Erdem, Rossi and Wedel (2006, 606) the models often exhibit simultaneously structural and reduced form components because theory rarely is sufficiently detailed to completely specify a structural model.

[3] Orthogonality between observed and unobserved characteristics is commonly assumed in econometrics. However, also other points of view exist, e.g. Hausman (1978.)

$$\ln(mc_j) = w_j\gamma + \omega_j \tag{25}$$

Taking in to account these all above, the following steps are required for computing the instruments and interactions and then estimating the market equilibrium. (Berry et al. 1995, 863.)

(i) estimate via simulation the market shares implied by a model
(ii) solve for the vector of demand unobservables implied by the simulated and observed market shares
(iii) calculate the cost side unobservable from the difference between price and markups computed from the shares
(iv) calculate the optimal instruments and interact them with the computed cost and demand side unobservables.

Berry et al. (1995, 868-887) applied their model for US automobile market. They started by estimating coefficients using simplistic regression of $\ln(s_j)$-$\ln(s_0)$ on product characteristics (horse power-to-weight ratio, air conditioning, fuel consumption, size) and price. They ran basic OLS regression and IV regression (instruments described above.) IV regression yielded much more plausible results than OLS which is quite expected and indicates that correcting for the endogeneity of prices matters. Then they estimated the same coefficients using BLP specification which includes in addition to demonstrated above demand side equations cost side equations as well. The demand side parameters of BLP specification could be compared with the parameters estimated using simple regression. Interestingly only the constant term and the coefficient of size differed a great deal from the basic OLS regression. According to their interpretation, this tells that there is a positive average percentage markup and this markup increases in size. They could also computed estimated demand elasticities with respect to the characteristics and the price, own and cross-price elasticities and substitution to the outside good. The last means the fraction of consumers who will switch to outside good instead of one of the modeled goods when the price of a chosen product increases. They compared substitutions to the outside good calculated from the logit model with those calculated from BLP and under logit specification approximately 90% of every model opt would substitute to outside good. Under BLP specification, the figures were between 10% and 27%.

As it can be read from above, the BLP has been a great improvement to the basic logit model, but requires much more data, especially from the cost side and more complex computing, because the GMM estimation is required in computing instruments and unobservables. The major benefits of BLP are more reliable cross elasticities and substitution patterns. In the next subchapter, I will move on to models, which includes advertising in discrete choice models. They are actually extensions of BLP as we can see.

3.3 Discrete Choice Models in Advertising Context

In this subchapter, I will briefly introduce how discrete choice models have been applied to the research of the influence of advertising. One approach is provided by Goeree (2008.) In that paper, she is modeling limited information and advertising in the US personal computer industry. She notes that in the US personal computer market over $2 billion is used annually on advertising and top firms advertise more and earn higher markups than average. The modeling by Goeree is based on BLP but it adds to it by allowing consumer taste heterogeneity and informational asymmetries. Goeree argues that traditional models with full information assumption lead too elastic demand curves and incorrect conclusions regarding the intensity of competition. In the paper is also demonstrated how to estimate a model of limited information without micro-level advertising data which can be difficult to obtain.

The basic specification with utility function consisting of observed and unobserved (by the econometrician) characteristics and interactions between them as well as of the price is similar to BLP (Berry et al., 1995) described above. The price and unobserved characteristics of outside good are normalized to zero. The probability that consumer i purchases product j at time t is thus (Goeree 2008, 1025):

$$s_{ijt} = \sum_{\mathcal{S} \epsilon \mathcal{C}_j} \prod_{\ell \epsilon \mathcal{S}} \phi_{ilt} \prod_{k \notin \mathcal{S}} (1 - \phi_{ikt}) \frac{\exp(\delta_{jt} + \mu_{ijt})}{y_{it}^{\alpha} + \sum_{r \epsilon \mathcal{S}} \exp(\delta_{rt} + \mu_{irt})} \tag{26}$$

In the equation δ denotes the utility that consumer obtains from the good j, μ includes interactions between observed and unobserved characteristics.$\mathcal{C}_j$ is the set of all choice sets that include product j. ϕ_{ijt} is the term of probability that the consumer i is informed about the product j. y_{it}^{α} is a term from the presence of outside good. This is a pretty simple and nice equation and handy for a couple of products, but as the number of products increases the computational burden grows. If the choice set was observed, the computational burden would decrease and therefore Goeree (2008, 1025) notes that it is possible to simulate a choice set and then only one probability per individual must be computed. Thus the term of information technology (ϕ_{ij}) describes the effectiveness of informing consumers about the products:

$$\phi_{ij} = \frac{\exp(\gamma_j + \lambda_{ij})}{1 + \exp(\gamma_j + \lambda_{ij})} \tag{27}$$

The components of the term are the same for each consumer and γ_j contains vectors measuring the effectiveness of the media at informing consumers, the vector of media, number of ads and the product age parameter as the consumers might be more informed about the product the longer it has been in the market. The term λ_{ij} captures the consumer information heterogeneity and allows for consumers to be informed about the product even in case of no advertising occurs. The term in the equation (27) depends upon the own product advertising only and allowing for spillovers would greatly complicate the model. Thus, according to Goeree (2008) the consumer being informed of one product does not effect on her being informed of another product. In the modeling of Goeree (2008), the market share is a function of prices and advertising. The smaller the information technology term is the smaller the product market share. If ϕ_{ij}=1 for all products the market share would be the standard full information choice probability. Goeree (2008) takes the market size given by the number of households in the US.

In the supply side equations Goeree (2008, 1028) takes the same specification as is taken in BLP (Berry et al. 1995) and thus the marginal cost is log-linear consisting of observed and unobserved cost characteristics and parameters to be estimated. Goeree assumes that firms are non-cooperative Bertrand-Nash competitors (as in BLP). Goeree follows BLP in choosing endogeneity correcting instruments. The advertising magnitude depends on the product markup. The more differentiated the product is the less it is prone to the competition. The firms advertise the product the more they make the sale of the product and the optimal price of the product depends on the characteristics of all products offered. Advertising in a certain media depends on the marginal cost of advertising in that media. Thus, suitable instruments will be functions of the product characteristics, product cost shifters and advertising cost shifters of all other products.

In the estimation Goeree (2008, 1033) applies GMM that consists five “sets” of moments:

(i) from the demand which match the predicted market shares to the observed ones

(ii) from the pricing decisions which express an orthogonality between the cost side unobservable and instruments

(iii) from advertising media decisions which express orthogonality between advertising residuals and instruments

(iv) from purchase decisions which match the model’s predictions for the probability individuals purcahse from the firm f (conditional on observed characteristics) to observed purchases

(v) from media exposure decisions which match the model’s predictions for exposure to media m (conditional on observed characteristics) to observed exposure

The moments (i)-(iii) are macro moments and moments (iv)-(v) are micro moments.

According to Hansen (1982) and BLP (1995), Goeree (2008) uses GMM to find the parameter values that minimize the objective function $\Lambda' Z A^{-1} Z' \Lambda$, where A is a weighting matrix that is a consistent estimate of $E[Z'\Lambda\Lambda' Z]$ and Z are instruments orthogonal to the composite error term Λ. This estimation should be repeated until moments are close to zero.

Goeree (2008, 1042-1051) ran first estimations of demand and cost side parameters as in BLP. She also ran regression to estimate information technology parameters. She estimated substitution patterns as well by calculating cross-price elasticities of demand and advertising semi-elasticities. Interestingly, for some firms advertising of one product has negative effects on other products sold by that firm but it is less negative than for some rival products. She also estimated advertising markups and median product price elasticities under limited and full information. The high estimated markups are partially explained by the unawareness of the consumers of many products that are for sale. Thus, results change dramatically under limited and full information. Estimated markups can be up to almost 90% higher under limited information and elasticities of demand decrease notably as well under the limited information.

Barroso and Llobet (2012) researched the awareness of consumers of new products in a market of infrequently purchased goods. Such goods are according to them e.g. automobiles, computers, cell phones and digital cameras. Awareness of products increases over time and thus it is reasonable to concentrate the advertising on the early phases of the product life cycle. Advertising obviously increases consumers' awareness of a product and thus has an influence on their choice sets, which was mentioned by Goeree (2008) as well. Neither Barroso and Lloebet (2012) nor Goeree (2008) take a stand on the advertising dynamics as was done by Hubé et al. (2005). The previous ones are in favour of upfront advertising, but tell little about the temporal allocation of optimal advertising investments in the beginning of the life cycle.

The choice sets of consumers, however, are usually not available for the researcher and thus they must be estimated, like Goeree (2008) has done. Barroso and Llobet (2012, 776) assume that the choice set is specific for each consumer and evolves over time. They include advertising to the utility function of a consumer as well. Just as Goeree (2008), Barroso and Llobet (2012) assume that the probability that a good belongs to the choice set of a consumer is possible without advertising as well and that choice set is independent of the other products included in it. This assumption according to Barroso and Lloebet (2012, 777) rules out the cognitive constraints (like a limited capability of remembering) and information spillovers. The second choice set assumption is that it is independent on the characteristics of a consumer. Thus, the probability that the good j belongs to the choice set of consumer i at time t is:

$$\phi_{jt} = \frac{e^{\omega_{jt}}}{1 + e^{\omega_{jt}}} \tag{28}$$

The latent variable ω_{jt} captures the awareness level of product j at time t and has the following transition equation:

$$\omega_{jt+1} = \lambda\omega_{jt} + \varsigma_{jt} \tag{29}$$

Thus, the awareness of each period depends on the awareness of the previous period though the carryover coefficient λ and the last term gets value one or zero depending on the impact of advertising. The parameter ω_{jt} can be denoted as the initial awareness of product j introduced to the market in period t. The initial awareness depends on the annual average advertising expenditure incurred by the seller of the good j to advertise its brand period t. Barroso and Lloebet (2012) assume that the stock of awareness accumulates and depreciates over the time (just like Nerlove and Arrow (1962)). The value of the carryover coefficient λ equal to or higher than 1 does not mean the absence of forgetting, but rather that the proportion of consumers who learn about the product increases over time. The awareness probability (ϕ_{jt}) in their specification has S-shaped form meaning that the awareness grows exponentially at early stages and slows down as the product becomes well-known. The awareness process ends at the moment when the awareness remains stable over time. Market shares are estimated as a function of individual purchase probabilities and a distribution of consumers' characteristics.

The firms are assumed to be in Barroso and Lloebet (2012) Berntrand-Nash competitors as well as in BLP (1995) and Goeree (2008). The firms have a dynamic profit maximization problem, because the awareness of their products develops over time. Advertising expenditures have two effects on profits: advertising increases consumer utility and thus market share at a higher cost. The advertising expenditures of the current period have a dynamic effect on the advertising decisions (both own and competitors') in the future periods. This kind of approach gives support for upfront advertising policy. Barroso and Lloebet (2012) mention that one of the major caveats in their model is that exit of a product is assumed to be exogenous and deterministic. Further, for estimating unobserved characteristics they applied GMM in a similar way as in BLP (1995) and Goeree (2008.)

Barroso and Lloebet (2012, 780-789) used their specification for analyzing Spanish automobile industry. They estimated the demand equation parameters using the logit model and $\ln(s_j)$-$\ln(s_0)$ as a dependent variable. As explanatory variables are used: price, size, maximum speed, gas mileage and engine displacement over the weight of the car. They use annual and month dummies as well to control for common variations in the market over time and seasonal patterns. They included brand dummies as well to control for the effect of the image of the brand. They conducted OLS regression, IV regression (the price instrumented) and IV regression (the price and advertising instrumented.) The differences between OLS and endogeneity corrected IV regressions were quite the same as in BLP (1995) and Goeree (2008.) However, the main finding was that a model that exogenously imposes the end of the awareness process likely cannot disentangle the dynamic effect of advertising on awareness from other relevant effects of advertising.

Next Barroso and Lloebet (2012, 780-789) conducted further developed models: BLP extended with the advertising parameter in the utility function, the model of Goeree, when advertising affects on the awareness, but the probability of inclusion of the good in the choice set grows deterministically as a function only of the time the product has been in the market (static model), static and dynamic models with a discount factor of firms being 0 and finally the developed in their paper dynamic model. As a dependent variable is now monthly market share which is calculated by dividing units sold by the market size, which is the number of households. Among explanatory variables are included monthly, annual and brand dummies to control the fixed effects and firm-specific factors. The bias caused by the assumption that firms behave as single good producer is found out to be sufficient little. They conducted unreported regression as well where the (depreciated) advertising investments of the previous periods are taken into account.

Their basic findings are that advertising increases consumer utility but it has an even more significant role in the awareness process of new goods. The awareness process can last from 2-6 years and after that the awareness remains stable as it was mentioned above. The average awareness process takes three years. Also in the market with infrequently purchased goods with the regular introductions of new goods advertising is a significant means of increasing initial sales. In the industries of this kind, a large component of firm's costs represents advertising investments.

In my own analysis, I will use mainly basic logit model taking as a starting point represented by Berry (1994) that goods differ from each other by mean utility levels and they are defined to be differences in logarithmic market shares. The explained variable will be the difference between logarithms of market shares of a good and outside good (the utility of which is normalized to zero) and as explanatory variables is included advertising both, as a periodical investment and as a stock. I will describe my own research in detail in Chapter 5. Table 1 contains comparison between Berry et al. (1995), Goeree (2008), Barroso and Lloebet (2012) and this research.

Table 1 Comparison of Researches in the Field of Discrete Choice

	Berry et al. 1995	Goeree 2008	Barroso and Lloebet 2012	This research
Endogeneity	Corrected by using estimated instruments	Corrected by using estimated instruments	Corrected by using estimated instruments	Uncorrected
Information assumption	Full information	Limited through information technology parameter	Limitation taken into account as awareness levels of the products	Full information
Goodwill advertising	No	No	Taken into account as an advertising variable in the utility function	Taken into account as an adstock variable in the utility function
Awareness advertising	No	Awareness effects through the information technology parameter	Taken into account as awareness stock variable	Taken into account as a product maturity function and as an adstock variable
Entry and exit	Exogenous	Exogenous	Exogenous	Exogenous
Demand side data	Required sales volumes	Required sales volumes, media exposure and demographic information	Required sales volumes	Required sales volumes
Cost side data	Required maginal cost (estimate)	Required marginal cost (estimate) and advertising investments	Required marginal cost (estimate) and advertising investments	Required advertising investments
Market size	Taken as given (number of households)	Taken as given (number of households)	Taken as given (number of households)	Taken as given (a sophisticated guess of the number of annual acquisitions)
Main contribution	Substitution between products and endogeneity correction	The influence of limited information	The influence of advertising on the utility and its contribution to the awareness process	The differences in the influence of advertising between countries, media and advertisers using same data.

In this and previous chapters, I have described advertising as a means of industry conduct and how it can influence on the market performance and structure. I have also considered the modeling of consumer choice which is an important part of analysis of the impact of advertising. Advertising can impact on the consumer choice through increasing the probability that a good belongs to the consumer choice set (captive segment) and through making a consumer aware of the characteristics of a good and increasing the utility of a consumer (competitive segment). Advertising can be treated as a current period phenomenon only or as an accumulating and depreciating stock. In the next chapter, I will briefly describe the smartphone industry and its current state in order to give useful background information about industry that I am going to research.

4 Description of Smartphone Industry

As an umbrella for the smartphone industry can be considered the information and communications technology industry (ICT). The industry went through a wave of deregulation during the past decade and in many countries state monopolies have privatized and new competitors have shown up. Traditional phone calls still generate the major profits of the industry, but the things are changing. Telecommunications are nowadays more about texts and images rather than a voice. (World Bank. The Little Data Book on Information and Communication Technology 2012.) Therefore the smartphone market is an interesting subject to be researched. In telecommunications industry success in the field of private customers and small business relies mostly on the brand name. The industry can be considered as an industry with infrequently purchased products with the frequent introductions of new goods. Therefore the role of advertising should be combined to the industry analysis.

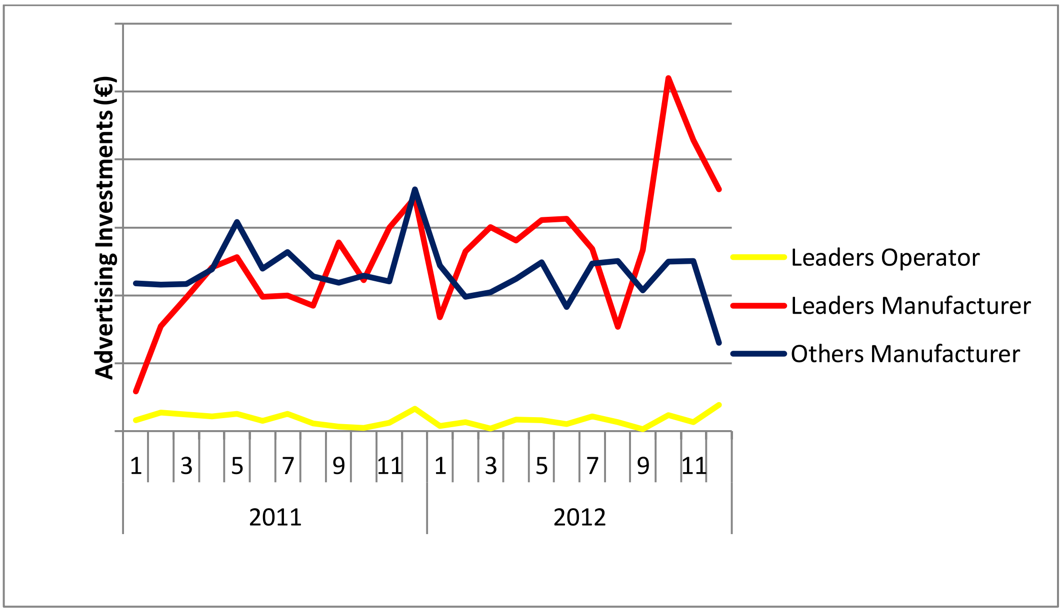


Figure 1 Leading Brands' Manufacturers' Advertising Investments and Other Brands' Manufacturers' Advertising Investments and Operators' Advertising Investments on Leading Brands

Source: Confidential dataset of advertising investments and author's calculations

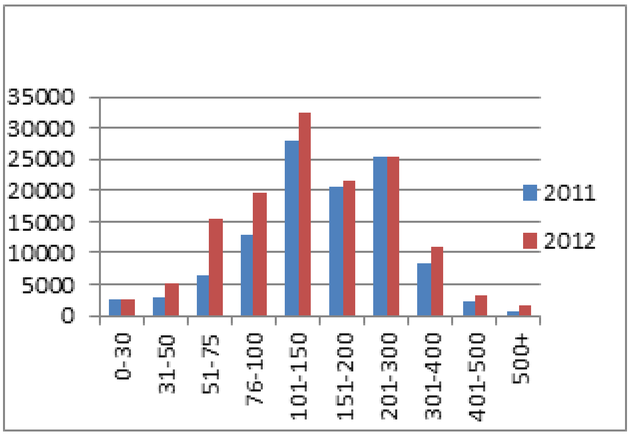
From Figure 1 can be easily seen that the most of the advertising in the industry consists of manufacturers' investments. Operators advertise mostly their own brands, but spend some fraction on the advertising of the handsets of the leading brands as well. In fact this conclusion is probably biased, because smartphones and subscriptions are often sold in ties and thus operators' role can be significantly more important than the figure above demonstrates. By the end of the period, the leading brands' advertising investments have peaked in comparison with other brands.

The success in the smartphone industry depends not only on the handsets, but on the operating system (OS) as well. Companies manufacturing handsets only must make OS licensing decisions in order to stay relevant. Out of significant handset producers, only Apple has its own OS. The OS decisions and customer-lock strategies are said (Kenney and Pon, 2011) to be the core components of survival for companies in the smartphone industry. In the OS, there is a network effect as well. When one operating system gets more users, it attracts them even more.

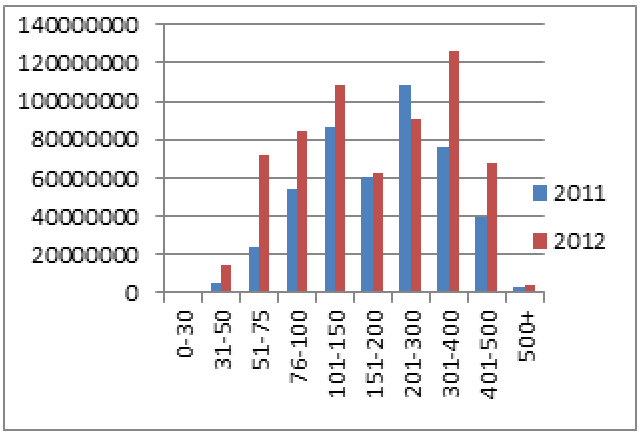
The smartphone industry itself is still rather young. The definition of smartphone is nowadays somewhat ambiguous, but smartphones can be said to combine mobile phones' and PCs' characteristics. According to Kenney and Pon (2011) smartphone industry has more diverse factors than PC industry. It is at early stage of development and technological innovation is rapid. They note that old incumbents from mobile phone industry (e.g. Nokia) are losing their positions to the newer entrants or growing incumbents from PC and internet industries (e.g. Apple and Google.) Based on Kenney's and Pon's paper (ibid) in early 2011 the leading smartphone industry factors were: Nokia, Apple, Google, Motorola, Samsung and HTC. Google's profit model is advertising, whereas the rest rely on handsets. Apple's profit model includes also downloads and Nokia is trying them as well. In this paper, I will concentrate on handset market and therefore Google as a brand is excluded from the research.

Based on Koski's and Kretschmer's (2009) empirical paper about new product development and firm value in mobile handset market it can be said that a firm with technological leadership is more valuable. This is even though the innovative research and development are risky and costly and imitative innovations would generate profits more easily and quickly. In the same paper, they found out that the most product introductions are of imitative character. Also such introductions increase firm value, but less than truly innovative introductions. In their earlier paper (Koski and Kretschmer 2007) they stated that the mobile phone industry has moved towards horizontal differentiation. The aim is nowadays to create segmentation and devices to meet the preferences of different consumer groups by new innovations rather than improve the quality of devices. In that paper it is noted that there has been a vertical product homogenization process going on. As devices are converging towards technically more homogenous products and horizontal differentiation is becoming the main means of relaxing price competition, the role of advertising is also probably growing. Advertising is required for both, to inform buyers about different features and to persuade consumers to purchase.

Based on GfK market data, smartphones sales were over 459 million in 2011. Sales reached 630 million in 2012. In Figure 2 are demonstrated the quantity of products in different price bands (2a) and sales volumes by the price band (2b) in 2011 and 2012.



(2a)



(2b)

Figure 2 Number of Products in Different Price Bands (2a) and Sales Volumes (2b) in Different Price Bands in 2011 and 2012

Source: GfK and author's calculations

As we can see from the graphs, the amount of products has increased the most in the cheaper price bands. Also the number of devices sold has increased in them the most. It is also interesting to note that purchases have increased significantly in the more expensive price bands. So, the smartphone is becoming more common as the number of products increases in the cheaper price bands. It could also be a sign of imitative innovation. Same time, the willingness to pay more has increased as the acquisitions in the more expensive price bands have increased notably as well. Besides quality improvements, the increase of acquisitions in more expensive price bands could be a signal of segmentation. The most demanding consumers are willing to pay more for the product matching their preferences.

When describing an industry, the attention should be paid to the industry structure as well. Figure 3 shows the market shares of eight leading brands in the global smartphone market.

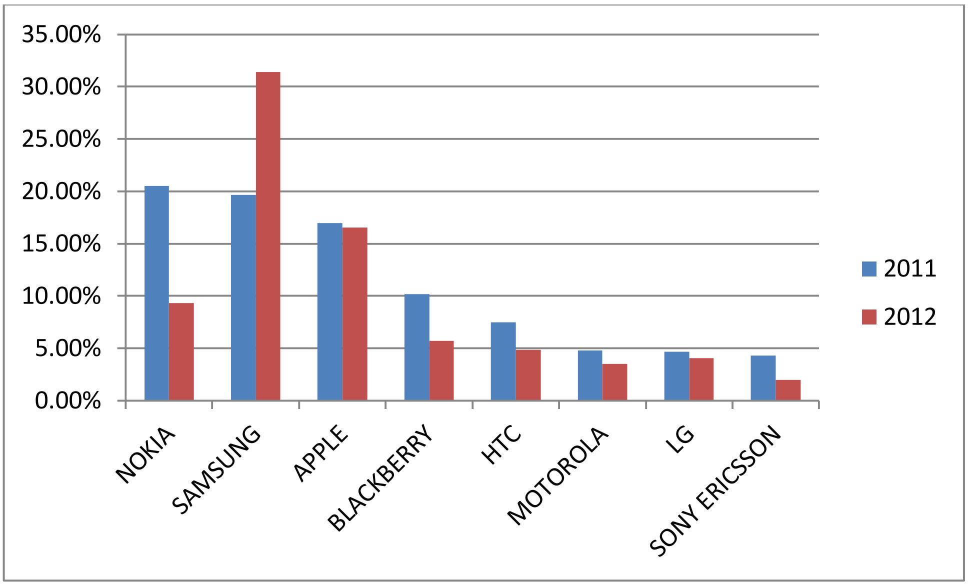


Figure 3 Market Shares of the Leading Brands in 2011 and 2012

Source: GfK and author's calculations

The smartphone industry has a huge number of small factors and some larger ones with a significant market share. The chosen companies above have had a market share of over 1% in both years. A very simple way to analyze the industry structure is the concentration ratio. CR_4 is the sum of the market shares of the four largest firms. CR_8 is the sum of the eight largest respectively. In 2011, CR_4 was 0,67 and in 2012 it was 0,63. CR_8 0,89 and 0,79 respectively. This kind of concentration of 50%-80% means medium concentration and such industry is likely an oligopoly. However, the concentration ratio provides little information about the competition in the industry. Therefore it can only be considered as a signal of an oligopolistic nature of an industry.

Somewhat more sophisticated tool for analyzing the industry is Herfindahl-Hirschman index (HHI). It is calculated from the formula: $HHI = \sum_{i=1}^{N} s_i^2$, where s_i is a market share of firm i and N is the number of firms in the market. HHI is usually calculated using the 50 largest firms in the market or all of the firms, if there is less than 50 firms. For smartphone industry HHI in 2012 is 0,15 and in 2011 it is 0,13. Interpreted this means that industry is in 2012 moderately concentrated and unconcentrated in 2011 0,15 being the limit value. Nevertheless, Herfindahl-Hirschman index has its pitfalls as well. The largest are the definition of the market and substitutability. If one company has a significant market share in a market, it does not necessarily mean a harmful monopoly, if consumers have reasonable substitutes. In case of smartphones, they could be laptops, tablets and mobile phones. It also ignores geographical aspects: one firm can hold an almost monopolistic position in one area and be the same time almost non-existent in another.

To conclude, the smartphone industry is a rather young industry and its definition can be somewhat ambiguous. The industry can be considered moderately concentrated with a few large factors and a tremendous amount of smaller ones. The industry is moving from vertical improvements towards horizontal differentiation and segmentation. Smartphone acquisitions continue to grow and the prices continue to fall. Same time willingness to pay higher prices in some segments has increased.

5 Data Analysis

In this chapter, I conduct my data analysis. I intend to keep the analysis simple and transparent and to connect some parts from the models represented in Chapter 3 to it. My main goal is to compute advertising elasticities of market shares and this way try to explain the impact of advertising investments on the market share in different markets, by different media and advertisers. The applied logit model does not fit for computing substitution between products, but it is applicable in estimating the effectiveness of the advertising across the countries, media and advertisers. At first, I take into account the effect of advertising as a periodical investment but then I will include advertising into the regression as a stock that depreciates and accumulates by the time as Nerlove and Arrow (1962) and Barroso and

Lloebet (2012) already assumed. I try to find out if advertising elasticity is higher in some countries, through some media or if the advertising of some advertiser is more elastic. I start by representing the datasets and move on to the methodology and model. I will test the robustness and sensitivity of the model as well and further discuss findings.

5.1 Data Description

The analyzed data has been gathered from two sources. The confidential dataset contains monthly information about advertising spending by the product, advertising channel (cinema, online, outdoor, print, radio, tv and other) and advertiser (manufacturer, operator and retailer). The other dataset is provided by GfK and contains information on the monthly basis about sales volumes, retail prices and characteristics by the product. The time span of the research is 23 months starting from January 2011. The period is good for this analysis taking into account the life cycle of the smartphones. I have chosen high-end smartphones as research objects. The reason for that is that their sales volumes have increased the most during the previous years as demonstrated in Chapter 4. They are also more differentiated and innovative in comparison with cheaper ones and therefore fit better discrete choice framework. The price of the chosen products has been above €300 at least at some phase during the research period and they are the products of the leading brands. The most binding constraint in choosing products was the match between the datasets. Only such products could be chosen which have both sales and advertising observations during the research time span. The advertising investment dataset contains the observations of brand general advertising as well, but only such products targeted advertising of which is observed are included in the analysis. The chosen products are demonstrated in Table 2.

Table 2 Researched Products and Their Sales Starts

	Available	
Product	Month	Year
Nokia C7	10	2010
Nokia E7	2	2011
Nokia N8	10	2010
Nokia Lumia 900	5	2012
Nokia Lumia 800	11	2011
Samsung Galaxy Note	9	2011
Samsung Galaxy Note II	9	2012
Samsung Galaxy S	6	2010
Samsung Galaxy S II	4	2011
Samsung Galaxy S III	5	2012
Apple iPhone 4	6	2010
Apple iPhone 4S	10	2011
Apple iPhone 5	9	2012
HTC Desire S	2	2011
HTC One S	4	2012
HTC One X	5	2012
HTC Sensation X*	10	2011
LG Optimus 3D	7	2011
Sony Xperia T	9	2012
Blackberry Bold 9900	8	2011

*Aggregated HTC Sensation XE and HTC Sensation XL.

Source: GSMArena.com

The chosen products have been slightly aggregated such that products with the same launch time and very little variation are treated as one product. That is both because of simplicity and because the advertising observations were not so accurately targeted either. This also relaxes the primarily unrealistic assumption of firms as single good producers (e.g. Barroso and Lloebet 2012.) Firms usually concentrate on one product in the same segment in a time. However, there can be some variation among products (e.g. storage capacity), but usually there are not simultaneously products of one brand aimed at the same segment competing with each other. As we can see from Table 2, there are products which have been launched during the research period at different points of it as well as products which have been available already at the beginning of the research period (C7, N8, Galaxy S and iPhone 4).

The exits of products are assumed to be deterministic and exogenous and are not considered in the analysis. By combining the datasets of advertising observations and sales observations I have obtained an unbalanced panel dataset consisting of 23 periods (months).

The researched markets are the smartphone handset markets in the United Kingdom, the United States, India, China, Russia, Germany, Italy, Indonesia and Saudi Arabia. The selected countries represent the global smartphone market comprehensively by including both developed and emerging markets. I tested the model first by researching only the market of United Kingdom. As Berry (1994) and Berry et al. (1995) noted, the market size can be either estimated or observed. I assume that the market size is observed. The same assumption was made by Berry et al. (1995), Goeree (2008) and Barroso and Lloebet (2012) as well. They used as a market size the number of households in the country. They investigated automobile and personal computer markets and therefore that was a well-justified assumption in their papers.

However, the smartphone market is somewhat different from the automobile or personal computer market. The number of households would be a too small market in many cases. As a starting point for the market size determination I took the population of the country, say the UK, for instance, which is slightly over 63 million people. (CIA – The World Factbook.) All the mobile phone owners can be considered potential smartphone owners. According to Wallblog the mobile phone ownership has reached the 50% milestone in 2000 being currently almost 100%. Actually, according to Wired.com the number of mobile phone subscriptions in developed markets exceeds 100% meaning that people on average have more than one mobile phone subscription.

Based on Recon Analytics analysis of handset replacement cycle (International Comparison: The Handset Replacement Cycles, 2011), it is currently 22 months i.e. approximately two years in the UK. The smartphone penetration rates and transfer rates from feature phones to smartphones have been represented also by other sources (e.g. Wired.com and Smartphone Market Growth in Saudi Arabia). When defining the market size, I exclude under 14-year-old and over 65-year-old inhabitants, assume that a current feature phone user can switch to the smartphone with the probability of 50% and 50% of current smartphone owners are annually changing their smartphone handset. I can get the market size of 20 million for the smartphones in the UK. That figure is used as a market size in market share calculations in the analysis.

Determination of the market size described above fits the developed countries well. However, it is probably not completely plausible in defining the marked size of emerging markets especially in case of high-end smartphones. There the substitution to high-end smartphones is probably more income sensitive. Therefore in addition to described above "the rule of thumb" in the determination of market size, I compared the smartphone sales volumes in GfK dataset in 2011 and January-November 2012 and corrected the market size respectively if the primary assumption seemed incorrect. Interestingly, there has been a moderate growth (in line with the general growth in the industry mentioned in Chapter 4) in sales volumes in almost every country from 2011 to 2012 but in China was sold almost 100 million smartphones more between January and November 2012 in comparison with the sales in 2011. The market sizes applied in the research are demonstrated in Table 3. Market sizes are represented on the annual basis. Monthly market sizes can be obtained by dividing them by 12.

Table 3 Market Sizes

Country	Market size (million)
CHINA	200
GERMANY	25
INDIA	20
INDONESIA	20
ITALY	15
RUSSIA	15
SAUDI ARABIA	17
UK	20
USA	150

This kind of market size determination might intuitively appear too simplistic. I will check the sensitivity of the model to the market size in the subchapter 5.4. I find this kind of market size determination fairly good enough. The market size is crucial, because it determines the market share of the outside good, which is an essential part of the explained variable. The market shares of the outside goods are demonstrated in Figure 4.

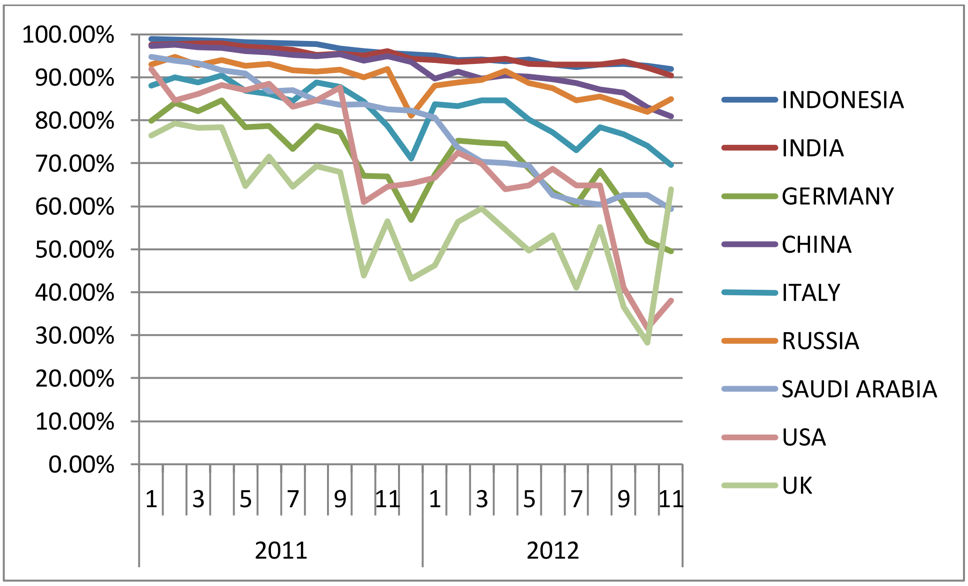


Figure 4 Market Shares of Outside Good by Country

The market shares of outside good are decreasing by the time. That can be connected with the upfront advertising. The advertising cycle of a typical product is demonstrated in Figure 5. At the beginning of the research period there were probably many products advertising of which had discontinued (e.g. iPhone 3) but they still had significant market shares. From Figure 4 can be seen that the market share of the outside good is the highest in the emerging markets where the market size of high-end smartphones is more ambiguous to define.

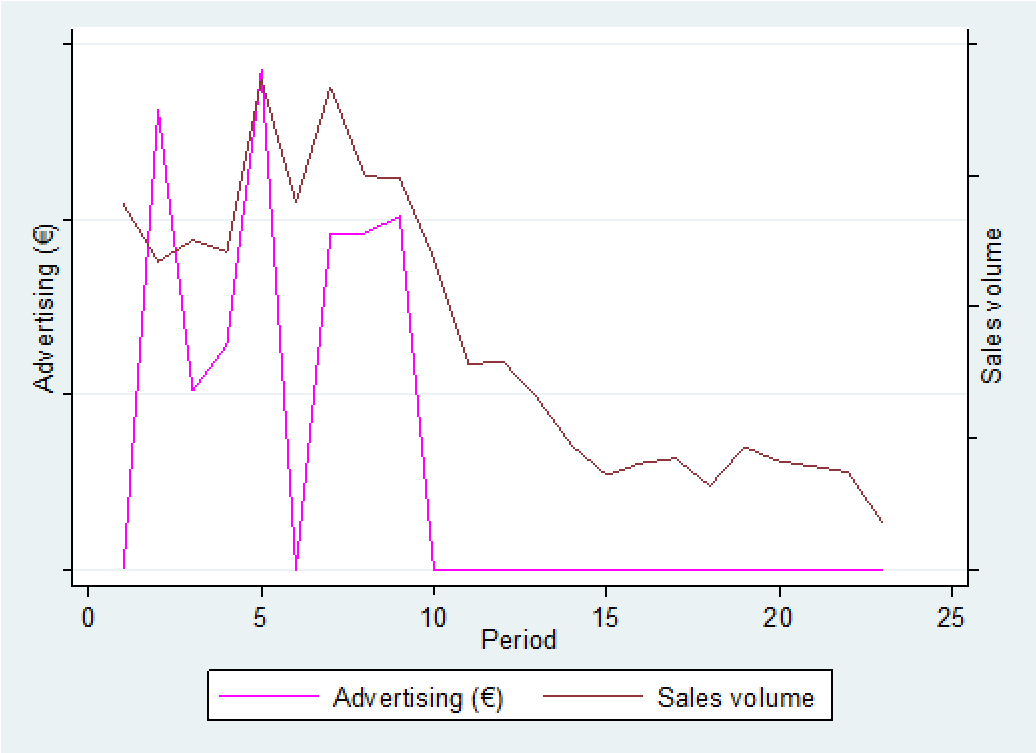


Figure 5 Typical Evolution of Advertising Investments and Sales Volumes of a Product in the Choice Set

Source: Confidential dataset of advertising investments, GfK and author's calculations

I will include in the model the advertising as a stock. The advertising stock accumulates by the following formula:

$$S_{At} = A_t + 0{,}5 * S_{At-1} \tag{30}$$

In the formula (30) the advertising stock at time t is S_{At} and advertising at time t is A_t. The depreciation rate is assumed to be 50%. In Figure 6 are demonstrated advertising stock and sales volume of the same example good. As we can see, the advertising stock follows the sales volumes much smoother than periodical advertising investments only. The advertising stock of an example good completely disappears in approximately half a year after the end of advertising.

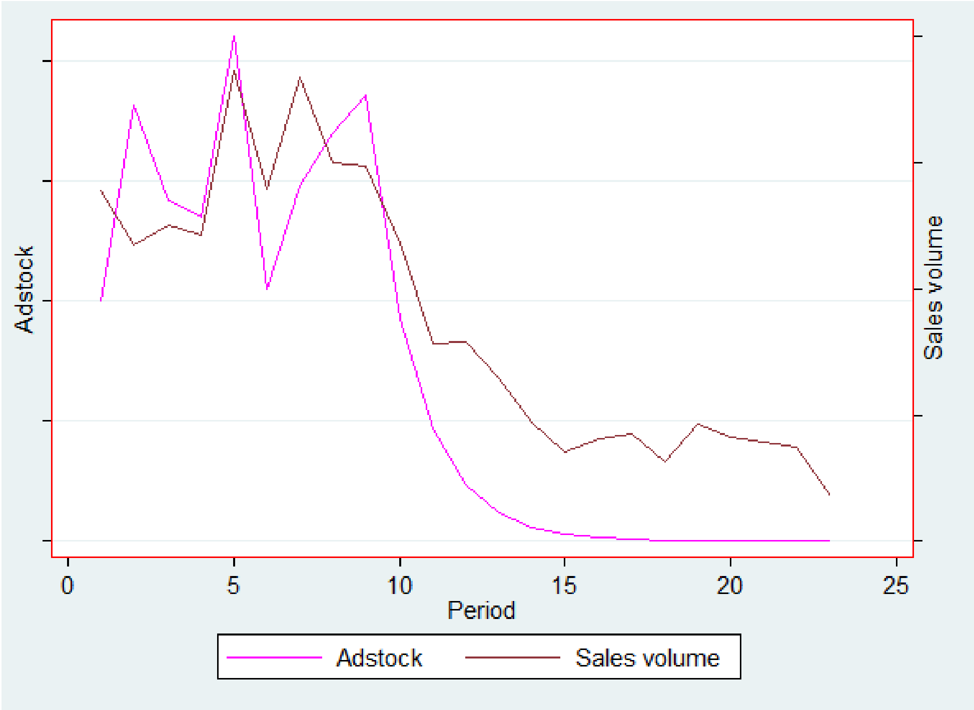


Figure 6 Typical Evolution of Advertising Stock and Sales Volumes of a Product in the Choice Set

Source: Confidential dataset of advertising investments, GfK and author's calculations

Table 4 provides summary statistics by country of the average values of sales volumes (Volume), advertising investments (S_prod_tot) and advertising stock (Adstock) variables. I have also computed cost-per-acquisition (Cpa) ratios for each country simply by summing up monthly advertising investments per product and dividing them by summed up monthly sales volumes per product.

Table 4 Summary Statistics of Used Variables

	Volume		S_prod_tot		Adstock		Cpa	
Country	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
CHINA	124022.1	193672.4	492768.5	1213491	429478.2	1127117	4.792462 *	9.603624*
GERMANY	48668.74	81601.03	863441.9	1445484	887999.4	887999.4	28.33571	58.92416
INDIA	7907.558	8816.422	396294.5	754619	291881.7	652037.7	10.03132	14.13161
INDONESIA	6594.292	10162.27	8862.5	12528.59	85842.7	223407.5	0.320901	1.385977
ITALY	18255.85	30994.56	586790	844900.4	342235.8	718240	12.28183	22.90772
RUSSIA	11718.97	13609.64	242463.3	577487.1	212208.5	500310.5	12.95082	22.17478
SAUDI ARABIA	27920.89	32192.21	148542.9	259805.7	95962.41	217312.7	2.941036	6.762914
UK	58259.11	99220.51	494644.9	589691.5	490618.2	709986	14.72121	23.92096
USA	634905.2	845171.1	2273328	6633152	1962200	6636432	5.279557	8.790225

*Cpa for China computed without product Xperia T

The cpa ratios have probably a downward bias in some countries, which is caused by the measurement error of advertising investments. In this part has been described the used data and the main background assumptions of the analysis. Next I will continue to describe the methodology and the model.

5.2 Methodology and Model

In this paper, I use as a starting point the same as Berry (1994) and Berry et al. (1995) i.e. a logit model. I include advertising into the regression which was done by Barroso and Lloebet (2012) as well. I use the panel data and the main interest is in the responses of market shares to the advertising. The product characteristics are time invariant and therefore they are controlled out in this analysis. The advertising is included in a logarithmic form, because it can capture the diminishing marginal utility. The linear form would give unrealistically increasing marginal utility for the advertising. I use as an explained variable the difference of the logarithms of market shares of inside and outside goods, which is the difference of mean utility levels when the utility of the outside good is normalized to zero. The similar specification has been used by Berry et al. (1995) as well. In the regression tables the explained variable is referred to as LHS.

Explanatory variables are logarithms of advertising investments (or accumulating and depreciating stock of advertising investments), price, seasonality (by including month and year dummies) and the cube of product maturity. The product maturity is included in the cube in order to capture the non-linear character of its. The product maturity effects intuitively (and based on the literature represented above) positively on the sales in the beginning and at some point its effect turns negative. The coefficient of third degree term was still significant and different from zero and therefore it is included. I include also brand dummies or product dummies to control brand or product specific effects. The similar approach was used by Barroso and Lloebet (2012) as well. I do not use any instruments to correct the endogeneity of prices, because they are hard to find and the estimation of them would require cost side information and applying less convenient methods described in Chapter 3. Including product and brand dummies is actually one way of controlling the omitted variable bias by generating the fixed effects model with dummy variables. Therefore I will call the model with brand dummies the brand fixed effect model and the model with product dummies the product fixed effects model. The model can be extended by dividing the advertising into channels (cinema, online, outdoor, print, radio, tv) or into advertisers (manufacturer, operator, retailer).

The estimation equation has the following form:

$$\ln s_{jt} - \ln s_{0t} = constant + \alpha * price_{jt} + \beta * log\_s\_prod\_tot_{jt} + \gamma_1 * product\_age_{jt} + \gamma_2 * product\_age_{jt}^{\ 2} + \gamma_3 * product\_age_{jt}^{\ 3} + \mathrm{A}_t + \mathrm{B}_t + \Gamma_j + \Delta_j + \varepsilon_{jt} \tag{31}$$

In the equation (31) A is a vector of coefficients for calendar months, B is a vector of coefficients for years, Γ is a vector of coefficients for brand, Δ is a vector of coefficients for product and ε_{jt} is the error term. The month and year dummies are included in every regression. The brand dummies are included in brand fixed effects regressions and product dummies in product fixed effects regressions.

From the estimated parameters can be computed advertising elaticities. The basic way of calculating elasticities was described in Chapter 3. Some pitfalls concerning the elasticities with logit models mainly caused by the IIA property were mentioned as well. However, they give some understanding how elastic market shares are with respect to the advertising. When calculating elasticities should be taken into account the form of the variable in the model. If the variable appears in the linear form, the own elasticity can be calculated applying formula (12) in Chapter 3. The cross elasticity is obtained from the formula (13). The elasticity depends only on the coefficient, advertising investment and market shares and there is only one cross elasticity against other goods. So it is not possible to compute the full elasticity matrix. The case with elasticities becomes even simpler if the variable is in logarithmic form. The own elasticity can be computed from the formula (14) and the cross elasticity from the formula (15). Thus, the own elasticity is the closer to the estimated coefficient the smaller the market share is. The smaller the market share of other good is, the less the cross elasticity is. The logarithmic advertising is therefore a very convenient way for the analysis of this kind. It describes the diminishing marginal utility of advertising investments realistically and estimated coefficients can be interpreted as advertising elasticities. In the next subchapter, I will introduce the results of some regressions.

5.3 Results

I start by testing the model by including the advertising in linear form as well, which allows computing elasticities by including advertising investments in the formula. Table 5 contains the results of linear and logarithmic regressions applying pooled OLS, brand fixed effects and product fixed effects models. In these regressions, I tested the model with the British market only.

Table 5 Outputs of Linear and Logarithmic Regressions with OLS, Brand and Product Fixed Effects in the UK Market

	OLS, log UK	Brand FE, log, UK	Product FE, log, UK	OLS, lin, UK	Brand FE, lin, UK	Product FE, lin, UK
	LHS	LHS	LHS	LHS	LHS	LHS
(mean) price	0.00821	0.00101	0.00151	0.00797	0.000828	0.00155
	(0.00099)***	(0.00102)	(0.00088)*	(0.00103)***	-0.00103	(0.00088)*
log_s_prod_tot	0.05070	0.02022	-0.00480			
	(0.01095)***	(0.00957)**	(0.00830)			
product_age	0.64158	0.57263	-4.04553	0.6771	0.58365	-4.02244e+00
	(0.14658)***	(0.11406)***	(0.65302)***	(0.14896)***	(0.11464)***	(0.64798)***
product_age2	-0.04534	-0.05103	-0.04455	-0.05162	-0.05379	-0.0444
	(0.01310)***	(0.01012)***	(0.00840)***	(0.01324)***	(0.01007)***	(0.00833)***
product_age3	0.00084	0.00096	0.00089	0.00102	0.00104	0.00089
	(0.00032)***	(0.00025)***	(0.00020)***	(0.00032)***	(0.00024)***	(0.00020)***
s_prod_tot				1.2082E-06	0.0000003526	-2.311E-07
				(0.0000003560)***	(0.0000002850)	(0.0000002342)
Seasonality dummies	Yes	Yes	Yes	Yes	Yes	Yes
Product dummies	No	No	Yes	No	No	Yes
Brand dummies	No	Yes	No	No	Yes	No
Constant	-10.20410	-1.93667	-35.24235	-1.03204e+01	-1.88026e+00	-3.50491e+01
	(0.93542)***	(1.03484)*	(4.30041)***	(0.95174)***	(1.04320)*	(4.26613)***
Observations	277	277	277	277	277	277
R-squared	0.40	0.66	0.80	0.37	0.65	0.80

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

The pooled OLS yields the highest and the most significant coefficients for both logarithmic and linear specifications. In order to hold, the pooled OLS requires the exogeneity of the explanatory variable. The endogeneity of prices has been discussed in Chapter 3 already and that is probably one reason why the price gets positive coefficients in the regressions above. The other reason is that the market share of the inside goods grows by the time with new introductions and therefore the sales of more expensive products occur more. This is one pitfall of the specification, but since I can obtain plausible coefficients for the advertising I do not find it too serious a problem. The endogeneity of advertising is not as straightforward as the endogeneity of prices, but some bias probably exists because advertising gets negative coefficients in some regressions. This can be due to measurement error for instance.

I computed product specific elasticities applying formulas (12)-(15). These are not worth reporting because of their implausibility discussed above. The elasticity computed from the linear specification takes into account the advertising investment as well. Therefore the deviation was higher among them than among the elasticities computed form the logarithmic specification. Interestingly, some products of Samsung and Apple obtained the elasticities of over 1 from the linear specification (high advertising investments count more). Same time their elasticities were lower from the logarithmic specification (high market shares count more). This proves the correlation between market shares and advertising investments. Elasticities computed using the logarithmic specification almost equal to the estimated coefficients. Thus, as mentioned above, the logit model is handy in comparing the differences between the advertising elasticities by countries, channels or advertisers. Including advertising in logarithmic form in the estimated equation allows us both to fulfill the assumption of diminishing marginal utility and returns to scale as well as treat the obtained coefficient β as the advertising elasticity.

I continue by dividing the advertising investments into channels. I apply the logarithmic specification so we can see approximate elasticities directly from the coefficients. I ran regression by using the British data only and by using the data of all countries. Table 6 contains the results of regression.

Table 6 Advertising Divided by Channels

	UK	All Countries
	LHS	LHS
(mean) price	0.00109	0.00264
	(0.00098)	(0.00052)***
product_age	0.61555	0.61644
	(0.11039)***	(0.04361)***
product_age2	-0.05283	-0.04202
	(0.00971)***	(0.00368)***
product_age3	0.00100	0.00076
	(0.00024)***	(0.00009)***
log_s_CINEMA	0.05873	0.00931
	(0.01566)***	(0.00850)
log_s_ONLINE	-0.00193	-0.00809
	(0.01152)	(0.00541)
log_s_OUTDOOR	-0.00058	0.00413
	(0.01401)	(0.00640)
log_s_PRINT	0.03752	0.02262
	(0.01177)***	(0.00464)***
log_s_RADIO	-0.03831	-0.00283
	(0.03733)	(0.01159)
log_s_TV	-0.02746	0.01858
	(0.01125)**	(0.00457)***
Seasonality dummies	Yes	Yes
Brand dummies	Yes	Yes
Country dummies	No	Yes
Constant	-1.40306	-7.27606
	(1.30461)	(0.57077)***
Observations	277	2273
R-squared	0.69	0.43

Standard errors in parentheses
* significant at 10%; ** significant at 5%;
*** significant at 1%

The regression run by advertising channels does not yield very significant results neither on a country level nor on the whole sample level. I assume that one main reason is that the data does not capture the product level advertising accurately enough and thus its division into advertising investments by channels is not accurate enough either. However, the coefficients for cinema and print are significant and reasonable as well. In the whole sample level print and tv got significant and plausible coefficients. The qualitative aspects of advertising are not of the main interest in this paper. However, the cinema would be such advertising channel that suits well for persuasive and captive advertising. Print suits well for both persuasive and informative advertising as was mentioned by Kaldor (1950-51) as well. Discussing the results of the regression above should be kept in mind that the advertising is included as monetary investments only. The investments are probably the highest for print and tv in most of the countries. The advertising response by the channel could probably be captured better if advertising was measured in GRP because it captures the exposure better.

Next I divide the advertising investments by advertiser. Hence the division between operator and retailer in the data is somewhat ambiguous I aggregated all non-manufacturer advertising into one variable s_OPRET. Table 7 contains the output of this regression.

Table 7 Advertising Divided by Advertisers

	UK	All Countries
	LHS	LHS
(mean) price	0.00068	0.01074
	(0.00099)	(0.00079)***
log_s_MANUFACTURER	0.02615	0.00607
	(0.00540)***	(0.00344)*
log_s_OPRET	-0.01509	0.00058
	(0.02898)	(0.01241)
product_age	0.38861	1.03147
	(0.11347)***	(0.06842)***
product_age2	-0.03000	-0.06438
	(0.00984)***	(0.00574)***
product_age3	0.00045	0.00120
	(0.00024)*	(0.00014)***
Seasonality dummies	Yes	Yes
Brand dummies	Yes	Yes
Country dummies	No	Yes
Constant	-1.69568	-15.11340
	(1.17273)	(0.76578)***
Observations	276	2273
R-squared	0.66	0.31

Standard errors in parentheses

* significant at 10%; ** significant at 5%;
*** significant at 1%

The coefficients of manufacturer's advertising are significant in both regressions. The coefficients of non-manufacturer advertising are not significant and they are implausible (negative in the UK). This actually proves that Figure 1 in Chapter 4 is misleading and the data roughly underestimates the non-manufacturer advertising investments. One reason for this is that operators' advertising has been encoded in the data with operator's brand and product name even if the operator was advertising the tie of a subscription and handset. Again should be remembered that the data contains only monetary investments. The effectiveness of non-manufacturer advertising investments should be taken into account in non-monetary terms as well. The operator or retailer will advertise and sell in ties only such products which are good for the image of their own brand. Therefore, if a product is advertised by a non-manufacturer, it should be taken as a recommendation for that product. The assumption is supported by the fact that almost no operators' advertising was observed for the products of other than leading brands. However, this regression does not tell anything about the manufacturers' retailers' or operators' domination. This could be discussed more thoroughly with the data of the acquisitions of handsets alone and in ties with subscriptions. Then again the role of operating system should be taken into account as well.

By so far I have concentrated mainly on the British market. I have also taken into account the effect of advertising for one period only. However, there can be advertising even before the product availability in the market and then obviously no sales occur. It is obvious that also this kind of advertising has effect on sales. Also the advertising of previous periods can have impact on purchase decision. Therefore I use the advertising stock variable in the next regression. I report pooled OLS regression output in Table 8

Table 8 Pooled OLS Regression by Country with Advertising Stock Variable (logstock)

	CHINA	GERMANY	INDIA	INDONESIA	ITALY	RUSSIA	SAUDI ARABIA	UK	USA
	LHS	LHS	LHS	LHS	LHS	LHS	LHS	LHS	LHS
(mean) price	0.00745	0.01153	0.01034	0.00348	0.00799	0.00532	0.00292	0.00743	0.01501
	(0.00085)***	(0.00079)***	(0.00090)***	(0.00090)***	(0.00068)***	(0.00075)***	(0.00121)**	(0.00097)***	(0.00151)***
logstock	0.10702	0.03122	0.09810	0.02448	0.03049	0.08340	0.07666	0.10831	0.02637
	(0.01028)***	(0.00775)***	(0.00815)***	(0.01292)*	(0.01131)***	(0.01309)***	(0.01601)***	(0.01638)***	(0.01236)**
product_age	0.96343	1.07243	0.22488	0.52717	0.37149	0.45414	0.34449	0.36863	0.19018
	(0.12058)***	(0.09729)***	(0.10887)**	(0.13413)***	(0.10004)***	(0.12738)***	(0.17402)**	(0.14872)**	(0.14231)
product_age2	-0.06232	-0.07145	-0.00921	-0.03522	-0.01476	-0.02519	-0.01068	-0.03257	-0.01503
	(0.00991)***	(0.00872)***	(0.00890)	(0.01108)***	(0.00834)*	(0.01080)**	(0.01381)	(0.01289)**	(0.01252)
product_age3	0.00129	0.00133	0.00013	0.00063	0.00013	0.00043	0.00010	0.00075	0.00043
	(0.00023)***	(0.00021)***	(0.00021)	(0.00026)**	(0.00020)	(0.00025)*	(0.00032)	(0.00031)**	(0.00030)
Seasonality dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-14.37715	-13.22642	-10.88647	-9.88856	-10.83137	-10.51456	-8.50764	-10.07568	-10.27546
	(0.73586)***	(0.60665)***	(0.66860)***	(0.85275)***	(0.61598)***	(0.83778)***	(1.07352)***	(0.90046)***	(1.10130)***
Observations	249	294	250	261	281	265	261	277	135
R-squared	0.58	0.63	0.53	0.15	0.47	0.31	0.27	0.44	0.60

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Pooled OLS gives positive and significant coefficients for advertising stock variable in every country. The coefficient of the price is positive, but that bias has been covered already at the beginning of the analysis. I ran the regressions with the brand and product fixed effects (i.e included brand and product dummies) as well. Including product dummies makes the coefficients of logstock somewhat smaller in every country and non-significant in India. In other countries, there is no effect on significance. Including brand dummies makes coefficients non-significant in Germany, Italy and in the USA. The value of coefficients changes only a little from the regression with product dummies. Table 9 contains summary of advertising coefficients β computed using periodical advertising investments only (log_s_prod_tot) and advertising stock (logstock) for each researched countries with pooled OLS, brand fixed effects and product fixed effects regressions. The r-squared is the highest for the product fixed effects regressions and lowest for the pooled OLS.

Table 9 Advertising Coefficients (β) by Country for Periodical Advertising (log_s_prod_tot) and Advertising Stock (logstock) from Pooled OLS, Brand Fixed Effects and Product Fixed Effects Regressions

	log_s_prod_tot			logstock		
	Pooled OLS	Brand Fixed Effects	Product Fixed Effects	Pooled OLS	Brand Fixed Effects	Product Fixed Effects
CHINA	0.02759	0.02414	0.02373	0.10702	0.05997	0.06357
	(0.01052)***	(0.01052)***	(0.00765)***	(0.01028)***	(0.01259)***	(0.01313)***
GERMANY	0.01282	0.00710	0.00855	0.03122	0.01656	0.05895
	(0.00831)	(0.00831)	(0.00739)	(0.00775)***	(0.01295)	(0.01696)***
INDIA	0.06770	0.03071	0.01196	0.09810	0.05661	0.00814
	(0.00922)***	(0.00922)***	(0.00716)*	(0.00815)***	(0.00985)***	(0.01363)
INDONESIA	-0.00199	0.06085	0.02635	0.02448	0.03349	0.13455
	(0.03796)	(0.03796)	(0.02367)	(0.01292)*	(0.00780)***	(0.02867)***
ITALY	0.01277	0.00088	0.01188	0.03049	0.00101	0.02758
	(0.00834)	(0.00834)	(0.00658)*	(0.01131)***	(0.01175)	(0.01381)**
RUSSIA	0.02610	0.02032	0.02544	0.08340	0.03660	0.05273
	(0.01048)**	(0.01048)**	(0.00882)***	(0.01309)***	(0.01657)**	(0.02048)**
SAUDI ARABIA	0.01652	-0.00956	-0.01633	0.07666	0.05915	0.02799
	(0.01635)	(0.01635)	(0.00867)*	(0.01601)***	(0.01466)***	(0.01533)*
UK	0.05070	0.02022	-0.00480	0.10831	0.07860	0.02741
	(0.01095)***	(0.01095)***	(0.00830)	(0.01638)***	(0.01255)***	(0.01176)**
USA	-0.00417	0.01367	0.01631	0.02637	0.01310	0.02546
	(0.01162)	(0.01162)	(0.00939)*	(0.01236)**	(0.01487)	(0.01122)**

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

China and Russia obtained significant coefficients from each regression. The highest elasticities are (according to the product fixed effects) in China, Indonesia and Russia. According to pooled OLS the highest coefficients are in China, India and United Kingdom. The lowest coefficients according to product fixed effects are in USA, Italy, Saudi Arabia and UK, whereas according to pooled OLS in USA, Italy and Indonesia. Generally, China has obtained pretty high and USA pretty low coefficients in every regression.

As it can be seen from the previous regressions, the data does not capture the investments by the channel or by the advertiser sufficiently. Therefore I am critical of the other aspects of the data as well. I move on to conduct the sensitivity analysis and robustness checks of the model.

5.4 Sensitivity Analysis and Robustness Check

I start the robustness check by replacing the advertising investment targeted by the product (variable s_prod_tot) by replacing it with the advertising investment of the whole brand at the same time. It is possible that the data has a downward bias concerning the advertising investments targeted by the product. The advertising (as demonstrated in Figure 5) is upfront and the researched products are the flagship products of the brands. The products of the same brand with slight variation and the same launch time have been aggregated into one product, because they cannot be considered competing with each other. Therefore it is not too misleading to assume that the whole brand advertising aims at increasing the sales of these products. In Table 10 is demonstrated the same regression as in Table 3 but now with the advertising investments of the whole brand (variable log_s_prod_tot2).

Table 10 Outputs of Linear and Logarithmic Regressions with OLS, Brand and Product Fixed Effects in the UK Market Using Brand Total Advertising as Advertising Investment

	OLS, log UK	Brand FE, log, UK	FE, log, UK	OLS, lin, UK	Brand FE, lin, UK	Product FE, lin, UK
	LHS	LHS	LHS	LHS	LHS	LHS
(mean) price	0.00834	0.00101	0.00151	0.00849	0.000818	0.00153
	(0.00099)***	(0.00102)	(0.00088)*	(0.00103)***	-0.00103	(0.00088)*
log_s_prod_tot2	0.03269	0.01268	-0.00305			
	(0.00754)***	(0.00658)*	(0.00567)			
product_age	0.64274	0.57282	-4.04162	0.65828	0.57715	-3.99255e+00
	(0.14731)***	(0.11424)***	(0.65290)***	(0.15198)***	(0.11511)***	(0.64831)***
product_age2	-0.04575	-0.05131	-0.04450	-0.05019	-0.05346	-0.04498
	(0.01317)***	(0.01014)***	(0.00840)***	(0.01354)***	(0.01017)***	(0.00845)***
product_age3	0.00085	0.00097	0.00089	0.001	0.00103	0.0009
	(0.00032)***	(0.00025)***	(0.00020)***	(0.00033)***	(0.00025)***	(0.00020)***
s_prod_tot2				0.0000000346	0.0000000111	-0.0000000105
				(0.0000000190)*	(0.0000000168)	(0.0000000143)
Seasonality dummies	Yes	Yes	Yes	Yes	Yes	Yes
Brand dummies	No	Yes	No	No	Yes	No
Product dummies	No	No	Yes	No	No	Yes
Constant	-10.23193	-1.89040	-35.22291	-1.03750e+01	-1.69799e+00	-3.49335e+01
	(0.93976)***	(1.03508)*	(4.30102)***	(0.96827)***	-1.03958	(4.26888)***
Observations	277	277	277	277	277	277
R-squared	0.39	0.66	0.80	0.35	0.65	0.80

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Again pooled OLS gives the highest and the most significant coefficients for advertising investments. The coefficients are somewhat lower than in Table 5.

Next I will conduct the regression by the advertiser using the brand level advertising investments (variables manufacturer_tot and opret_tot) by countries. Table 11 contains the output of the brand fixed effects regression.

Table 11 Brand Level Advertising by Advertiser and Country

	CHINA	GERMANY	INDIA	INDONESIA	ITALY	RUSSIA	SAUDI ARABIA	UK	USA
	LHS	LHS	LHS	LHS	LHS	LHS	LHS	LHS	LHS
(mean) price	0.02119	0.03946	0.03207	0.00954	0.01319	0.00020	0.00460	0.00065	0.03305
	(0.00235)***	(0.00260)***	(0.00302)***	(0.00246)***	(0.00192)***	(0.00150)	(0.00251)*	(0.00099)	(0.00494)***
log_manufacturer_tot	0.01827	-0.03368	0.00727	0.55562	0.02013	0.02860	0.05057	0.05937	-0.00944
	(0.02474)	(0.02835)	(0.03424)	(0.26521)**	(0.03250)	(0.01544)*	(0.05730)	(0.01876)***	(0.06774)
log_opret_tot	-0.02397	-0.00802	-0.00279	-0.64644	-0.04964	-0.00942	-0.08709	-0.03312	0.03320
	(0.02819)	(0.03274)	(0.03952)	(0.29929)**	(0.03712)	(0.01773)	(0.06570)	(0.02183)	(0.07685)
product_age	1.74786	2.22091	0.75841	1.12959	0.69527	0.56849	1.25560	0.39538	0.75966
	(0.18211)***	(0.18569)***	(0.17811)***	(0.18573)***	(0.14763)***	(0.10826)***	(0.21395)***	(0.11288)***	(0.34149)**
product_age2	-0.11277	-0.13596	-0.02785	-0.07455	-0.03248	-0.03673	-0.08035	-0.03123	-0.03751
	(0.01452)***	(0.01632)***	(0.01444)*	(0.01486)***	(0.01291)**	(0.00846)***	(0.01687)***	(0.00984)***	(0.02914)
product_age3	0.00234	0.00272	0.00041	0.00141	0.00045	0.00062	0.00151	0.00048	0.00076
	(0.00033)***	(0.00040)***	(0.00033)	(0.00035)***	(0.00031)	(0.00020)***	(0.00039)***	(0.00024)**	(0.00070)
Seasonality dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Brand dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-25.54039	-36.34989	-27.14363	-19.75094	-15.64705	-5.76098	-12.27715	-1.90822	-21.00117
	(2.00766)***	(2.16720)***	(2.16816)***	(2.07859)***	(1.76684)***	(1.58782)***	(2.20874)***	(1.02131)*	(3.21386)***
Observations	249	294	250	262	281	264	261	276	136
R-squared	0.61	0.64	0.51	0.42	0.44	0.54	0.44	0.66	0.51

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

The division into advertisers does not yield neither very significant nor plausible coefficients especially concerning the non-manufacturer advertising. This can be due to inaccurate measurement of advertiser variables in the data even on the brand level.

Next I will conduct the regression by including the advertising stock variable but now accumulating with the brand level advertising investments (logstock2). Table 12 contains the output of the pooled OLS regression.

Table 12 Pooled OLS Regression by Country with Advertising Stock Variable (logstock2) with Brand Level Advertising Investments

	CHINA	GERMANY	INDIA	INDONESIA	ITALY	RUSSIA	SAUDI ARABIA	UK	USA
	LHS	LHS	LHS	LHS	LHS	LHS	LHS	LHS	LHS
(mean) price	0.00797	0.01178	0.01033	0.00348	0.00823	0.00561	0.00298	0.00826	0.01529
	(0.00085)***	(0.00077)***	(0.00093)***	(0.00090)***	(0.00068)***	(0.00082)***	(0.00122)**	(0.00097)***	(0.00150)***
logstock2	0.08137	0.02634	0.06487	0.01745	0.01525	0.05135	0.04499	0.07531	0.01616
	(0.00811)***	(0.00649)***	(0.00586)***	(0.00883)**	(0.00799)*	(0.01027)***	(0.01080)***	(0.01342)***	(0.00913)*
product_age	0.99995	1.07391	0.23564	0.53581	0.40618	0.51477	0.38646	0.40333	0.18889
	(0.12223)***	(0.09716)***	(0.11221)**	(0.13426)***	(0.10011)***	(0.12996)***	(0.17490)**	(0.15225)***	(0.14335)
product_age2	-0.06567	-0.07169	-0.01024	-0.03578	-0.01669	-0.03050	-0.01335	-0.03496	-0.01463
	(0.01005)***	(0.00871)***	(0.00918)	(0.01111)***	(0.00836)**	(0.01102)***	(0.01391)	(0.01317)***	(0.01262)
product_age3	0.00136	0.00133	0.00015	0.00064	0.00016	0.00054	0.00015	0.00078	0.00041
	(0.00023)***	(0.00021)***	(0.00021)	(0.00026)**	(0.00020)	(0.00026)**	(0.00032)	(0.00031)**	(0.00030)
Seasonality dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-14.40848	-13.31516	-10.61214	-9.84201	-10.90963	-10.48972	-8.42693	-10.27456	-10.39513
	(0.74459)***	(0.60436)***	(0.68580)***	(0.85296)***	(0.61902)***	(0.88077)***	(1.08605)***	(0.91762)***	(1.11177)***
Observations	249	294	250	261	281	265	261	277	135
R-squared	0.57	0.63	0.50	0.15	0.47	0.27	0.26	0.42	0.59

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

The coefficients become smaller in comparison with Table 8. The coefficients of Italy and USA become less significant but remain significant at 10% significance level.

One mentioned above problematic moment is the definition of the market size, especially in the emerging markets. The share of the outside good is the most crucial factor in defining the market size. I test the sensitivity of the model by changing the market sizes and run the regressions above with new market sizes.

Table 13 Market Sizes for Sensitivity Analysis

Country	Market size (million)
CHINA	50
GERMANY	20
INDIA	5
INDONESIA	5
ITALY	10
RUSSIA	10
SAUDI ARABIA	8
UK	15
USA	120

The decreasing trend in the market shares of the outside good obviously remains unchanged. Now that the market sizes have reduced, the market share of the outside good has reduced as well. I will run the same regression as in Table 9 but with new market sizes and therefore the explained variable is LHS2.

Table 14 Pooled OLS Regression by Country with Advertising Stock (adstock) and Smaller Market Sizes

	CHINA	GERMANY	INDIA	INDONESIA	ITALY	RUSSIA	SAUDI ARABIA	UK	USA
	LHS2	LHS2	LHS2	LHS2	LHS2	LHS2	LHS2	LHS2	LHS2
(mean) price	0.01095	0.02075	0.01498	0.00348	0.01086	0.00783	0.00680	0.00985	0.02381
	(0.00138)***	(0.00166)***	(0.00159)***	(0.00090)***	(0.00112)***	(0.00110)***	(0.00167)***	(0.00130)***	(0.00303)***
logstock	0.09763	-0.01216	0.10564	0.02448	0.00777	0.09457	0.06207	0.08410	-0.00504
	(0.01668)***	(0.01635)	(0.01439)***	(0.01292)*	(0.01850)	(0.01935)***	(0.02217)***	(0.02193)***	(0.02482)
product_age	1.41083	1.87511	0.66805	0.52717	0.69185	0.77773	0.88621	0.62985	0.66767
	(0.19563)***	(0.20532)***	(0.19231)***	(0.13413)***	(0.16355)***	(0.18824)***	(0.24090)***	(0.19906)***	(0.28587)**
product_age2	-0.09139	-0.12063	-0.03643	-0.03522	-0.03354	-0.04613	-0.04394	-0.04871	-0.04725
	(0.01608)***	(0.01840)***	(0.01573)**	(0.01108)***	(0.01364)**	(0.01596)***	(0.01912)**	(0.01725)***	(0.02515)*
product_age3	0.00188	0.00228	0.00065	0.00063	0.00048	0.00085	0.00073	0.00105	0.00109
	(0.00037)***	(0.00045)***	(0.00036)*	(0.00026)**	(0.00032)	(0.00038)**	(0.00044)*	(0.00041)**	(0.00060)*
Seasonality dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-17.84201	-20.47359	-14.24706	-9.88856	-13.40775	-13.46107	-12.30291	-12.13582	-15.97488
	(1.19387)***	(1.28022)***	(1.18107)***	(0.85275)***	(1.00706)***	(1.23807)***	(1.48609)***	(1.20522)***	(2.21218)***
Observations	249	294	250	261	281	265	261	277	135
R-squared	0.46	0.52	0.39	0.15	0.37	0.28	0.24	0.34	0.47

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

The advertising stock coefficients become negative and non-significant in Germany and in the USA. Actually, what happens is that the market share of the outside good becomes negative in some months in these countries, which leads to the outcome seen in Table 14. In other countries, the changes in significance or the size of the coefficient are not as dramatic. Thus, the model is not too sensitive to slight changes in the market size, but the market size may not fall behind from observed sales volumes, which is clear intuitively as well. One of the problems is the assumption of static market size. The market size has obviously grown in some countries notably during the research period. The growth has been the largest in China, but the initial level was so low that the market share of the outside good does not become too low and therefore the coefficient does not change very much even though the market size is reduced from 200 million to 50 million.

My final test is to check the effect of the depreciation rate of the advertising stock. It has been assumed to be 50% in the earlier regressions, but now I assume it to be 20%. I run the same regression as in Table 8 with original market sizes, but with a lower depreciation rate.

Table 15 Pooled OLS by Country with Advertising Stock (logstock3) Variable with Depreciation Rate of 20%

	CHINA	GERMANY	INDIA	INDONESIA	ITALY	RUSSIA	SAUDI ARABIA	UK	USA
	LHS	LHS	LHS	LHS	LHS	LHS	LHS	LHS	LHS
(mean) price	0.00781	0.01168	0.01090	0.00352	0.00822	0.00561	0.00325	0.00802	0.01484
	(0.00085)***	(0.00077)***	(0.00094)***	(0.00089)***	(0.00067)***	(0.00077)***	(0.00121)***	(0.00098)***	(0.00153)***
logstock3	0.11021	0.03461	0.09256	0.02644	0.02599	0.08629	0.07392	0.09358	0.02710
	(0.01067)***	(0.00830)***	(0.00811)***	(0.01207)**	(0.01097)**	(0.01384)***	(0.01553)***	(0.01741)***	(0.01220)**
product_age	0.93936	1.07174	0.21181	0.53353	0.38726	0.44988	0.36678	0.39889	0.18239
	(0.12078)***	(0.09702)***	(0.11113)*	(0.13391)***	(0.09989)***	(0.12797)***	(0.17309)**	(0.15389)**	(0.14177)
product_age2	-0.06200	-0.07207	-0.00910	-0.03605	-0.01602	-0.02678	-0.01365	-0.03551	-0.01447
	(0.00994)***	(0.00869)***	(0.00908)	(0.01108)***	(0.00831)*	(0.01080)**	(0.01375)	(0.01324)***	(0.01246)
product_age3	0.00129	0.00134	0.00012	0.00064	0.00016	0.00046	0.00016	0.00079	0.00041
	(0.00023)***	(0.00021)***	(0.00021)	(0.00026)**	(0.00020)	(0.00025)*	(0.00032)	(0.00031)**	(0.00030)
Seasonality dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-14.42060	-13.31975	-11.05627	-9.95530	-10.93641	-10.68531	-8.70307	-10.32176	-10.17210
	(0.73771)***	(0.60325)***	(0.68703)***	(0.85068)***	(0.61451)***	(0.85064)***	(1.07344)***	(0.92143)***	(1.11137)***
Observations	249	294	250	261	281	265	261	277	135
R-squared	0.58	0.64	0.51	0.15	0.47	0.31	0.27	0.41	0.60

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

The regression does not seem to be very sensitive to the depreciation rate of the advertising stock. The coefficients of some countries have become slightly higher and of others lower. Only the coefficient of Indonesia becomes less significant, but remains significant at 5% significance level. Thus the model is not sensitive to the depreciation rate of advertising stock which is good, because it is the parameter the value of which is based on the guess. In the next subchapter, I will discuss findings.

5.5 Findings and Discussion

Having completed the data analysis and checked for the robustness and analyzed the sensitivity it is time to move on to discuss findings. This discussion should be begun by recaping the major econometric constraints that restrict the interpretation and generalizability of the results. The first is the measurement error. The measurement error in the data is proven. Some advertising observations have disappeared during the data processing, because they have not been encoded in the data accurately enough. Therefore there is too much noise in coefficients obtained for different media or advertisers. Some of the coefficients are neither significant nor plausible (being even negative). Only advertising at the cinema and in the printed media got reasonable and significant coefficients to the UK and printed media and TV on the whole sample level regression. However, the data measures only monetary investments and therefore it does not necessarily capture the response of market share to different advertising channels as well as would capture advertising measured in GRP.

The coefficients for non-manufacturer (i.e. operators' and retailers') advertising were implausible as well and probably suffer from the measurement error. When considering non-manufacturer advertising should be taken into account the reputational aspects as well. Operators seem to advertise only the products of the leading brands and it shows that reputational aspects count in their advertising decisions. They will advertise and sell in ties only such products which increase the goodwill of their own brand. The role of the operators could be described more thoroughly with the data of the acquisitions of handsets alone and in ties with subscriptions. The role of retailers remains ambiguous even then. Taking into account the reputational aspects of the retailers' own brands it is obvious that bad products are not advertised. However, it is based on this data impossible to say whether the manufacturers, operators or retailers dictate the conditions in the smartphone market.

The second major econometric constraint is omitted variable bias. This is proven to occur as the price gets significant positive coefficients. The other reason for that is the increasing share of inside goods in the choice set by the time. This problem could be evaded by collecting the data for the longer period and accumulating the advertising stock, say, for a year before the beginning of the research period. Then the share of inside goods could be held fixed during the research period. The main reason for omitted variable bias confirmed in the literature as well is the endogeneity of prices. Prices are correlated with omitted (unobserved) variables. The omitted variables could be correlated with advertising as well, even though I obtained more reasonable coefficients for the advertising in most of the regressions than for the price. One way of relaxing omitted variable bias was applying fixed effects regression by including dummy variables for products or brands. These regressions yielded somewhat smaller and in some cases less significant coefficients than the pooled OLS regression. However, the coefficients of pooled OLS can be more biased even though they appear nicer. The dummies cannot control out the effect of omitted variables that are correlated with advertising and sales and vary by the time. Therefore all the regressions probably suffer from the omitted variable bias at some level.

Applying elasticity formulas with logit models turned out to be unreasonable as literature confirms. In this paper, the main purpose was to estimate elasticities by the countries, media and advertisers and not to compute substitution matrices for the products. Therefore I do not find that so problematic. Including advertising variable in logarithmic form in the utility function allows us to take into account the diminishing marginal utility of advertising and to treat the estimated coefficient β as advertising elasticity.

Advertising is more reasonable to treat as a stock than just a periodical phenomenon. The regressions with advertising stock yielded more significant and larger coefficients for advertising than regressions where the advertising effect lasts only one period. Treating the advertising as a stock allows pre-launch advertising to effect on sales as well. Table 9 contains the information concerning coefficients from different regressions and the elasticities are different in all of them. Only pooled OLS regression with advertising stock yielded significant coefficients for all the countries. The elasticities are the highest in most of the regressions in China and United Kingdom. The lowest elasticities are in Germany, Italy and the USA. Ignoring the possible errors and biases in the results this could be realistic. There might be more demand for advertising in China than in the USA for instance, where the advertising market is more saturated and therefore the responses of sales to advertising are higher in China as well.

Having covered the advertising as a part of the economic system, written about discrete choice models and conducted the analysis of smartphone market based on the product sales and advertising investment datasets it is time to finish the paper. In the next chapter, I will conclude the literature review and empirical parts of the paper.

6 Conclusions

The main function of advertising is to increase the sales. This can happen in many ways: by providing information about excellent characteristics of a good or by persuading consumers to buy a good because it simply is so great in itself. The advertising has been divided in the literature into persuasive and informative at an early stage and the same division remains in the newer papers as well. However, the division is not straightforward. All advertising is persuasive in a sense that it aims at making consumers to purchase the advertised good, informative in a sense that all advertisements contain at least the name or the logo of a good or a company. The advertising has some demand as well. If consumers did not get the information through the ads, they would search for it in other sources. The efficiency of advertising as an information channel has been questioned. However advertising has occurred and remains an important means of the industry conduct.

There are several reasons why firms advertise. One of the major reasons nowadays is that the advertising has become a part of the Nash equilibrium in the industries. Advertising has probably made possible for some firms to obtain the leading role in the market and the continuance of such equilibrium requires continued advertising. Advertising can therefore create a sunk cost barrier of entry in an industry. Unlike investments in the machinery and plant, the advertising investment cannot be recovered in case of the exit or failure of a company. The concentrated industry structure has its pros and cons. It makes possible capital requiring R&D projects and thus new innovations. The larger companies can have the economies of scale in production and therefore they provide cheaper goods. On the other hand, they have market power which reduces consumer surplus as they can charge higher margins. In such industries, collusion is a common phenomenon. However, in empirical papers concerning the consumer choice usually has been assumed Bertrand Nash competition and firms as single good producers. However, the latter might not be too misleading either if the choice set is modeled reasonably. In this paper, I concentrated on the most expensive high-end smartphones and firms usually have one flagship product in time. Therefore the firms' own products in the same price bands can be assumed not to compete between each other.

The choice of durable consumer goods in the market with the frequent introductions of new goods (e.g. PCs and cellular phones) is a good example of a discrete choice situation. A decision maker faces the choice set that must contain all the possible alternatives (exhaustive) and choosing one means not choosing any other (mutually exclusive). This requires the introduction of the outside good which means choosing anything else but the goods belonging to the choice set (other good outside the choice set, substitutes or not any good at all). The choice situations have been modeled in many ways. The basic starting point is to derive the population behavior rule from individual choice probability. The main challenge is that the researcher cannot observe all the characteristics that effect on a decision. The unobserved characteristics can be correlated with other explanatory variables. It has been developed different methods solving for such endogeneity. One of the most famous ones is using instruments that are correlated with explanatory variables but not with the error term. Good instruments can be difficult to find and therefore has been created methods for estimating them. Usually, it requires applying GMM. Also fixed effects models are applied to explain the omitted variable bias. They are usable if the omitted variables are time invariant and their influence is time invariant as well. In this paper, the product characteristics represent the omitted variables which are time invariant and therefore I assumed that they can be controlled out. However, most of the regressions yielded a positive coefficient for the price and thus the regressions obviously suffer from omitted variable bias.

One of the simplest discrete choice models is multinomial logit which was applied in this paper as well. The products are assumed to differ only by mean utility levels. The utility levels are by definition the differences between logarithmic market shares. When the utility of outside good is normalized to zero the explained variable is the difference between the logarithmic market shares of the good and the outside good. The market share of the outside good depends on the market size definition. In the literature it is usually taken as known. I also took it as known. In case of high-end smartphones, the market size definition especially in the emerging markets is challenging. However, the regressions yielded quite similar results despite even notable changes in market size and therefore the model is not too sensitive to them. However, the market sizes may not be determined too low compared with the observed sales.

The derivatives and elasticities can be simply calculated from the multinomial logit model. The model however represents unrealistic substitution patterns, which have been attempted to correct in many ways in the literature. The unrealistic substitution patterns mean that substitution depends only on the coefficient, variable value and on the market shares. However, the unsuccessful attempt to compute elasticities proves that higher advertising investments and larger market shares have a correlation. I included advertising in the logarithmic form because it captures the diminishing marginal utility of the advertising. The advertising should be treated as a stock that depreciates and accumulates over time. The regressions where advertising was treated as a stock yielded more significant and plausible results. Treating the advertising as a stock allows the pre-launch advertising to effect on sales as well. Assuming sufficiently small market shares for the products, in the logarithmic specification the advertising elasticity is the value of the estimated coefficient and cross elasticity with respect to the other goods is very small. The model with advertising stock yielded significant and plausible coefficients for most of the researched countries. Applying pooled OLS, brand fixed effects or product fixed effects regression yielded different coefficients and the order of magnitude of elasticities changed by regressions as well. The highest elasticities gained United Kingdom and China whereas the lowest elasticities gained the USA and Germany. Russia and China got significant coefficients in every regression. Despite possible errors, the result could be reasonable taking into account that there is demand for advertising as well and in the USA the advertising is more saturated than e.g. in emerging markets and therefore the responses of sales to advertising investments could be lower there. This is in line with earlier literature which has obtained higher elasticities for Europe than the USA. However, in this research, some European countries, like Germany and Italy, obtained very low elasticities as well.

Discrete choice models have been applied in the advertising as well. Advertising has been included in the utility function as it was done in this paper as well. The advertising has been included as a parameter in the information technology term too. The information technology term represents the probability that a product belongs to the choice set of a consumer (i.e. a consumer is aware of the product). This kind of limited information approach yields much less elastic demand than the assumption of full information. I did not find it necessary to plug in the information technology parameter because the choice set products of this paper are the flagship products of the leading brands and it is reasonable to assume that all consumers considering the smartphone purchase are aware of them.

In this paper, I have tried to take a simple but plausible approach to the impact of advertising investments on the market share on a product level in the high-end smartphone market. The market is oligopolistic, but most of the papers assume that the market equilibrium quantities are Bertrand Nash equilibrium quantities. However, some exceptions exist, like Dubé et al. (2005.) Another common simplifying assumption is that firms are single product producers.

This can be considered realistic if the research concentrates on the one segment of products as it was done in this paper. Firms probably do not have several competing products in the same segment at the same time. If there are, they are probably horizontally differentiated to capture the preferences of more consumers. In this paper, the products with the same launch time and with little differentiation were aggregated into one product and thus the single good producer assumption will not be too misleading. The other common assumption in the literature is that belonging of one good to the consumer's choice set (consumer is aware of it) is independent of other goods in the choice set. So, the information spillovers do not exist, which can be an unrealistic assumption. However, the assumption of one good (at least in an aggregated sense) in the market in a time per brand in the same segment could relax this assumption. Intuitively it is reasonable to assume that a consumer is aware of the same brand's other goods, but not necessarily of the other brands' goods.

The contribution of advertising to the market structure is somewhat ambiguous according to the literature and after completing this research. The positive correlation between market shares and advertising investments exists. The own advertising is according to the logit model less elastic to the demand, the larger the market share is. Same time the cross elasticity is larger the larger the market share is. This is actually the curse of the IIA property, which does not allow modeling the captive segment of advertising sufficiently enough. Above all in the literature the effect on general demand has not been covered comprehensively and already Kaldor (1950-51) mentioned it to be challenging. Neither the effect on selective demand is straightforward. However, the effect on it has been covered more in the literature. The information technology parameter (Goeree, 2008), awareness processes (Barroso and Lloebet, 2012), advertising stock and product age function in this paper are attempts to cover the choice set evolution. Still in these researches the exit of goods is assumed to be exogenous and deterministic. The market should be considered dynamic (as was done by Doraszelski and Markovich, 2007) with the constant entries and exits of goods and buyers switching from outside good to inside goods and vice versa. Obviously, collusion should be taken into account as well, but the models would not be nice and simple anymore. To summarize, the larger the market share the higher the advertising investments. According to Kaldor (1950-51) the higher advertising investments overshadow the lower ones and lead to the concentration. This can be returned to the competing SCP hypotheses: traditional SCP hypothesis (large companies advertise more and get more sales therefore) and efficient market hypothesis (the most efficient companies get more sales and therefore can afford to advertise more).

The elasticities in the smartphone industry were not researched earlier. Thus this paper can be an opening to this kind of research. Neither the elasticities between different markets were analyzed on the basis of the same model and data earlier. The earlier papers have concentrated on one market (e.g. US and Spanish automobile industries or US PC industry). As I have mentioned above, the smartphone industry has not been researched to the end yet. The regressions of this paper contain both the measurement error and the omitted variable bias. Correcting omitted variable bias more comprehensively probably requires the data and estimations concerning the cost side as well and applying less convenient estimation methods for instruments to correct the endogeneity of explanatory variables. Also more complex, but more relaxed from IIA property models could be applied to this industry in order to compute more realistic cross elasticities and substitution patterns between products. The complete substitution matrix between products could tell us more about the causality between market share and advertising investments, but then the product characteristics and even cost side estimates should be included in the model. Also the attention should be paid to the data gathering, because some more information concerning the elasticities between advertising channels and advertisers could be obtained even using the specifications of this paper with clearer data. One improvement concerning the advertising channels could be measuring advertising in GRP instead of absolute monetary terms.

The effect of advertising conducted by different advertisers remained ambiguous in this paper. Therefore cannot be said whether the manufacturers' or operators' domination prevails in the smartphone market. Also the definition of the product is not as straightforward as it was in the papers concerning automobiles and personal computers. As it was covered in Chapter 4, the handset is not the only thing that matters in the smartphone industry. Also the operating system counts. Obviously, the operators' subscriptions which are often sold in ties with the handset play a significant role in the sales of handsets. In general the concept of the product has expanded nowadays and smartphone industry is not an exception. The network effect of operating systems is one thing that should be taken into account in the future researches considering smartphones. The role of operators in the sales process should be researched more accurately as well. The data of the acquisitions of handsets alone and in ties with subscriptions would reveal a great deal about the operators and their role in the smartphone market.

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Data

GfK market dataset

Confidential dataset of advertising investments