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Understanding the Role of the Internet in the Digital Age: A Multichannel, Multistudy Examination

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Deutsches Abstract

Das Internet nimmt eine bedeutende Rolle im modernen Alltag ein und beeinflusst damit in erheblichem Maße das Konsumentenverhalten. Diese vorliegende Arbeit untersucht in drei empirischen Projekten die Bedeutung von Vertriebs- und Kundenakquisitionskanälen im Internet. Die Ergebnisse von Projekt I zeigen positive Effekte kundeninitiierter Migrationen von direkten zu indirekten Kanälen und offline zu Internetkanälen auf die Kundenbeziehung. Die Ergebnisse von Projekt II decken einen U-förmigen Einfluss des Wettbewerbs um Werbeplätze auf Suchmaschinen (Advertiser Competition) auf das Klick- und Kaufverhalten auf. Zusätzlich wird durch die Ergebnisse deutlich, dass Konsumenten bei zunehmendem Advertiser Competition, und damit bei einem Überangebot an ähnlichen Auswahlmöglichkeiten, die Suchkosten nicht durch einfache Entscheidungsheuristiken reduzieren. Projekt III zeigt, durch die Untersuchung der Reihenfolgeeffekte und Effekte doppelter Darstellung, die Wirkung organischer und bezahlter Suchergebnisse und deren Wechselwirkungen auf das Klickverhalten.

English Abstract

The Internet has come to occupy a central place in modern everyday life and influences consumer behavior profoundly. This thesis takes a close look at the importance of distribution and customer acquisition channels on the Internet in three different empirical projects. *Project I* shows positive effects of customer-initiated channel migration from direct to indirect channels and offline to Internet channels on the customer relationship. The results of *Project II* demonstrate a U-shaped effect of advertiser competition on consumer click-through and conversion behavior on search engines. In addition, the results show that consumers do not reduce cognitive efforts by applying simple decision heuristics with increased advertiser competition and thus choice overload. *Project III* illustrates, investigating order effects and double exposure on search engine result pages, the impact of organic and paid search results and the effect of their interdependency for click-through behavior.

Summary

The Internet has come to occupy a central place in modern everyday life. Not only do technological enhancements reduce search and transaction costs, but the Internet plays a key role in world wide economic growth. With this influence on consumers' daily routine, different facets of consumer behavior are subject to change. Research in the marketing discipline has observed appreciable changes in consumers' search behavior and purchase behavior, especially as various new electronic channels for customer acquisition and distribution emerge. Although a multitude of scientific studies thus work to gain a deeper understanding of the role of the Internet as a channel for customer acquisition and distribution, some fundamental research questions remain unanswered.

This thesis takes a close look at customer channel migration and search engine marketing as highly relevant fields for research on the Internet, using three different empirical projects. Extensive literature reviews in both areas reveal considerable research gaps. Customer channel migration is widely understood as customers' channel choice decisions in consecutive transactions over time. Even though it has been taken into consideration in several scientific publications in the past decade, the behavioral consequences of channel migrations between direct and indirect, online and offline channels have not been investigated. Therefore, *Project I* investigates the treatment effects of customer-initiated channel migration in a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix of relationship breadth (purchase frequency over time, as sales and revenues) and depth (cross-buying). For this first project, customer-initiated channel migration is defined as a voluntary change in the individual customer channel setting when the majority of transactions in the consecutive period move to a different channel in the 2 × 2 channel matrix.

Research into search engine marketing has arisen in the past decade with the increasing importance of search engines for both consumer information searches and companies' advertising activities. In search engine marketing research and managerial practice, paid search advertising and (search engine) optimization of organic search results are distinguished. Extant literature focuses on consumers' click-through behavior on paid search results (paid click-through) rather than on organic search results (free click-through) or the interdependencies between paid and organic search results. This thesis accounts for both types and their interdependencies in *Projects II* and *III*. Even though competition is a central component of companies' overall performance, little research has investigated the influence of competition between companies advertising on search engines. Advertiser competition on search engines indicates the extent of the assortment structure for consumer's choice. Therefore, *Project II* tests the effects of advertiser competition on overall (free and paid click-through), free, and paid click-through behavior. These results are extended to purchase behavior.

Next, this thesis builds on findings from banner advertising research, showing that lateral or upper placements of advertisements considerably affect consumer click-through behavior. The analogue differentiation for paid search advertising, paid top (upper placement) versus paid side (lateral placement), has not been applied. Despite, investigations of the simultaneous display of paid and organic search results in empirical research projects the effect of their interdependencies have not been distinguished for additional paid side or paid top search results. The same gap holds for differentiations between the effects of the interdependencies on overall and free click-through behavior. *Project III* investigates these research gaps by testing the role of order effects on consumer click-through behavior. This project also accounts for the effects of double exposure on search engine result pages on overall and free click-through behavior. These results extend to the effects of double exposure with increasing levels of advertiser competition.

Results

Project I demonstrates—using a quasi-experimental study via Mahalanobis-metric matching and conditional difference-in-differences estimation on a company database from a leading international airline—that the causal effects of three types of customer-initiated channel migration affect relationship breadth and depth. On the intermediation dimension (direct versus indirect), this project reveals that customer-initiated channel migration from indirect to direct channels does not lead to positive treatment effects on relationship breadth or depth, as prior empirical publications have suggested. For the service distribution dimension (offline versus online), the treatment effects of customer-initiated channel migration from offline to online channels surprisingly reveal that migration from offline to online channels does not lead to negative effects on relationship breadth and depth. Customer-initiated channel migration from indirect offline to direct online channels combines the effects of intermediation and service distribution. The conditional difference-in-differences estimations reveal positive causal effects on sales and cross-buying, whereas the effect on revenue is negative. The results of *Project I* therefore contribute to a better understanding of the causal effects of customer-initiated channel migration on customer relationships. These causal effects of customer-initiated channel migration on intermediation and service distribution dimensions lead

to a broader understanding of the role of the Internet as channel for distributing services. Furthermore, the results reveal the importance of reconsidering and revising prior findings about the impact of direct and indirect channels on measures of the strength of the customer–company relationship.

By applying a mixed-method research design with data from a counterbalanced online experiment and proprietary company data from five leading European retailers advertising on Google, *Project II* shows that the relationship between advertiser competition and click-through and conversion rates is U-shaped. That is, the results of this experimental and descriptive study confirm that the relationship between advertiser competition, as an indicator of increasing choice assortment, and overall, free, and paid click-through rates is U-shaped. Therefore, the click-through rates are highest for low levels of advertiser competition with limited choice. For medium levels, the click-through rates are lowest. With increasing levels of advertiser competition, these click-through rates improve again. The results reveal the same U-shaped influence of advertiser competition on conversion rate, though the U-shaped relationship is not as distinct as that for click-through behavior. In addition, the results surprisingly show that consumers do not reduce cognitive efforts by applying simple heuristics to click on higher ranked paid search results with increasing choice overload.

Finally, *Project III* investigates the influences of order effects, double exposure, and the interaction between advertiser competition and double exposure on overall and free click-through behavior. Building on the theoretical fundaments of the primacy–recency paradigm and mere exposure, this mixed-method research design with observational and experimental data shows that order effects influence consumer click-through behavior. Thus it highlights the importance of differentiating among paid top, paid side, and organic search results for further research on search engine marketing. Primacy effects are present comparing the causal effects of both single top and single organic to single side exposures. Furthermore, the analysis on the causal effects of double exposure, in a simultaneous display of paid and organic search results on click-through behavior, reveals positive and negative effects. Double exposures of paid top and organic search results positively affect overall click-through behavior. These results are changing for free click-through behavior. The experimental analyses show that double side and double top exposure lead to negative, cannibalizing effects on free click-through rate. Furthermore, the marginal effect of double exposure for increasing levels of advertiser competition on click-through behavior only increases for the interaction of double top exposure and advertiser competition on free click-through behavior.

Managerial Implications

With these efforts, the present dissertation contributes managerial implications to customer channel migration and search engine marketing fields. *Project I* implies that direct channels for distributing services do not encourage more relationship depth, because the migration to direct channels actually has negative effects for relationship depth. The results also confirm that migration from offline to online channels leads to more breadth in customer relationships. *Project II* sheds further light on more diverse search engine marketing strategies to achieve more traffic, more conversions, or lower cost per conversion. For attracting more traffic, companies should invest in keywords with low (0–19%) or high (90–99%) levels of advertiser competition. If companies conduct paid search advertising campaigns with the goal to enhance their sales, advertiser competition of 10–19% or greater than 80% is best. Nevertheless, managers should account for the costs per conversion to reduce acquisition costs, which are lowest for advertiser competition of 10–19%. Finally, *Project III* highlights the impact of paid search advertising activities, in addition to organic search results, on consumer click-through behavior. The cannibalization coefficient, an easy-to-implement marketing decision model, helps managers estimate interdependencies between double exposure through paid and organic search results and free click-through behavior and thus to calculate true cost per clicks. The results of the experimental design suggest decreasing free click-through rates of 9.42% for additional paid side results and 28.63% for paid top positions, with increasing respective costs for the same number of click-through.

Overall, the findings highlight the need for more experimental and mixed-method research designs on Internet-related research topics. Research should expand the fields of customer channel migration and search engine marketing, based on theoretical foundations. The fundamental issues of the Internet should be explored further from theoretically based mixed-method perspectives and not only data-driven and modeling perspectives, for the good of the marketing discipline.

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List of Abbreviations

α	Cronbach's alpha
AC	Advertiser competition
AC^2	Quadratic effect of advertiser competition
a_i	Individual unobserved effects
AIC	Akaike information criterion
ANOVA	Analysis of variance
AP	Average position
APSA	Attitudes toward paid search (with knowledge that paid search advertising is displayed (Experiment 2, *Project III*))
APSU	Attitudes toward paid search (without knowledge that paid search advertising is displayed (Experiment 2, *Project III*))
ATG	Attitude toward Google
ATPSA	Attitude toward paid search (Experiment 1, *Project III*)
β	Estimate
B2B	Business to business
B2C	Business to consumer
χ^2	Chi square
CFA	Confirmatory factor analysis
CICM	Customer-initiated channel migration
CLV	Customer lifetime value
CMV	Common method variance
CPC	Cost per click
CR	Conversion rate
CRB	Cross-buying
CT	Click-through
CTR	Click-through rate
CUSAMS	Customer asset management of services
D^2	Mahalanobis distance
df	Degrees of freedom
ΔfCTR	Cannibalization quotient
ΔIAC	Percentage of total paid clicks in a double exposure scenario
DID	Difference-in-differences estimation

DV	Dependent variable
ε	Error term
e.g.	Exepmli gratia (= for instance)
EFA	Exploratory factor analysis
ε_{iti}	Individual error term with $E(\varepsilon_{iti}) = 0$ and $Var(u_i) = \sigma^2_u$
et al.	Et alii
EU	European Union
EUR	Euro, currency of the European Union
EV	Explained variance
F	F statistic from F-test
fCTR	Free click-through rate
F_D	Free click-through in double exposure scenarios
FKZ	Förderkennzeichen
FLY	Booked flights, sales
F_S	Free click-through in single exposure scenarios
G8	The Group of Eight; Is a forum of the heads of the government of France, Germany, Italy, Japan, United Kingdom, United States, Canada, and Russia
GDP	Gross domestic product
H	Hypothesis
H_0	Null hypothesis
h^2	Communality
I-t-t	Item-to-total correlation
i.e.	Id est (=that is)
IAC	Measure of the incremental clicks
ISS	Internet search skill
ISSA	Internet search skill (Experiment 1, *Project III)*
KMO	Kaiser-Meyer-Olkin
LM	Lagrange multiplier test statistic
M	Mean
Max	Maximum
MCMC	Markov Chain Monte Carlo
Min	Minimum

mp3	Patented digital audio encoding by Moving Picture Experts Group
MSA	Measures of sample adequacy
n.a.	Not applicable
n.s.	Not significant
O_D	Overall click-through in double exposure scenarios
OLS	Ordinary least squares
O_S	Overall click-through in single organic exposure scenarios
p	Probability
P	Participant number (*Observational Study, Project III)*
p.	Page
pp.	Pages
P_D	Paid click-through in double exposure scenarios
PRB	Percentage reduction in bias
P_S	Paid click-through in single organic exposure scenarios
Q_1, q_1	First quarter
Q_2, q_2	Second quarter
Q_3, q_3	Third quarter
Q_4, q_4	Fourth quarter
R^2	R squared
$\overline{R}^2$	Adjusted R squared
REAL	Realism
REV	Revenue
RMSE	Root-mean-square error
RQ	Research question
RR	Relative risk
S	Scenario (Experiment 2, Project III)
SA	Supplement (Experiment 1, Project III; Experiment 2, Project III)
S.E.	Standard error
SAT	Satisfaction
SD	Standard deviation
SEE	Search engine expertise
SEO	Search engine optimization
SERP	Search engine result page

SS	Sum of squares
SSE	Sum of squared errors of prediction
t	T value
t_{01}	Period between t = 0 and t = 1
t_{12}	Period between t = 1 and t = 2
TV	Television
$\hat{u}^2$	Obtained squared OLS residuals
u_i	Unobserved effect with $E(u_i) = 0$ and $Var(u_i) = \sigma^2_u$
URL	Uniform Resource Locator
U.S.	United States of America
USD	The United States Dollar
USP	Unique selling proposition
vs.	Versus
$\bar{x}^A_{i,n}$	Mean of predictor variable n after matching (treatment group)
$\bar{x}^A_{j,n}$	Mean of predictor variable n after matching (control group).
$\bar{x}^B_{i,n}$	Mean of predictor variable n before matching (treatment group).
$\bar{x}^B_{j,n}$	Mean of predictor variable n before matching (control group).
y	Criterion or dependent variable in regression analysis
Y_{it}	Dependent variable in difference-in-differences estimation
z	Z standardized value

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A. General Introduction

"I see little commercial potential for the Internet for at least 10 years."
Bill Gates (1994)[1]

In the past two decades, the role of the Internet has gained more and more importance in everyday life. Although this enormous development was not necessarily predicted (see Gates 1994), today, the Internet is an essential contributor to the gross domestic products (GDP), with an estimated 21% share of GDP growth in the past five years (see Pélissié du Rausas et al. 2011),[2] and initiating changes in many facets of consumer behavior. Researchers observe profound changes in the way consumers search for information, purchase products or services, and communicate with friends, other consumers, colleagues, or companies (e.g., Klein and Ford 2003; Mathwick and Rigdon 2004; Verhoef, Neslin, and Vroomen 2007; Hennig-Thurau et al. 2010; Libai et al. 2010).

With the evolution of the Internet, new electronic channels for information, communication, and distribution also have appeared, including search engines, social network websites, microblogging websites, review websites, price comparison websites, and plenty of different intermediaries in different industry contexts. These developments and new channels create multiplicity in the channel structure of the companies, suggesting both opportunities and challenges at once (van Bruggen et al. 2010). This multiplicity is finding expression in the areas of information, communication, customer acquisition, and distribution (e.g., Hoffman and Novak 2000; Hennig-Thurau et al. 2010; van Bruggen et al. 2010; Rutz and Bucklin 2011). This dissertation therefore addresses customer acquisition and the distribution of services (or products) through Internet channels, as outlined in the following sections.

The Internet as a channel for distribution is strongly connected to multichannel customer management and customer channel migration. In its top research priorities, the Marketing Science Institute (2004, 2010) has assigned considerable importance to both of these research areas. Many publications have shown recently that multichannel customers are more loyal (e.g., Wallace, Giese, and Johnson 2004), purchase higher quantities (e.g., Kumar and

1 Gates (1994) cited by Christensen-Dalsgaard (2005), p. 321.
2 This level refers to all G8 countries plus Brasilia, China, India, South Korea, and Sweden. Growth in GDP stems from companies with business models that are purely based on Internet technologies, as well as firms distributing their products and services (completely or partly) over the Internet or applying Internet technology–enabled communication strategies (Pélissié du Rausas et al. 2011).

Venkatesan 2005), and are more profitable (e.g., Campbell and Frei 2010). Strongly connected to this field of research is the notion of customer channel migration, which refers to customers' channel choice decisions for single or repeated transactions, such as when they abandon a channel, add a channel, or switch to another channel (Thomas and Sullivan 2004). The influences of customer channel migration are particularly pertinent if customers transform from single-channel to more loyal, more profitable multichannel customers. Research on customer channel migration started with early research projects on multichannel customer management (Thomas and Sullivan 2004, 2005), but studies focusing on the impact of customer channel migration from offline to Internet channels[3] on customer relationships (see *Chapter B*/1.2) remains scarce, despite its considerable importance for understanding the role of the Internet. Prior research suggests inconsistent effects of Internet channel usage on the customer–company relationship (e.g., Brynjolfsson and Smith 2000; Ariely 2002; Ansari, Mela, and Neslin 2008; Campbell and Frei 2010). Moreover, the causal relationship between multichannel usage and customer channel migration, as well as measures for the strength of this relationship, have been neglected (Neslin and Shankar 2009). These shortcomings provide the starting point for research on customer channel migration and the role of the Internet in this thesis. In particular, I investigate the causal effects of different types of customer channel migration, such as from offline to Internet channels, on the breadth and depth of customer relationships in *Project I* (e.g., Bolton, Lemon, and Verhoef 2004).

Furthermore, the Marketing Science Institute (2010) has proposed, against the background of a general framework for understanding customer experience and behavior that further research should focus on gaining insights into how marketing activities influence consumers on their path to purchase. In this field, the Internet—with its diverse channels for online marketing activities—plays a central role for customer acquisition. Channels for online marketing include affiliate marketing, display advertising, fan pages on social networks, online video websites, recommendation agents, and search engine marketing (e.g., Drèze and Hussherr 2003; Duffy 2005; Bo and Benbasat 2007; Rangaswamy, Giles, and Seres 2009; Hennig-Thurau et al. 2010). A recent industry survey among 190 marketing decision makers showed that search engine marketing is perceived as the channel with the greatest impact on the overall financial performance of German and British companies (Ackermann and Wangenheim 2009), as reflected by companies increasing ratios of return on investments in search engine

[3] The terms Internet channel and online channel are used interchangeably in this dissertation.

marketing activities (Bughin et al. 2011).[4] Current developments in empirical marketing research address this managerially relevant topic with various research projects on search engine marketing (see *Chapter C*/2), yet some fundamental questions remain unanswered. In particular, the influences of advertiser competition (*Project II*), order effects, and double exposure (*Project III*) on consumer click-through and conversion behavior remain unclear.

The following sections outline the conceptual frameworks and research questions of the three projects on distribution of services and customer acquisition through Internet channels:

Project I: Behavioral Consequences of Customer-Initiated Channel Migration

The first project implements a conceptual framework for understanding customer channel migration, with dimensions related to intermediation (direct vs. indirect; e.g., Bolton, Lemon, and Verhoef 2004; von Wangenheim 2006) and service distribution (online vs. offline; e.g., Hitt and Frei 2002; Campbell and Frei 2010). To distinguish the multiplicity of channels in the services sector, I employ a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix. This conceptual framework can investigate the causal effects of customer-initiated channel migration (CICM) on the breadth and depth of the relationship. Verhoef, Franses, and Hoekstra (2001) and Bolton, Lemon, and Verhoef (2004) have introduced the concepts of relationship length, breadth, and depth to asses the value of customers on three dimensions of the customer–company relationship. This dissertation applies relationship breadth and depth as measures of relationship intensity. Relationship breadth measures purchase frequency over time; relationship depth operationalizes cross-buying or add-on buying activities (e.g., Blattberg, Getz, and Thomas 2001; Verhoef, Franses, and Hoekstra 2001; Bolton, Lemon, and Verhoef 2004). Therefore, the causal effect of three different scenarios of CICM on relationship breadth and depth are analyzed with the research question in *Project I: How do different types of customer-initiated channel migration affect relationship breadth and depth?* These scenarios of CICM investigated in this project are those from indirect to direct channels, from offline to online channels, and from indirect offline to direct online channels.

[4] Bughin et al. (2011) report average advertisers return on search engine marketing investments of 7:1.

Project II: When Choice Overload is No Bad Thing–How Advertiser Competition Impacts on Click-Through Behavior and Conversion in Search Engines

This second project investigates the impact of *advertiser competition* on overall, organic, and paid click-through behavior, as well as on paid conversion behavior.[5] *Project II* thus builds on the suggestion of Yang and Ghose (2010) to employ advertiser competition to gain further insights into consumers' click-through and conversion behavior for search engine result pages. Therefore, this project investigates the causal effect of advertiser competition on different aggregation levels of click-through behavior. The distinction of overall, organic, and paid click-through follows prior research, which focuses on the effects of paid search results (Ghose and Yang 2009; Ji, Rui, and Hansheng 2010; Rutz and Bucklin 2011; Rutz and Trusov 2011), organic search results (Dou et al. 2010), or the interdependencies between them (Ghose and Yang 2008; Yang and Ghose 2010). The impact of these areas for search engine marketing activities is unique, thus overall, organic, and paid click-through behavior has not been differentiated yet. *Project II* takes the first steps toward revealing the effect of advertiser competition on overall, organic, and paid click-through rates, as well as paid conversion rates, by answering two following research questions: *How does advertiser competition affect click-through behavior?* and *How does advertiser competition affect conversion behavior?*

Project III: Does Paid Search Advertising Really Pay Off? The Impact of Exposure and Order Effects on Click-Through Rate

The third project examines the influence of *order effects*, *double exposure* and the interaction between *advertiser competition and double exposure* on overall and free click-through behavior. With the investigation of order effects, this project accounts for developments in traditional banner advertising research and demonstrates the need to distinguish advertising positions on lateral or upper areas (e.g., Briggs and Hollis 1997; Benway 1998). Therefore, it strives to answer first the research question: *How does message order affect click-through behavior?* Furthermore, noting the indications of interdependencies between paid and organic listings (Yang and Ghose 2010), I consider the impact of double exposure to extend these findings to overall and free click-through behavior with another research question: *How does double exposure through the simultaneous display of paid and organic search result affect*

[5] Overall click-through subsumes clicks on organic search results (free click-through) and paid search results (paid click-through). Organic and free click-through behavior, both applied in this thesis, is used interchangeably.

click-through behavior? Finally, an extension of the second research question based on the interaction between advertiser competition and double exposure provides a more differentiated view of the impact of double exposure for increasing levels of advertiser competition on click-through behavior: *How does increasing advertiser competition affect the impact of double exposure on click-through behavior?*

Overall then, this dissertation strives to make three contributions with regard to the role of the Internet in the digital age. First, it focuses on the causal effects of customer-initiated channel migration on the breadth and depth of the relationship, which clarifies the theoretical and managerial importance of direct and indirect Internet channels for distributing services. Second, this dissertation emphasizes theoretical and managerial findings regarding the causal effect of advertiser competition on click-through and conversion rate. Third, it provides theoretical and managerial insights into the effectiveness of paid search advertising by investigating the causal effects of order and double exposure on click-through behavior, as well as the relevance of double exposure for click-through improvements with increasing advertiser competition. Figure 1 provides a summary of the research questions pursued in this thesis.

Research Questions		
Customer-Initiated Channel Migration (CICM)	**Search Engine Marketing: A Behavioral Perspective**	
Project I: *Behavioral Consequences of CICM*	**Project II:** *When Choice Overload is No Bad Thing*	**Project III:** *Does Paid Search Advertising Really Pay Off?*
Research Question: How do different types of customer-initiated channel migration affect relationship breadth and depth?	**Research Question 1:** How does advertiser competition affect click-through behavior? **Research Question 2:** How does advertiser competition affect conversion behavior?	**Research Question 1:** How does message order affect click-through behavior? **Research Question 2:** How does double exposure through simultaneous display of paid and organic search result affect click-through behavior?

Figure 1: Research Questions

Thesis structure

This dissertation is structured as in Figure 2: Having introduced the relevance of research into Internet topics and the research questions of this thesis, in *Chapter B* I establish the conceptual basis for customer-initiated channel migration and describe *Project I*. To study the behavioral consequences of customer-initiated channel migration, I adopt transaction and switching cost theory as theoretical bases. By using Mahalanobis-metric matching, this project applies a statistical procedure for quasi-experimental research designs with customer data from a leading, global service provider. *Chapter C* adopts a behavioral perspective toward search engine marketing. After outlining the fundamentals of research on search engine marketing, *Project II* investigates the impact of advertiser competition on click-through and conversion behavior in search engines. This project, based on consumer choice theories, mixes experimental research design and descriptive research designs with proprietary company data from five European retailers that advertise on Google. *Project III*, using a multimethod research design (observational and two experimental studies), studies the influence of order effects and double exposure on consumer overall and free click-through behavior. Moreover, this project combines the effects of advertiser competition and double exposure to investigate how the influence of double exposure on click-through behavior changes with increasing levels of advertiser competition. *Chapter D* finally combines the central findings of the three different projects and details their results and implications from a general point of view.

Understanding the Role of the Internet in the Digital Age: A Multichannel, Multistudy Examination		
A. General Introduction		
B. Customer-Initiated Channel Migration (CICM)	**C. Search Engine Marketing: A Behavioral Perspective**	
Conceptual Background: Multichannel Customer Management & Customer Channel Migration **Project I:** *Behavioral Consequences of CICM* Theoretical Basis: Transaction Cost & Switching Cost Methodology: Quasi-Experimental Design Theoretical & Managerial Implication	Conceptual Background: Search Engine Marketing & Advertiser Competition **Project II:** *When Choice Overload is No Bad Thing* Theoretical Basis: Consumer Choice Methodology: Experimental Design (Study 1) & Descriptive Design (Study 2) Theoretical & Managerial Implications	Conceptual Background: Search Engine Marketing & Advertiser Competition **Project III:** *Does Paid Search Advertising Really Pay Off?* Theoretical Basis: Order Effect & Mere Exposure Methodology: Observational Design (Study 1) Experimental Design (Study 2 & Study 3) Theoretical & Managerial Implications
D. Concluding Remarks		

Figure 2: General Structure of the Thesis

B. Customer-Initiated Channel Migration

In recent years, previously unknown communication and distribution channels emerged along with the development and deployment of new information and communication technologies. Therefore, companies make use of at least some of these new channels to gain competitive advantages and better survive in the face of increasing competition that emerges with this progress. This associated channel multiplicity has dramatically changed service industries and increased complexity in distribution and communication (van Bruggen et al. 2010).

New channels for company–customer interaction and customer–customer interaction, such as social networks (e.g., Facebook), microblogging (e.g., Twitter), and review websites (e.g., Tripadvisor, Holidaycheck), as well as new channels for service selling, including price comparison websites (e.g., PriceRunner, uSwitch, TopTarif) and intermediaries (e.g., Hotwire, Expedia, Groupon) create both opportunities and challenges. As opportunities, these different channels allow customers to choose the most convenient option among a set of different channels for each transaction or interaction (Blattberg, Kim, and Neslin 2009).[6] Thus it is not surprising that a multichannel environment positively influences sales, profitability, and loyalty. Myers, Pickersgill, and van Metre (2004), Kumar and Venkatesan (2005), and Thomas and Sullivan (2005) show that multichannel usage leads to increasing sales. Research into the relationship between multichannel behavior and customer profitability also shows that multichannel customers are significantly more profitable than single-channel customers (e.g., Hitt and Frei 2002; Kumar and Venkatesan 2005; Thomas and Sullivan 2005; Venkatesan, Kumar, and Ravishanker 2007; Ansari, Mela, and Neslin 2008; Campbell and Frei 2010). Wallace, Giese, and Johnson (2004) also find that multichannel strategies can enhance customer satisfaction and loyalty.

Yet a multichannel environment also creates considerable challenges because of its negative effects on traditional channels. If newly introduced channels are too similar to the well-established channels, cannibalization between channels can lead to financial loss (e.g., Deleersnyder et al. 2002; Biyalogorsky and Naik 2003; Coelho, Easingwood, and Coelho 2003; Pauwels and Neslin 2008). Different distribution channels also entail different acquisition costs (Villanueva, Yoo, and Hanssens 2008) and acquire customers with different lifetime values (e.g., Verhoef and Donkers 2005; Villanueva, Yoo, and Hanssens 2008), though

[6] I adopt the channel definition proposed by Neslin et al. (2006), who include distribution and communication channels, which are not always distinguishable. A channel thus is a "customer contact point, or a medium through which the firm and the customer interact" (Neslin et al. 2006, p. 96). For more details see *Chapter B/1.1.*

if the new channel is properly established, these differences can exert positive effects (e.g., Deleersnyder et al. 2002; Geyskens, Gielens, and Dekimpe 2002).

Customer channel migration captures these opportunities and challenges, including how the introduction of new channels to a given set prompts changes in the customers' channel settings and can transform (single-channel) customers into more profitable multichannel customers. Accordingly, customer channel migration affects the financial performance of companies. By focusing on customer channel migration as the underlying consumer channel-switching behavior in a multichannel environment, recent research pursues a better understanding of behavioral antecedents and consequences (e.g., Thomas and Sullivan 2005; Verhoef, Neslin, and Vroomen 2007; Ansari, Mela, and Neslin 2008; Böhm 2008; Konus, Trampe, and Verhoef 2009). This "dynamic process in which a current customer repeatedly makes choices to frequent one of a retailers channel options (e.g., brick-and-mortar, catalog, Internet)" (Thomas and Sullivan 2004, p. 2) is not limited to retailing but also emerges in services industry. This is of special interest because recent research on customer channel migration suggests that the segment of migrating customers is more profitable than the segment of non-migrating customers (Thomas and Sullivan 2005; Ansari, Mela, and Neslin 2008).

Service providers, including hotels, airlines, telecommunication companies, and insurance companies, operate both direct and indirect channels (e.g., Bolton, Lemon, and Verhoef 2004; Verhoef and Donkers 2005; Coughlan et al. 2006; von Wangenheim 2006), though current research on multichannel customer management and customer channel migration pays little attention to this kind of channel structure. Therefore, a better understanding is needed of the behavioral consequences when customers migrate between direct and indirect channels. Although the Internet is a primary channel, little and often-contradictory knowledge explains its impact on the financial contributions of customers and thus the financial performance of companies (e.g., Hitt and Frei 2002; Verhoef and Donkers 2005; Böhm 2008; Gensler, Leeflang, and Skiera 2011; Pauwels et al. 2011). Consequently, more insights on how migration between direct and indirect, as well as online and offline, channels affects customer relationships with the service provider are desirable.

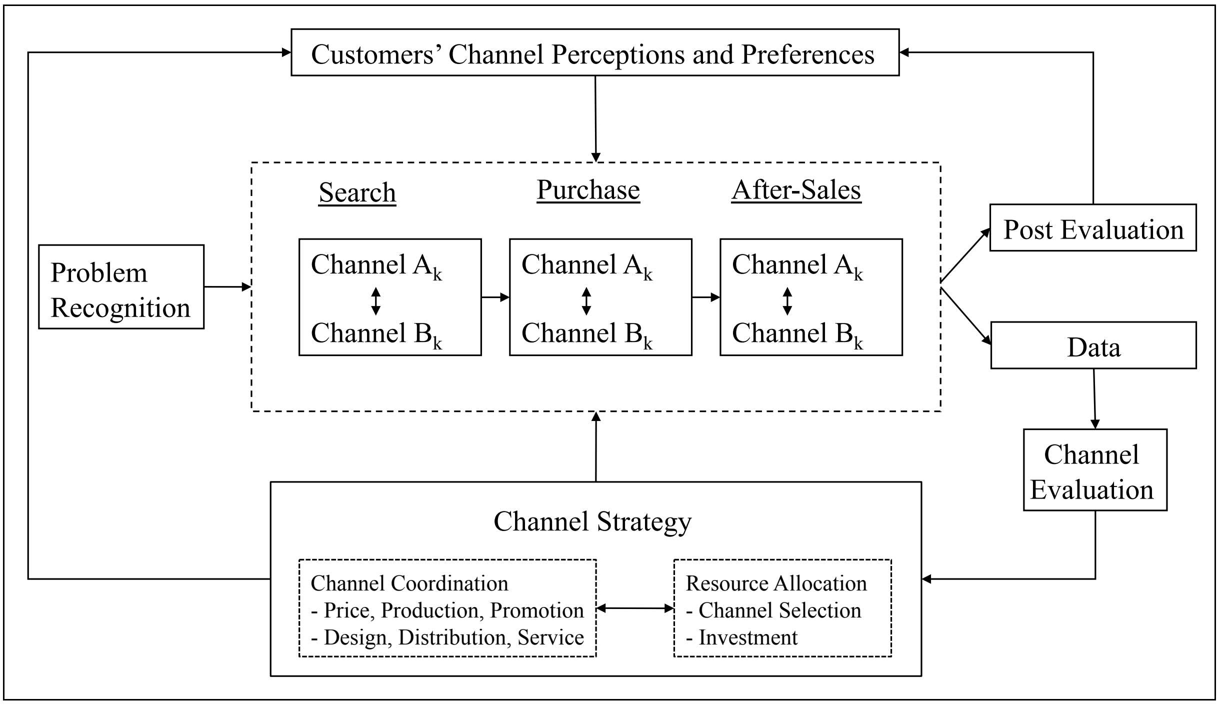
This project merges the two channel structures (service distribution and intermediation) into a 2 (direct vs. indirect) × 2 (online vs. offline) matrix for customer-initiated channel migration to investigate a central research question: How do different types of a customer-initiated channel migration (e.g., from direct to indirect, from offline to online) affect relationship breadth and depth?

First, I will clarify the role of customer channel migration in the context of multichannel customer management and develop a framework for customer-initiated channel migration (CICM). Second, I derive hypotheses based on transaction and switching cost theory to investigate the behavioral consequences of CICM. Third, I present the results of a quasi-experimental design, using time-series data from a large globally operating airline. Finally, I conclude this section with theoretical and managerial implications of this study, as well as implications for further research in the field of customer (-initiated) channel migration.

1 Conceptual Basis

The emergence of multichannel strategies in companies' distribution scope has led to the proliferation of research into channel migration (e.g., Blattberg, Kim, and Neslin 2009). The enduring relevance of multichannel customer management and customer channel migration has been highlighted in the Marketing Science Institute's top research priorities such as "managing and maintaining customers through multiple channels" (Marketing Science Institute 2004, p. 10) and "delivering value through enhanced media and channels" (Marketing Science Institute 2010, p. 7).

Neslin et al. (2006) and Blattberg, Kim, and Neslin (2009) offer comprehensive frameworks that include customers' and companies' perspectives in multichannel customer management (Figure 3). I refer to this conceptualization as a summary of the main empirical results from previous multichannel customer management research, as well as to systematize the role of customer channel migration. Both Neslin et al. (2006) and Blattberg, Kim, and Neslin (2009) integrate customers' and firms' decision processes in a multichannel environment. Specifically, a customer might recognize a particular need and therefore search in different channels from different companies, select one channel and company for the purchase, and receive after-sales services in the same channel. This search, purchase, and after-sales stages depend on the customer's channel perceptions and preferences, which in turn are influenced by companies' channel strategies. The customer's evaluation of the process then influences future perceptions and preferences. In general, the multichannel management process starts with an analysis of data from the customer decision process (search, purchase, after-sales) to evaluate the channels and suggest changes to the company's channel strategy (see Neslin et al. 2006; Blattberg, Kim, and Neslin 2009).



Notes: The different channels are captured with A and B (e.g., Channel A and Channel B): the index k distinguishes different companies.
Source: Adapted from Blattberg, Kim, and Neslin (2009) and Neslin et al. (2006).

Figure 3: Framework for Multichannel Customer Management

Because customer channel perceptions and preferences; search, purchase, and after-sales stages; channel evaluation; and channel strategy are strongly interconnected with customer channel migration, it is important to summarize the main results from recent empirical research. *Chapter B*/1.1 focuses on the main developments in multichannel customer management first. This project focuses on the behavioral consequences of CICM, so the insights from recent empirical research on customer channel migration (*Chapter B*/1.2) help outline research gaps and highlight the contributions of this project, as well as establish the conceptual framework for CICM.

1.1 Fundamentals of Multichannel Customer Management

Although new consequences have emerged from new channels, channel management and channel strategy are not new topics to marketing literature. In traditional sales channel management, the focus is on the company's point of view, and the relationship between the company and its distributors takes central stage, along with the marketing mix (e.g., El-Ansary and Stern 1972; Webster 1991). In contrast, modern channel management literature centers on the customer as a strategic contributor that creates additional value for the company (e.g., Boulding et al. 2005; Payne and Frow 2005; Rangaswamy and van Bruggen 2005). Therefore, Neslin et al. (2006, p. 96) define multichannel customer management as "the design, deployment, coordination, and evaluation of channels to enhance customer value through effective customer acquisition, retention, and development."

In recent publications on channels for customer relationship management, two aggregation levels and definitions appear. On the one hand, Kumar and Reinartz (2006) use the term "channel" in two distinct ways. The first usage refers "to the flow of the organization's offerings (e.g., physical goods or information) to the ultimate end users (end customers), as well as that of the sales proceeds or realizations from the customer back to the marketing firm," whereas the second "refers to the mode of communication between a firm and its customers" (Kumar and Reinartz 2006, p. 292). On the other hand, differentiation between channels of communication and distribution also is disappearing, in line with Neslin et al.'s (2006, p. 96) previously cited definition of a channel as "a customer contact point, or a medium through which the firm and the customer interact."

The first special issue of the *Journal of Interactive Marketing* on multichannel marketing in spring 2005 (Shankar and Winer 2005) offered an impetus for further research in this research field, and many publications have appeared in international peer-reviewed marketing journals. These fundamental developments and the three main challenges for customer channel migration, following the conceptualization of Neslin et al. (2006), are consumer behavior in a multichannel setting, evaluating channels and resource allocation across channels, and coordinating channel strategies (see also Blattberg, Kim, and Neslin 2009),[7] as summarized next.

Consumer behavior in a multichannel setting

To shed further light on consumer behavior in a multichannel environment, the first step is a deeper understanding of the determinants of channel choice. Plenty of research has focused on this fundamental question. Neslin et al. (2006) thus define six major determinants of customer channel choice: channel attributes, channel integration, individual differences, marketing, situational factors, and social influence.

[7] In their original conceptualization, Neslin et al. (2006) and Blattberg, Kim, and Neslin (2009) separated the topics evaluating channels and resource allocation across channels. However, the two topics are closely interconnected, so I combine the respective empirical results.

Perceptions of *channel attributes* are based on the theory of reasoned action[8] (e.g., Fishbein and Ajzen 1975; Ajzen and Fishbein 1980; Blattberg, Kim, and Neslin 2009). Amongst other attributes, after-sales, assortment, ease of use, purchase effort, price, privacy, search convenience, search effort, service, and risk are potential determinants of customer channel choice decisions (for an overview, see Neslin et al. 2006; Blattberg, Kim, and Neslin 2009). Verhoef, Neslin, and Vroomen (2007) reveal how customers perceive catalogue, Internet, and store channels with regard to different attributes;[9] by analyzing the surveyed perceptions of 396 representative Dutch customers, they show that the catalogue channel is weak on service and negotiation but high on enjoyment features, whereas the Internet benefits on search convenience and information comparison dimension but performs poorly on privacy. Compared with other channels, the Internet performs similarly on search effort. Finally, the store channel is strong with regard to privacy, risk reduction, and service but inferior for search convenience.

Channel integration aims to create an environment in which customers can easily choose the most convenient channel or channel combination (e.g., Neslin et al. 2006; Blattberg, Kim, and Neslin 2009; Neslin and Shankar 2009). Convenience through integrated channels can lead to positive effects on customer behavior, such as synergy instead of cannibalization (e.g., Deleersnyder et al. 2002; Biyalogorsky and Naik 2003) or higher overall customer satisfaction (e.g., Montoya-Weiss, Voss, and Grewal 2003a). The determinants of channel integration also reflect *individual differences* among customers, including demographics (Gupta, Su, and Walter 2004; Verhoef, Neslin, and Vroomen 2007; Ansari, Mela, and Neslin 2008), previous channel experience (e.g., Montoya-Weiss, Voss, and Grewal 2003b; Keen et al. 2004; Verhoef, Neslin, and Vroomen 2007; Ansari, Mela, and Neslin 2008), and stage in the customer life cycle (e.g., Valentini, Neslin, and Montaguti 2011). In addition, *marketing activities*, such as e-mail messages, catalogues, or promotions, may influence customer channel choice decisions (e.g., Myers, Pickersgill, and van Metre 2004; Thomas and Sullivan 2005; Knox 2006; Venkatesan, Kumar, and Ravishanker 2007; Ansari, Mela, and Neslin 2008; Pauwels and Neslin 2008).

Finally, *situational factors* and *social influence* affect customer channel choice decisions. As situational factors, Nicholson, Clarke, and Blakemore (2002) distinguish antecedent states

[8] The theory of reasoned action assumes that behavioral intentions, and thus behavior, depend on attitudes and subjective norms (see Fishbein and Ajzen 1975; Ajzen and Fishbein 1980).

[9] These attributes are: information comparison, search effort, search convenience, assortment, price promotion, enjoyment, clientele, service, risk, purchase effort, negotiation, buying time, after-sales, quick obtain, and privacy (Verhoef, Neslin, and Vroomen 2007). Also see *Chapter B*/1.2 and Figure 5.

(e.g., mood), physical settings (e.g., geography, weather, store atmosphere), social settings (e.g., group), task definition (e.g., information search, purchasing), and temporal perspectives (e.g., time, season). Task definition has captured additional research interest, as authors such as Mahajan, Srinivasan, and Wind (2002), Mathwick, Malhotra, and Rigdon (2002), and Verhoef, Neslin, and Vroomen (2007) show that different channels are suitable for different task definitions, whether goal-directed shopping, experiential shopping, or information searches. In the social setting determinant suggested by Nicholson, Clarke, and Blakemore (2002), Neslin et al. (2006) include clientele (Verhoef, Neslin, and Vroomen 2007), social norms (Keen et al. 2004), and parenthood (Nicholson, Clarke, and Blakemore 2002).

Besides the determinants of customer channel choice decision, Konus, Verhoef, and Neslin (2008), with a sample of Dutch consumers, test attitudes toward channels for searching and purchasing and find three customer segments in a multichannel context: uninvolved shoppers, multichannel enthusiasts, and store-focused shoppers. Uninvolved shoppers (no distinct preferences for channels) exhibit low levels of brand/retailer loyalty, shopping enjoyment, and price consciousness but higher innovativeness. Low levels of brand/retailer loyalty, high innovativeness, and high shopping enjoyment characterize multichannel enthusiasts. This segment also expresses positive attitudes toward searching and purchasing in multiple channels. Finally, store-focused shoppers exhibit high levels of brand/retailer loyalty, higher shopping enjoyment, low levels of innovativeness, and unfavorable attitudes toward other channels.

Finally, a variety of research supports the empirical observation that multichannel shoppers buy more, provide more revenue, and are more loyal customers with a higher share of wallet than single-channel customers (e.g., Myers, Pickersgill, and van Metre 2004; Kumar and Venkatesan 2005; Thomas and Sullivan 2005; Neslin et al. 2006; Ansari, Mela, and Neslin 2008). With this research in mind, Neslin and Shankar (2009, p. 72) conclude that the "empirical evidence that the average multichannel customer buys more than the single channel customer is reaching the point of empirical generalization."

Evaluating channels and resource allocation across channels

Because the introduction of new channels to a multichannel environment influences the company's financial performance considerably, research on the economic contribution of an added channel clearly is important. Prior research offers four key insights: (1) how customer behavior differs across diverse channels, (2) the impact of adding different channels on future economic contributions to companies' performance, (3) the influence of different multichannel customer segments, and (4) the allocation of resources across channels.

Verhoef and Donkers (2005) investigate the impact of customer acquisition channels on loyalty and cross-buying. Measuring the performance of website, television and radio, print, direct mail, outbound telephone, magazines, and word of mouth, they show that the channels contribute to different extents to customer retention and cross-buying. Outbound telephone, magazines, and websites lead to higher retention rates than for a particular customer base. Television and radio, direct mail, word of mouth, and print channels instead lead to lower retention rates. To encourage future cross-buying behavior, firms should acquire customers through the former rather than the latter methods.

Yet the different channels also demand different costs to acquire new customers. Villanueva, Yoo, and Hanssens (2008) show that online banner ads, television, radio, magazine, e-mail and newspaper advertisements, as well as direct mailing, add more economic value in the short run. Other channels, such as links from websites, magazine or newspaper articles, and referrals from friends, colleagues, professional organizations, associations, or search engines, add more long-term economic value. Deleersnyder et al. (2002) and Biyalogorsky and Naik (2003) show that supplementing an offline channel with an Internet channel does not necessarily decrease sales. Pauwels and Neslin (2008) assess the revenue impact if a brick-and-mortar store joins a company's channel portfolio, along with catalog and Internet channel. Adding the offline channel leads to cannibalization effects for the catalog, but the Internet is not affected. They also reveal that adding the brick-and-mortar store leads to greater retention, through more frequent interactions with the customer.

A deeper understanding of different multichannel customer segments is needed to evaluate channel performance too. Kushwaha and Shankar (2007) investigate a store-only, web-only, and multichannel customer segment with data from a large apparel and shoe company. The store-only segment offers the highest margins to the financial success and is more sensitive to discounts; customers from the web-only and multichannel segments instead are more sensitive to list prices. Overall, the average return is lowest for the web-only segment and highest for the multichannel segment. This finding contributes further to the empirical generalization that multichannel customers are more profitable (see Neslin and Shankar 2009).

Finally, the results of Verhoef and Donkers (2005) and Villanueva, Yoo, and Hanssens (2008) can show that the long-term and short-term value, as well as retention rates or cross-buying behavior by customers, depend on the acquisition channel. Therefore, companies must extensively gauge the aims of their channel selection decisions for different acquisition costs levels. Kushwaha and Shankar (2007) suggest an approach for an optimal resource allocation of marketing activities across different customer and channel segments. The optimization relies on measures such as company profit, purchase frequency and quantity, product return propensity, and contribution margin. By estimating the optimal resource allocation for a large shoe manufacturer with direct mail, retail store, and Internet channels, these authors demonstrate that sending product and promotional catalogues can maximize profits, especially among multichannel shoppers of various types (shopping in all three channels, shopping in store and direct mail channel, and shopping in store and Internet channel).

Coordinating channel strategies

The coordination of channel strategies includes price, production, and promotion, as well as design, distribution, and service (see Figure 3). In general, channel coordination can span three aggregation levels. First, full integration as a holistic approach coordinates all channels to maximize profits. Second, limited integration exists if companies source some channels out to third parties. Third, full separation occurs if each channel is managed as a separate entity (e.g., Gulati and Garino 2000; Berger, Lee, and Weinberg 2006).

Different potential advantages and disadvantages likely determine the level of coordination of channel strategies. Potential benefits connected to channel coordination include economies of scale (Neslin et al. 2006); decreased channel conflict by differentiating offerings and prices; compensation for weaknesses and strengths across channels (e.g., Zettelmeyer 2000; Fang-Fang and Xiaolin 2001; Achabal et al. 2005; Berger, Lee, and Weinberg 2006); a better quality customer database, including higher service levels and stronger customer relationships (e.g., Stone, Hobbs, and Khaleeli 2002; Sousa and Voss 2006); higher entry barriers for potential competitors and the prevention of channel partners from becoming competitors (Neslin et al. 2006); and better interorganizational communication (Neslin et al. 2006). In contrast, it can also induce a loss of flexibility, the need for large investments or higher fixed costs (Sousa and Voss 2006), demand for channel management expertise, and decreased incentives for third-party intermediaries and partners (Neslin et al. 2006) as potential costs for channel coordination.

Phenomena such as research shopping or forced channel migration also demand high levels of channel coordination (see *Chapter B*/1.2). Research shopping is the behavior when customers search and purchase in different channels (e.g., Verhoef, Neslin, and Vroomen 2007; Konus, Verhoef, and Neslin 2008; Pauwels et al. 2011). For example: a customer is searching for a product in the store but purchases the product on the Internet. Forced channel migration, which moves certain customers from one channel to another channel to enhance the firm's overall profits, requires high levels of channel coordination and knowledge about the customers, including their financial contributions in each channel setting (e.g., Konus, Trampe, and Verhoef 2009).

1.2 Fundamentals of Customer Channel Migration

This chapter provides the conceptual and theoretical foundation for *Project I*. Therefore, this section presents the fundamentals of customer channel migration (see *Chapter B*/1.2), before moving to the central research question for this study (*Chapter B*/2) and the foundation of the conceptualization of customer-initiated channel migration (see *Chapter B*/2.1).

Substantial research on customer channel migration focuses on a single customer's channel choice decision for a single or repeated purchase. Customer channel migration is "a dynamic process in which a current customer repeatedly makes choices to frequent one of a retailers channel options (e.g., brick-and-mortar store, catalog, Internet)" (Thomas and Sullivan 2004, p. 2). In addition, Blattberg, Kim, and Neslin (2009, p. 647) emphasize a double meaning; stating that customer channel migration "can be thought of simply as channel choice, but we use it to convey choices over time." I build on these two dimensions of single choice and choice over time to clarify the concept of customer-initiated channel migration in *Chapter B*/2.1.

Customer channel migration behavior prompts substantial changes in certain attributes of the customer relationship. A migration from a brick-and-mortar store to the Internet store, for example, can lead to lower costs to serve the customer but also might be connected to different prices. Customers in direct channels are more costly than those in intermediated or third-party operated channels, because the costs for communication are mainly covered by the third party or the manufacturer (e.g., Bolton, Lemon, and Verhoef 2004; von Wangenheim 2006; Campbell and Frei 2010; Gensler, Leeflang, and Skiera 2011). Even when companies aim to transform less profitable, single-channel customers into more profitable, multichannel customers (e.g., Kumar and Venkatesan 2005; Neslin et al. 2006; Ansari, Mela, and Neslin 2008; Neslin and Shankar 2009), they lack research insights into the underlying customer channel migration that enables such multichannel buying (Neslin and Shankar 2009).

Literature studying customer channel migration distinguishes two types of customer channel migration, voluntary and forced migration. In the case of a voluntary channel migration, customers decide to cancel, switch, or to add a certain channel in their relationship with the company (e.g., Thomas and Sullivan 2004, 2005; Ansari, Mela, and Neslin 2008). In contrast, with involuntary or forced channel migration,[10] the company initiates the channel migration, often due to the unprofitability of the customer or channel (Blattberg, Kim, and Neslin 2009), which can lead to customer reactance toward the company (e.g., Mazis, Settle, and Leslie 1973; Clee and Wicklund 1980; Konus 2010). I review the empirical findings on voluntary channel migration first, then focus on the research shopper phenomenon, and finally close this chapter with results from forced channel migration research. I provide an overview in Table 1.

Thomas and Sullivan (2004) were the first authors to emphasize the relevance of customer channel migration for multichannel customer management and its impact on customer profitability. With customer data from a major U.S. retailer that used physical stores, catalogues, and an Internet store, these authors investigate differences in relationship length, purchase frequency, cross-buying, and total spending across the different possible channel combinations. Their results show that customers who use all three channels have extended relationships with the retailer, higher purchase frequency, higher levels of cross-buying, and higher overall spending than customers who add only one additional channel (double-channel) or single-channel customers.

[10] Note "forced channel migration refers to the process of moving customers from one channel to another channel through coercive actions that enhance the efficiency of the firm's channel operations" (Konus 2010, p. 50).

Author	Industry	Channels	Channel Migration	Research Interest
Thomas and Sullivan 2004	Retailing	Retail store, catalog, Internet store	Voluntary	Impact of different channel combinations
Thomas and Sullivan 2005	Retailing	Retail store, catalog, Internet store	Voluntary	Marketing communication process influencing channel migration
Knox 2006	Retailing	Internet, catalog, email	Voluntary	Impact of marketing communication on channel migration
Gensler, Dekimpe, and Skiera 2007	Home-shopping (TV)	Call-center, Internet store	Voluntary	Channel migration behavior
Venkatesan, Kumar, and Ravishanker 2007	Apparel manufacturer	Full price store, discount store, Internet store	Voluntary	Drivers of the first and second channel migration
Ansari, Mela, and Neslin 2008	Retailing	Catalog, Internet store, email	Voluntary	Model of channel migration
Böhm 2008	Retail bank	Retail bank, Internet bank	Voluntary	Channel migration to the Internet
Valentini, Neslin, and Montaguti 2011	Subscription book retailer; Retailer	Retail store, catalog, Internet store, email	Voluntary	Evolution of the channel choice decision over time
Verhoef, Neslin, and Vroomen 2007	Different product & service categories[11]	Store, catalog, Internet store	Research shopping	Customer behavior in searching and purchasing
Pauwels et al. 2011	Retailing	Retail store, informational website	Research shopping	Impact of online search on offline sales
Konus, Trampe, and Verhoef 2009	Energy	Letter, Internet	Forced	Consumer response to forced channel migration

Table 1: Previous Customer Channel Migration Literature

Thomas and Sullivan (2005), Knox (2006), Venkatesan, Kumar, and Ravishanker (2007) as well as Ansari, Mela, and Neslin (2008) all show that marketing communications, in addition to several other drivers, can influence customer channel migration.[12] Thomas and Sullivan (2005) develop a marketing communication process to estimate the probabilities that different customer segments will change their channel setting. They aim to develop a communication strategy that can influence channel choices; in so doing, they observe two customer segments. The first segment buys by catalog and/or the Internet, whereas the second segment is loyal to brick-and-mortar stores. Their analyses of a major U.S. retailer's customer database indicate that increasing marketing communication influences customers in the first segment to repurchase from the catalog, whereas customers in the second segment repurchase from brick-and-

[11] In Verhoef, Neslin, and Vroomen's (2011) study, every respondent evaluated one of six different categories (product or service): books, clothing, computers, electronic appliances, loans, and vacations.

[12] Pauwels and Neslin (2008) find support for the effect of marketing communication on customers' behavior. Marketing communication through direct mailing or media advertising for example affects not only the success of adding a new channel but also sales in existing channels.

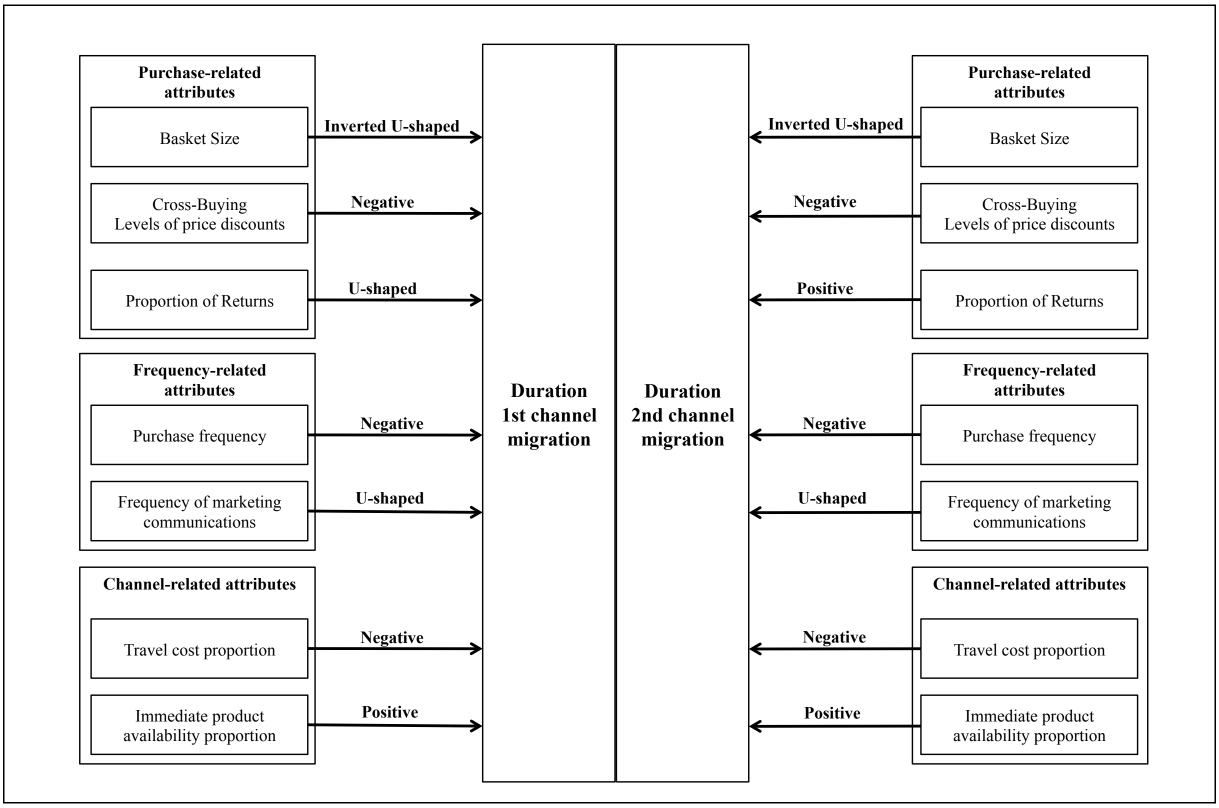
mortar stores. Thus, marketing communication plays a minor role in predicting channel migration; the prior purchase channel is a much better predictor of channel choice.

Knox (2006) also studies how different channels for marketing communication (e-mail, catalog) influence channel migration to online (Internet) or offline (catalog and ordering by phone, mail, and fax) channels. Estimating a model of repeat buying behavior with data from a major U.S. retailer, Knox (2006) shows that ending with marketing communication drives customers from the offline segment to purchase online. In the segment of migrated customers, marketing communications (e-mail and catalog) increase the proportion of Internet sales.

Venkatesan, Kumar, and Ravishanker (2007) develop and empirically test a framework for evaluating the impact of interaction characteristics,[13] going beyond the impact of marketing communication, on customer channel migration duration.[14] With a database from an apparel manufacturer with three distinct channels (full-price brick-and-mortar store, discount brick-and-mortar store, and Internet store), the authors identify drivers of the duration of the first and second channel migrations. They thus confirm, for example, that the frequency of marketing communications affects the duration for the first and second channel migration in a U-shaped manner, as displayed in Figure 4. The two sides of this figure display different drivers of the duration for a first (left) and second (right) channel migration, with their influences labeled on the arrows (e.g., inverted U-shaped, negative).

[13] Venkatesan, Kumar, and Ravishanker (2007) include channel-related attributes (travel cost proportion, immediate product availability proportion), purchase-related attributes (basket size, cross-buying, level of price discounts, proportion of returns), and frequency-related attributes (purchase frequency, frequency of marketing communications) as interaction characteristics.

[14] Although Venkatesan, Kumar, and Ravishanker (2007) began by investigating channel adoption in their study, their operationalization of adopting an additional channel fits the definition of customer channel migration by Thomas and Sullivan (2004), which provide the basis for the general customer channel migration framework for this thesis.



Source: Own illustration based on Venkatesan, Kumar, and Ravishanker (2007, p. 127).

Figure 4: Drivers of Channel Migration Duration

Ansari, Mela, and Neslin (2008) develop and estimate a model of customer channel migration with data from a retailer of consumer durables and apparel products that operates a catalog and Internet store for sales and the catalog and e-mail for marketing communication. Customer characteristics (age, income, children), marketing communication (catalog or e-mail), and channel experience all influence customers' channel migration behavior. Ansari, Mela, and Neslin (2008) also detail that the group of non-migrating customers is older, has lower income, and has fewer children than the migration group. The estimation analyses further reveal that the incremental revenue generated through marketing communications with the catalog is smaller than that via e-mail. The authors thus reveal that migrating customers are not heavy users in general and are attracted to the Internet. Furthermore, they are exposed to more marketing communications and migrate more often in response to marketing communications.

In contrast with these empirical research projects, Valentini, Neslin, and Montaguti (2011) develop and estimate a model to measure the evolution of channel choice decisions over time.

They thus identify the best time to right-channeling[15] customers. With four years of data from a major European book retailer in a subscription-oriented setting and a U.S. retailer for durables and apparel, the authors show that the customer channel choice decision process changes over time. Moreover, the effects of marketing communication differ from the trial period before subscribing and the period of the subscription. In particular, marketing communication e-mails in the trial period that push the customer to choose the catalog over the store fail to do so, though they increase the probability of using the Internet. In the post-trial period, e-mail marketing communication can affect catalog choice over the Internet but more effectively can increase preference for the Internet over the store. In replicating their analysis for the retailer, Valentini, Neslin, and Montaguti (2011) find a decreasing impact of marketing communications.

Unlike these studies on customer channel migration, Gensler, Dekimpe, and Skiera (2007) and Böhm (2008) focus on the impact of the Internet channel on customer channel migration behavior and customer retention. Gensler, Dekimpe, and Skiera (2007) analyze customer data from a large European TV home-shopping company with two direct channels (call center and Internet) and find, among other things, that the fraction of customers considering a migration is significantly larger for call center than for Internet channel customers. Böhm (2008), in the empirical analysis of customer data from a large European retail bank, shows that migrating customers to the Internet channel increases the overall retention rate. In detail, Internet usage in the banking sector reduced the probability of churn by 87%. Thus Böhm (2008) argues that the migration of customers to the Internet can be a more effective means than cross-buying to increase customer retention.

In addition, voluntary channel migration occurs not just in succeeding purchase processes (transactions) but also during a single, which leads Verhoef, Neslin, and Vroomen (2007) to introduce the research shopper phenomenon. They define research shopping as “when one of the used search channels is not used for purchase“ (Verhoef, Neslin, and Vroomen 2007, p. 136). Surveying 396 Dutch consumers, they find that attribute-based decision making,[16]

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[15] Right-channeling customers refers to companies’ efforts to encourage migration to channel(s) that add value for the company, as well as for the customer (e.g., Myers, Pickersgill, and van Metre 2004; Neslin and Shankar 2009; Valentini, Neslin, and Montaguti 2011).

[16] “This mechanism is based on consumer perception that one channel excels on attributes that determine search, while the other channel excels on attitudes that drive purchase“ (Verhoef, Neslin, and Vroomen 2007, p. 132).

scarcity of channel lock-in,[17] and cross-channel synergies[18] influence the outcome that searching the Internet and purchasing in stores is the most popular form of research shopping. Particularly, these authors develop a framework for understanding how customers choose their channels for search and purchase. Figure 5 displays attributes with statistically significant (positive or negative) influences on the selection of store, Internet, or catalog channels for these two different tasks.

Pauwels et al. (2011) build on the idea of the research shopper phenomenon by Verhoef, Neslin, and Vroomen (2007) to investigate how searching for information on the Internet affects offline sales in stores. With customer data from a large department store from the Netherlands, these authors show that offline revenues increase most for customers visiting an informational website with high frequency. Their results reveal that online search and offline purchase have complementary characteristics. Furthermore, online marketing communications with price information increase offline sales in the short run, whereas online marketing communications without price information increase them in the long run.

As I mentioned previously, forced channel migration also has found its way into customer channel migration research. For example, in empirical research, Konus, Trampe, and Verhoef (2009) investigate the impact of forced customer channel migration on customer reactance, customer satisfaction, and customer compliance. With three different experimental studies, they show that forced channel migration leads to customer reactance,[19] which influences customer satisfaction. Offering monetary incentives to customers can alleviate such reactance; however, high and low value customers do not vary much in their responses to forced channel migration.

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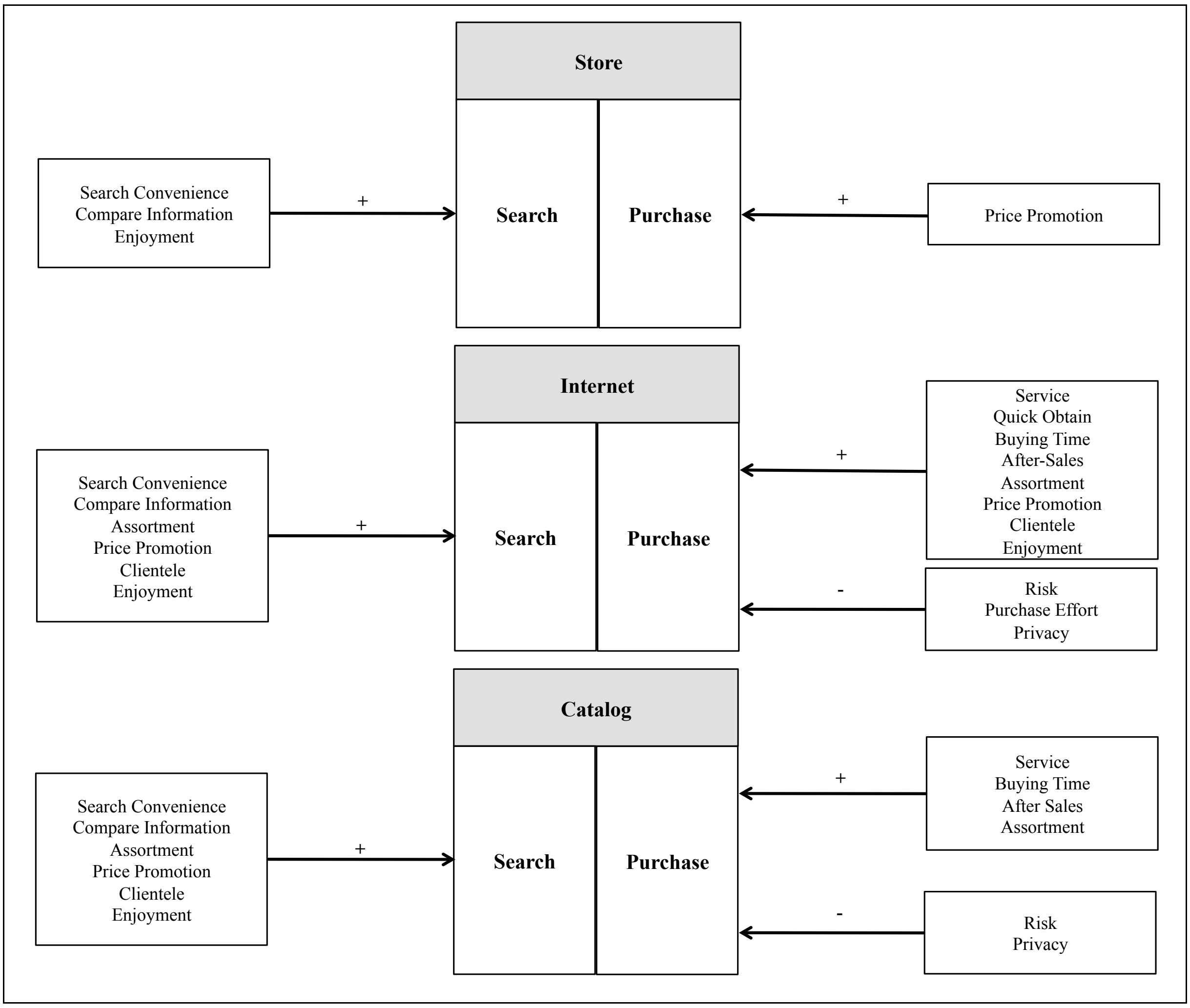
[17] Channel lock-in refers to the assumption that higher attitudinal levels for searching on one channel are highly correlated with higher attitudes toward purchasing in the same channel. With scarce channel lock-in, for example in the case of the Internet, the channel instead is perceived as channel for information search, but not as a channel for purchase (see Verhoef, Neslin, and Vroomen 2007).

[18] With cross-channel synergy, Verhoef, Neslin, and Vroomen (2007) refer to consumers' perception of economic benefits, because their searching in one channel supports better purchase decisions in another channel, largely because they feel that they are better informed.

[19] Customer reactance also mediates the relationship between forced customer channel migration and satisfaction (Konus, Trampe, and Verhoef 2009).



Notes: The reported attributes are statistically significant at a 10% level.
Source: Own illustration based on Verhoef, Neslin, and Vroomen (2007, p. 140).

Figure 5: Customer Perceptions of Attributes for Search and Purchase Channels

This overview of recent developments in research on customer channel migration highlights a particular feature, namely, the relevance of investigating the causal influence of customer channel migration on future behavior. Thus, a general conceptual framework for investigating different types of customer channel migration behavior is necessary, which in turn demands further investigation of their causal inferences.

2 Project I: Behavioral Consequences of Customer-Initiated Channel Migration

The previous *Chapters B*/1.1 and 1.2 revealed the considerable gap related to understanding the causal effects of channel migration. It would be interesting to know whether different types of customer channel migration have positive effects on customer relationships. This question is even more important considering that prior research on multichannel customer management and customer channel migration has not tested any causal links in the customer relationship (see Neslin and Shankar 2009). Furthermore, previous research shows that different channels acquire and retain customers with different customer lifetime values (e.g., Verhoef and Donkers 2005; Villanueva, Yoo, and Hanssens 2008). Moreover, current research does not consider channel migration between direct and indirect or online and offline channels in a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix. This project strives to understand whether the association between different types of customer-initiated channel migration and relationship intensity is causal. To measure the intensity of the customer–firm relationship, I build on the concept of relationship breadth and depth (Verhoef 2001; Bolton, Lemon, and Verhoef 2004). Thus, an obvious research question is:

Research question:	*How do different types of customer-initiated channel migration affect relationship breadth and depth?*

Prior to the empirical examination of this general research question, I outline the conceptualization of customer-initiated channel migration, the theoretical framework of transaction and switching cost theory, and the hypotheses development for this chapter.

2.1 Conceptualization of Customer-Initiated Channel Migration

The overview of scientific investigations on customer channel migration in *Chapter B/*1.2 showed that many different channels are subject to recent research. However, central criteria distinguishing these channels' characteristics (e.g., online versus offline, direct versus indirect, personal versus non-personal) are rarely applied. I follow the structural–structuring distinction of Dwyer and Sejo (1987) and the application of physical structure to multichannel issues by Kabadayi, Eyuboglu, and Thomas (2007), with intermediation (Weitz and Jap 1995; Bolton, Lemon, and Verhoef 2004; Sa Vinhas and Anderson 2005; von Wangenheim 2006) and service distribution (e.g., Hitt and Frei 2002; Campbell and Frei 2010)[20] as connective dimensions for channel structuring. Accordingly, I base the conceptual framework for customer-initiated channel migration in this dissertation largely on the considerations of Hitt and Frei (2002) and Bolton, Lemon, and Verhoef (2004). Whereas Hitt and Frei (2002) were among the first authors to note the differences between online (PC banking) and offline (traditional banking) customers, Bolton, Lemon, and Verhoef (2004) differentiated in their

[20] Although the general idea of the service distribution dimension builds on literature on self-services, the importance of such research is minor, because the motivation and theoretical framing of this project are derived from literature on multichannel customer management and customer channel migration.

CUSAMS[21] framework, channels with personal contacts to employees of the service provider (direct) from those of a channel partner (indirect).

Developing the conceptual framework to systematize channels in service industries demands a higher level of abstraction (see Figure 6). As a result, two main dimensions of the channel characteristics can be distinguished as intermediation and service distribution. The intermediation dimension captures whether the channel is directly or indirectly operated. Generally speaking, channels in which customers purchase services directly from the service provider can be compared with channels in which customers purchase services through an intermediary. The service distribution dimension captures whether the channel is online or offline, thus covering both personal and Internet-mediated distribution (via the service provider or an intermediary) of the service to the customer and processing of the transaction.

In service practice, numerous industries combine both dimensions of the conceptual channel framework (e.g., airlines, financial service providers, insurance, telecommunications). Therefore, direct channels, such as in the airline industry, can be classified as channels that allow a customer to directly purchase from a call center, e-mail, company-owned stationary agency, or company-owned Internet platform. Purchases by indirect channels are intermediated by an independent stationary agency, independent retailer, or external Internet platform (von Wangenheim 2006). My research framework focuses on the intermediation and service distribution perspective by investigating customer channel migration (see Figure 6).

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21 CUSAMS is a framework for customer asset management of services (see Bolton, Lemon, and Verhoef 2004).

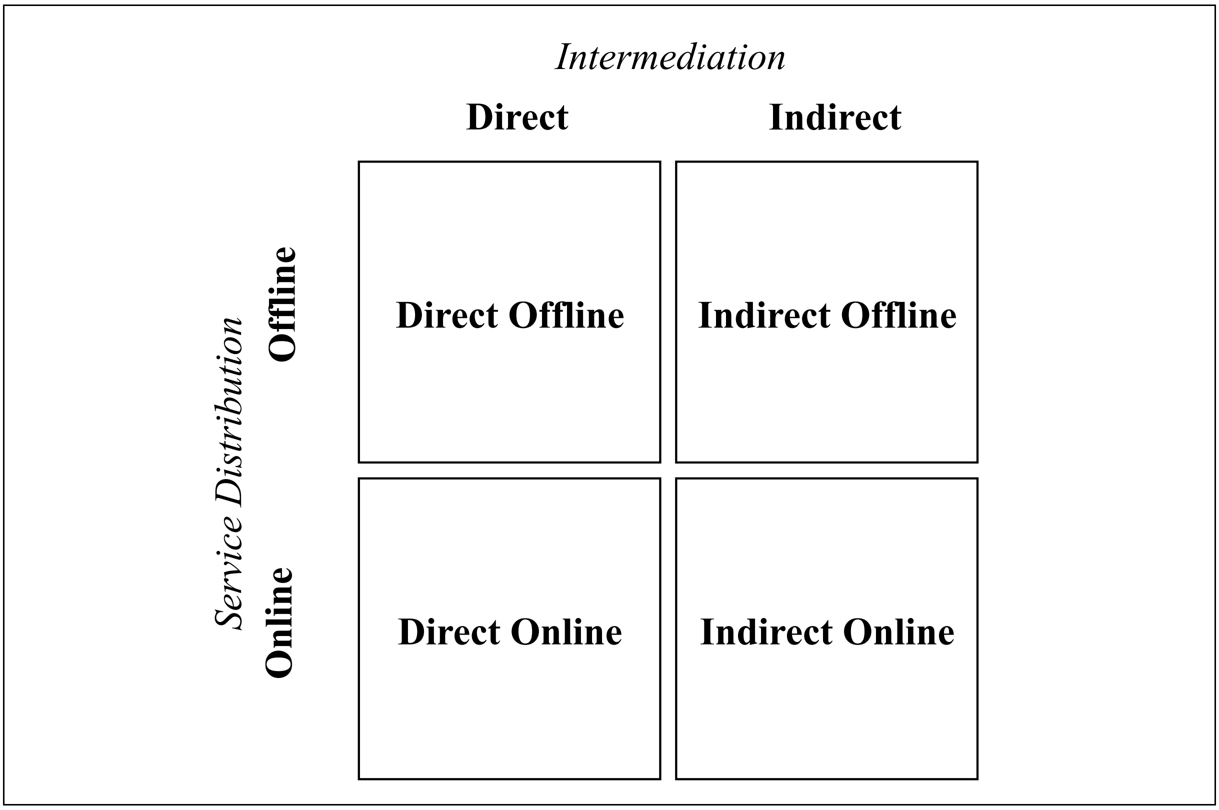


Figure 6: Conceptual Channel Framework for Project I

In this conceptual framework, four main types (and their combinations[22]) of channel migration are possible: (1a) migration from indirect to direct channels, (1b) migration from direct to indirect channels, (2a) migration from offline to online channels, and (2b) migration from online to offline channels. These types are not considered in present scientific work, so the concept of customer-initiated channel migration is introduced to capture the phenomenon. In general, customer-initiated channel migration (CICM) and the associated channel choice decision falls under the influence of the customer. Therefore, the reasons for CICM might include following: Dissatisfaction with a channel setting or better competitive offers in a different channel setting might prompt CICM. Alternatively, CICM might occur in situations in which customers change their location to regions where the company does not offer the service in the familiar channel (e.g., Hadden et al. 2006).

Using the definitions of Blattberg, Kim, and Neslin (2009) and Thomas and Sullivan (2004), I understand customer-initiated channel migration as customer channel migration in a 2 (direct vs. indirect) × 2 (online vs. offline) matrix in consecutive periods. Periods of inactivity are not taken into account. In general, adding an additional or new channel to a channel set or

[22] For instance, the combination of the migration types (1a) and (2a) would result in a customer-initiated channel migration from indirect offline to direct online channels.

substituting a given channel is regarded as CICM only if more than 50% of the transactions are performed through this new or additional channel. In addition, CICM represents a voluntary form of change in the personal channel setting. Therefore, I define customer-initiated channel migration as follows:

> *Customer-initiated channel migration describes a voluntary migration in the customer's channel setting if the majority (>50%) of transactions in the consecutive period occur in the new or additional channel in a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix.*

2.2 Theoretical Basis

The aim of *Project I* is to shed light on the unexplored causal relationships between CICM and relationship breadth and depth. Therefore, the hypothesis development depends on three pillars. The first pillar comprises transaction cost and switching cost theory, following Dholakia et al. (2010). These authors suggest establishing further research in the broad field of multichannel customer management using the theory of transaction cost. The second pillar is the conceptual framework of Bolton, Lemon, and Verhoef (2004), who propose the aforementioned framework of relationship length, depth, and breadth in a service setting. The third pillar, complementing the theoretical and conceptual framework, builds on recent empirical findings regarding the influence of the Internet channel on customer behavior.

Transaction cost and switching cost theory

Transaction cost theory, a theoretical structure of the new institutional economics (Williamson 2000), has its origin in the landmark concept of Coase (1937).[23] The underlying unit of transaction cost theory is a single transaction (Commons 1934), so the application to CICM is evident: Transaction costs encompass different sorts of costs, either monetary or non-monetary, that must be borne by the involved parties to realize a transaction. Furthermore, transactions by different channels might be more or less expensive and convenient for customers. The fundamental behavioral assumption for transaction cost theory is the collaboration of a principal and an agent, acting with bounded rationality and opportunism (Williamson 1981). Counteracting bounded rationality and opportunism to reduce transaction costs, the economic exchange between actors can be organized by contracts. Thus, transac-

[23] In a description of the nature of the firm, Coase (1937) explains why it is profitable to establish a firm rather than trading each good or service in a bilateral form on a market, using the price mechanism. He advises including costs incurred when the contracting parties use the price mechanism for each exchange transaction (e.g., costs for negotiation and concluding a contract).

tion costs occur for initiation, agreement, processing, control, and adjustment of the relationship (Williamson 1985).

Closely connected to this theory is the concept of switching costs (Klemperer 1987). These “onetime costs that customers associate with the process of switching from one provider to another” (Burnham, Frels, and Mahajan 2003, p. 110) also transfer to settings in which consumers face new technologies or new information systems (Shapiro and Varian 1999). These costs are not necessarily monetary in nature and occur any time the customer is confronted with a decision to switch (Klemperer 1987). Costs for switching a provider, technology, or information system are difficult to monetize, such as: “search costs, transaction costs, learning costs, loyal customer discounts, customer habit, emotional cost and cognitive effort, coupled with financial, social, and psychological risk on the part of the buyer“ (Fornell 1992, p. 10). In recent studies on customer relationship management, switching costs are identified as factors that cause customer churn (e.g., Taylor and Neslin 2005; Blattberg, Kim, and Neslin 2009). Although Reinartz and Kumar (2000) argue that switching costs play a minor role in non-contractual settings compared with contractual settings, customers in non-contractual settings still can be confronted with switching costs that influence their behavior (e.g., Reichheld and Teal 1996; Taylor and Neslin 2005).

Burnham, Frels, and Mahajan (2003) develop a framework for consumer perceptions of switching costs that consists of procedural, financial, and relational switching costs. The authors consider economic risk, evaluation, learning, and set-up costs as procedural switching costs. Benefit loss and monetary loss costs are financial switching costs; personal relationship loss and brand relationship loss constitute relational loss costs.

In detail, *economic risk costs* refer to those costs associated with a lack of information when customers change their provider (e.g., Jackson 1985; Samuelson and Zeckhauser 1988; Guiltinan 1989; Klemperer 1995; Burnham, Frels, and Mahajan 2003). In contrast, *evaluation costs* encompass the time spent and efforts undertaken to gather information about switching alternatives (e.g., Shugan 1980; Samuelson and Zeckhauser 1988; Burnham, Frels, and Mahajan 2003). *Learning costs* are often specific to a certain provider and refer to the costs connected to the time and efforts invested in acquiring skills to use the new product or service properly (e.g., Wernerfelt 1985; Alba and Hutchinson 1987; Eliashberg and Robertson 1988; Guiltinan 1989; Burnham, Frels, and Mahajan 2003). Then, *set-up costs* refer to the time and effort invested in information acquisition and exchange prior to starting the relationship with the new alternative (e.g., Guiltinan 1989; Klemperer 1995; Burnham, Frels, and

Mahajan 2003). Mainly present in contractual settings, b*enefit loss costs* include economic advantages when staying with the current provider, such as the potential loss of points earned in a loyalty program when switching providers (e.g., Guiltinan 1989; Burnham, Frels, and Mahajan 2003). *Monetary loss costs* are onetime costs directly linked to switching, independent of the costs for purchasing a new product or service itself (e.g., Porter 1980; Guiltinan 1989; Heide and Weiss 1995; Klemperer 1995; Burnham, Frels, and Mahajan 2003). The *personal relationship loss costs* arise if direct relationships or interactions with the employees of the current provider are tight (e.g., Porter 1980; Guiltinan 1989; Klemperer 1995; Burnham, Frels, and Mahajan 2003). Finally, *brand relationship loss costs* refer to the affective losses from changing a brand or company of the provider (e.g., Porter 1980; Aaker 1992; Burnham, Frels, and Mahajan 2003). In the services industry and CICM in a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix, the eight types of switching costs listed by Burnham, Frels, and Mahajan (2003) are not equally relevant for each type of channel migration.

Consider, for example, an airline customer who has booked most of his or her flights with an independent stationary agency (indirect offline channel). Switching to another channel, such as the service provider's own Internet platform (direct online channel), leads to the perception of considerable switching costs. This customer perceives economic risk costs because of uncertainty about the new channel; evaluation costs to evaluate the possible channel alternatives to the original channel; learning costs to acquire the skills to operate the service provider–owned Internet platform and book flights; set-up costs for registering on the service provider's Internet platform; personal relationship loss costs because he or she may have dealt for years with the service employees of the independent stationary agency; and brand relationship loss costs because he or she changes from one brand (independent stationary agency) to the service provider's brand.

Although the number of relevant switching cost typologies and perceived level of switching costs differ from individual to individual and channel to channel, some of them will be at least partially considered by each customer before migrating. The perception of switching costs directly influences a customer's loyalty to his or her channel setting (e.g., Fornell 1992; Patterson and Smith 2003; Bell, Auh, and Smalley 2005). In turn, a customer initiates a channel migration only if the perceived benefits of the new channel are higher than the perceived costs associated with switching (e.g., Shapiro and Varian 1999; Jones, Motherbaugh, and Beatty 2002). The general assumption that a CICM has a positive effect on the customer relationship if it appears that the perceived benefits are higher than the perceived costs thus underlies the hypothesis development. Nevertheless, the characteristics of direct versus indirect and online versus offline channels might cause different causal relationships.

In their influential work, Bolton, Lemon, and Verhoef (2004) propose influences of different channels in a service setting on relationship length, depth, and breadth. These propositions, combined with transaction and switching cost theory, as well as insights from research on Internet channels, lead to the underlying assumptions for the different types of customer-initiated migration. In the principal channel setting of CICM, as presented in *Chapter B*/2.1, the dimension of intermediation distinguishes direct and indirect channels. Settings with an interaction between the customer and the employee or website of the service provider, and channel settings with interaction between the customer and the employee or website of an independent agency (intermediary), thus are in opposition. Although direct and indirect channels differ fundamentally when they are online or offline, the underlying principle of directness or indirectness applies in both cases. Using and enabling direct channels has positive effects on future usage (von Wangenheim 2006), because purchasing by direct channels from the service provider represents an exhibition of trust and loyalty toward the service provider (Bolton, Lemon, and Verhoef 2004). Furthermore, von Wangenheim (2006) also argues that customers in direct channels are more knowledgeable and have more expertise with the offerings of the service provider, which serves as indicator of higher relationship intensity. Therefore, I assume that:

Hypothesis 1 (H1):	*Customer-initiated channel migration from indirect to direct channels has a positive effect on (a) sales, (b) revenues, and (c) cross-buying.*

In the channel setting of CICM, the service distribution dimension distinguishes offline and online channels. Settings marked by interaction between the customer and the employee of the service provider or intermediary, and channel settings with an interaction between the customer and the Internet platform of the service provider or intermediary thus can be differentiated. Although online and offline channels are different when they are direct or indirect, the underlying principle of the impact of personal or online distribution applies.

Internet channel usage and migration to Internet channels lowers search costs (Klein and Ford 2003), which increases the likelihood of switching to an alternative service provider or intermediary, due to the lower transaction and switching costs (e.g., Shapiro and Varian 1999; Brynjolfsson and Smith 2000). Consequently, negative effects on long-term sales and loyalty arise (e.g., Ansari, Mela, and Neslin 2008). Additionally, Thomas and Sullivan (2004) show that the adoption of the Internet channel does not enhance the total spending of multichannel customers. From the perspective of personal relationship loss costs, the lack of interaction with sales and service personnel could lead to a loss of psychological bonds between the service provider and the customer and thus foster negative effects on sales and revenues (e.g., Ariely 2002). This negative effect of a loss of direct interaction in the case of CICM to online channels also limits chances for additional sales (e.g., flights), higher revenues, and offerings of cross-buying opportunities (e.g., Bolton, Lemon, and Verhoef 2004; Ansari, Mela, and Neslin 2008). Summarizing, I hypothesize:

Hypothesis 2 (H2):	*Customer-initiated channel migration from offline to online channels has a negative effect on (a) sales, (b) revenue, and (c) cross-buying.*

Finally, the effects of CICM from indirect to direct channels and from offline to online channels can be combined. Then the positive effect of CICM from indirect to direct channels encounters the negative effect of CICM from offline to online channels. On the one hand, the CICM to a direct channel offers the possibility of creating stronger economic and social bonds with the customer (e.g., Bolton, Lemon, and Verhoef 2004; von Wangenheim 2006). On the other hand, the Internet leads to lower search, transaction, and switching costs (Shapiro and Varian 1999; Brynjolfsson and Smith 2000; Klein and Ford 2003). I posit that the negative effect of the online environment, with its lower search, transaction, and switching costs, will be weaker, whereas the positive effect of stronger economic and social bonds with the company in the direct online channel will be stronger, because the lower search and transaction costs also occur in the direct online channel of the service provider. This reasoning leads to the following assumption:

Hypothesis 3 (H3):	*Customer-initiated channel migration from indirect offline to direct online channels has a positive effect on (a) sales, (b) revenue, and (c) cross-buying.*

Figure 7 summarizes these hypothesized directions of the effects of customer-initiated channel migration on relationship breadth and relationship depth. In addition to the three hypothesized paths, further patterns are possible. Due to restrictions of the database, *Project I* can only investigate these three different types though.

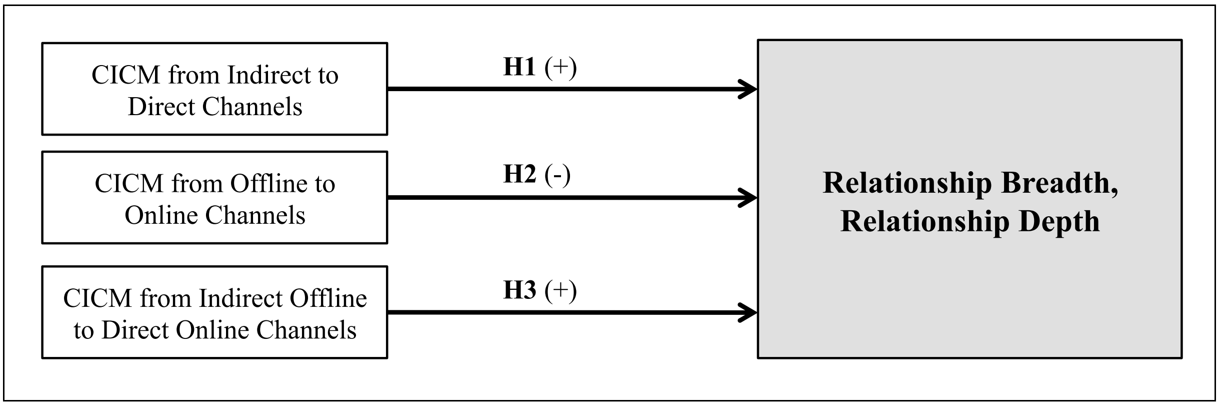


Figure 7: Summary of Hypothesized Effects (Project I)

2.3 Methodology and Data Set

This *Chapter B*/2.3 describes the methodology of *Project I* pertaining to causal inferences (*Chapter B*/2.3.1), as well as a detailed description of the dataset (*Chapter B*/2.3.2).

2.3.1 Methodology

This study aims to reveal the causal relationship between different types of customer-initiated channel migration (CICM) and relationship breadth and depth. Data derived from a large customer database of a global operating service provider include the development of different variables (e.g., sales, revenue, cross-buying, channel) over time. Thus, it is possible to observe customer behavior over time. Therefore, a quasi-experimental research design is applied to test the causal relationship. In contrast with randomized experiments (e.g., Fisher 1935), quasi-experiments lack either a randomized assignment of the subjects or units to specified conditions or a pretested observation of outcome variables (Shadish, Cook, and Campbell 2002). As Shadish, Cook, and Campbell (2002, pp. 13-14) explain, “quasi-experiments share with all other experiments a similar purpose—to test descriptive causal hypotheses about manipulable causes—as well as many structural details, such as the frequent presence of control groups and pretest measures, to support a counterfactual inference about what would have happened in the absence of the treatment.” Figure 8 illustrates the principle underlying quasi-experimental research design with treatment and control groups.[24] Both treatment and control groups exhibit behavior before and after the (non-) treatment. In

[24] Quasi-experimental research designs with statistical matching procedures are subject to the limitation that some selection bias might exist after the matching procedure on unobserved measures (Campbell and Stanley 1963; Shadish, Cook, and Campbell 2002). This can limit the appropriateness of calling the treatment effect a causal effect. Nevertheless, authors such as Shadish, Cook, and Campbell (2002) assert that quasi-experimental designs enable generalized causal inference. This thesis adapts their approach and thus refers to causal effects.

this project, CICM is considered the treatment for the experimental group. Customers with no channel migration (no treatment) form the control group. In this quasi-experimental setting, pretreatment behavior is adapted to estimate customer behavior and match similar pairs of treatment and control customers, whereas the post treatment behavior reveals the treatment effect (e.g., von Wangenheim and Bayon 2007).

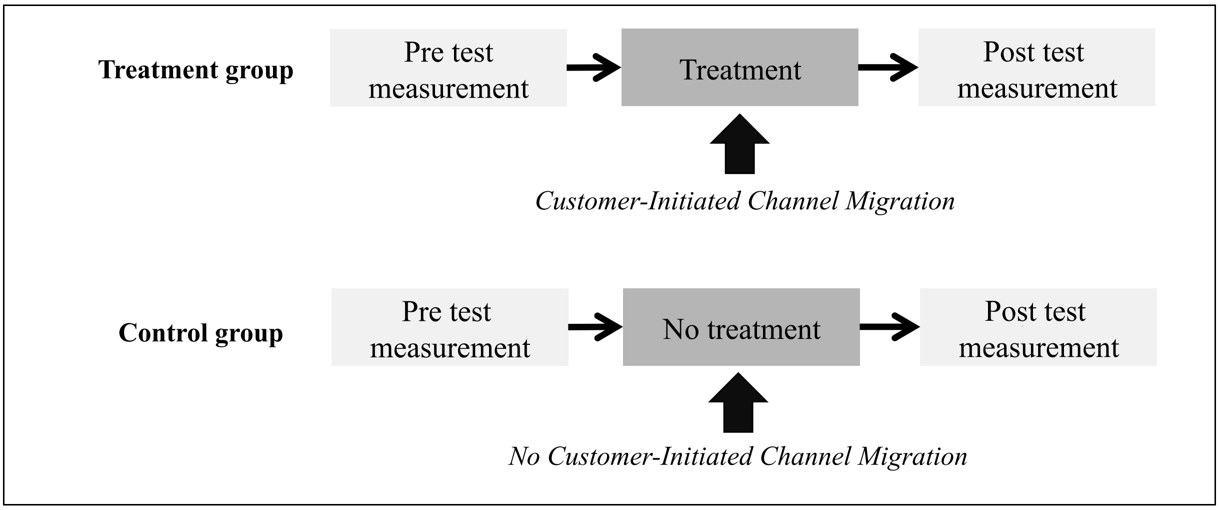


Figure 8: Quasi-Experimental Research Design (Project I)

To attain comparable treatment and control groups, diverse matching procedures can be applied. Heckman's sample selection model, propensity score matching, matching estimators, Mahalanobis-metric matching, and propensity score analysis with nonparametric regression are five models that have received considerable attention in studying causal inference (e.g., Cochran and Rubin 1973; Cochran 1983; Gu and Rosenbaum 1993; Costanza 1995; Heckman, Ichimura, and Todd 1998; Dehejia and Wahba 1999; Rosenbaum 2002); for an overview, see Guo and Fraser 2010). Matching procedures are applied in descriptive studies to measure systematic differences induced by a certain treatment between control and treatment groups (Rosenbaum and Rubin 1984), frequently in social science and econometric literature. In recent years, matching procedures have found their way into marketing literature (e.g., von Wangenheim and Bayon 2007; Böhm 2008; Bronnenberg, Dub, and Mela 2010; Gensler, Leeflang, and Skiera 2011). In this study, I apply Mahalanobis-metric matching and also conduct conditional difference-in-differences estimation to evaluate the impact of three different types of CICM (treatment) on behavioral measures (relationship breadth and depth).

Mahalanobis-metric matching is appropriate for matching treatment and control units for three reasons. First, this multivariate extension of the univariate nearest available pair matching procedure fits well, because the confounding variables and measures for estimating the effect of the treatment are observable, determined before matching, and congruent (e.g., Cochran and Rubin 1973; Rubin 1973a; Rubin 1973b; Zhao 2004). Second, some migration types have small sample sizes (see Table 2; Zhao 2004). Third, "Mahalanobis matching is relatively robust under different settings" (Zhao 2004, p. 100).

The procedure is displayed in Figure 9. In the *first step*, the Mahalanobis distance[25] scores are estimated by a linear regression analysis with selected matching variables as predictors. These distance scores, indicating similarity in selected matching variables before the treatment occurs (e.g., flights, revenue, cross-buying before the treatment), provide the basis for matching the nearest available neighbors of treatment and control units through a matching procedure in step two. In the *second step*, the treatment and control units are matched pairwise according to their distance scores. This matching can be based on different algorithms, including greedy matching (e.g., nearest neighbor, caliper, and nearest neighbor with a caliper), optimal matching, and fine balance (Rubin 1979; Rubin 1980; Böhm 2008; for an overview, see Guo and Fraser 2010, pp. 144-154).[26]

Applying a Mahalanobis-metric matching procedure with greedy nearest neighbor matching with a five-to-one digit matching algorithm enables matching of the treatment and control groups (Rubin 1979; Rubin 1980; Parsons 2001). Therefore, a general linear model (see Equation 1) is applied to estimate the Mahalanobis distance scores, which indicates the similarity in the matching variables of booked flights, revenue, and cross-buying. Equation 1 and the results of the general linear regression estimate the Mahalanobis distance scores. Prior behavior is considered to measure the distance of each customer from the mean of all relevant variables. The values of flights (FLY), revenue (REV), and cross-buying (CRB) during the estimation period from Q1 to Q8 are included in the general linear model.[27]

$$y = \beta_0 + \beta_1 FLY + \beta_2 CRB + \beta_3 REV + \varepsilon. \qquad (1)$$

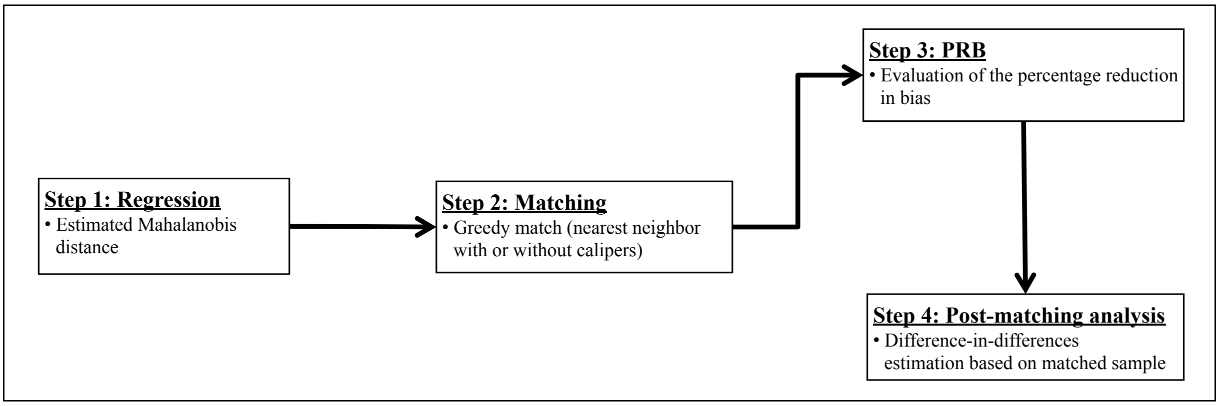
The estimated similarity scores (here Mahalanobis distance scores) of customers in the treatment and control group then are matched. Figure 9 shows a greedy nearest neighbor matching procedure. The five-to-one digit-matching algorithm is applied to match a customer migrating in his or her channel setting with a customer with a similar score who does not migrate. In

[25] The Mahalanobis distance (D^2) (Mahalanobis 1936) is a standardized measure of Euclidean distance, equal to the distance of each observation from the mean of all observations' predictor variables in a multivariate setting and hence a multidimensional space (e.g., Hair et al. 2010).

[26] Böhm (2008) applies a covariate matching procedure with Mahalanobis distance scores.

[27] This general linear model for estimation of Mahalanobis distance scores is the same for the matching procedures of H2, and H3. The general underlying equation will not be repeated there.

a greedy five-to-one digit matching procedure, pairs of treatment and control with a difference in Mahalanobis distance (D^2) scores, $D^2(x_i)$ for treatment and $D^2(x_j)$ for control, are matched by minimum distance (min $\|D^2_i - D^2_j\|$). Therefore, five to one fractional digits are evaluated step by step. The cases excluded on a five-digit basis are then evaluated on four, three, two, and one digits (see Parsons 2001; Guo and Fraser 2010).



Source: Own illustration based on Rubin (1980), von Wangenheim and Bayon (2007, p. 40), and Guo and Fraser (2010, p. 129).

Figure 9: Procedure for Mahalanobis-Metric Matching

In a *third step*, the percentage reduction in bias (PRB) calculates the extent to which the bias is removed in the matched sample. This measure indicates the quality of the matching procedure. Then the PRB indicates the degree to which the matching procedure can reduce the difference in the distribution of the predictor variables of the treatment and control groups after matching. Therefore, the PRB compares the means of the treatment and control groups of each predictor variable before and after the matching procedure (Rosenbaum and Rubin 1984; von Wangenheim and Bayon 2007; see Equation 2).

$$PRB_n = 1 - \left| \frac{\bar{x}^A_{i,n} - \bar{x}^A_{j,n}}{\bar{x}^B_{i,n} - \bar{x}^B_{j,n}} \right| \quad , \tag{2}$$

where:

PRB_n = Percentage reduction in bias (PRB) for a certain predictor variable n.

$\bar{x}^A_{i,n}$ = Mean of a certain predictor variable n after matching (treatment group).

$\bar{x}^A_{j,n}$ = Mean of a certain predictor variable n after matching (control group).

$\bar{x}^B_{i,n}$ = Mean of a certain predictor variable n before matching (treatment group).

$\bar{x}^B_{j,n}$ = Mean of a certain predictor variable n before matching (control group).

In a *fourth step*, post-matching analysis is conducted with the matched treatment and control groups (see Figure 9). Therefore, conditional difference-in-differences estimation determines the average treatment effect (Heckman et al. 1998). In contrast with difference-in-differences (DID) estimation,[28] conditional difference-in-differences estimation (see Equation 3) combines the matching estimator and the difference-in-differences estimator in regressing the differences between matched individuals of the treatment and control group (Heckman et al. 1998; Böhm 2006). In conditional DID, not just two periodical estimations (before and after treatment) but multi-periodical estimations are utilized. These multi-periodical estimations, modeling time-series trends, are far more often used than simplifying two periods before and after difference-in-differences estimations (Bertrand, Duflo, and Mullainathan 2004).

$$Y_{it} = \beta_0 + \beta_1 \times \text{Period} + \beta_2 \times \text{Treatment} + \beta_3 \times \text{Period} \times \text{Treatment} + u_i + \varepsilon_{iti}, \tag{3}$$

where:

Period = Time period before the treatment (Q1–Q8, values 1 to 8) and time period after the treatment (Q9–Q16, values 9 to 16).

Treatment = 0 for no channel migration from Q5–Q8 to Q9–Q12.

Treatment = 1 for channel migration from Q5–Q8 to Q9–Q12.

Period × Treatment = For interaction between period and treatment.

u_i = Unobserved effect with $E(u_i) = 0$ and $Var(u_i) = \sigma^2_u$.

ε_{iti} = Individual error term with $E(\varepsilon_{iti}) = 0$ and $Var(u_i) = \sigma^2_u$.

[28] The difference-in-differences estimation controls for systematic differences between a treatment and control group by subtracting the change from before to after of non-treated participants from the change from before to after of treated participants in a panel regression (e.g., Heckman et al. 1998; Hujer, Caliendo, and Radic 2004; Angrist and Pischke 2009).

In detail, the estimates of the difference-in-differences estimation in Equation 3 measure: β_0 measures, such as the average cross-buying of a customer in the control group in the periods before the treatment; β_1 to capture changes in all cross-buying values in the sample from periods before to periods after the treatment; the coefficient β_2, which is the effect of the effect of being in the treatment or control group, not because of the customer-initiated channel migration; and β_3 to measure, say, the change in cross-buying due to customer-initiated channel migration (see Angrist and Pischke 2009; Wooldridge 2009). To interpret the conditional difference-in-differences estimations, only the interaction effect *Period* × *Treatment* is considered. Although the main effects also are reported, this approach follows authors such as von Wangenheim and Bayon (2007), Angrist and Pischke (2009), and Wooldridge (2009), who only report the estimates of the interaction effect *Period* × *Treatment*.

2.3.2 Data Set

To test the hypotheses on the behavioral consequences of CICM, I analyze a random subsample of the customer database of a global airline. This database contains detailed individual information on the booking channels, sales (booked flights), revenues, and cross-buying for a period of 16 quarters.[29]

The major interest of this further analysis is on how CICM of different types influence relationship breadth and depth, so the explanation of the different channels is essential. In more detail, the booking channels are pooled as follows (see Figure 10):

1. The direct offline channel includes direct sales by stationary agencies in towns or at airports of an airline.
2. The indirect offline channel includes sales by indirect agencies, indirect chains, indirect retailers, and other indirect offline channels.
3. The direct online channel includes sales via direct Internet platforms.
4. The indirect online channel includes sales via indirect Internet platforms.

[29] All values for revenue, booked flights, and cross-buying are distorted for confidentiality reasons, but reflect correct relative values.

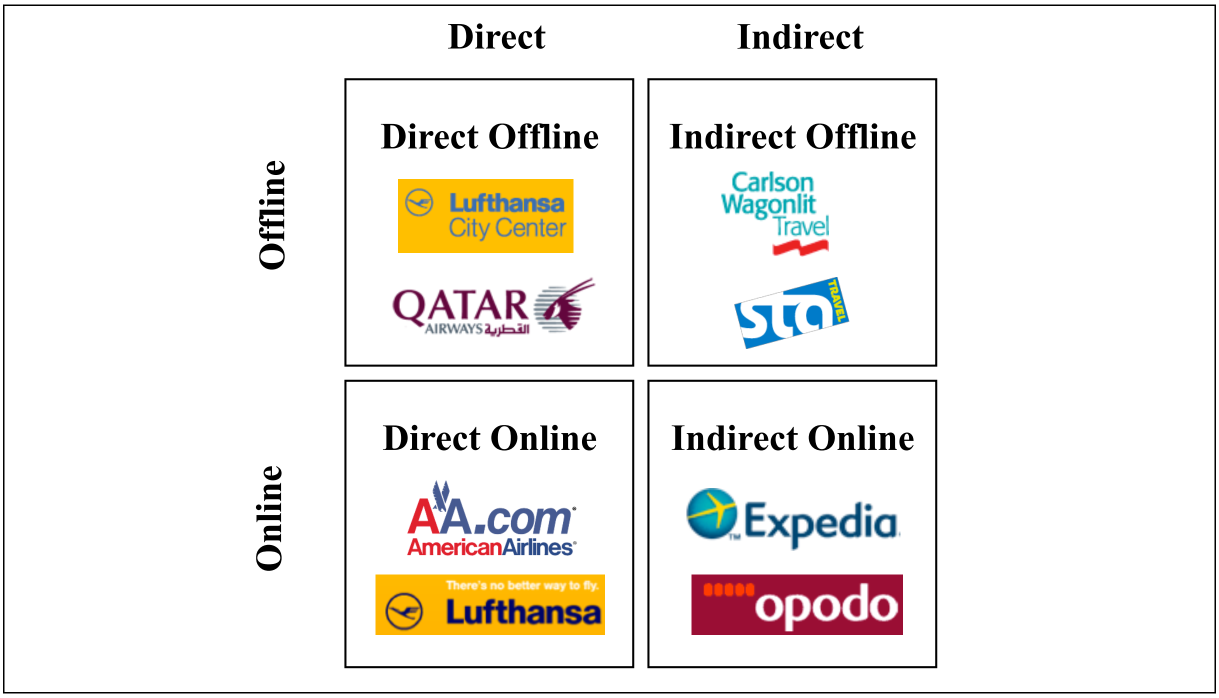


Figure 10: Channel Matrix Applied to the Aviation Industry

The original database contains 80,700 customers and 461,774 flights.[30] Assigning the booked flights to the distribution channel through which the sales were processed, the majority of the sales are conducted in indirect channels, with a share of 89.81% of all booked flights. The indirect offline channel dominates, with 413,400 flights among the offline channels, whereas the direct offline channel covers 37,342 flights. Because online distribution of aviation services was in an early stage, it is not surprising that the share of distribution via online channels (2.39% of overall booked flights) is lower than for offline channels, with 9,706 flights booked through the direct online and 1,326 flights through the indirect online channel.

This underrepresentation of direct or online channels suggests further alignments of the dataset. Before conducting statistical procedures for each hypothesized assumption, different sub-data sets are obtained. To investigate the causal effect of CICM on relationship breadth and depth, I start with the complete dataset of N = 80,700 customers. This population is then reduced for each hypothesis with the corresponding migration types (see Table 2).

[30] For *Project I*, flights and sales are treated as equivalent.

Migration Type	Description	Sample Size
I	Indirect Offline (No Migration)	6,183
II	Indirect Offline to Direct Offline	278
III	Indirect Offline to Indirect Online	3
IV	Indirect Offline to Direct Online	43
V	Direct Offline (No Migration)	391
VI	Direct Offline to Indirect Offline	263
VII	Direct Offline to Direct Online	54
VIII	Indirect Online to Indirect Offline	1
IX	Direct Online (No Migration)	3
X	Direct Online to Direct Offline	3
XI	Direct Online to Indirect Offline	3

Notes: A customer is assigned to one of the eleven migration types if he or she booked more than 50% of flights by that specific channel setting in Q5–Q8 and Q9–Q12. For example, customer A with more than 50% of flights booked through indirect offline channels in Q5–Q8 and more than 50% of flights booked through direct offline channels in Q9–Q12 is assigned to migration type II. Customer B, with more than 50% of flights booked through indirect offline channels in Q5–Q12, instead is assigned to migration type I.

Table 2: Sample Sizes for Different Migration Types

To analyze the impact of CICM from indirect to direct channels on relationship breadth and depth, N = 6,461 (migration type I and migration type II) customers build the population for these tests. For CICM from offline to online channels, a subset of N = 445 customers (migration types V and VII) is further analyzed. Finally, to examine the causal effect of CICM from indirect offline to direct online, N = 6,226 customers (migration types I and IV) are obtained for further matching procedures.

This first project of this thesis aims to explore the behavioral consequences of CICM on relationship breadth and depth, so the operationalization and summary statistics of the related measures appear next. Relationship depth[31] is operationalized following Verhoef, Franses, and Hoekstra (2001) and Bolton, Lemon, and Verhoef (2004). Therefore, the frequency of usage (booked flights) and the level of usage (revenue) are both included as components of relationship depth. The average number of booked flights per customer and quarter is .28 (SD = 1.05), whereas the average revenue per customer and quarter is EUR 103.94 (SD = 375.55).

[31] Bolton, Lemon, and Verhoef (2004, p. 273) define relationship depth as “the frequency of the service usage over time. It is also reflected in customers’ decision to upgrade and purchase premium (higher margin) products instead of low-cost variants.”

Relationship breadth[32] is operationalized following Lemon and von Wangenheim (2009), who extend the concept of cross-buying[33] from Blattberg, Getz, and Thomas (2001) and Bolton, Lemon, and Verhoef (2004) with add-on services from additional service providers in a multipartner loyalty program. Cross-buying includes transactional data from car rental, hotel booking, and other categories, such as credit card, subscriptions, shopping, lifestyle, or telecommunications. In summary, the average level of cross-buying per quarter in the customer database is EUR 107.44 (SD = 901.89).[34]

Figure 11 displays the research setting for analyzing the behavioral consequences of CICM. Over 16 quarters of customer data, pre- and postmigration behavior is displayed. The eight quarters of transactional behavior between Q1 and Q8 (t_{01}, grey area) build the basis for estimating the Mahalanobis distance scores and matching treatment and control groups. The behavior measured by the predictor variables of this period is estimated for matching treatment and control units via Mahalanobis-metric matching. If customers change their channel setting from Q5–Q8 to Q9–Q12, they are assigned to the treatment group. Otherwise, they are assigned to the control group. Furthermore, the period between Q13 and Q16 (t_{12}, white area) is used to estimate the treatment effect.

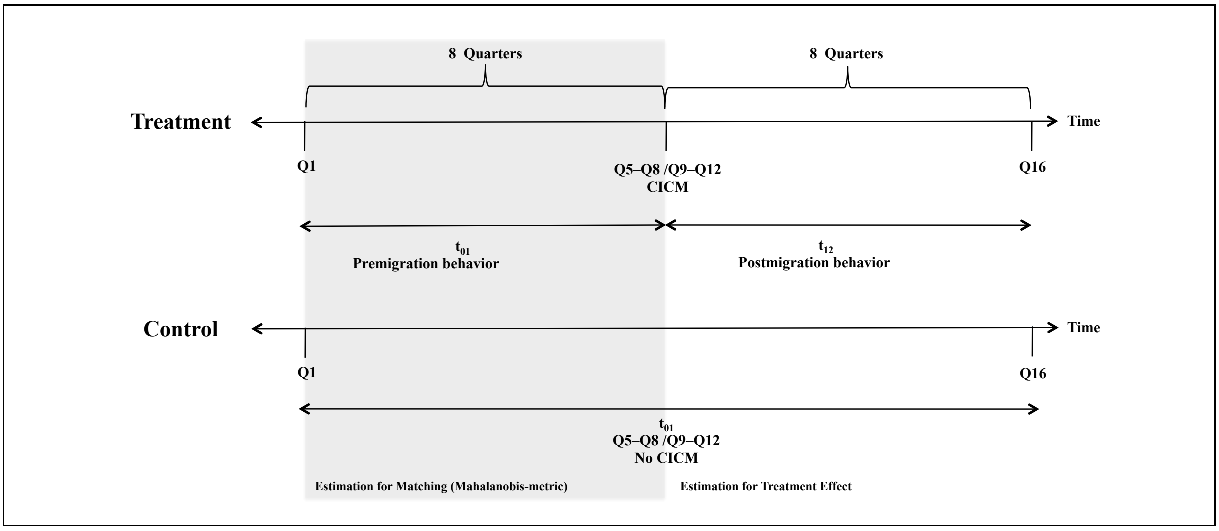


Figure 11: Research Setting for (Post) Matching Analysis

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[32] Bolton, Lemon, and Verhoef (2004) and Blattberg, Getz, and Thomas (2001) classify relationship breadth as cross-buying or add-on buying of products or services. More specifically, they reduce this transaction type to products or services of one company over time.

[33] This thesis uses the terms cross-buying and cross-selling. Cross-buying captures the process of add-on buying from a customer's perspective and cross-selling from a company's perspective. Thus, they capture the same transactions and financial values from two distinct perspectives (e.g., Kumar, George, and Pancras 2008).

[34] The level of cross-buying in the different categories is measured in loyalty units (e.g., dots, miles, points) that a customer receives per transaction volume of purchased service or product in Euros. For simplification, I assume that 1 loyalty unit equals EUR 1.

2.4 Results

This chapter reports the results of the Mahalanobis-metric matching and conditional difference-in-differences estimation for the hypothesized causal relationships between different types of customer-initiated channel migration and relationship breadth and depth. The causal effect of CICM from indirect to direct channels is analyzed first (*H1*), followed by the causal effects of CICM from offline to online channels (*H2*) and the combined migration from indirect offline to direct online channels (*H3*).

In *H1*, I argue that CICM from indirect to direct channels leads to higher sales, revenue, and cross-buying. Applying a Mahalanobis-metric matching procedure with greedy nearest neighbor matching through a five-to-one digit matching algorithm, the treatment (migration type I) and control (migration type II) groups can be matched. The general linear model (see Equation 1) is applied to estimate the Mahalanobis distance scores (see Appendix 1), which indicate the similarity in three matching variables: flights, revenue, and cross-buying. The sample for measuring the treatment effect of a CICM from indirect to direct channels contains 244 matched pairs, based on a four-digit greedy matching procedure.

Table 3 reports the overall group means before and after matching the customers to the nearest neighbor on four digits with the Mahalanobis distance scores. As the percentage reduction in bias (PRB) shows, posterior bias in the observed variables before matching the observations declined by a considerable extent. The greedy nearest neighbor matching procedure creates a treatment and control sample with comparable characteristics.

Before Matching			**After Matching**		
Control (N = 6,183)	**Migration (N = 278)**	**Variable**	**Control (N = 244)**	**Migration (N = 244)**	**PRB**
38.69	23.07	Flights	11.06	8.88	**86.04%**
10,067.98	7,647.54	Cross-Buying	2,276.30	2,199.50	**96.83%**
11.486.7	7,798.28	Revenue	3,156.87	2,778.46	**89.74%**

Table 3: Overall Group Means Before and After Matching (H1)

Next, a comparison of the treatment and control group tests the hypotheses. Figure 12 displays the time series of number of flights, revenue, and cross-buying for treatment and control groups. This first impression of CICM from indirect to direct channels on future behavior exhibits two different treatment effects: the minimized difference of the distribution of the dependent variables of the treatment and control group (Q1–Q8) and the impact of CICM on future values of relationship breadth and depth (Q9–Q16). The initial results from the post-matching analysis, to estimate the treatment effect as illustrated in Figure 12, form the basis for the conditional difference-in-differences estimation. This econometric procedure is applied to test the causal relationship between channel migration and the behavioral consequences related to booked flights, revenue, and cross-buying.

The treatment effect of CICM from indirect to direct channels on booked flights (H1a), revenue (H1b), and cross-buying (H1c) is estimated with a random effects panel regression (see von Wangenheim and Bayon 2007).[35] In the random effects regression model, parameter β_3 (see Equation 3) captures the treatment effect of channel migration on flights, revenue, and cross-buying.[36] The random effects regression in Table 4 indicates two different results. First, the hypothesized direction cannot be confirmed, because CICM from indirect to direct channels leads to .02 lower sales, to 151.91 lower revenue, and .15 lower cross-buying. Second, the interaction effect of *Period × Treatment* is only significant for revenue.[37] The results of the conditional difference-in-differences estimation do not support *H1*.

[35] Von Wangenheim and Bayon (2007) argue that random effect panel regression models can be applied for conditional difference-in-differences estimation, whereas Angrist and Pischke (2009) refer to fixed effect panel regression. In additional tests to evaluate this procedure, I applied the Hausman (1978) specification test procedure to find whether a random or fixed effects model was preferable (Greene 2008). The results (H1a: $\chi^2(3) = 0$, $p = 1.00$; H1b: $\chi^2(3) = 0$, $p = 1.00$; H1c: $\chi^2(3) = 0$, $p = 1.00$) show that a random effects model is the preferred specification for the H1 data for *Project I*. This procedure, repeated for the conditional difference-in-differences estimation for each hypothesis test, consistently supports a general procedure with random effects models; the tests are not detailed any further.

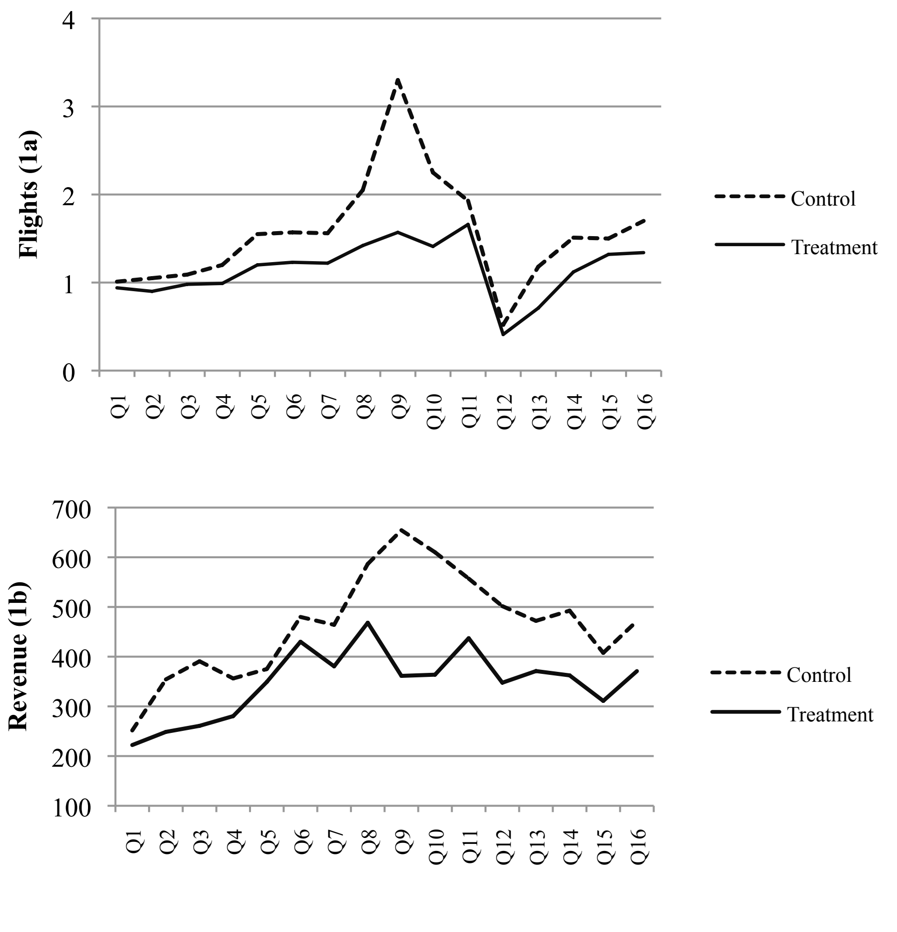
[36] For each subtypes of model 1, the dependent variable varies: For model 1a, it is sales, in model 1b revenue, and in model 1c cross-buying.

[37] As outlined in *Chapter B/2.3.1*, the results of the main effects are ignored when interpreting the interaction term *Period × Treatment* in difference-in-differences estimations (von Wangenheim and Bayon 2007; Angrist and Pischke 2009; Wooldridge 2009). Hair et al. (2010) suggest, determining whether the interaction effect in regression analysis is significant, not by the significance of the main effects but by the change in R^2 after extending the main effects model with the interaction effect. Nevertheless, it must be mentioned that model 1b shows significant changes in the revenues before and after the treatment.

Parameter	Model 1a (flights)			Model 1b (revenue)			Model 1c (cross-buying)		
	Estimate	S.E.	*p*	Estimate	S.E.	*p*	Estimate	S.E.	*p*
Intercept	1.35	.10	< .0001	1,501.66	142.2	< .0001	163.25	68.84	< .05
Period	.03	.01	< .0001	219.55	49.23	< .0001	35.94	3.73	< .0001
Treatment	-.29	.15	< .05	-177.21	201.1	.378	-30.45	97.36	.7545
Period×Treatment	-.02	.01	.113	-151.91	69.63	< .05	-.15	5.28	.977
N (Cross-Sections)	488			488			488		
Sum of Squares	33,948.52			5,760,744,354			9,028,523,787		
R^2	$R^2 = .00$			$R^2 = .01$			$R^2 = .02$		

Notes: Flights (a) and cross-buying (c) are calculated with a time-series of 16 quarters; revenue (b) uses an annual time series of four years.

Table 4: Results of Conditional DID for Hypothesis 1



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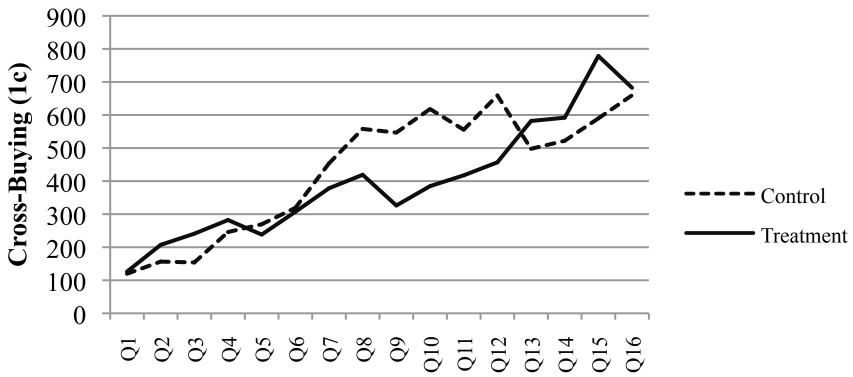


Figure 12: Comparison of Treatment and Control Group for Sales (Flights), Revenue, and Cross-Buying (H1)

I proposed in *H2* that CICM from offline to online channels leads to lower sales (a), revenue (b), and cross-buying (c). Again, a Mahalanobis-metric matching procedure with greedy nearest neighbor matching through a five-to-one digit matching algorithm is applied to match the treatment and control group. The underlying general linear model does not change compared to Equation 1. The only difference for *H2* is another subsample (N = 654) of the customer database for treatment (migration type VII) and control (migration type V) groups.

The results of the linear regression analysis for estimating the Mahalanobis distance scores are reported in Appendix 1. To match customers from the treatment and control group with minimum differences in the Mahalanobis distance score (min $||D^2_i - D^2_j||$; see *Chapter B*/2.3.1), the consumers are matched to 22 pairs based on a four-digit greedy matching procedure.[38] Again, the reported percentage reduction in bias (PRB) shows considerable elimination of bias (between 69.87% and 97.48%) in the distribution of booked flights, cross-buying, and revenue after the treatment and control group are matched. Only in the case of revenue is the PRB less than 70%, which is not problematic.[39]

[38] See footnote 27.
[39] Von Wangenheim and Bayon (2007) also suggest PRB values around 70% to considerably reduce bias.

Before Matching			After Matching		
Control (N = 391)	**Migration (N = 263)**	**Variable**	**Control (N = 22)**	**Migration (N = 22)**	**PRB**
14.2	19.76	Flights	6.95	7.09	**97.48%**
5,872.33	6,593.85	Cross-Buying	1,333.45	1,181.82	**78.98%**
4,669.02	3,951.94	Revenue	1,642.68	1,426.64	**69.87%**

Table 5: Overall Group Means Before and After Matching (H2)

The comparison of the measurements for relationship breadth and depth for evaluating the causal inference in Figure 13 suggest results in conflict with the proposed hypothesis. The results of the conditional difference-in-differences estimation (see Table 6) reveal evidence for this effect in the time-series data of relationship breadth and depth for matched customers. *H2* proposes that a CICM from offline to online channels leads to decreasing levels of sales, revenue, and cross-buying, so negative estimates for the interaction effect of *Period* × *Treatment* are expected. Contrary to the hypotheses, the conditional difference-in-differences analysis reveals positive effects of a CICM from offline to online channels. The estimated treatment effects of this CICM suggest that customers migrating from offline channels to online channels book .04 more flights, create EUR 163.95 more revenue, and engage 48.52 more Euros of cross-buying. This effect is only statistically significant for cross-buying (model 2c).[40] In summary, the quasi-experimental analysis does not support *H2*.

Parameter	**Model 2a (flights)**			**Model 2b (revenue)**			**Model 2c (cross-buying)**		
	Estimate	S.E.	*p*	Estimate	S.E.	*p*	Estimate	S.E.	*p*
Intercept	.88	.23	< .0001	867.68	195.6	< .0001	146.89	152.5	.336
Period	.00	.02	.960	-92.14	76.12	.228	13.69	12.80	.285
Treatment	-.131	.315	.677	-188.80	276.7	.496	-258.78	215.7	.231
Period×Treatment	.04	.03	.163	163.95	107.7	.130	48.52	18.11	< .01
N (Cross-Sections)	44			44			44		
Sum of Squares	2,090.25			109,636,600			858,471,647.60		
R^2	$R^2 = .01$			$R^2 = .01$			$R^2 = .03$		

Notes: Flights (a) and cross-buying (c) are calculated with a time-series of 16 quarters; revenue (b) uses an annual time series of four years.

Table 6: Results of Conditional DID for Hypothesis

[40] As in model 1b, the significant interaction effect of *Period* × *Treatment* in model 2c is accompanied by non-significant effects of *Period* and *Treatment*.

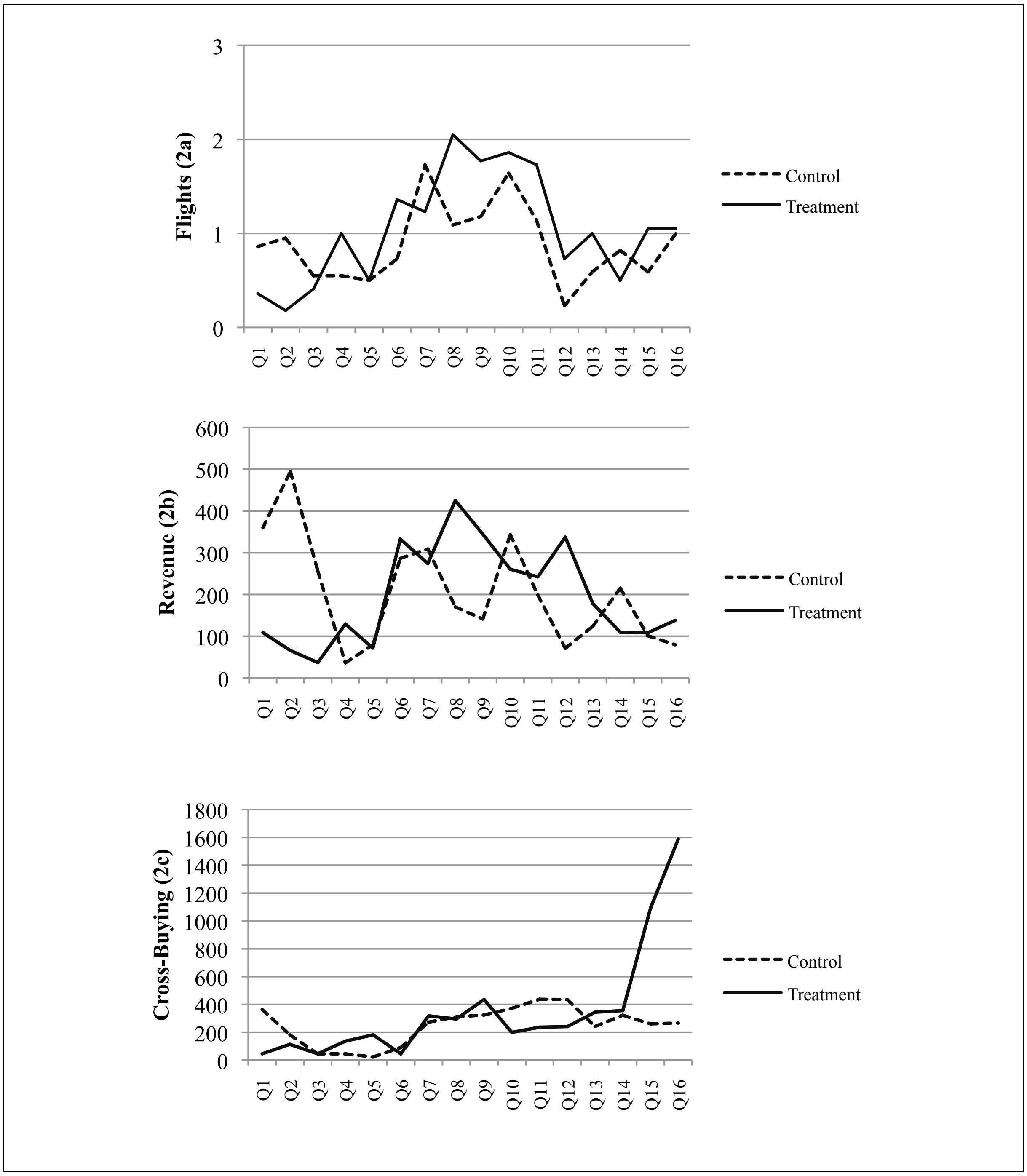


Figure 13: Comparison of Treatment and Control Group for Sales (Flights), Revenue, and Cross-Buying (H2)

Finally, I combine the effects of CICM from indirect to direct channels with those from off-line to online channels in *H3*, and argue that CICM from indirect offline channels to direct online channels has a positive effect on sales (a), revenue (b), and cross-buying (c). For estimating the Mahalanobis distance scores for Mahalanobis-metric matching, Equation 1 again is applied. The treatment group (migration type IV) and control group (migration type I) form the subsample (N = 6,226) for these further analyses.

The results of the general linear regression analysis, conducted to match treatment and control groups, are reported in Appendix 1. On the basis of the estimated Mahalanobis distance scores, 36 pairs of treatment and control units are matched with a four-digit greedy matching procedure. Considerable assimilation of the distribution of the measures of relationship breadth and depth is achieved; the PRB is between 77.32% and 90.24%.

Before Matching			**After Matching**		
Control (N = 6,183)	**Migration (N = 43)**	**Variable**	**Control (N = 36)**	**Migration (N = 36)**	**PRB**
38.69	23.07	Flights	9.69	6.61	**80.26%**
10,067.98	7,647.54	Cross-Buying	1,833.31	1,647.03	**90.24%**
11.486.7	7,798.28	Revenue	3,031.33	2,194.64	**77.32%**

Table 7: Overall Group Means Before and After Matching (H3)

In the matched sample, the time-series data for booked flights (sales), revenue, and cross-buying offer initial insights into the causal effect of CICM from indirect offline to direct online channels (see Figure 14). The time-series graphs for flights and cross-buying suggest a positive causal effect of the treatment on future usage, whereas the time-series of revenue illustrates a negative effect. Conditional difference-in-differences estimation is applied to reveal the treatment effect of this combined channel migration path. The average treatment effects (interaction term *Period* × *Treatment*) in Table 8 show that customers who migrated their channel setting from indirect offline channels to direct online channels purchased .07 more flights than those who did not migrate their channel setting. The same positive effect can be revealed for cross-buying behavior. Migrating customers spend EUR 31.41 more than customers in the control group. Still, a CICM from indirect offline to direct online negatively affects customers' revenue. The results of the conditional difference-in-differences estimation reveal that customers in an indirect offline channel setting after the migration period create EUR 54.82 more revenue than customers migrating to direct online channels.

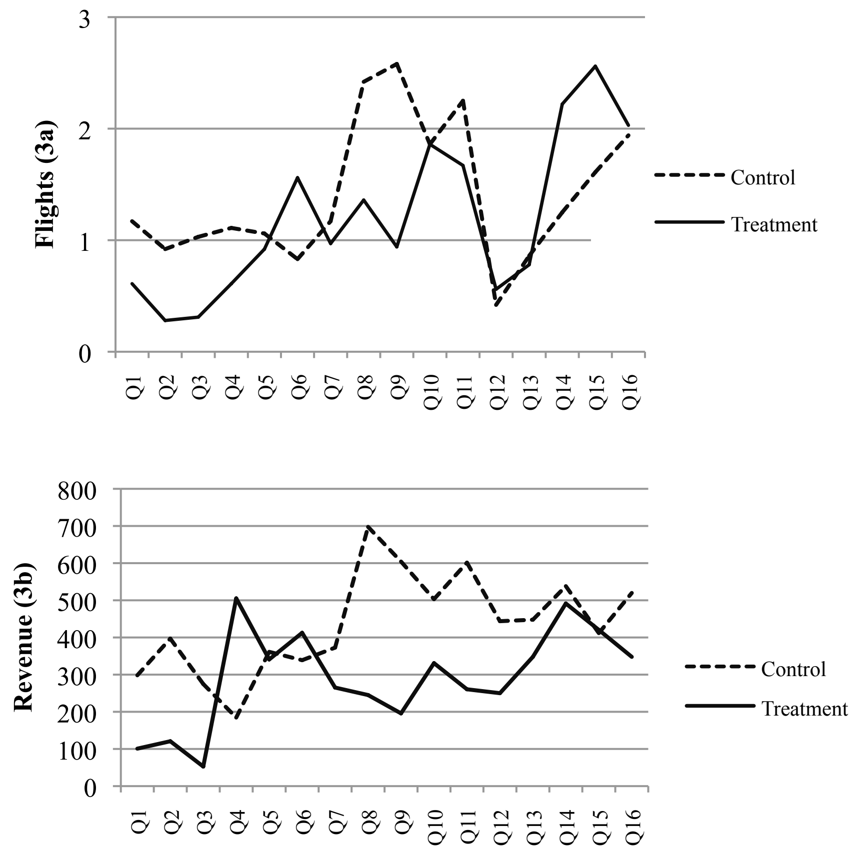
In summary, the results of conditional difference-in-differences estimation for *H3* reveal two effects. First, the hypothesized positive effect of CICM on usage behavior is reflected in the statistically significant effect on flights and cross-buying.[41] Second, the effect on revenue is statistically non-significantly and directed against the hypothesized positive direction. Hence, *H3* received partial support.

[41] In models 3a and 3c, the significant interaction effects of *Period* × *Treatment* combine with significant effects of *Period* and *Treatment* in case of flights, but non-significant main effects for cross-buying.

Parameter	Model 3a (flights)			Model 3b (revenue)			Model 3c (cross-buying)		
	Estimate	S.E.	*p*	Estimate	S.E.	*p*	Estimate	S.E.	*p*
Intercept	1.12	.29	< .001	1,422.60	362.8	< .001	214.21	125.4	< .10
Period	.04	.02	< .05	235.12	112.8	< .05	8.06	9.07	.375
Treatment	-.73	.41	< .10	-483.20	513.0	.347	-165.16	177.4	.352
Period×Treatment	.07	.03	< .01	-54.82	159.6	.731	32.41	12.83	< .05
N (Cross-Sections)	72			72			72		
Sum of Squares	4,972.72			650,863,604.50			1,155,902,044		
R^2	$R^2 = .03$			$R^2 = .03$			$R^2 = .02$		

Notes: Flights (a) and cross-buying (c) are calculated with a time-series of 16 quarters; revenue (b) uses an annual time series of four years.

Table 8: Results of Conditional DID for Hypothesis 3



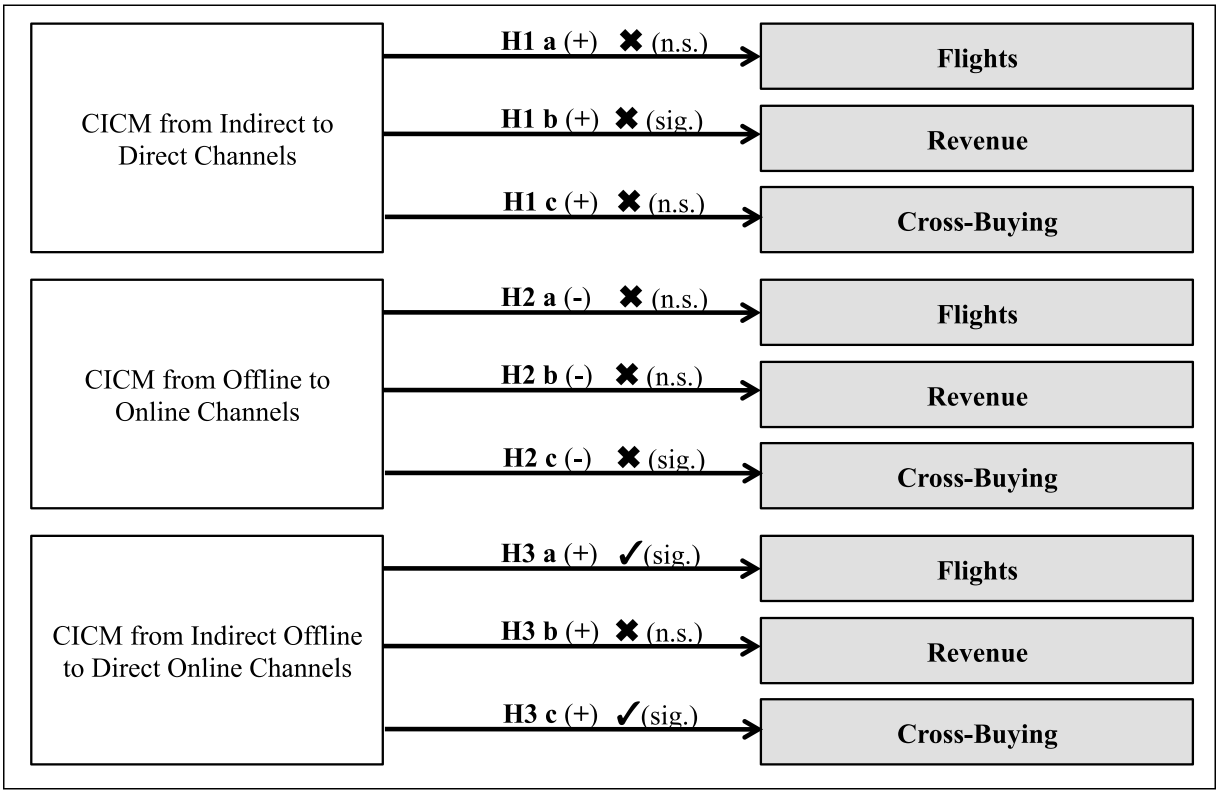
(Continued on the next page)

Figure 14: Comparison of Treatment and Control Group for Sales (Flights), Revenue, and Cross-Buying (H3)

2.5 Conclusion

Research on the behavioral consequences of customer-initiated channel migration helps service providers better evaluate how the introduction of new channels affects their customer equity. This question is of particular importance, because the implementation of new channels occurs with considerable competitive constraints and often is a necessity to compete. Consequently, it is useful to understand which customer channel migration in a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix affects relevant measures of the customer–company relationship positively or negatively, and to what extent.

The results of this project (as summarized in Figure 15) regarding the behavioral consequences of customer-initiated channel migration show the causal effect of CICM on relationship breadth and depth. With data from a large globally operating service provider, I can show that a customer-initiated channel migration from indirect to direct channels does not lead to positive effects on the relationship, whereas a CICM from offline to online channels positively affects future levels of relationship breadth and depth. In addition, a combined CICM from indirect offline to direct online channel leads to positive effects on sales and cross-buying, but its causal effect on revenue after the migration period is negative.



Notes: a. The figure summarizes the results of the three different types of customer-initiated channel migration for flights, revenue, and cross-buying.
b. After the hypothesis number, the figure shows the direction of the proposed hypothesis in parentheses.
c. Symbols indicate if each hypothesis is confirmed (✓) or not (✖). The last parenthesis indicates if this effect is statistically significant (sig.) or non-significant (n.s.).

Figure 15: Summary of the Results of the Hypotheses Tests (Project I)

2.6 Discussion

In *Project I*, I analyze the causal effect of three types of customer-initiated channel migration on relationship breadth and depth: CICM from indirect to direct channels, from offline to online channels, and from indirect offline to direct online channels are investigated. These different causal relationships will be discussed in more detail in the following sections that provide theoretical and managerial implications, as well as implications for further research.

2.6.1 Theoretical Implications

Prior research in the field of customer relationship management has appealed to researchers to undertake more theory development (e.g., Bolton, Lemon, and Verhoef 2004) and introduce transaction cost theory to multichannel customer management (e.g., Dholakia et al. 2010). On the one hand, I confirm hypotheses grounded in transaction and switching cost theory, enriched with theory from service distribution and intermediation, and thus show that

CICM affects relationship breadth and depth. On the other hand, the unconfirmed hypotheses represent the more relevant theoretical contribution. These results do not show that the underlying theoretical fundament is not applicable; instead, they contribute considerably to evolving theory in the area of intermediation and service distribution.

The results of *Project I* also add to the vast literature on multichannel customer management and customer channel migration. With respect to this, I reveal the causalities between customer-initiated channel migration and relationship breadth and depth (see Neslin and Shankar 2009), which are a considerable theoretical implication, because CICM underlies any multichannel customer behavior. From the perspective of transaction and switching cost theory, a positively or negatively directed causal relationship between CICM and relationship breadth and depth is obvious; prior research reveals supporting arguments. Most substantially, a customer migrates his or her channel setting if the perceived costs associated with migrating to a new channel setting are lower than the perceived benefits of staying with the old channel setting (e.g., Shapiro and Varian 1999; Jones, Motherbaugh, and Beatty 2002). If this cost–benefit calculation is satisfied, it can lead to higher satisfaction and loyalty and thus more relationship breadth and depth (e.g., Hitt and Frei 2002; Neslin and Shankar 2009; Campbell and Frei 2010).

Intermediation

On the intermediation dimension (indirect versus direct channels), the results of *Project I* reveal that migration from indirect to direct channels does not lead to positive effects on the customer–company relationship, as recent literature had suggested for usage and enabling of direct customer–company communications (e.g., Bolton, Lemon, and Verhoef 2004; von Wangenheim 2006). Instead, CICM from indirect to direct channels causes the customer to exhibit lower relationship breadth and depth compared with a matched control group that did not migrate to direct channels. Even though the effect is only statistically significant for revenue, indirect channels are outperforming direct channels in the airline sector.

To crosscheck this surprising customer behavior, I performed additional analysis for customer-initiated channel migration from direct to indirect channels. Matching N = 674 unmatched cross sections (migration types V and VI) with N = 97 matched pairs via Mahalanobis-metric matching, conditional difference-in-differences estimations reveal positive estimates and treatment effects (interaction term *Period* × *Treatment*). The average treatment effect of a CICM from direct to indirect channels leads to a significant increase in sales

($\beta = .03$; $p < .05$),[42] whereas the treatment effects for revenue ($\beta = 35.04$) and cross-buying ($\beta = 1.25$) are positive but not statistically significant (see Appendix 2). This plausibility check for the causal relationship between the intermediation dimension and relationship breadth and depth supports the empirical finding from testing *H1*.

This result remains surprising. The general wisdom and empirical results suggest that direct channels enhance company knowledge, relationship intensity, and future usage behavior by customers (e.g., Frazier 1999; Bolton, Lemon, and Verhoef 2004; Achabal et al. 2005; von Wangenheim 2006). For that reason, companies and service providers such as Vodafone, O2, Apple, the Walt Disney Company, and many others invest millions to build flagship stores or company-owned Internet stores worldwide (e.g., Kozinets et al. 2002; Tedeschi 2007; Borghini et al. 2009). Recent developments in other industries further support the superiority of indirect channels. For example, Dell's strategy change, after it had long conducted business exclusively with direct sales, pinpoints the relevance of these indirect sales for customer relations and the company's financial performance (Darlin 2007). Answering customers' requirements, Dell closed its direct stores to concentrate on technology-mediated direct sales (via Internet or phone) or indirect retailers (Dell 2008).

In the case of service industries as well as in other industry sectors, indirect channels (e.g., independent retailers and agencies in online and offline channels) are associated with larger assortments of products or services from different providers or companies. Chernev (2003) argues that larger assortments are advantageous for consumers, who then can purchase the service or product that best matches their preferences. Hence, I argue if consumers purchase the service or product of a certain company, among a larger assortment of comparable goods or services with increased market transparency, they are likely to build stronger relationships with the service provider matching their own preferences if they are satisfied with the product or service.

Service Distribution

On the service distribution dimension (online versus offline channels), the results of *Project I* suggest that migration from offline to online channels does not lead to negative effects in the customer–company relationship, as prior scientific publications have suggested (e.g., Shapiro and Varian 1999; Brynjolfsson and Smith 2000; Ariely 2002; Ansari, Mela, and Neslin

[42] As for the previous significant effects of the interaction term *Period* × *Treatment* in conditional difference-in-differences analysis, the significant effect of *Period* has to be mentioned here.

2008). Instead, the case of a CICM from offline to online channels reveals that customers migrating their channel setting exhibit higher levels of relationship breadth and depth than their matched controls that do not migrate to online channels. Although this effect is only significant for cross-buying ($p < .01$) and slightly non-significant for flights ($p = .16$) and revenue ($p = .13$), online channels are superior with regard to relationship breadth and depth.

This result is unexpected because the empirical generalization implies that online channels lead to lower search, transaction, and switching costs and thus lower profitability (e.g., Shapiro and Varian 1999; Brynjolfsson and Smith 2000; Klein and Ford 2003; Campbell and Frei 2010). However, interactive online tools or modern Internet stores appear able to compensate for the loss of personal interaction with employees of the service provider or third-party intermediaries (e.g., Bucklin and Sismeiro 2009; Huang, Lurie, and Mitra 2009). These online tools are associated with not only higher accessibility (24 hours 7 days a week) but also greater convenience for customers (e.g., Brynjolfsson, Yu, and Smith 2003; Montoya-Weiss, Voss, and Grewal 2003a; Gensler, Leeflang, and Skiera 2011). Results from research on online banking adoption show for example that customers are more profitable after the adoption of the online channel—though in these studies, online banking adopters already were more profitable before adopting the online channel. Thus it is still not clear if profitability arises because of the online channel adoption and persists over time (e.g., Hitt and Frei 2002; Campbell and Frei 2004; Xue, Hitt, and Chen 2011). This project shows that online channel customers exhibit and, more specifically, migration to the online channel causes higher levels of relationship breadth and depth.

Mixed CICM

The results of *Project I* about the combined effect of service distribution (online versus offline) and intermediation (direct versus indirect) show that the effect of service distribution on the relationship between the customer and the service provider is stronger than the effect of intermediation. This result allows for further differentiation of the theoretical assumptions of Bolton, Lemon, and Verhoef (2004) and the results of the empirical investigation of von Wangenheim (2006) on the intermediation category, as well as the conclusions of Shapiro and Varian (1999), Brynjolfsson and Smith (2000), Hitt and Frei (2002), Campbell and Frei (2004), and Xue, Hitt, and Chen (2011) regarding the service distribution category. In the case of CICM, the positive empirical effect of service distribution (i.e., the treatment effects for CICM from offline to online channels in *H2*) is stronger than the negative empirical effect of intermediation (i.e., treatment effects of CICM from indirect to direct channels in *H1*) on sales and cross-buying.[43] However, this effect changes for the treatment effect on revenue. Customers migrating from indirect offline channels to direct online channels exhibit lower levels of revenue. A recent study has supported the causal effect of CICM from indirect offline to direct online channels on revenue. According to Gensler, Leeflang, and Skiera (2011), online channel usage (directly operated channel) in the banking sector has a 50% greater effect on revenue than the effect of reduced costs to serve.

2.6.2 Managerial Implications

From a managerial point of view, the results of this quasi-experimental study also reveal interesting insights in the causal effects of customer-initiated channel migration on relationship breadth and depth. Even if the positive or negative (causal) influence of each migrating customer on the overall performance of the company might be negligible, transferring such effects from a random sample of the customer database, as in this case, to the whole database, will strongly affect the customer equity of a service provider. This section therefore outlines the managerial implications of this study for relationship depth and breadth, as well as general managerial implications.

Regarding the depth of the relationship, booked flights and revenue are relevant. The causal effects of different types of CICM on sales (FLY) are predominantly positive (see Figure 16), ranging from -.02 fewer flights per quarter for a CICM from indirect to direct channels to .07 more flights per quarter for a CICM from indirect offline to direct online channels. Almost equivalent are the causal effects on revenue (see Figure 16). The negative causal effect of CICM to direct channels on sales is reflected in the negative effect on revenue (EUR –151.91). This finding is even more problematic and challenging for the introduction of direct channels, because decreasing revenues occur together with increasing expenses for the service provider to serve the customer in direct channels. This main result gains further importance as customers migrate from indirect offline to direct online channels: They result in significantly higher sales but lower revenues (EUR -54.82 per year) than their matched controls. This effect is not surprising because customers generally realize the cheapest prices in the airline sector through the direct online channel, according to Stiftung Warentest (2011), the leading consumer safety group in Germany.

[43] In *Project I*, I differentiate theoretical and empirical effects. The former is based on the hypothesized relationship between the treatment and the behavioral outcome; the latter is based on the results of the quasi-experimental analysis in this study.

If their goal is to improve relationship depth, managers should recognize that CICM from indirect to direct channels as well as from indirect offline to direct online channels causes negative effects and is associated with increased costs to serve the customer. The results of this study suggest that managers should take one step back from introducing or extending direct channels.

If managerial focus instead is on gaining more relationship breadth, through increased cross-buying, both migration from offline to online channels (EUR 48.52 per quarter) and from indirect offline to direct online channels (EUR 32.41 per quarter) causes positive effects (see Figure 16). These positive causal effects of (direct) online channels on relationship breadth suggest that interactive online tools and modern Internet stores are strong in terms of offering and selling cross-selling opportunities.

For marketing managers of service providers, the results offer essential insights into the strategic relevance of CICM. In contrast with the widely held belief, neither the online channel nor the indirect channel cause damage to relationship breadth or depth. Moreover, both channels contribute to a considerable extent to the overall financial success of the service provider. Therefore, service companies should focus their strategic channel management decisions more on these two channels. Developments in recent years, with ever-increasing numbers of third-party intermediaries and online channels, promote this strategic direction. Therefore, service providers should concentrate on differentiating their services from competitors, evaluate the challenges and opportunities of new intermediated channels, and invest in satisfying customers. These three factors are inevitable for survival in highly transparent and competitive environments, characterized by decreasing search, transaction, and switching costs.

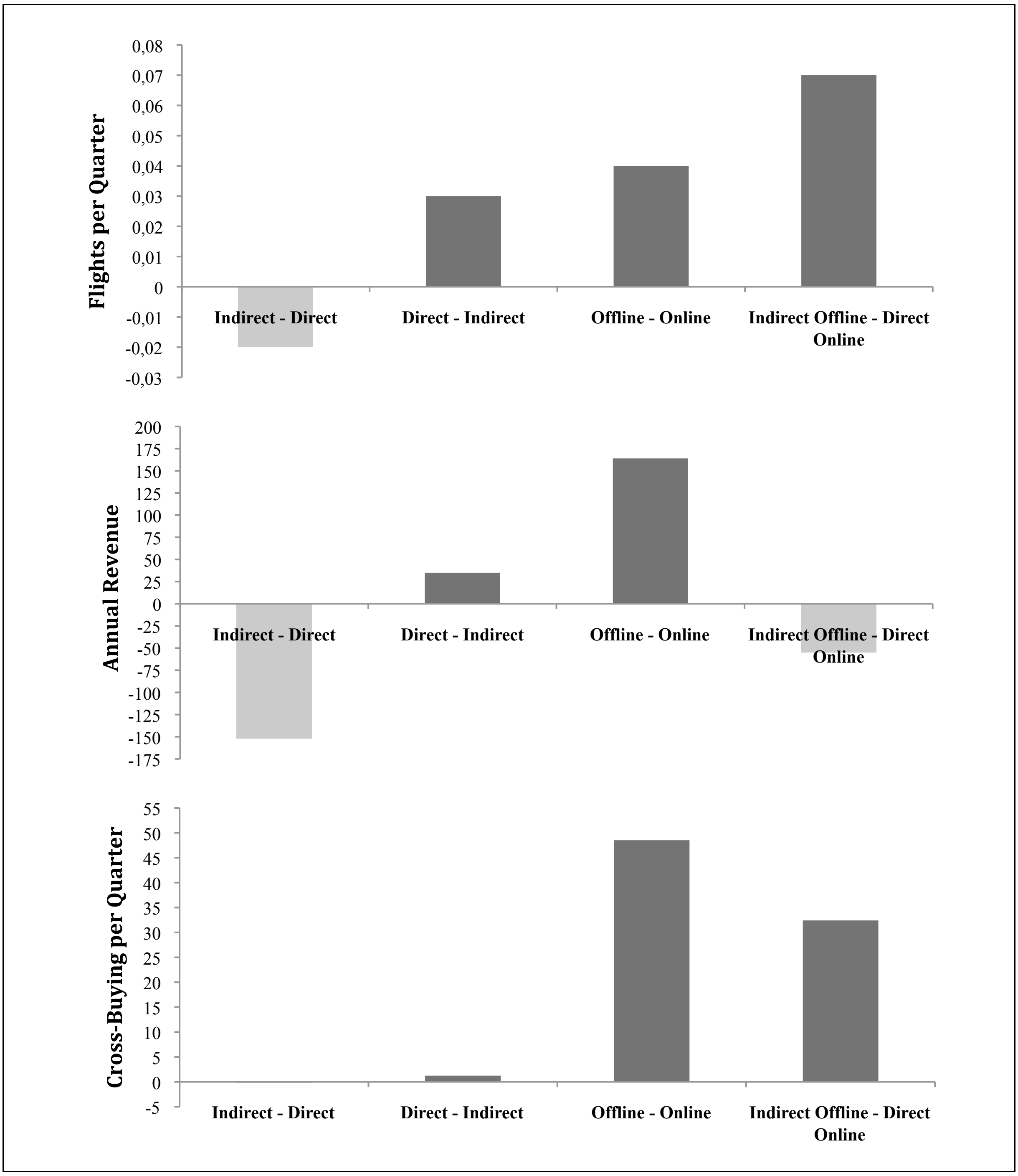


Figure 16: Treatment Effects of Customer-Initiated Channel Migration on Measures of Relationship Breadth and Depth

Managers of service providers also should exercise caution in pricing their services differently in various channels, though it might be necessary due to a diverse cost structure or negative causal effects of CICM to direct channels on revenue. Although some channels in a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix might seem appropriate for price discrimination, the circumstances of channel multiplicity and high price transparency are dangerous and can cause unfairness perceptions among customers (e.g., Neslin et al. 2006; van Bruggen et al. 2010). In addition, focusing on customer lifetime value in terms of relationship breadth, depth, and length, can provide a broader picture of overall financial contributions. Therefore, relationship breadth with cross-selling amounts and further opportunities can be taken into account if managers want to evaluate the contribution of different channels to the company's overall performance. In turn, the financial loss of decreasing revenues, if a customer migrates from indirect offline to direct online channels, can be partially absorbed by increasing levels of cross-buying behavior.

2.6.3 Implications for Future Research

In further research, theoretical, methodological, and empirical enhancements are possible. These implications partly reflect the limitations of this study. From a theoretical perspective, the application of transaction and switching cost theory, as well as the implementation of the conceptual framework of a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix, is particularly imperative for further research. Authors such as Dholakia et al. (2010) suggest the introduction of transaction cost theory into the field of multichannel customer management. This study makes a first move in this direction, especially focusing on the framework of Burnham, Frels, and Mahajan (2003). This conceptual framework of consumer perceptions of switching costs could be applied further and investigated in the context of customer channel migration to gain further insights into this theoretically relevant field. The developed framework for connecting the perspectives of service distribution and intermediation to customer channel migration lights a way to enhance a multidimensional perspective in this research field. Additional dimensions, such as pricing and product policy, could enable further managerial and theoretical relevant research projects. Furthermore, supplementary insights should explain the causal effect of different types of CICM on relationship measures and thus strengthen understanding of customer channel migration overall. As starting point, the role of customer satisfaction could be further investigated. Shankar, Smith, and Rangaswamy (2003) show that customer satisfaction with the service provider is equal, no matter whether the service is delivered online or offline, though the effect for loyalty appears to differ. If the service is delivered online, loyalty to the service provider is higher.

Experimental settings and especially, field studies could enhance the methodological perspective in further research and thus reveal and crosscheck the causal effects of CICM in settings with randomized assignments. Although the applied quasi-experimental design with Mahalanobis-metric matching procedures results in treatment effects, which can be interpreted in causal relations, “it is still possible that the adoption decision is correlated with behavior changes in ways we cannot observe” (Xue, Hitt, and Chen 2011, p. 306). Therefore, laboratory experimental studies and field studies with different internal and external validity levels could shed further light on behavior that cannot be observed with a quasi-experimental setting or data from a customer database.

Other empirical improvements could be achieved with databases that can transfer the conceptual 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix framework to other service settings and industries. A more diverse picture of the treatment and control groups in various possible customer-initiated channel migration settings would be delightful, including migration from indirect online to direct online channels and vice versa. In the airline and tourism sector, the effect of CICM to indirect online channels plays a non-negligible role for managerial practice. Finally, repeated customer channel migrations over time could be interesting to study, including the causal effects on measures of relationship breadth, depth, and length if the customer migrates periodically? For such research, the revealed behavioral consequences of this study and the suggestions for further research provide good starting points.

C. Search Engine Marketing: A Behavioral Perspective

Search engines have fundamentally changed consumer information search behavior and accounted for 131,35 billion global searches per month in December 2009 (comScore 2010). During recent years, search engines have become a very common medium in Internet users' daily lives (e.g., Pavlou and Fygenson 2006; Fallows 2008), enabling faster information search and appropriate search results dependent on the used keywords. From companies' perspective, search engines are a major field for firms' marketing activities on the Internet (Rangaswamy, Giles, and Seres 2009). This is not further surprising because paid search advertising surpasses other online marketing activities in the relevance from an Internet user's point of view, in the amount of high-quality traffic on advertisers' websites, and the costs for performance-based marketing activities from an advertiser's perspective (Ackermann and von Wangenheim 2009; Chan and Park 2009; Ghose and Yang 2009). Even though research on banner advertising suggests increased advertising awareness, brand awareness, site visits, and purchase intention (e.g., Sherman and Deighton 2001; Ilfeld and Winer 2002; Drèze and Hussherr 2003; Manchanda et al. 2006), only small percentages of users converge into a final purchase (Moe and Fader 2004). Classical banner advertising also faces active consumer avoidance behavior (e.g., Drèze and Hussherr 2003; Cho and Cheon 2004). Thus, response rates to banner advertisings have decreased considerably in recent years (Hollis 2005). Therefore, it is highly relevant that insertion of advertisements (sponsored links; paid results) on a search engine result page (SERP) provide an appealing alternative to classical banner advertising.

Two aspects have particular importance according to a behavioral perspective on search engine marketing. First, the order effects of search result exposure on consumer click-through behavior must be taken in account. Results from research on banner advertising suggest differences in how top- and side-displayed banner advertisings are perceived and how they affect consumer click-through behavior (e.g., Chatterjee, Hoffman, and Novak 2003; Drèze and Hussherr 2003). Yet, only one publication in search engine marketing literature differentiates paid top and paid side search results (Jansen 2007). Although not quite as neglected, the situation is similar for paid and organic search results (e.g., Jansen 2007; Ghose and Yang 2008; Jansen and Spink 2009; Yang and Ghose 2010). This distinction between paid and organic search results is of particular interest, because a simultaneous display of paid and organic search results can lead to increasing success (e.g., click-through rate, conversion, revenues) of search engine marketing activities (Yang and Ghose 2010). Second, the competition between the advertisers not only affects bidding behavior and optimization strategies, but also leads to assimilation of the search results (e.g., Rutz, Trusov, and Bucklin 2011), which again influences Internet users' click-through behavior (e.g., Yang and Ghose 2010; Rutz and Trusov 2011).

Achieving the aim to be top listed in paid search heavily depends on the characteristic of the keyword. In this respect, the competition between advertisers bidding on a certain keyword must be taken in account (Park and Park 2010). In this bidding process and the resultant positioning, not only the absolute amount of the bid itself but also certain quality factors (e.g., relevance of the ad text for a consumer search, relevance of the keyword) play a central role in achieving top positions (see Katona and Sarvary 2010). Therefore, high competition between advertisers[44] for popular keywords leads to both higher bids and assimilated ad texts across advertisers to achieve better quality factors. In turn, there are very similar paid search result texts. In addition, the more attractive and competitive a given keyword is, the more difficult it is to be the first result listed in organic results. This competition between companies causes assimilation in the organic results as well. The assimilation of paid and organic search results with increasing levels of advertiser competition complicates consumer choice. Consequently, the evaluation of the paid and organic search results impedes with higher competition between the advertisers. Rutz and Trusov (2011) attempt to integrate this aspect of advertiser competition to explain click-through behavior. Nevertheless, there is a considerable gap in understanding the influences of advertiser competition on consumer click-through and conversion behavior. Thus, the following two research questions are addressed with *Project II*:

Research question 1: How does advertiser competition affect click-through behavior?

Research question 2: How does advertiser competition affect conversion behavior?

To optimize the ranking position, as well as the interdependencies between organic and additional paid search result, players from all industries and sectors (B2B and B2C) try to signal their major relevance for a certain keyword to increase click-through rates. Therefore they pursue the goal to achieve top listed paid and organic search positions. In this context, the question arises from both managerial and research perspectives regarding whether efforts undertaken for higher positions and supplementary efforts in paid search advertising—in ad-

[44] Google measures advertiser competition for a keyword on a metric scale from 0 to 1, where 0 is the lowest level. The level of advertiser competition defines the number of advertisers bidding on the keyword relative to all other keywords on Google during a 12-month period (see Google 2011b; Rutz and Trusov 2011).

dition to the optimization of organic search results—influence click-through behavior and increase generated traffic. Yang and Ghose (2010), show that simultaneously listed paid and organic search results significantly increase overall click-through rate in comparison with just an organic search result. However, this study cannot control for whether the interdependency effect exists for both an additional paid top and paid side result. This distinction is central for consumer click-through behavior, according to results from banner advertising research (e.g., Briggs and Hollis 1997; Benway 1998). Nor is any distinction made between the origins of the additional clicks. Hence, the question of whether the clicks are free, attracted through the organic search results, or had a cost, attracted through the paid search results, has not been addressed. These gaps lead to the third and fourth research questions pertaining to search engine marketing, which is addressed in *Project III:*

Research question 3: How does message order affect click-through behavior?

Research question 4: How does double exposure through the simultaneous display of paid and organic search results affect click-through behavior?

Although paid search advertising is a multi-billion dollar market, little research has focused on how search engine result pages for certain keyword characteristics influence consumer click-through behavior. This thesis will enter this wide field by answering the four key questions in the field of search engine marketing with both *Project II* and *Project III*. In addition, a connection arises between the empirical *Project II* on the research questions 1 and 2 and *Project III* on research questions 3 and 4, because *Project III* examines the relevance of double exposure for increasing levels of advertiser competition.

The remainder of this section of the thesis is organized as follows: In *Chapter C*/1.1, I introduce the conceptual basis of search engine marketing. Then, the relevance of search engines as a research subject is outlined (*Chapter C*/1.2). In a third step, the fundamentals of search engine marketing research are exposed (*Chapter C*/2). Thereby, the different independent variables (*Chapter C*/2.1) and dependent variables in search engine marketing research (*Chapter C*/2.2) can be categorized and illustrated. Finally, the empirical findings on performance indicators (*Chapter C*/2.3.2) and user behavior dimensions in search engine marketing (*Chapter C*/2.3.1) appear. Then in *Chapter C*/3, I provide the general research methodology, including the research framework (*Chapter C*/3.1), the observational (*Chapter C*/3.2) and quantitative (*Chapter C*/3.3) research methodology, and the measurement of latent variables (*Chapter C*/3.4).

Next, *Chapter C*/4 presents *Project II,* examining the influence of advertiser competition on overall, free, and paid click-through behavior, as well as paid conversion behavior. Specifically, *Chapter C*/4 introduces the topic. In *Chapter C*/4.1 I provide the conceptual background and hypothesis development of this study. The experimental investigation of the influence of advertiser competition on overall, paid, and free click-through behavior is outlined in *Chapter C*/4.2. These results are validated in a descriptive study with data from five leading European retailers advertising on Google in *Chapter C*/4.3. *Chapter C*/4.4 closes with managerial and theoretical contributions, as well as implications for further research and managerial activities.

Chapter C/5 presents *Project III*, which empirically investigates the impact of order and exposure effects on click-through behavior. This chapter begins with a short introduction to the general topic of *Project III* (*Chapter C*/5) and the conceptual basis (*Chapter C*/5.1). The observational study identifies drivers of click-through behavior (*Chapter C*/5.2). Next, the hypothesis development is based on order effects (*Chapter C*/5.3.1) and double exposure (*Chapter C*/5.3.2). In the first experimental study of *Project III*, the derived theoretical modes of action are tested for a single experimental search scenario (*Chapter C*/5.4). The second experimental study of *Project III* builds on the findings of the first experiment to test the impact of order effects and double exposure on overall, paid, and free click-through behavior (*Chapter C*/5.4). This chapter closes with a discussion of the results and managerial implications (*Chapter C*/5.6).

1 Conceptual Basis

1.1 Areas for Search Engine Marketing

As sources of information and a site for keyword-centered or contextual advertising, search engine result pages are divided into three distinct areas:

1. Organic search results

2a. Paid top search results

2b. Paid side search results.

Both latter channels are commonly known as paid search or sponsored links (see Figure 17; green: paid top and paid side results; yellow: organic results). In this thesis, search engine marketing is the generic term used to subsume the areas of paid search advertising and search engine optimization. Hereafter, I refer to organic search results if the results are listed on the search engine results page because of search engine optimization activities. In contrast, paid search results include listings on the search engine result page, which appear on the basis of paid search activities. The differentiation between organic and paid search results relies on these distinctions.

Figure 17: Search Engine Result Page

Organic search results appear in the center of the search engine result page, ranked according to their relevance for a certain user's search query (e.g., Page et al. 1998).[45] To improve the ranking, search engine optimization of the landing page[46] is applied. Search engine optimization (SEO), which refers to all efforts undertaken to optimize the content on the landing page to increase the relevance, is under the purview of computer science literature rather than marketing or management literature. Therefore, I do not focus further on the technical details of search engine optimization but rather stress the consequences of SEO on relevant behavioral dimensions of the consumers. As a short overview of technical influences, Table 9 displays three distinct factors that influence the organic ranking on a search engine result page. According to Moran and Hunt (2009) ranking factors, page ranking factors, and query ranking factors can be distinguished.

Factor(s)	Description and Further Details
(1) Ranking factors	a. Page factors (e.g., potency of the linked websites on the landing page, number of page visitors) b. Query factors (e.g., congruence of the entered search keywords and the displayed terms on the search result, title, text body)
(2) Page ranking factors	Link popularity, length or depth of the URL, content actuality or time since latest content update, text style (e.g., grammar), web design, and spam techniques
(3) Query ranking factors	a. Keyword prominence (e.g., where the keyword is located on the landing page, more on the beginning or rather at the footnote) b. Keyword frequency c. Keyword density (proportion of keyword frequency and number of words on the landing page) d. Query intent (navigational, informational, or transactional search query) e. Contextual relevancy (e.g., personal characteristics received from personalized or targeted services and browsing behavior like gender, location etc.) f. Term rarity g. Term proximity (e.g., closeness of the words on the page and the entered search term)

Source: Own illustration, based on Moran and Hunt (2009), pp. 298-305.

Table 9: Factors Influencing the Position of Organic Results

In contrast, *paid search results* are in general displayed in two distinct areas on the search engine result page. For keywords with many bidding advertisers, the top listed paid search results are displayed, usually one to three paid top results. Regardless of whether the corre-

45 For more details on the mathematical ranking algorithm for relevance (called PageRank), see Page et al. (1998) and Brin and Page (1998).

46 Landing pages are websites linked from the search results to a third-party website that corresponds to a certain keyword. For example, if a search engine user enters the search term "flight" into a search engine, such as Google, the search engine result page as displayed in Figure 17 appears. In the hypothetical case, a user decides to click on the first organic listing and thus links to "Skyscanner.net". This site displayed on "Skyscanner.net" is the landing page.

sponding keywords are highly attractive to advertisers or not, laterally displayed search results also appear. In this section, the number of displayed paid search results often differs.[47] These differences again result from the total amount of advertisers who aim to display their paid search results for a certain user search term. Certainly, there are more than a few keywords with only paid top results displayed, such as for company-specific keywords (e.g., Lufthansa, Nokia, Siemens).[48]

Furthermore, the allocation of paid side and paid top results can vary for at least two reasons. First, the allocation can differ on various search engine result pages for a certain query, such that the second, third, or fourth SERP might have other allocations of paid top and paid side search results than the first SERP. Second, differences are possible from search query to search query, even for the same keyword(s).

1.2 Search Engine Marketing as a Research Subject

In recent years, search engines and search engine marketing activities have become a main field in managerial (e.g., Enquiro 2007; Laffey 2007; Abraham 2008; Brooks and Magun 2008; Google 2008; Blankenbaker and Mishra 2009) and academic (e.g., Bradlow and Schmittlein 2000; Rangaswamy, Giles, and Seres 2009; Rutz and Bucklin 2011) publications. From the start of research focusing on the phenomenon of search engine marketing, paid search advertising has gained considerable attention in marketing, management, and information systems literature. These academic works adopt the perspectives of the search engine, advertiser, or consumer. The application of search engine clickstream data offers an almost inexhaustible data source for empirical research and model validation in this field. Search engine clickstream data, defined "as the electronic record of a user's activity" (Bucklin and Sismeiro 2009, p. 36) on a search engine encompass information about individual behavior (view, click, conversion, order volume), as well as campaign and overall performance measures (views, click-through rate,[49] cost per click, conversion rate[50]).

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47 Although Google (2011a) states that a paid search advertising with an average position between one and eight is displayed on the first search engine result page, result pages for certain search queries, such as "Flug München Berlin" display up to eleven (three top listed, eight side listed) paid search results (see Appendix 3).

48 An exemplary search engine result page with a paid top search result only, is displayed in Appendix 4.

49 The click-through rate (CTR) is the number of Internet users clicking on a link or advertisement (clicks) divided by the number of Internet users viewing a website or search engine result page and thus, consciously or unconsciously, the advertisement (views). The costs of consumer clicks on paid search results of an advertiser are invoiced on a cost per click (CPC) basis, so the advertiser is charged per click (e.g., Novak and Hoffman 1997).

50 The conversion rate (CR) is the ratio of the number of Internet users accomplishing the targeted objective (purchasing a product, request submitting) on the linked website (conversions), divided by the number of In-

A general overview of scientific studies of search engine marketing is in Table 10, which categorizes scientific management, marketing, and information systems studies according to their research design and empirical data basis. In terms of research design, modeling and estimation studies (e.g., Ghose and Yang 2009; Yang and Ghose 2010; Rutz and Trusov 2011), along with quantitative studies (e.g., Dou et al. 2010; Ji, Rui, and Hansheng 2010; Rutz and Bucklin 2011), dominate the domain of search engine marketing. Only two quantitative studies collect primary data (Gauzente 2009; Dou et al. 2010).[51] Pure modeling (Sen 2005) and qualitative (e.g., Jansen 2007; Jansen and Spink 2009) studies are also exceptions. The data source for quantitative empirical, modeling, and estimation studies mainly consists of search engine data (e.g., Zhang, Jansen, and Spink 2009; Park and Park 2010) or data from single advertising companies (e.g., Yang and Ghose 2010; Rutz and Bucklin 2011). Advertiser data can be further broken down into individual clickstream data, either in B2B (e.g., Chan, Xie, and Wu 2009) or B2C (e.g., Ghose and Yang 2010) contexts. Furthermore, aggregated B2C clickstream data (e.g., Rutz and Bucklin 2011), keyword data (e.g., Rutz and Bucklin 2007), and aggregated keyword data (e.g., Ghose and Yang 2008) all exist. In recent work on search engine marketing, individual keyword data or aggregated click data provide the most often selected basis for empirical studies.

ternet users clicking on the link or advertisement and, forwarded to the linked website (visits) (e.g., Bucklin, Rutz, and Trusov 2009; Rutz and Trusov 2011).

[51] Gauzente (2009) conducts survey research; Dou et al. (2010) apply an experimental research design.

		Discipline		Research Design				Data									
Serial Number	**Author(s)**	*Marketing & Management*	*Information Systems*	*Modeling*	*Modeling & Estimation*	*Qualitative*	*Quantitative*	*Clickstream Data (B2B)*	*Clickstream Data (B2C)*	*Aggregated Click-stream Data (B2C)*	*Keyword Data*	*Aggregated Keyword Data*	*Search Engine Data*	*Individual Evaluation*	*Observation*	*Survey/Experiment*	*Single Firm*
(1)	*Sen (2005)*		×	×													
(2)	*Jansen and Molina (2006)*		×			×								×			
(3)	*Jansen and Resnick (2006)*		×			×									×		
(4)	*Jansen (2007)*		×			×								×			
(5)	*Rutz and Bucklin (2007)*	×					×			×	×						×
(6)	*Agarwal, Hosanagar, and Smith (2008)*	×			×						×						×
(7)	*Ghose and Yang (2008)*	×			×							×					×
(8)	*Chan, Xie, and Wu (2009)*	×					×	×									×
(9)	*Gauzente (2009)*	×					×									×	
(10)	*Ghose and Yang (2009)*	×			×					×							×

(Continued on next page)

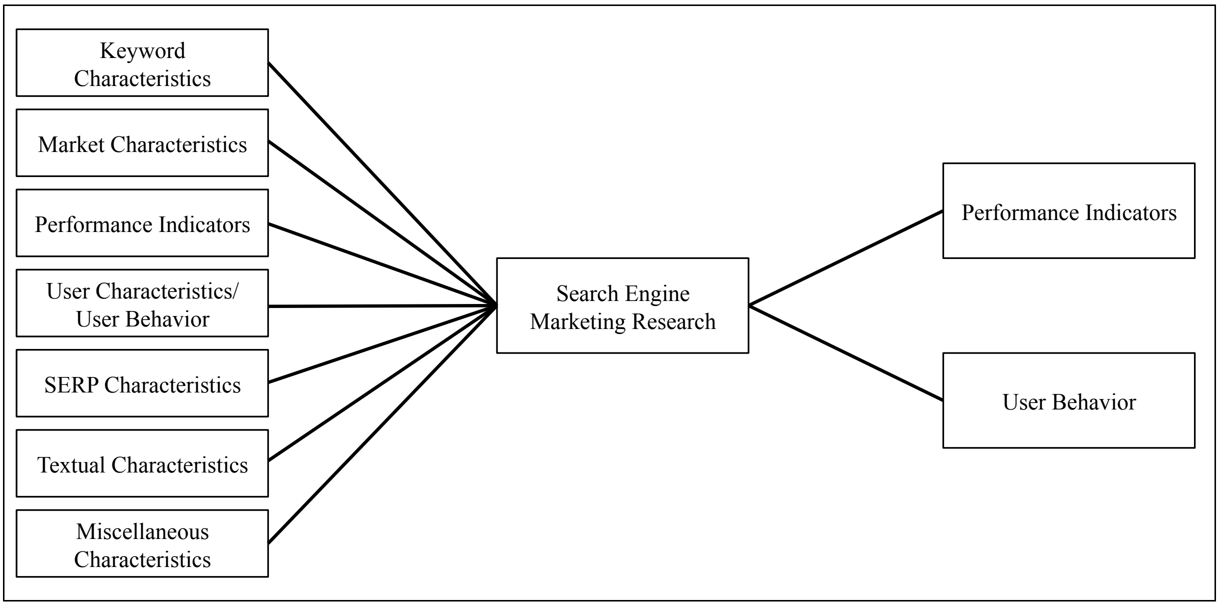
Serial Number	Author(s)	Discipline		Research Design				Data									
		Marketing & Management	*Information Systems*	*Modeling*	*Modeling & Estimation*	*Qualitative*	*Quantitative*	*Clickstream Data (B2B)*	*Clickstream Data (B2C)*	*Aggregated Click-stream Data (B2C)*	*Keyword Data*	*Aggregated Keyword Data*	*Search Engine Data*	*Individual Evaluation*	*Observation*	*Survey/Experiment*	*Single Firm*
(11)	*Jansen and Spink (2009)*		×			×							×				
(12)	*Zhang, Jansen, and Spink (2009)*		×		×								×				
(13)	*Dou et al. (2010)*		×				×									×	
(14)	*Ghose and Yang (2010)*	×			×				×								×
(15)	*Ji, Rui, and Hansheng (2010)*	×					×										×
(16)	*Park and Park (2010)*	×			×								×				
(17)	*Yang and Ghose (2010)*	×			×					×							×
(18)	*Animesh, Viswanathan, and Agarwal (2011)*		×				×				×						×
(19)	*Rutz and Bucklin (2011)*	×					×			×							×
(20)	*Rutz and Trusov (2011)*	×			×				×		×						×

Notes: a. The serial numeration of each publication in the first column reflects the assignment of the empirical studies in Table 11 and Table 12, performed to classify independent and dependent variables.
b. If a study corresponds to a subcategory of discipline, research design, or data, this match is shown with a × in the corresponding cell.

Table 10: Categorization of Disciplines, Research Design, and Data Basis of Scientific Studies on Search Engine Marketing

2 Fundamentals of Search Engine Marketing

To provide an overview of the fundamentals of search engine marketing, I develop a framework for categorizing and summarizing recent research activities in *Chapter C*/2. Even though a multiplicity of studies investigate search engine marketing topics, clear categorizations of the applied independent and dependent variables are missing. Figure 18 depicts and summarizes the conceptual framework for *Chapters C*/2.1–2.3. On the left, the main categories of applied independent variables in empirical research on search engine marketing appear. The clusters of performance indicators and user behavior represent the two main categories of dependent variables. In *Chapter C*/2.1, the applied independent variables will be outlined. The following *Chapter C*/2.2 introduces dependent measures in recent search engine marketing research. Finally, *Chapter C*/2.3 summarizes the results of recent empirical studies that combine the influence of the clustered independent and dependent variables.



Notes: The categories of independent variables or controlled factors applied in search engine marketing research projects are displayed on the left. On the right, categories for dependent variables are shown.

Figure 18: Conceptual Framework of Independent and Dependent Variables in Empirical SEM Research Projects

2.1 Independent Variables in Search Engine Marketing Research

The independent variables applied in empirical studies on search engine marketing can be condensed into seven different categories: keyword characteristics, market characteristics, performance indicators, user characteristics and user behavior, search engine result page (SERP) characteristics, textual characteristics, and miscellaneous characteristics. An overview of applied independent variables or controlled factors in scientific studies on search engine marketing is in Table 11 (pp. 82–83).

The *keyword characteristics* category (see Figure 19) subsumes different dimensions that describe keyword properties in search engine marketing settings. These observable characteristics of keywords depend on user actions (branded, generic, or retailer-specific keyword; length, location; the keyword itself), as well as advertiser activities (match type, rank[52]).

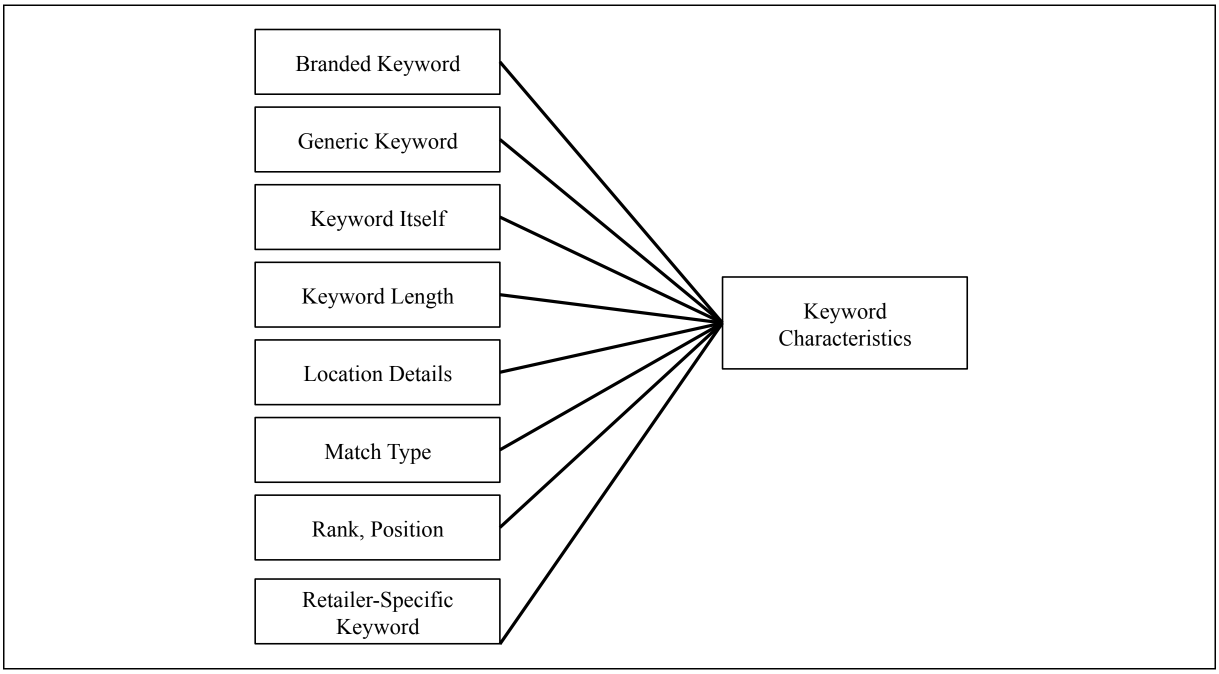


Figure 19: Keyword Characteristics as Independent Variables

In more detail, *branded keyword* includes details on the brand name users searched in a specific query. An example of a branded keyword is: "Flight Delta Airlines". Retailer-specific keywords, as applied in Ghose and Yang (2008, 2009, 2010) encompass retailer brands like "flight Expedia" or "mp3 Amazon". Branded keyword is quite popular as independent variable in empirical research settings (e.g., Rutz and Bucklin 2007; Ghose and Yang 2008; Rutz and Bucklin 2011). A generic keyword (Ghose and Yang 2010; Rutz and Bucklin 2011) is the relevant category for search queries without retailer or brand specifications (e.g., flight, hotel, car). These three subcategories (branded, retailer-specific, and generic keyword) of keyword characteristics thus cannot be treated as substitutes; rather, they constitute the possibilities for grouping keywords (dummy variable) to reveal an impact on the dependent vari-

[52] The ranking of the search results is relevant in the organic search results and the paid search results. For the organic search results, rank only depends on the relevance of a company's website for a certain search query (see *Chapter C*/1.1). For paid search results, rank is affected not only by advertiser activities (maximal bid) but also competitors' and by the search engine that takes the bids (e.g., Ghose and Yang 2009; Yang and Ghose 2010).

ables. The length of the keyword (Ghose and Yang 2008; Ghose and Yang 2009; Zhang, Jansen, and Spink 2009; Ji, Rui, and Hansheng 2010), measured in number of words for a search query; location information (Rutz and Bucklin 2007); and the keyword (Rutz and Bucklin 2007; Animesh, Viswanathan, and Agarwal 2011) can predict the success of search engine marketing. Advertisers try to improve the visibility of their organic and paid search results by influencing rank and match type.[53] Match type is limited to paid search, whereas rank influences both organic and paid listings. Hence, it is not surprising that the impact of rank or position (e.g., Jansen and Resnick 2006; Ghose and Yang 2010; Park and Park 2010; Animesh, Viswanathan, and Agarwal 2011) is more relevant in recent empirical studies than is match type (e.g., Rutz and Trusov 2011).

The category of *market characteristics* focuses on parameters that arise from the competition between advertisers in the broad sense (see Figure 20). Competitive intensity and advertiser competition focus on competition between the advertisers in paid search advertising markets. For example, Animesh, Viswanathan, and Agarwal (2011) specify the concentration of competing firms with the same unique selling proposition using competitive intensity. Additionally, differentiation strategy, and unique selling proposition are related to the competitive intensity from the perspective of Animesh, Viswanathan, and Agarwal (2011). Rutz and Trusov (2011) rely on the advertiser competition metric from Google AdWords.[54] All in all, market characteristics in the paid search advertising environment, up to this point in time, have been more or less neglected in search engine marketing research.

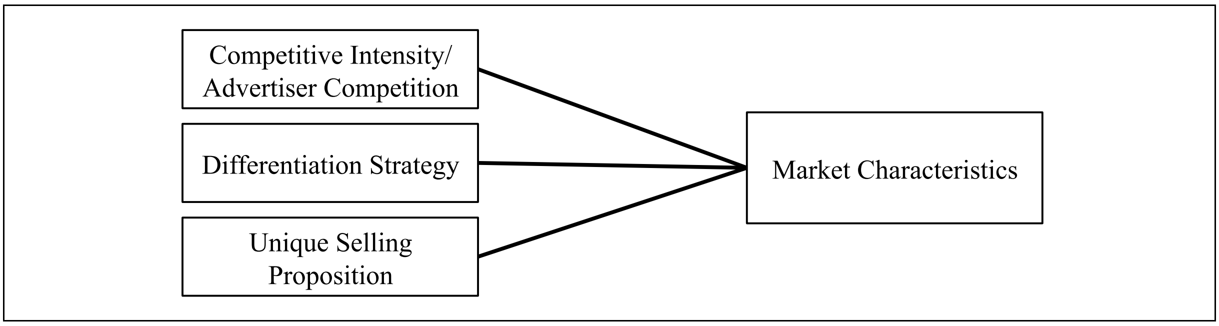


Figure 20: Market Characteristics as Independent Variables

[53] Match types constitute four categories: broad, phrase, exact, and negative. Google (2011c) defines broad matches as the display of an ad with "similar phrases and relevant variations". Phrase matching is displaying paid search results "for searches that match the exact phrase" (Google 2011c). Exact matches arise when the exact phrase is included; a negative match excludes specified keywords from displaying the ad (Google 2011c).

[54] See footnote 44.

The category of *performance indicators* (see Figure 21) includes such metrics as cost per click, landing page quality, paid click-through rate (CTR), and search volume, which predict the impact of some success measures on subsequent key performance indicators in sponsored search (e.g., conversion rate, keyword rank). Ghose and Yang (2009) use, among other things, cost per click, landing page quality, and paid CTR to predict additional sponsored search metrics; Rutz and Bucklin (2007) include paid CTR to analyze profitability. Rutz and Trusov (2011) also add search volume as a supplementary predictor for CTR.

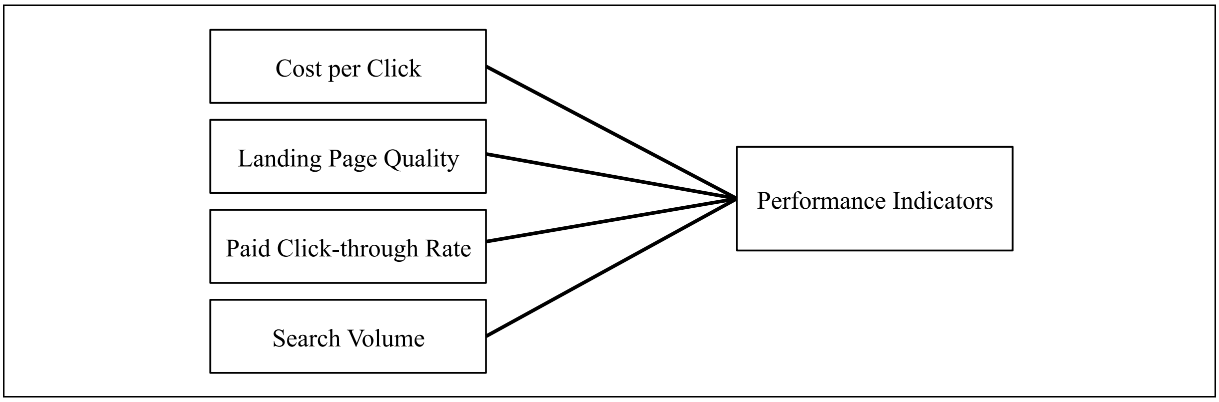


Figure 21: Performance Indicators as Independent Variables

Controlled *user characteristics and user behavior* can be used further to describe search behavior, click behavior, and attitudinal or behavioral measures. These three subcategories are diverse, and no favored variables can be identified. In the subcategory of *search behavior* (see Figure 22), nine independent variables emerge: branded search behavior (Rutz and Bucklin 2011), generic search behavior (Rutz and Bucklin 2011), informational search queries (Jansen and Spink 2009), Internet search skill (Dou et al. 2010), navigational search queries (Jansen and Spink 2009), number of interactions with the search engine (Zhang, Jansen, and Spink 2009), search experience (Jansen and Resnick 2006), time of first query (Zhang, Jansen, and Spink 2009), and transactional search queries (Zhang, Jansen, and Spink 2009).

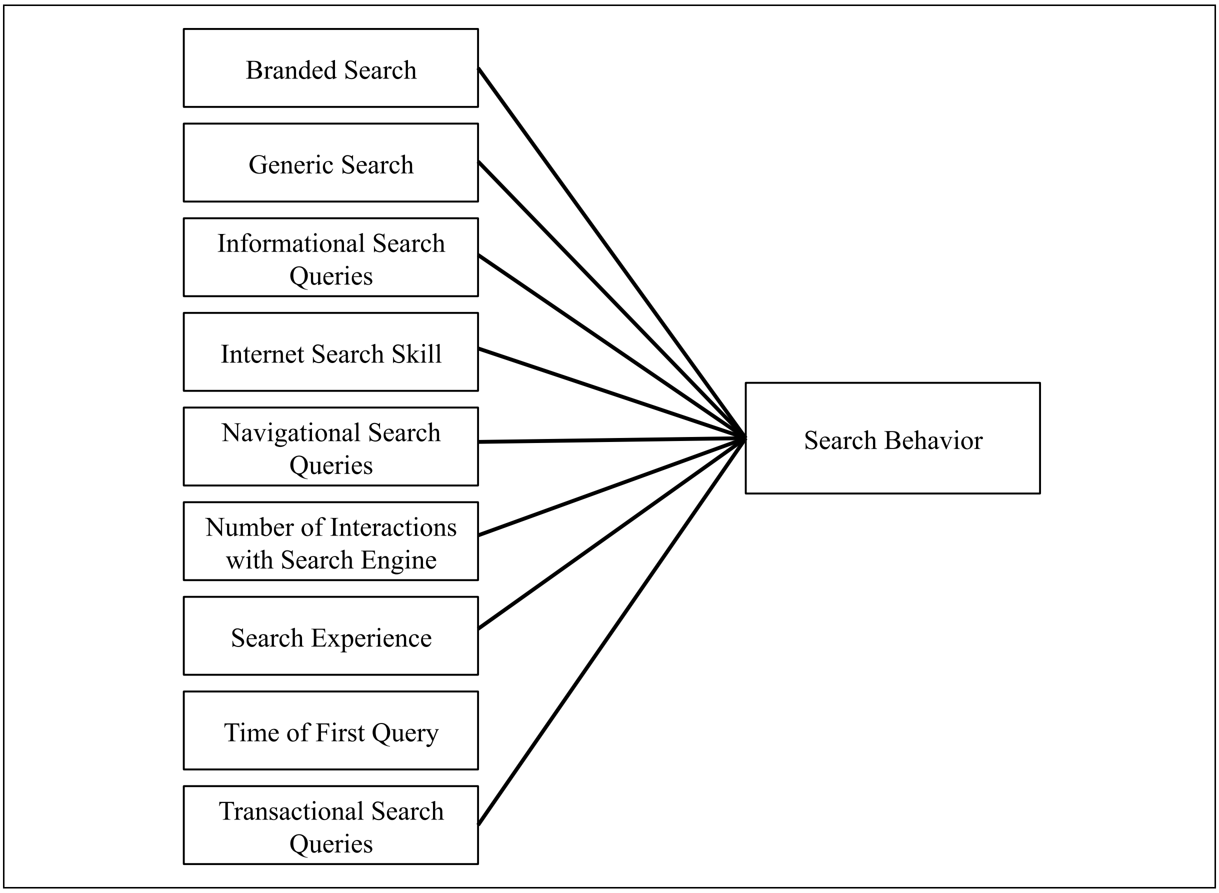


Figure 22: Search Behavior as Independent Variables

In the second subcategory of *click behavior*, the number of organic clicks[55] (Zhang, Jansen, and Spink 2009), sum of rank[56] (Zhang, Jansen, and Spink 2009), and time span after click (Ghose and Yang 2010) appear (see Figure 23). Finally, attitude toward paid link (Gauzente 2009), information need (Jansen and Resnick 2006), past satisfaction (Gauzente 2009), self-efficacy (e.g., for searching; Jansen and Resnick 2006; Gauzente 2009), and time spent on the Internet (Zhang, Jansen, and Spink 2009) all make up the subcategory of *attitudinal and behavioral measures* (see Figure 23).

[55] This thesis uses the terms organic and free click, organic and free click-through, and organic and free click-through rate synonymously.
[56] The sum of rank refers to “the total rank of links opened by each user” (Zhang, Jansen, and Spink 2009, p. 9).

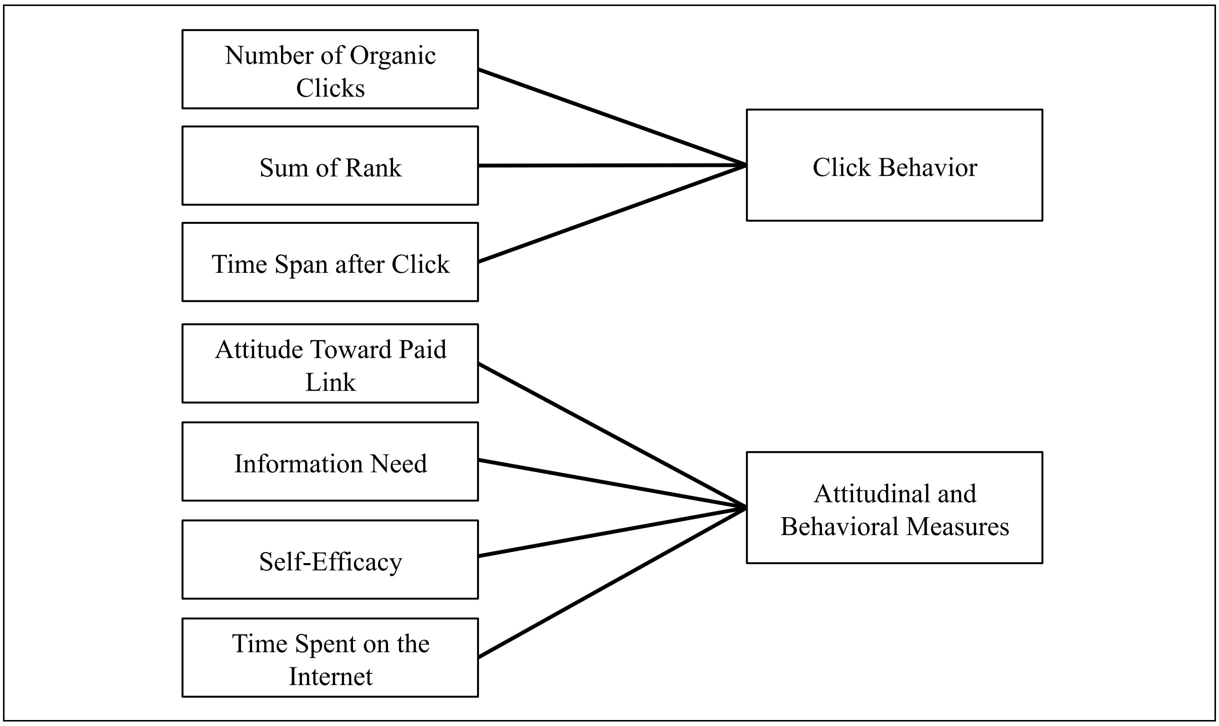


Figure 23: Click Behavior, Attitudinal and Behavioral Measures as Independent Variable

The category of *search engine result page characteristics*, as displayed in Figure 24, has wide circulation in empirical research projects. In general, four subtypes can be mentioned: labeling of paid search, organic search results, paid search results, and paid top and paid side listings. In the case of labeling paid search, Jansen and Spink (2009) investigate the impact of paid search results, not marked as advertisements and integrated in organic search results, on consumer click-through behavior. Jansen and Molina (2006), Jansen (2007), Ghose and Yang (2008), Dou et al. (2010), and Yang and Ghose (2010) examine the impacts of different facets of organic search results on the performance of search engine marketing. However, paid search advertising has gained considerably more attention in empirical research projects (e.g., Jansen and Molina 2006; Rutz and Bucklin 2007; Agarwal, Hosanagar, and Smith 2008; Chan, Xie, and Wu 2009; Ji, Rui, and Hansheng 2010; Rutz and Trusov 2011). The differentiation of paid top and paid side search results has been neglected, with the exception of Jansen (2007).

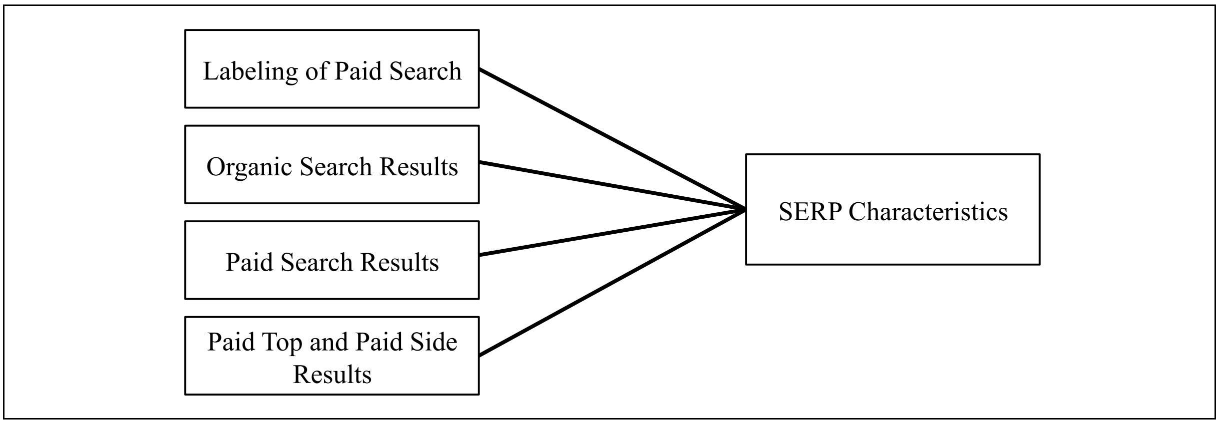


Figure 24: SERP Characteristics as Independent Variables

Textual characteristics of search results, displayed in Figure 25, also have attracted little attention. Characteristics such as calls for action in the search results, keywords in title, number of words in the body, and number of words in the headline (Rutz and Trusov 2011) belong to the category of textual characteristics in search engine marketing.

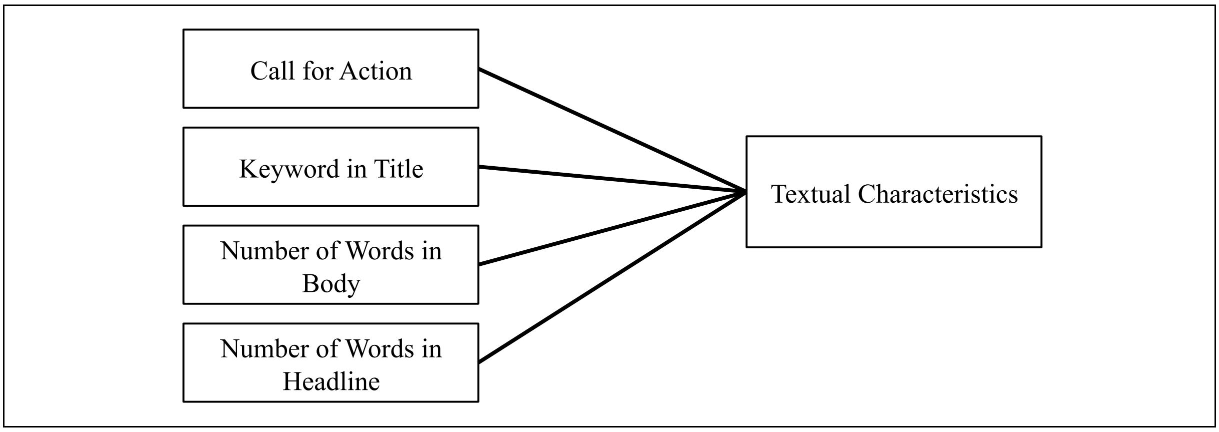


Figure 25: Textual Characteristics as Independent Variables

As *miscellaneous characteristics* (see Figure 26), advertisers' bidding behavior (Ghose and Yang 2009) and time period effects (Ghose and Yang 2009, 2010) are potential factors that influence sponsored search metrics (Ghose and Yang 2009) and purchase behavior (Ghose and Yang 2010). Additional independent variables include browser type (Zhang, Jansen, and Spink 2009), different search engine types (e.g., metacrawler, e-commerce search engines, general purpose search engines; Jansen and Molina 2006), known versus unknown brands as a search result (Dou et al. 2010), and price of the advertised product (Rutz and Trusov 2011).

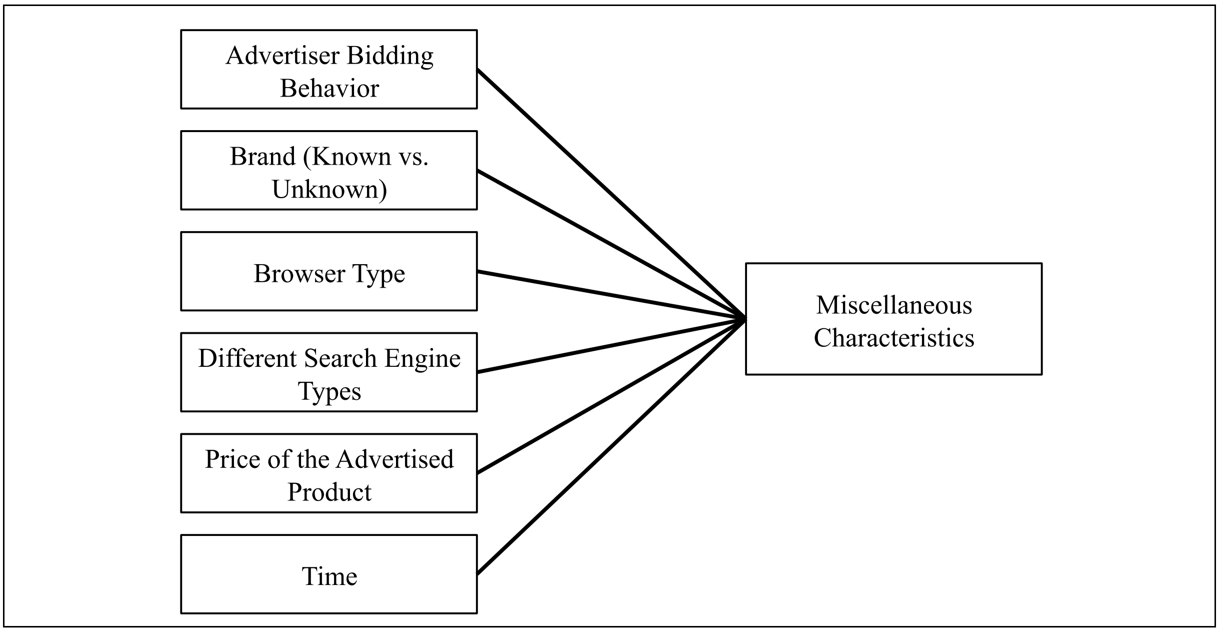


Figure 26: Miscellaneous Characteristics as Independent Variables

2.2 Dependent Variables in Search Engine Marketing Research

The amount of dependent variables for testing performance in search engine contexts is limited, in contrast with the variety of independent variables applied in empirical research projects. For an overview of the applied dependent measures in scientific studies on search engine marketing, see Figure 27 and Table 12.

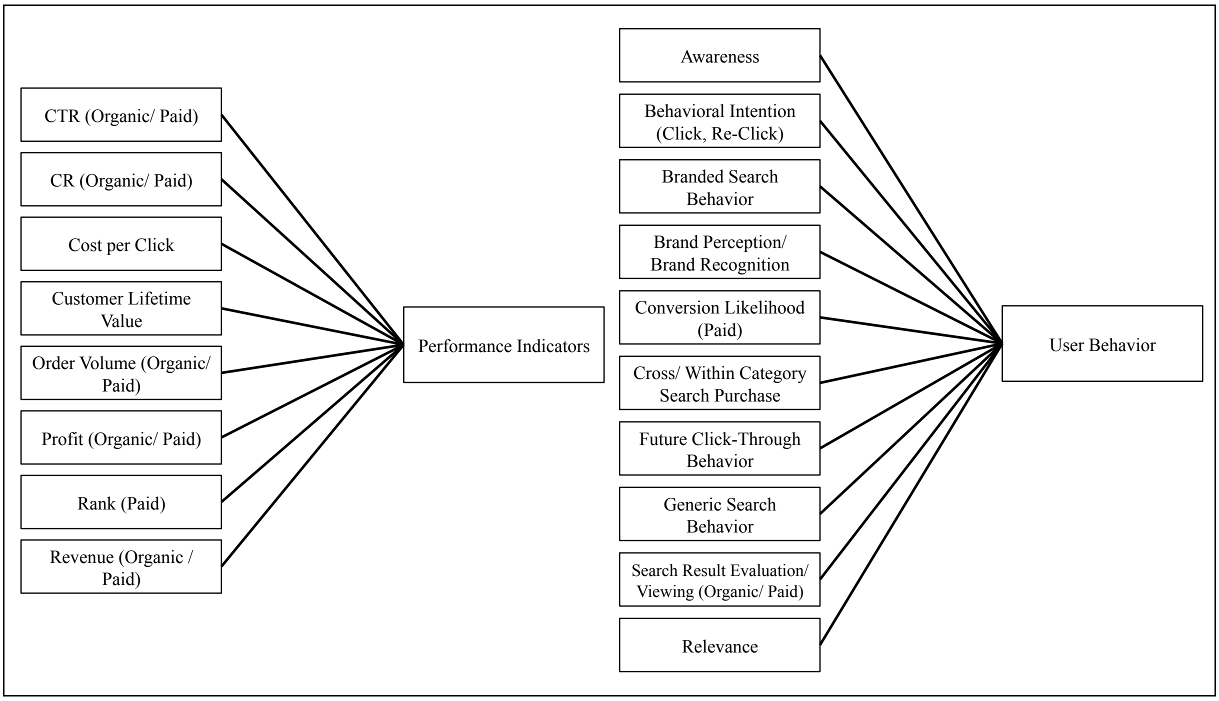


Figure 27: Performance Indicators and User Behavior as Dependent Variables

On the one hand, *performance indicators* concentrate on measures such as click-through rate (CTR), conversion rate (CR), order volume, cost per click, customer lifetime value, profit measures, and revenue measures, as well as rank of paid search results. *Click-through rate* as a performance measurement is the most common dependent variable; it consists of *organic* click-through rate (Jansen and Spink 2009; Yang and Ghose 2010), and *paid* click-through rate (e.g., Ghose and Yang 2009; Jansen and Spink 2009; Park and Park 2010; Yang and Ghose 2010; Animesh, Viswanathan, and Agarwal 2011; Rutz and Trusov 2011). Here, the CTR for paid search results is the one used most often. *Conversion rate* inspections also can be distinguished into *organic* (Ghose and Yang 2008; Yang and Ghose 2010) and, again the more popular, *paid* (Rutz and Bucklin 2007; Ghose and Yang 2008; Ghose and Yang 2009; Rutz and Trusov 2011) conversion rate measurement. This distinction between organic and paid search results also applies to *order volume* (*organic*: Chan, Xie, and Wu 2009; *paid*: Chan, Xie, and Wu 2009; Ghose and Yang 2009), *profit* (*organic*: Ghose and Yang 2008; *paid*: Agarwal, Hosanagar, and Smith 2008; Ghose and Yang 2008; Ghose and Yang 2009), and *revenue* (*organic*: Yang and Ghose 2010; *paid*: Agarwal, Hosanagar, and Smith 2008) examinations. Additionally, Ghose and Yang (2009) investigate *cost per click* and *rank* in paid search advertising as dependent variables in their empirical study. In contrast, Chan, Xie, and Wu (2009) concentrate with *customer lifetime value* on a longitudinally oriented performance measurement.

On the other hand, *user behavior* dimensions appear in eight empirical studies as dependent variables. Jansen and Molina (2006), similar to Jansen (2007), address user *relevance perceptions* of different search results. Gauzente (2009) however, investigates the *intention to click* or *re-click* on a certain search engine result. This approach is similar to Zhang, Jansen, and Spink's (2009), who focus on *future click-through behavior*. Rutz and Bucklin (2011) address further specifications of consumer search behavior by concentrating on the measures of branded search behavior, generic search behavior, and awareness. Likewise, Jansen and Resnick (2006) investigate search behavior. Unlike Rutz and Bucklin (2011) though, they differentiate the evaluation and viewing of organic and paid search results.

The behavioral perspective in Ghose and Yang (2010) and Dou et al. (2010) are distinct from other empirical publications focusing on user behavior. Ghose and Yang (2010) focus on performance-closer behavioral approaches. These authors investigate the conversion probability across and within search categories.[57] Dou et al. (2010) instead take users' brand perceptions and brand recognition on search engine result pages as dependent variables.

2.3 Empirical Findings in Search Engine Marketing Research

This description of recent findings in empirical research is structured around the investigated dependent variables. I thus concentrate on revealing coherence between the independent and dependent variables, as well as similarities or differences between applied empirical approaches. An overview of the researched relations in search engine marketing is in Table 13.

2.3.1 Empirical Findings on User Behavior Dimensions

User behavior dimensions are of particular importance as dependent variables, because the measurement of online and search engine marketing success not only focuses on direct click or purchase activities as a reaction to exposure but also on target variables, such as awareness or brand perception (e.g., Drèze and Hussherr 2003; Economist 2006). These approaches are exceptions in search engine marketing research, more so than in other online marketing disciplines, though some of the conducted empirical research projects enter this field.

With their approach directly connected to investigate target variables other than click or purchase behavior, Dou et al. (2010) deserve special mention. These authors experimentally investigate the impact of the rank of search results from unknown brands on the perception and recognition of these brands. If unfamiliar brands are directly listed before familiar brands, they are better recalled when schema (as implicit beliefs) of the displayed order are activated. Furthermore, the perception of a certain brand attribute is more positive for users with low Internet search skills when the brand attributes activate the implicit beliefs of a ranking schema.

Jansen and Molina (2006) and Jansen (2007) explore user relevance perceptions of paid and organic search results as a first tier of influence in user search and click behavior. Jansen and Molina (2006) can reveal that organic links are more relevant than paid links, even though the results cannot show that more relevant links are ranked highest on a search engine result page.[58] With a similar approach, Jansen (2007) shows with individually (three raters) evalu-

[57] Across–search category purchase means "consumers who start a search for a product in one category eventually purchase products from a different category, in addition to purchases from the original category they searched" (Ghose and Yang 2010, p. 5). Within–category purchase is present if a "click on a given sponsored ad [...] lead[s] to purchases of different products within a given category" (Ghose and Yang 2010, p. 2).

[58] The relevance perceptions of more than 3,200 search results are evaluated by four independent raters (Jansen and Molina 2006).

ated data that paid top and paid side links are perceived as more relevant than organic links.[59] In more detail, comparing top and side listed paid links shows that top listed paid results are rated as more relevant than side listed ones. The empirical study of Jansen and Resnick (2006) targets a similar direction. They investigate the impact of paid search advertising on consumer information search on the Internet. The relationship of viewing paid search results with search self-efficacy, search experience, information need, and rank order of the search results are analyzed. Users tend to view and evaluate organic search results before taking paid search results into account. Furthermore, search self-efficacy and search experience do not change the probability of viewing sponsored search results. This analysis shows that the ranking of paid search advertisements does not affect users' evaluations.

In contrast, empirical work by Gauzente (2009), Zhang, Jansen, and Spink (2009), Ghose and Yang (2010), and Rutz and Bucklin (2011) focuses more on clicks or conversion as familiar behavioral dimensions. Gauzente (2009) proposes a framework that predicts the behavioral consequences of paid link exposition in different search situations. She reveals a significant relationship between users' attitude toward paid links and behavioral intentions to click on a paid link. Past satisfaction with the company is a significant predictor of (future) click-through behavior. Building on a neural network analysis of search engine transaction log data, Zhang, Jansen, and Spink (2009) identify nine factors influencing the future propensity to click on a search engine result page. The number of interactions, sum of rank, average query length, browser type, and time range[60] positively and statistically significant affect future click behavior. However, the mean number of organic clicks, vertical type rate, and time of first query have significant negative impacts on future click-through behavior.

Connecting within and across search category searches, Ghose and Yang (2010) develop and validate a model mapping consumer behavior from search to purchase. The authors analyze the relationship between search for products within a specific category and purchase within this category. With individual consumer data on a single firm level, they reveal substantial spillover from searching in one category and buying in that category as well as in an additional category. These cross-category purchases are most likely when keywords are retailer specific but less likely with branded or generic keywords. Higher ranked paid search results are more likely to lead to conversion, whereas an increasing time span elapsing after a click leads to decreasing conversion likelihood.

[59] All in all, the raters evaluated the displayed paid top, paid side, and organic search results of 108 e-commerce queries on three search engines (Jansen 2007).

[60] Time range = "log out time – log in time" (Zhang, Jansen, and Spink 2009, p. 9).

In similar strategy Rutz and Bucklin (2011) empirically investigate spillover from generic to branded paid search with a dynamic linear model. Their results reveal that generic search behavior positively affects branded search behavior, but not vice versa. An exposition to brand-related paid search information thus can lead to awareness and spillover in subsequent search activities. Rutz and Bucklin (2011) thus partly close the gap between independent variables applied as performance indicators and user behavior–centered dependent variables, as they refer to branded and generic keyword characteristics. These keyword characteristics have been proven significant predictors of click-through and conversion measures.

2.3.2 Empirical Findings on Performance Indicators

Performance indicators have particular importance, because the measurement of search engine marketing activities and their success has attained considerable attention from managerial and research perspectives (e.g., Novak and Hoffman 1997; Bughin, Shenkan, and Singer 2008). As Table 12 shows, *click-through rate* and *conversion rate* have gained considerable attention as objective metrics in search engine marketing research. Because search engine results can be divided into organic and paid search results, a differentiation between organic (or free) and paid click-through or conversion rates is axiomatic.

Yang and Ghose (2010) model and estimate the interrelations between paid and organic search results on organic and paid click-through and conversion rates. Their primary focus is on the wide field of organic and paid search effectiveness. Therefore they investigate if an additional organic search result on a search engine result page affects consumers' click-through and conversion behavior for paid search advertisements, and vice versa. The empirical findings of Yang and Ghose (2010) condense the approaches to search and purchase behavior–related performance indicators between the poles of paid and organic search results. Their empirical analyses suggest on a firm level that click-through on organic search results has positive interdependencies with click-through on paid search results, and vice versa. With a field experiment, they furthermore show that the combination of an organic and paid search result leads to significantly higher CTR, conversion rate, and revenues than would be the case for only an organic result. Additional Bayesian analyses reveal that rank significantly and

Independent Variable	***Source(s)***
1. Keyword characteristics	
1.1 Branded keyword	**(5), (7), (10), (14), (19), (20)**
1.2 Generic keyword	**(14), (20)**
1.3 Keyword itself	**(3), (5)**
1.4 Length	**(6), (7), (10), (12), (15)**
1.5 Location information (city)	**(5)**
1.6 Match type	**(20)**
1.7 Rank, position, order	**(3), (5), (6), (14), (15), (16), (18), (20)**
1.8 Retailer specific keyword	**(7), (10), (14)**
2. Market characteristics	
2.1 Competitive intensity, advertiser competition	**(18), (20)**
2.2 Differentiation strategy	**(18)**
2.3 Unique selling proposition	**(18)**
3. Performance indicators	
3.1 Cost per click (CPC)	**(10)**
3.2 Landing page quality	**(10)**
3.3 Paid click-through rate (CTR)	**(5), (10)**
3.4 Search volume	**(19)**
4. User characteristics / behavior	
4.1 Search behavior	
4.1.1 Branded search behavior	**(19)**
4.1.2 Generic search behavior	**(19)**
4.1.3 Informational search queries	**(11)**
4.1.4 Internet search skill	**(13)**
4.1.5 Navigational search queries	**(11)**
4.1.6 Number of interactions with search engine	**(12)**
4.1.7 Search experience	**(3)**
4.1.8 Time of first query	**(12)**
4.1.9 Transactional search queries	**(11)**
4.2 Click behavior	
4.2.1 Number of organic clicks	**(12)**
4.2.2 Sum of rank	**(12)**
4.2.3 Time span after click	**(14)**

(Continued on next page)

Independent Variable	*Source(s)*
User characteristics / behavior (cont.)	
4.3 Attitudinal and behavioral measures	
4.3.1 Attitude toward paid link	**(9)**
4.3.2 Information need	**(3)**
4.3.3 Past satisfaction	**(9)**
4.3.4 Self-efficacy (for searching)	**(3), (9)**
4.3.5 Time spent on the Internet	**(12)**
5. SERP characteristics	
5.1 Labeling of paid search	**(11)**
5.2 Organic search results	**(2), (4), (7), (11), (12), (13), (17)**
5.3 Paid search results	**(2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (14), (15), (16), (17), (18), (19), (20)**
5.4 Paid top and paid side result	**(4)**
6. Textual characteristics	
6.1 Call for action	**(20)**
6.2 Keyword in title	**(20)**
6.3 Number of words in body	**(20)**
6.4 Number of words in headline	**(20)**
7. Miscellaneous characteristics	
7.1 Advertiser bidding behavior	**(10)**
7.2 Brand (known versus unknown)	**(13)**
7.3 Browser type	**(12)**
7.4 Different search engine types	**(2)**
7.5 Price of the advertised product	**(20)**
7.6 Time	**(10), (14)**

Notes: a. The numerical labels of the source(s) in the second column correspond to the serial numeration of each publication in the first column of Table 10.
b. If an empirical study examines multiple independent variables, the numerical label is assigned to each independent variable.

Table 11: Categorization of Independent Variables in Empirical Studies on Search Engine Marketing

Dependent Variables	*Source(s)*
1. Performance indicators	
1.1 Click-through rate (CTR) organic	**(17), (11)**
1.2 Click-through rate (CTR) paid	**(4), (10), (11), (15), (16), (17), (20)**
1.3 Conversion rate (CR) organic	**(7), (17)**
1.4 Conversion rate (CR) paid	**(5), (7), (10), (17), (20)**
1.5 Cost per click (CPC)	**(10)**
1.6 Customer lifetime value (CLV)	**(8)**
1.7 Order volume organic	**(7)**
1.8 Order volume paid	**(7), (10)**
1.9 Profit organic	**(7)**
1.10 Profit paid	**(6), (7), (10)**
1.11 Rank paid	**(10)**
1.12 Revenue organic	**(17)**
1.13 Revenue paid	**(6)**
2. User behavior	
2.1 Awareness	**(19)**
2.2 Behavioral intention (click, re-click)	**(9)**
2.3 Branded search behavior	**(19)**
2.4 Brand perception and recognition	**(13)**
2.5 Conversion likelihood (paid)	**(14)**
2.6 Cross and within search category purchase	**(14)**
2.7 Future click-through behavior on SERP	**(12)**
2.8 Generic search behavior	**(19)**
2.9 Organic search result evaluation	**(3)**
2.10 Organic search result viewing	**(3)**
2.11 Paid search result evaluation	**(3)**
2.12 Paid search result viewing	**(3)**
2.13 Relevance	**(2), (4)**

Notes: a. The numerical labels of the source(s) in column two correspond to the serial numeration of each publication in the first column of Table 10.
b. If an empirical study examines multiple dependent variables, the numerical label is assigned to each dependent variable.

Table 12: Categorization of Dependent Variables in Empirical Studies on Search Engine Marketing

negatively affects *paid CTR*. Measures such as retailer- or brand-specific keyword, length of the keyword, and time do not significantly affect paid CTR.[61] In contrast for estimations of *organic CTR*, rank and retailer- or brand-specific keywords and length have significant effects, though time still does not have a significant impact on CTR.[62] Bayesian estimations of *paid conversions* reveal positive and statistically significant impacts of CTR and retailer-specific keywords. Rank, brand, length, and time influence paid conversions insignificantly but negatively. Estimating *organic conversions,* Yang and Ghose (2010) disclose significant effects for rank and brand-specific keywords but non-significant effects for CTR, retailer-specific keywords, length, and time.[63]

Other empirical studies with performance indicators as dependent variables combine click-through and conversion reflections only to a limited extend with paid and organic search results. Authors, such as Animesh, Viswanathan, and Agarwal (2011), Ji, Rui, and Hansheng (2010), and Park and Park (2010) focus their empirical investigations on *paid click-through* behavior only. Ghose and Yang (2009) and Rutz and Trusov (2011) establish their analysis on *paid conversion rates*. Moreover, the empirical work by Rutz and Bucklin (2007) concentrates on *paid conversion rate*, complemented by *organic conversion rate* in Ghose and Yang (2008). These studies will be outlined next.

Animesh, Viswanathan, and Agarwal (2011) investigate the impact of differentiation strategy,[64] position of the ad (rank), and competitive intensity on *paid CTR*. The authors can demonstrate that different keywords (N = 36) and higher positions (rank) in the sponsored links have significant impacts on paid CTR. Even more, they can show that the impact of the unique selling proposition and rank is moderated by a differentiation strategy.[65] Park and Park (2010) develop and validate a model for consumer navigational paid search behavior. The results of the model validation show that consumer click behavior (*paid CTR*) strongly depends on the order and composition of the paid search results. Ji, Rui, and Hansheng (2010) investigate the impact of certain keyword characteristics, such as rank and length of

61 For paid CTR, the estimates are negative for retailer-specific keywords, keyword length, and time. The estimate of the coefficient brand-specific keyword is positive (Yang and Ghose 2010).

62 For organic CTR, the estimates are negative for rank and retailer-specific keyword. The estimates are positive for brand-specific keyword, length, and time (Yang and Ghose 2010).

63 The coefficients of rank, click-through rate, retailer, length, and time are negative. Only the coefficient for brand-specific keyword is positive (Yang and Ghose 2010).

64 Animesh, Viswanathan, and Agarwal (2011) distinguish price and quality differentiation strategies.

65 A unique selling proposition (USP), competitive intensity of the USP employed by the corresponding seller, and the interaction USP×competitive intensity do not significantly affect paid CTR. The interactions of rank×USP (positive estimate), competitive intensity×rank (positive estimate), and the three-way interaction of competitive intensity×rank×USP (negative estimate) significantly affect paid CTR (Animesh, Viswanathan, and Agarwal 2011).

the keyword on *paid CTR* and find that the ranking of the paid search results non-linearly affects CTR. The highest paid CTR is gained with average ranks between 1.5 and 2.5, followed by average positions between 1 and 1.5. Average positions higher than 2.5 gain the lowest paid CTR. Furthermore, Ji, Rui, and Hansheng (2010) can show that the length (number of characters) of the entered keyword significantly negatively affects CTR.

Ghose and Yang (2009) explore the two performance indicators, *paid CTR* and *paid conversion rate*, complemented with other performance indicators such as *rank* and *cost per click* as dependent variables. Using Markov chain Monte Carlo (MCMC) methods, the main results reveal significant effects of brand- and retailer-specific keywords, length, rank, and time on *paid CTR*.[66] The estimation results mostly persist for *paid conversion rate* predictions, though length is no longer a statistically significant coefficient, and landing page quality positively and significantly affects paid conversion rate.

In another empirical study with performance indicators as dependent variables, Rutz and Trusov (2011) develop and empirically estimate a two-tier consumer-level model. The authors analyze paid search advertising responses with keyword- and consumer-level data on a single product, single firm level. They evaluate the impact of ad position (rank) and textual details on paid CTR and conversion rate. Rutz and Trusov (2011) can show that consumer *paid CTR* is significantly influenced by keyword-specific factors such as match type (negative) and the brand (positive). The competitive environment with position of the ad (negative), advertiser competition (negative), and search volume (negative) also significantly affects paid CTR. Textual properties,[67] such as keyword in the title (positive), call for action (positive), and number of words in the headline (negative) and body (negative), are significant predictors of paid CTR. *Conversion rate* (second-tier) is significantly affected by match type (negative), branded keyword characteristics (positive), and price of the advertised product (negative).

Rutz and Bucklin (2007) show that *paid conversion rate* estimations improve significantly when covariates such as position and CTR on a keyword level, and keyword characteristics such as branded search term, U.S. state, city, and hotel details are included.[68] Ghose and Yang (2008) also develop and estimate a model to compare predictions of conversion rate,

[66] The effects are positive for retailer-specific keyword and time but negative for brand-specific keywords, length, and rank (Ghose and Yang 2009).
[67] Keywords in the advertising text body and keyword length affect paid CTR negatively but not significantly (Rutz and Trusov 2011).
[68] The influence of keyword position and U.S. state, city, and hotel details negatively impact paid CTR. The only predictors with positive influences are CTR and branded search query (Rutz and Bucklin 2007).

order volume, and profit for organic and paid search results. For *paid conversions*, retailer-specific information positively and statistically significantly affects the prediction.[69] For *organic conversions,* retailer- and brand-specific information and length are significant predictors.[70]

Closely connected to CTR and conversion rate are investigations of *order volume*, *profit*, and *revenue*. These performance indicators go beyond CTR and conversion rate, as mainly search behavior–related ratios, in extending product prices, costs, and sales figures to the purchase behavior–related ratios. Ghose and Yang (2008, 2009) are the only authors to combine search and purchase behavior–related performance indicators in their articles. They show that the *profits from paid search advertising* are higher on medium than on top or bottom positions, even though conversion rates on a search engine result page decline with increasing rank on the page. Therefore, higher positioned paid search advertisements lead to higher conversion rates.[71] The *value* of a click, and thus conversion, is higher in top positions, but costs more too (Ghose and Yang 2009).

Ghose and Yang (2008) reveal that retailer-specific keywords (positive) and keyword length (negative) are statistically significant predictors of *paid order volume*.[72] In the case of *organic order volume* prediction, retailer- and brand-specific keywords and length are significant influences.[73] Retailer-specific information in the keyword has a positive and statistically significant impact on *paid profit* prediction. This pattern changes for *organic profit* prediction, when retailer and brand information in the keyword, as well as keyword length, significantly influence profit prediction.

In a further empirical study, Agarwal, Hosanagar, and Smith (2008) introduce paid search placement position (paid rank) as control variable for measuring *paid profit* and supplementary *paid revenue* for an online retailer. The model estimations reveal that conversion rate is inversely U-shaped connected to position, whereas click-through rate decreases with the posi-

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[69] The coefficient estimate for brand is positive, whereas the estimate has a negative sign for length. Neither is significant (Ghose and Yang 2008).

[70] The coefficient estimates of retailer and brand are positive; length has a negative sign (Ghose and Yang 2008).

[71] An analysis on keyword rank by Ghose and Yang (2009) reveals retailer (negative), brand (negative), length (negative), cost per click (negative), prior click-through rate (negative), and time (positive) as significant predictors. Retailer (negative and significant), brand (positive and significant), length (negative and non-significant), landing page quality (negative and significant), prior rank (negative and significant), and time (negative and significant) impact cost per click for paid search advertisements.

[72] Brand-specific information in the keyword has a positive, but not significant, impact on *paid order volume* (Ghose and Yang 2008).

[73] Retailer- and brand-specific information have a positive influence, whereas the sign of the keyword length coefficient is negative (Ghose and Yang 2008).

tion of the paid search. The first paid top position thus is not necessarily the *revenue- or profit-maximizing position*. These findings are similar to those of Ghose and Yang (2009).

In addition, Chan, Xie, and Wu (2009) open a new field of performance measurement in search engine marketing. From an analytical customer relationship approach, they measure the customer lifetime value of clients, acquired through paid search advertising. Their results suggest that investments in paid search advertising lead to positive returns when accounting for offline sales and future repeated purchases.

Table 13 summarizes independent and dependent variables, as displayed in Tables 11 and 12, which are investigated in recent scientific studies on search engine marketing. Central influences with significant effects on *paid CTR* are: advertiser competition (negative), branded keyword (negative; positive), call for action in paid result (positive), keyword length (negative), keyword in paid search title (positive), number of words in paid result title (negative), number of words in paid result text body (negative), match type (negative), organic CTR (positive), rank (negative), retailer-specific keyword (positive), search volume (negative), and time (positive). Branded keyword (positive), length (positive), paid CTR (negative), rank (negative), and retailer-specific keyword (negative) have significant influences on *organic CTR*. The combination of paid and organic search results positively and significantly affects *overall CTR* and *overall conversion rate*. Significant influence on *paid conversion rate* is shown with branded keyword (negative; positive), landing page quality (positive), match type (negative), paid CTR (positive), price of advertised product (negative), rank (positive and negative), retailer-specific keyword (positive), and time (positive). For *organic conversion rate* branded keyword (positive), length (negative), rank (negative), and retailer-specific keyword (positive) have significant influences. These empirical results emphasize the relevance of research questions 1–4 for *Projects II* and *III* because results on the impact of advertiser competition on overall, paid, and organic CTR and paid conversion rate are sparse. This observation stands for knowledge on the effects of message order (whether the search result is displayed as organic, paid top, or paid side result) and double exposure on different types (overall, paid, and organic) of click-through behavior.

Serial Number	Author(s)	Independent Variable(s)							Dependent Variable(s)	
		1. Keyword Characteristics	*2. Market Characteristics*	*3. Performance Indicators*	*4. User Characteristics/ Behavior*	*5. SERP Characteristics*	*6. Textual Characteristics*	*7. Miscellaneous Characteristics*	*1. Performance Indicators*	*2. User Behavior*
(1)	*Sen (2005)*	-	-	-	-	-	-	-	-	-
(2)	*Jansen and Molina (2006)*	-	-	-	-	5.2; 5.3	-	7.4	-	2.13
(3)	*Jansen and Resnick (2006)*	1.7	-	-	4.1.7; 4.3.2; 4.3.4;	5.3	-	-	-	2.9 - 2.12
(4)	*Jansen (2007)*	-	-	-	-	5.2; 5.3; 5.4	-	-	-	2.13
(5)	*Rutz and Bucklin (2007)*	1.1; 1.3; 1.5; 1.7	-	3.3	-	5.3	-	-	1.4	-
(6)	*Agarwal, Hosanagar, and Smith (2008)*	1.4; 1.7	-	-	-	5.3	-	-	1.10; 1.13	-
(7)	*Ghose and Yang (2008)*	1.1; 1.4; 1.8	-	-	-	5.2; 5.3	-	-	1.3; 1.4; 1.7 - 1.10	-
(8)	*Chan, Xie, and Wu (2009)*	-	-	-	-	5.3	-	-	1.6	-
(9)	*Gauzente (2009)*	-	-	-	4.3.1; 4.3.3; 4.3.4	5.3	-	-	-	2.2
(10)	*Ghose and Yang (2009)*	1.1; 1.4; 1.8	-	3.1; 3.2; 3.3	-	5.3	-	7.1; 7.6	1.2; 1.4; 1.5; 1.8; 1.10; 1.11	-

(Continued on next page)

Serial Number	Author(s)	Independent Variable(s)							Dependent Variable(s)	
		1. Keyword Characteristics	*2. Market Characteristics*	*3. Performance Indicators*	*4. User Characteristics/ Behavior*	*5. SERP Characteristics*	*6. Textual Characteristics*	*7. Miscellaneous Characteristics*	*1. Performance Indicators*	*2. User Behavior*
(11)	*Jansen and Spink (2009)*	-	-	-	4.1.3; 4.1.5; 4.1.9	5.1; 5.2; 5.3	-	-	1.1; 1.2	-
(12)	*Zhang, Jansen, and Spink (2009)*	1.4	-	-	4.1.6; 4.1.8; 4.2.1; 4.2.2; 4.3.5	5.2; 5.3	-	7.3	-	2.7
(13)	*Dou et al. (2010)*	-	-	-	4.1.4	5.2	-	7.2	-	2.4
(14)	*Ghose and Yang (2010)*	1.1; 1.2; 1.7; 1.8	-	-	4.2.3	5.3	-	7.6	-	2.5; 2.6
(15)	*Ji, Rui, and Hansheng (2010)*	1.4; 1.7	-	-	-	5.3	-	-	1.2	-
(16)	*Park and Park (2010)*	1.7	-	-	-	5.3	-	-	1.2	-
(17)	*Yang and Ghose (2010)*	-	-	-	-	5.2; 5.3	-	-	1.1; 1.2; 1.3; 1.5; 1.12	-
(18)	*Animesh, Viswanathan, and Agarwal (2011)*	1.3; 1.7	2.1; 2.2; 2.3	-	-	5.3	-	-	1.2	-
(19)	*Rutz and Bucklin (2011)*	1.1	-	3.4	4.1.1; 4.1.2	5.3	-	-	-	2.1; 2.3; 2.8
(20)	*Rutz and Trusov (2011)*	1.1; 1.2; 1.6; 1.7	2.1	-	-	5.3	6.1; 6.2; 6.3; 6.4	-	1.2; 1.4	-

Notes: The numeration (e.g., 1.1, 1.2, 1.3) of the dependent and independent variables in this table aligns with the assignment to the corresponding subcategories in Table 11 and Table 12.

Table 13: Independent and Dependent Variables Applied in Empirical Studies

3 Research Methodology

3.1 Research Framework for Search Engine Marketing

Chapters C/1 and 2 show why search engines such as Google, Yahoo, and Bing are increasingly viable research subjects. Yet, little research considers how consumer click-through behavior is influenced by order effects, double exposure through interaction of paid and organic search results, and different levels of advertiser competition. This lack of research has particular importance because arguments from order effects,[74] mere exposure,[75] and consumer choice[76] literature suggest the need for new theoretical contributions for a deeper understanding of the impact of search engine marketing on consumer behavior. Yang and Ghose (2010) enter this field of research with aggregated consumer response data; their results suggest that click-through on organic search results on a firm level has positive interdependencies with click-through on paid search results, and vice versa. Rutz and Trusov (2011) are the first authors to integrate advertiser competition in modeling and estimating click-through behavior. Their results imply that higher levels of advertiser competition lead to lower CTR, though their finding is associated with two major constraints. First, their estimation results are based on only 80 major keywords for one advertising company. Second, only keywords resulting in high CTR are taken in account. This dissertation project aims to fill these gaps and contribute to a better understanding of the effects of order, double exposure, and advertiser competition.

To investigate the consequences of companies' search engine marketing activities on consumer behavior, I apply a two-tiered approach. First, the focus of *Project II* in *Chapter C*/4 examines research question 1 ("*How does advertiser competition affect click-through behavior?*") and research question 2 ("*How does advertiser competition affect conversion behavior?*"). This investigation raises the issue of how advertiser competition, a market characteristic (see Table 11), influences consumer click-through and conversion behavior. The influence of a market characteristic on user behavior is depicted as the arrow between advertiser competition and click-through and conversion behavior in Figure 28.

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[74] Order effects in this dissertation refer to the primacy–recency paradigm by Hovland and Mandell (1957) and specify the placement of search results on a search engine result page in paid top, paid side, or organic results (see *Chapter C*/5.3.1).

[75] The mere exposure effect, based on Zajonc (1968), generally means that "an individual is repeatedly exposed to a particular stimulus" (Zajonc 2001, p. 224; see *Chapter C*/5.3.2).

[76] Literature on consumer choice explains how consumers choose or purchase products when the assortment of similar products or choices is larger or smaller (e.g., Rolls et al. 1981; Iyengar and Lepper 2000; see *Chapter C*/4.1.2 and 4.1.3).

Second, the focus in *Project III* in *Chapter C*/5 centers on the proposed research question 3 ("*How does message order affect click-through behavior?)* and research question 4 ("*How does double exposure via simultaneous display of paid and organic search results affect click-through behavior?"*). Consequently, I control for whether the message order position (keyword characteristic; Table 11) significantly affects click-through behavior, as depicted in the connection between order effects and click-through behavior in Figure 28. Furthermore, I analyze if double exposure through simultaneous display of paid and organic search result significantly affects click-through behavior. This connection is displayed in Figure 28 with the arrow between double exposure (SERP characteristic see Table 11) and click-through behavior.

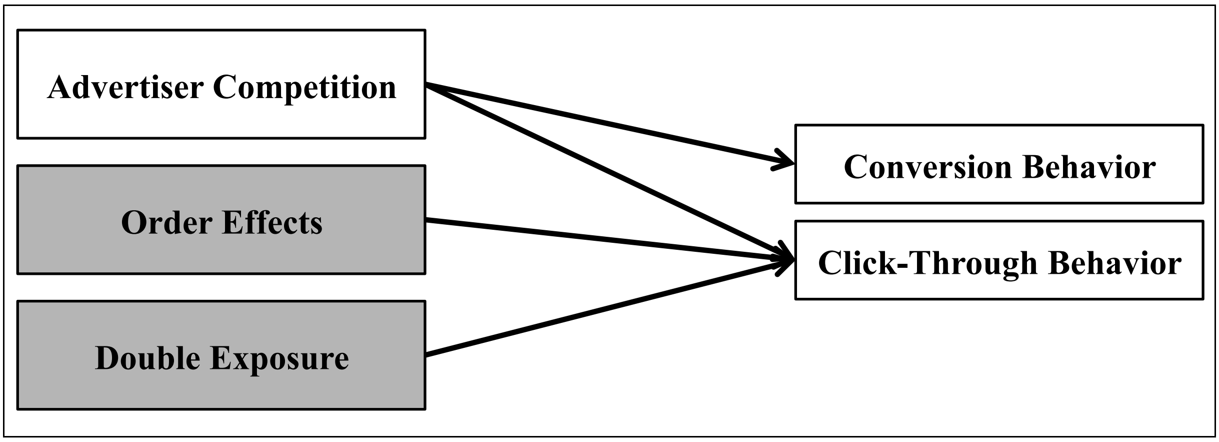

Figure 28: Research Model for Studying the Impact of Search Engine Marketing on Click-through Behavior (Projects II and III)

To deepen understanding in the broad research field of search engine marketing and to address the lack of applicability of academic marketing research to marketing decision making (e.g., Reibstein, Day, and Wind 2009), the general research design mixes observational and quantitative methods (e.g., Fielding and Fielding 1986). This approach is known as mixed-methods research, which aims to "form a more complete picture of the problem" (Creswell and Plano Clark 2007, p. 7). A mixed-methods research design enables the in-depth description and generalization of the phenomenon of search engine marketing (Huff 2009). Therefore, I use mixed-methods research designs in *Project II* and *III*. The goal of *Project II* is to examine the impact of advertiser competition on Internet users' click-through and conversion behavior. Thus the applied empirical research design combines data from an experimental investigation with secondary data from large European multichannel retailers (see Figure 29).

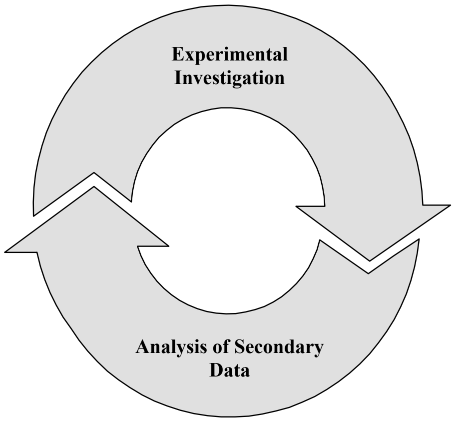

Figure 29: Mixed-method Research Design (Project II)

Project III sheds light on the widely unexplored impact of order and exposure effects on click-through behavior. Thus, the applied empirical research design mixes an observational study with two experimental investigations for causal inferences. Figure 30 displays the stepwise procedure for *Project III*.

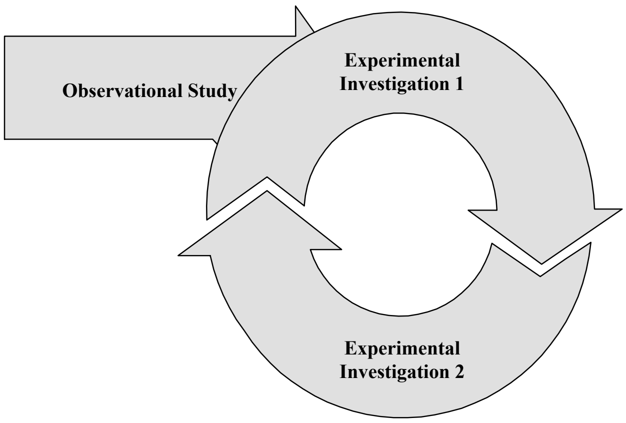

Figure 30: Mixed-method Research Design (Project III)

In *Chapters C*/3.2 and *C*/3.3, I introduce the two tiers of the applied mixed-methods research design. The observational research methodology is illustrated in *Chapter C*/3.2. A quantitative approach with experimental and secondary company data is further explained in *Chapter C*/3.3.

3.2 Observational Research Methodology

The mixed-method study of *Project III* uses screen recording and think-aloud protocol as observational methods to reveal the underlying patterns of how consumer click-through behavior is influenced by search engine marketing. Van Someren, Bernard, and Sandberg

(1994, p. 30) define the think-aloud method as an objective approach that "avoids interpretation by the subject and only assumes a very simple verbalization process." According to Ericsson and Simon (1993) and van Someren, Bernard, and Sandberg (1994), objectivity results from this combined approach, because the verbal data that support this observational methodology are accessible pure, and free of researchers' direct influences. The main goal of analyzing verbal reports as data is to draw inferences about human information processing (Ericsson and Simon 1980). In addition, data from screen recording are also free from external influences, except those resulting from human–computer interactions.

This observational research approach, which combines the recording of search and click-through behavior with the verbalization of the reasons for subjects' recorded behavior, is advantageous for two main reasons. First, from a technical perspective, the protocol data from the think-aloud method are structured according to the screened human–computer interactions, because the verbalizations of the subjects transform their underlying cognition during search task performance. In particular, this can help form an integrated picture of direct observations from user–search engine interactions with additional inferences about cognitive processes (Ericsson and Simon 1980; Benbunan-Fich 2001). Second, the methodological focus guarantees validity and credibility for the observational investigations (Corbin and Strauss 2008; Mitchell and Jolley 2010). In the observational study in *Chapter C*/5.2, the research subjects conduct real search tasks with think-aloud protocols and screen recording, alternating with real search tasks with screen recordings only. Therefore, the influence of the think-aloud protocol on their search behavior is controlled.

To analyze the observational material, I apply a combination of a qualitative content analysis methodology (Kassarjian 1977; Mayring 2002), enriched with statistics of click patterns from pure observation. In a summary qualitative content analysis, according to Mayring (2002), verbal data are analyzed in five steps: determination of the abstraction level and generalization of the statements; reduction of synonym statements; reduction by integrating the reduced statements at the determined abstraction level; compilation of the reduced and integrated statements to categories; and reviewing of the categories with the original data. In contrast with traditional summary qualitative content analysis (Mayring 2002), the final categories are relevant for subsuming the original statements in this inductive approach. Therefore, not only is the category system itself central in this observational research design, but the combination of categories, statements, and observed search, and click-through behavior are key as well.

3.3 Quantitative Research Methodology

The applied quantitative approaches aim to achieve a robust descriptions and interpretations in a mixed-method inquiry (Huff 2009). This research design applies two main sources of quantitative data: primary data collected with two major experimental designs and secondary data from large company databases.

In recent years, experimental designs have become among the most often used quantitative approaches in marketing research. Eschweiler, Evanschitzky, and Woisetschläger (2007) show that of 1,314 articles published in *Journal of Marketing*, *Journal of Marketing Research*, and *Journal of Consumer Research* from 1996 to 2006, 39.35% applied experimental designs. Experiments are becoming increasingly popular, because the causal relationship between a cause or treatment and the effect can be exposed (Shadish, Cook, and Campbell 2002). Experimental studies to investigate the effects of double exposure through simultaneously displayed paid and organic search results, as well as order effects and advertiser competition on click-through behavior, offer three main advantages: control of the stimuli, control of the positions, and traceability of the clicks on the search engine result page.

However, experimental designs for causal inferences and methodologies of survey research are prone to common method variance (CMV), a critical source of potential problems in behavioral research that causes measurement error and leads to incorrect or ambiguous conclusions (e.g., Campbell and Fiske 1959; Bagozzi and Yi 1991; Podsakoff et al. 2003). These measurement errors encompass random and systematic components[77] (e.g., Nunnally and Bernstein 1978; Fiske 1982). As a main driver of systematic measurement error, CMV is defined as "variance that is attributable to the measurement method rather than to the constructs the measures represent" (Podsakoff et al. 2003, p. 879) and can occur for a variety of reasons.[78] Although experimental designs are not generally unaffected by or immune to common method bias (see Podsakoff et al. 2003), experimental studies measuring independent and dependent variable from different sources remain unaffected. Therefore, the experimental settings in *Project II* and *Project III* of this thesis should not be affected by common method bias, and no further examinations of common method bias are conducted.

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[77] Random error components can hide statistically observed relationships between variables (Bagozzi and Yi 1991). Systematic measurement error, such as method variance (Bagozzi and Yi 1991), "is a particularly serious problem because it provides an alternative explanation for the observed relationship between measures of different constructs that is independent of the one hypothesized" (Podsakoff et al. 2003, p. 879).

[78] Podsakoff et al. (2003, pp. 881-885) cite four main potential sources of common method bias: common rater effects, item characteristic effects, item context effects, and measurement context effects.

Internal and external validity are substantial for drawing inferences in experimental research (Shadish, Cook, and Campbell 2002). Campbell (1957) poses two key questions to delimit internal and external validity and thus secure inferences from experimental research. With internal validity, he associates the question: “Did in fact the experimental stimulus make some significant difference in this specific instance?” (Campbell 1957, p. 289). In contrast, he associates external validity with the question: “To what populations, settings, and variables can this effect be generalized?” (Campbell 1957, p. 289). To achieve high internal and external validity, the manipulations in the experimental studies for this thesis were performed on original search engine result pages with relevant keywords. To ensure realistic conditions, the participants were invited to conduct experimental studies on a personal computer of their preference—a realistic condition for everyday search tasks. The guiding principles for preventing common method bias (Lindell and Whitney 2001; Podsakoff et al. 2003; Rindfleisch et al. 2008) thus have been followed in this thesis. The combination of experimental with secondary company data in *Project II* further support these efforts and enhance the robustness of the empirical results from theory testing in the experiments (e.g., Wagner, Hennig-Thurau, and Rudolph 2009).

3.4 Measurement of Latent Variables in Experimental Research

3.4.1 Construct Validity

In many fields of research in marketing, difficult-to-operationalize constructs cause that securing “of construct validity lies at the very heart of scientific progress in marketing” (Steenkamp and van Trijp 1991, p. 283). To assess construct validity, reliability and validity are central components of the measurement quality of complex constructs (Homburg and Giering 1996).

Construct validity emphasizes the importance of the components’ reliability and validity for construct measurement, defined as the degree to which a certain scientific construct achieves empirical and theoretical meaning (see Peter 1981). Reliability describes “the degree to which measures are free from random error and thus reliability coefficients estimate the amount of systematic variance in a measure” (Peter and Churchill 1986, p. 4). Construct validity exists “when the differences in observed scores reflect true differences on the characteristic one is attempting to measure” (Churchill 1979, p. 65). Overall, construct validity contains four subtypes: content, convergent, discriminant, and nomological validity (e.g., Peter 1981; Homburg and Giering 1996). Content validity focuses on contextual and semantic consensus among all variables or items in a measurement model and the construct to which they belong (see Bohrnstedt 1970). Convergent validity is existent if several efforts to measure one concept correspond (Bagozzi and Phillips 1982), such that there is high “correlation between responses obtained by maximally different methods of measuring the same construct” (Peter 1981, p. 136). The third subtype, discriminant validity, indicates that when a construct is not highly correlated to another construct, it should be delimitable from it (Campbell and Fiske 1959; Campbell 1960). The last subtype, nomological validity, “represents the degree to which predictions based on a concept are confirmed within the context of a larger theory” (Bagozzi 1979, p. 14). Assuming that a construct complies with the four types of validity, the validity of the construct measurement is confirmed (see Homburg and Giering 1996).

3.4.2 Analysis of Reliability and Validity

Before starting exploratory[79] or confirmatory factor analyses[80] (first- and second-generation analyses for reliability and validity), it is necessary to examine the suitability of the data for factor analysis. Therefore, Bartlett’s test of sphericity investigates the null hypothesis (H_0) that all correlations of the correlation matrix are equal to zero. If the null hypothesis is rejected, all correlations of the correlation matrix are above zero (see Bühner 2005; Janssens et al. 2008). A second basic requirement before the factor analysis applies the Kaiser-Meyer-Olkin coefficient (Kaiser 1970). Finally, the measures of sample adequacy (MSA) are inspected visually according to an anti-image correlation matrix (see Burgers et al. 2000).[81] If test criteria fulfill the inclusion levels (Table 14) of Bartlett’s test of sphericity, Kaiser-Meyer-Olkin, and measure of sample adequacy, they indicate that exploratory factor analysis is reasonable and can be applied to test first-generation reliability and validity.

[79] “Exploratory factor analysis (EFA) is designed for the situation where links between the observed and the latent variables are unknown or uncertain. The analysis thus proceeds in an exploratory mode to determine how and to what extent the observed variables are linked to their underlying factor” (Byrne 2001, p. 5).

[80] “[C]onfirmatory factor analysis (CFA) is appropriately used when the researcher has some knowledge of the underlying latent variable structure. Based on knowledge of the theory, empirical research, or both, he or she postulates relations between the observed measures and the underlying factors a priori and then tests this hypothesized structure statistically” (Byrne 2001, p. 6).

[81] A further basic requirement is testing for multicollinearity (see Haitovsky 1969). Because I conduct principal component analysis, multicollinearity is not relevant (Field 2009, p. 658).

Criterion	Inclusion level	Source
Bartlett's test of sphericity	$p < .05$	Field 2009, p. 660
Kaiser-Meyer-Olkin	KMO ≥ .50	Kaiser 1974, p. 35
Measure of sample adequacy	(1) MSA ≥ .30 (2) MSA ≥ .50 (3) MSA ≥ .60	(1) Burgers et al. 2000, p. 151 (2) Janssens et al. 2008, p. 256 (3) Bühner 2005, p. 210

Table 14: Criteria for Factor Analysis

To test the reliability and validity of the measurement models, both first- and second-generation criteria should be analyzed (Homburg and Giering 1996). As steps for a first-generation analysis of reliability and validity, Homburg and Giering (1996) suggest exploratory factor analysis (with measures such as communality and explained variance of the observed variables), Cronbach's alpha, and item-to-total correlation. Prior literature offers a wide range of inclusion levels for these measures. Table 15 summarizes the inclusion levels applied in this research project.

Criterion	Inclusion level	Source
Communality	$h^2 \geq .40$	Homburg and Giering 1996, p. 8
Cronbach's alpha	$\alpha \geq .70$	Nunnally and Bernstein 1978, p. 245
Explained variance	EV ≥ 50%	Merenda 1997, p. 158
Item-to-total correlation	(1) I-t-t ≥ .40; (2) I-t-t ≥ .50	(1) Bagozzi and Baumgartner 1994; (2) Zaichkowsky 1985, p. 343; Bearden, Netemeyer, and Teel 1989, p. 475

Table 15: Statistical Criteria for First-Generation Measurement Evaluation

The measurement of the latent variables in this thesis does not aim to develop or test structural equation models. In contrast, I attempt to obtain control variables that better explain observed behavior. Thus, first-generation tests for measurement reliability and validity are adequate, whereas second-generation reliability and validity tests are not necessary and not reported (e.g., Byrne 2010; Hair et al. 2010).[82]

[82] For second-generation reliability and validity tests, the results of a confirmatory factor analysis (CFA) are considered. This special form of causal analysis is applied to evaluate how good the data fit a predefined factor model. Therefore, "a factor structure is explicitly hypothesized and is tested for its fit with the observed covariance structure of the measured variables" (Floyd and Widaman 1995, p. 287). In general, confirmatory factor analysis outperforms exploratory factor analysis according to the restrictions of Cronbach's α and the criteria for evaluating validity with inferential statistics (e.g., Gerbing and Anderson 1988; Homburg and Giering 1996).

4 Project II: When Choice Overload is No Bad Thing—How Advertiser Competition Affects Click-Through Behavior and Conversion in Search Engines

With an estimated market size of USD 23.5 billion, paid search advertising has become a main tool in companies' marketing mix (Google 2009; comScore 2010).[83] In addition to pay-per-click billing, advantages in traffic quality, measurability, and accountability are reasons for the expansion of retailers' search engine marketing activities (e.g., Bughin, Shenkan, and Singer 2008; Bughin et al. 2011). Moreover, the central role of search engines in consumer information retrieval and purchase decision making (e.g., Peterson and Merino 2003; Xu and Kim 2008) also motivates companies' desire to appear at the top in both organic and paid listings on search engine result pages (SERPs). This is because higher paid or organic search results serve as a signal of relevance from a consumer perspective (Jansen 2007), attract higher click-through rates (e.g., Ji, Rui, and Hansheng 2010; Animesh, Viswanathan, and Agarwal 2011), and thus are more likely to convert into purchase (Ghose and Yang 2010).

In recent years, search engines have become a central field in management (e.g., Laffey 2007; Abraham 2008; Brooks and Magun 2008) and research-oriented (e.g., Rangaswamy, Giles, and Seres 2009; Rutz and Bucklin 2011) publications. Nevertheless, extant literature has focused on paid (Ghose and Yang 2009; Ji, Rui, and Hansheng 2010; Rutz and Bucklin 2011; Rutz and Trusov 2011) rather than organic (Dou et al. 2010) search results or the interdependencies between these two distinct result types (Ghose and Yang 2008; Yang and Ghose 2010). In addition to these perspectives, a differentiation between organic and paid click-through and conversion rates is obvious and necessary. Nevertheless, little research, other than the seminal work of Yang and Ghose (2010), has applied a combined approach for investigating the interdependencies between paid and organic search results. Such a combined approach is essential because companies' efforts to obtain higher listings in search results are not limited to paid results. In most cases, companies put forth efforts to appear in both paid and organic listings because the interdependencies between these search results promise a positive impact on click-through rates (Yang and Ghose 2010).

These efforts for obtaining higher listings in the search results are leading to a competitive environment between the advertising companies. Albeit competition is a central general component for the success, little research in search engine marketing addresses this topic. Although, Yang and Ghose (2010) also suggest that details on the competition between ad-

[83] Own calculation of the pay-per-click fees in search engines environment, based on 2009 annual report of Google (Google 2009) and comScore (2010).

vertisers can provide further insights into the explanation of search engine users' click-through behavior, to the best of my knowledge, only the work of Rutz and Trusov (2011) is a first attempt to integrate the aspect of advertiser competition to explain click-through behavior.[84] Their findings suggest that click-through rate is lower in a more competitive environment.

By applying a research setting with experimental data from a controlled online experiment as well as field data from five leading European retailers, I shed further light on this issue by investigating the impact of advertiser competition on overall, organic, and paid click-through behavior and on paid conversion behavior (see Figure 31). I pay special attention to the effect of advertiser competition, as a predictor of possible choice overload, on consumer click-through and conversion behavior. This study (*Project II*) can help services managers, retailing managers, or marketing managers in general better understand how choice overload measured with a readily accessible metric (i.e., advertiser competition) influences overall, organic, and paid click-through and paid conversion behavior.

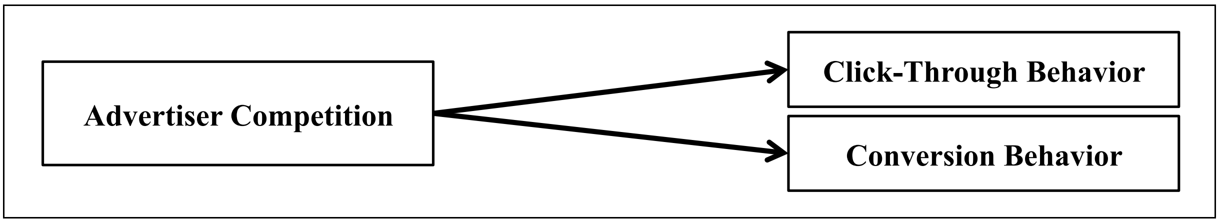

Figure 31: Research Model (Project II)

The study proceeds as follows: First, I introduce the conceptual background of search engine marketing. Second, I establish the theoretical basis to derive hypotheses on the impact of advertiser competition on click-through and conversion. Third, I test the hypotheses in a controlled online experiment and with proprietary company data from five European retailers advertising on Google. Finally, I conclude with a discussion of the implications of the results for further research and management.

[84] Google measures advertiser competition of a keyword on a metric scale from 0 to 1, where 0 is the lowest level. The level of advertiser competition defines the number of advertisers bidding on the keyword relative to all other keywords on Google during a period of 12-month (see Google 2011b; Rutz and Trusov 2011).

4.1 Conceptual and Theoretical Basis

4.1.1 Search Engine Marketing

In *Chapter C*/2 on the fundamentals of search engine marketing, I already introduced an extensive summary on search engine marketing. At this point of *Project II*, I will highlight the most central research findings for this project.

Research on search engine marketing emphasizes the relevance of click-through and conversion predictions. In this respect, not only keyword-specific factors (e.g., match type, branded keywords, retailer-specific keywords, length) but also the competitive environment and interdependencies between paid and organic search results are main predictors for future click and purchase behavior. As such, Rutz and Trusov (2011) develop and empirically estimate a two-tier consumer-level model to analyze paid search advertising response. They evaluate the impact of ad position and textual details on paid click-through and conversion rates. They show that consumer paid click-through rates is significantly influenced by keyword-specific factors, such as match type and brand. The competitive environment, including position of the ad, advertiser competition, and search volume, also significantly affects paid click-through rates. In addition, textual properties, such as keyword in the title, call for action, and number of words in the headline and body, are significant predictors of paid click-through rates. Conversely, match type, branded keyword characteristics, and price of the advertised product significantly affect conversion rates (second tier). Furthermore, Ghose and Yang (2009) show significant effects of brand- and retailer-specific keywords, length, rank, and time on paid click-through rates. These estimation results mostly endure for paid conversion rate predictions, with the distinction that length is no longer a statistically significant coefficient and landing page quality positively and significantly affects paid conversion rates.

Integrating paid and organic results, Yang and Ghose (2010) model and estimate the interrelationships between these two distinct types of results on organic and paid click-through and conversion rates. Their analyses suggest that on a firm level, click-through on organic search results has positive interdependencies with click-through on paid search results, and vice versa. With the results from a field experiment, the authors further show that the combination of an organic and paid search result leads to significantly higher click-through rates, conversion rates, and revenues than when only an organic result is listed.

These insights from empirical estimation and empirical research in the field of search engine marketing suggest the need for deeper concentration on the distinct types of click-through behavior and a focus on the effect of advertiser competition. In addition, the integration of conversion behavior is central even though analyzing records of consumer search engine interactions cannot reveal all relevant drivers of purchase intent.

4.1.2 Advertiser Competition and Consumer Choice in Search Engine Marketing

Competition is a central determinant of a company's performance (e.g., Weitz 1985; Hunt and Morgan 1995; Wang, Chen, and Wu 2011); however, the effect of competition between advertisers for scarce attention of potential customers on search engines is still widely neglected. In the current context, advertiser competition is relevant for both paid and organic search results (Rutz and Trusov 2011).

For companies to achieve higher paid positions, the absolute amount of the companies' bid itself and certain quality factors (e.g., relevance of the ad text for consumer search, relevance of the keyword) play a central role (see Katona and Sarvary 2010). Companies' efforts to realize high listings in paid search results lead to two interconnected outcomes: First, bidding on keywords for paid search advertising influences advertiser competition (Rutz and Trusov 2011), and second, a higher level of competition between advertisers on popular keywords leads to higher bids and assimilation of ad texts across companies to achieve better-quality factors. These outcomes tend to cause similar ad texts and, thus, choice overload.

However, search volume and, so, attractiveness of the different keywords, as indicated by advertiser competition, heavily influence optimization strategies for organic listings (e.g., Rutz and Trusov 2011). The more attractive and, thus, competitive a keyword is, the more difficult it is and the longer it takes to achieve top-listed organic search results. As in the case of paid search, the competition between companies to achieve better query factors for organic listings (e.g., congruence between the entered keywords and the displayed terms in the search result, title, and text body; see Moran and Hunt 2009) results in an assimilation of the organic results as well. This again affects choice overload and complicates consumer choice.

4.1.3 Hypothesis Development

Search engine result pages for certain keywords offer a variety of information and a large number of choices for navigational, informational, and transactional user activities depending on the level of advertiser competition. Consequently, the evaluation of paid and organic search results complicates with higher levels of competition between advertisers. These contact points between advertiser competition and organic and paid search results suggest a theoretical foundation of the effect of advertiser competition on consumer behavior based on the literature of consumer choice. The focus in consumer choice literature is on how consumers choose or purchase products when the assortment of similar products or choices is larger or smaller (e.g., Rolls et al. 1981; Iyengar and Lepper 2000). In the field of SERPs, the assortment of similar results enlarges with an increase in competition among advertisers for higher listings of organic and paid search results.[85]

Conventional wisdom suggests that the more alternatives consumers have to make their choice, the more they can benefit. This is consistent with economic theory and statistical sampling (e.g., Scheibehenne and Todd 2009; White and Hoffrage 2009). From this point of view "larger assortments should always be beneficial for consumers because they provide a potentially better match between consumers' own preferences and the product offering" (Chernev 2003, p. 170). Research by Zuckerman et al. (1978) and Kahn and Wansink (2004) supports these empirical findings. However, other research in psychology and marketing proves otherwise that an overload of choice or information can reduce the likelihood of a choice even being made (e.g., Malhotra 1982; Keller and Staelin 1987; Greenleaf and Lehmann 1995; Dhar 1997; Simonson 1999). Iyengar and Lepper (2000) show that consumers are more likely to buy a certain jam or chocolate and to choose topics for extra class assignments when a limited number of choice options are available rather than a larger number. Similarly, Boatwright and Nunes (2001) prove that reducing assortments can increase sales in reduced categories. Shah and Wolford (2007) combine these two conflicting perspectives of the positive and negative effects of larger assortments and show that buying behavior is a curvilinear function of the number of choices. Their results suggest that more choice does not automatically result in fewer purchases.

Whether or not more competition on search engine result pages leads to more or less choice has not been investigated empirically, but in the context of search engines, arguments exist for a curvilinear effect of advertiser competition on click-through and conversion behavior. In cases of low advertiser competition, only few organic and paid results are relevant to the entered search term, and thus the assortment is small. As a result, the click-through and conversion rates for the few relevant results might be high, whereas the irrelevant results receive almost no click-through. For medium levels of advertiser competition, consumers are faced with both relevant and more or less irrelevant results. Because distinguishing between the

[85] I verified this linkage between advertiser competition and textual characteristic of the search results in several discussions with four managers of a national and an international online marketing agency.

relevant and the irrelevant results is more difficult with medium levels than low levels of advertiser competition, some click or purchase decisions might result in no choice. Therefore, the click-through and conversion rates for relevant links decrease. Conversely, for high levels of advertiser competition, both organic and paid search results are highly relevant. Accordingly, the number of no-choice decisions decreases again. Thus, the number of click-through and, at a subsequent stage, the conversion rate increase compared with medium levels of advertiser competition. This combined perspective helps explain the impact of advertiser competition on click-through and conversion rates. Consequently, I predict the following:

Hypothesis 1 (H1):	*The relationship between increasing levels of advertiser competition and (a) overall, (b) organic, and (c) paid click-through rates is U-shaped.*

Relevant to *H1* is the question whether the U-shaped influence of advertiser competition also leads to second-tier conversion behavior. Ghose and Yang (2009) show that the relationship between click-through and conversion rates is mostly congruent, and thus I assume the same underlying effect of advertiser competition on conversion rates as I do for click-through rates:

Hypothesis 2 (H2):	*The relationship between increasing levels of advertiser competition and conversion rate is U-shaped.*

Investigating the influence of advertiser competition on consumer click-through, I view choice overload as a possible driver of simple click-through decision heuristics and conversion behavior. With steadily increasing assortments, companies try to satisfy consumers' need for more variety (Kahn 1995). Because consumers must choose among this larger number of assortments, their cognitive efforts tend to be high (e.g., Mogilner, Rudnick, and Iyengar 2008; Reutskaja and Hogarth 2009); thus, to reduce the associated search costs, they apply simple decision strategies (e.g., Anderson, Taylor, and Holloway 1966; Gigerenzer, Todd, and ABC Research Group 1999). Among these strategies are decisions for the first option exceeding the aspired level (Simon 1955) or consideration set decisions in which search costs and expected outcomes are balanced (Hauser and Wernerfelt 1990), which are taken into account. Such decision strategies serve as possible decision moderators when there is choice overload (Scheibehenne, Greifeneder, and Todd 2010). As such, both strategies (first option exceeding aspired level and consideration set) suggest that consumers prefer higher ranked paid search results with increasing levels of advertiser competition.

In short, I assume that for higher levels of advertiser competition, in which choice overload is more likely, consumers reduce their search costs or cognitive effort by selecting higher-ranked search results. I express this moderating hypothesis as follows:

Hypothesis 3 (H3):	*Consumers' preferences for higher-ranked search results are enhanced with increasing levels of advertiser competition.*

For testing the hypotheses in *Project II*, I analyze experimental and secondary company data. In the experimental study the theory is tested in an isolated way. Then, the relevance of these results is verified in the descriptive research design with field data for enhancing the robustness of the empirical results.

4.2 Experimental Study

4.2.1 Methodology

To avoid order effects in performing the experimental conditions, I conduct a counterbalanced design with six different scenarios (Campbell and Stanley 1963). In each experimental condition, I apply a 3 (top-listed paid, side-listed paid, no paid result) × 2 (relevant organic, no relevant organic result) between-subjects design with five random sampling groups to investigate the impact of advertiser competition on overall, organic, and paid click-through rate.[86]

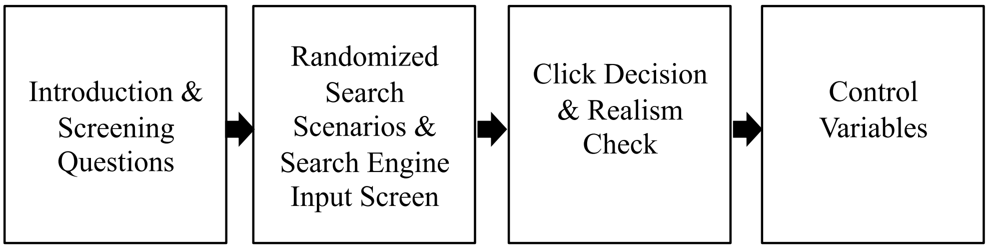

Figure 32: Experimental Procedure (Project II)

Figure 32 presents the experimental procedure, which is applied in *Project II*. After a brief introduction, screening questions on socio-demographic factors such as age group, gender, educational level, and Nielsen areas were assessed (see Appendix 5). With that, the representativeness for the German "online population" is secured. Then, the six experimental scenarios with different levels of advertiser competition were processed in random order. I ran-

[86] The scenarios "no relevant organic result", "top-listed, side-listed, and organic result" as well as "top-listed, side-listed, and no relevant organic result" are no realistic combinations in search engine marketing. Hence, these groups are not relevant for the experimental research design.

domly assigned participants to one of the following five groups in each of the six different experimental conditions: (1) paid top and organic (paid result and organic result), (2) paid side and organic (paid result and organic result), (3) organic (organic result), (4) paid top (paid result), or (5) paid side (paid result). The cell sizes are displayed in Table 16.

AC	**Organic Exposure**	**Paid Result Exposition**		
		Paid Top	**Paid Side**	**No**
AC = 0	*Yes*	N = 149	N = 152	N = 155
	No	N = 134	N = 154	n.a.
AC = .2	*Yes*	N = 149	N = 154	N = 145
	No	N = 146	N = 150	n.a.
AC = .4	*Yes*	N = 147	N = 162	N = 148
	No	N = 141	N = 146	n.a.
AC = .6	Yes	N = 152	N = 152	N = 148
	No	N = 149	N = 143	n.a.
AC = .8	*Yes*	N = 152	N = 160	N = 144
	No	N = 143	N = 145	n.a.
AC = 1	*Yes*	N = 146	N = 144	N = 154
	No	N = 153	N = 147	n.a.

Table 16: Cell Sizes (Experiment, Project II)

The search scenarios and the intended keywords were carefully selected. First, I came up with 58 keywords labeled according to the category (e.g., beauty and personal care, e-commerce, entertainment, electronic, gift and occasions, health, house and garden, Internet service, news and current occurrences, recreation, shopping, travel, transportation), the type of search (informational, navigational, or transactional search tasks; Broder 2002), the classification of the keywords (branded or generic; Rutz and Bucklin 2011), and market offering (product or service). For all 58 keywords, I obtained the advertiser competition, including monthly global and local searches, with the help of Google's "Keyword Tool" for the German market. Then, I ordered the keywords according to their level of advertiser competition in descending order and evaluated and carefully selected six keywords for advertiser competition (AC). The final keywords for the six experimental conditions are (1) price comparison (AC = 1), (2) individual photo calendars (AC = .8), (3) a magazine subscription (AC = .6), (4) soccer shirt national team (AC = .4), (5) rental Frankfurt central station (AC = .2), and (6) specialty wine from a gourmet store (AC = .0).

Original SERPs from Google are the basis of the manipulation. I manipulated these original SERPs for each of the six different keywords in the first paid top, first paid side, and first organic position (see Appendix 6). Consequently, the displayed real search results from Google for each keyword are only varying in terms of the manipulated first paid top, first paid side, and first organic positions. All other search results are similar for the five different groups.[87]

In each experimental scenario a vignette was given to frame the respondents to the search task (Alexander and Becker 1978; McFadden et al. 2005; see Appendix 8). Afterwards, a manipulated input screen from Google appears. Each participant was asked to enter his or her search term or keyword(s) of preference for the described search scenario. Then, the manipulated search engine result page was presented on which the participants were asked to click on the link they would choose in the described search scenario. Subsequently to their click-decision, subjects were asked to assess the realism of the presented search engine result page with a one-item seven-point Likert-type measurement according to Williams and Drolet (2005). This procedure was repeated for each search scenario. Closing this online experimental procedure, an additional control variable was assessed guaranteeing a more detailed sample description. Internet search skill was measured according to Mathwick and Rigdon (2004). For the operationalization of the applied measurement see Appendix 9.

4.2.2 Data

I collected the data in August 2010 by inviting participants from a European online market research panelist to take part in the study. The respondents were incentivized if they successfully completed the experimental online survey according to common practice and conditions of the online panel. The final sample with 744 respondents was representative of the German "online population" according to age group, gender, educational level, and Nielsen geographical areas.[88]

Internet usage in this sample is high, with 79.2% of the sample using the Internet several times a day and 14.7% using it once a day. Almost half the sample (49.7%) uses search engines several times a day, 12.6% use them on a daily basis, and 27% use them several times a week. In addition, the Internet search skill (ISS), measured with Mathwick and Rigdon's (2004) three-item, seven-point Likert-type scale, is high ($M_{ISS} = 5.63$, $SD_{ISS} = 1.08$).[89]

To run the regression analysis, I aggregated the individual click-through data according to two dimensions. First, I matched each observation to the five randomly assigned groups (top

[87] In Appendix 7 screenshots of the manipulated search engine result page for AC = 1 are displayed.
[88] The mean time for completing the experimental survey was 16 minutes.
[89] The reliability of the scale is good ($\alpha = .87$). The tests for reliability and validity of the applied multi-item measurements, as well as details on the applied single-item measurements in the experiment of *Project II* are reported in detail in Appendix 9.

and organic, side and organic, organic, top, and side). I repeated this assignment for each of the six different levels of advertiser competition. Second, the data set includes 30 aggregated observations with corresponding click-through rates.

4.2.3 Ecological Validity

In addition to the manipulated original SERPs from Google, I applied a second method to guarantee the realism of the selected keywords. Each participant was asked to enter his or her search term or keyword(s) of preference.[90] For that reason, a vignette was given to frame the respondents to each search task (Alexander and Becker 1978; McFadden et al. 2005). After respondents entered their individual search term in each condition, the manipulated SERP was displayed to the randomly assigned group.

To test whether the manipulation of the SERPs inadvertently evoked changes in the realism of the displayed result pages, I performed six realism checks (Darley and Lim 1993; Shimp, Hyatt, and Snyder 1993) using analysis of variance (ANOVA). I recorded the realism of the manipulation for the search engine result page group with a one-item measurement, which was repeated after each of the six different search tasks. I adapted the measure (see Appendix 9) from Williams and Drolet's (2005) advertising credibility scale. An ANOVA for each search task supports the effectiveness of the manipulated SERPs with no significant effects (for scenario 1 AC = .0: $F(4, 739) = 1.13$, $p > .10$; for scenario 2 AC = .2: $F(4, 739) = .31$, $p > .10$; for scenario 3 AC = .4: $F(4, 739) = 1.76$, $p > .10$; for scenario 4 AC = .6: $F(4, 739) = 2.27$, $p > .10$; for scenario 5 AC = .8: $F(4, 739) = .45$, $p > .10$; for scenario 6 AC = 1: $F(4, 739) = .98$, $p > .10$).[91]

4.2.4 Results

Controlling for the impact of advertiser competition is a relevant aspect to gain further insights into click-through behavior (Yang and Ghose 2010). I address this topic by investigating the overall (*H1a*), organic (is synonymous to free CTR) (*H1b*), and paid (*H1c*) click-through pattern for different levels of advertiser competition (see Figure 33).

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[90] Two independent raters coded the applied keywords. The inserted search terms for the search task of the individual photo calendars or magazine subscription show, for example, each, almost 80% accordance of the entered search terms with the keyword for the manipulated search engine result page. Participants entering one or several fantasy keyword combinations were excluded from further analyses.

[91] For more details see Appendix 17.

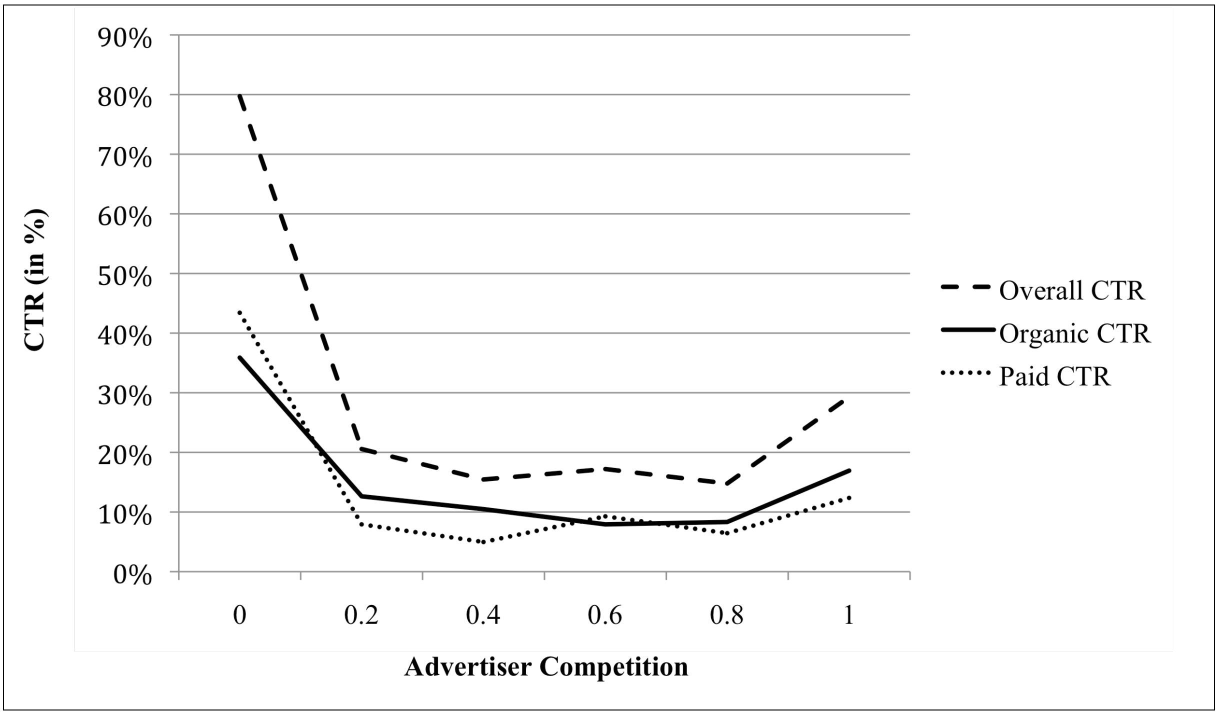

Figure 33: Overall, Organic, and Paid Click-Through Rates for Different Levels of Advertiser Competition (Experiment, Project II)

To test the hypothesized relationships between advertiser competition and click-through behavior, I perform ordinary least squares (OLS) regressions. To examine the U-shaped function of click-through for different levels of advertiser competition and different SERPs, I adapt a procedure similar to Reinartz and Kumar (2003). I use two basic OLS models. In model 1, I model the linear main effect for advertiser competition (AC) to ensure that the function is not inverted. In model 2, I include the quadratic effect AC^2 to test whether it is a U-shaped function. I apply standardized z-values for the regressors and the dependent variables to achieve comparative values of the beta coefficients (e.g., Cohen et al. 2003; Verhoef 2003; Agustin and Singh 2005).

I can support the hypotheses for overall, organic, and paid click-through rates, which are statistically significant at $p < .001$, for all suggested models (see Table 17). For these click-through rates, I find that the hypothesized signs are statistically significant (negative beta ($ß_1$) for AC and positive beta ($ß_2$) for AC^2). By including the quadratic term in the OLS models with the linear effect only, I can show that models 2a, 2b, and 2c, and thus the curvilinear

U-shaped models, help explain overall, organic, and paid click-through rates.[92] That is, overall, organic, and paid click-through rates initially decrease with increasing levels of advertiser competition and increase again after an inflection point. Therefore, *H1a*, *H1b*, and *H1c* are supported.

	Model 1a (Overall CTR)	Model 1b (Organic CTR)	Model 1c (Paid CTR)	Model 2a (Overall CTR)	Model 2b (Organic CTR)	Model 2c (Paid CTR)
Intercept	$-.19\times10^{-2}$ (.16)	$-.34\times10^{-2}$ (.22)	.01 (.19)	$-.19\times10^{-2}$ (.10)	$-.34\times10^{-2}$ (.14)	.01 (.14)
AC	-.52 (.16)**	-.48 (.22)*	-.49 (.19)***	-2.81 (.37)***	-2.76 (.51)***	-2.52 (.51)***
AC^2				2.38 (.37)***	2.37 (.51)***	2.11 (.51)***
N	30	18	24	30	18	24
R^2	.27	.24	.24	.72	.69	.58
Adjusted R^2	.25	.19	.20	.69	.65	.53
RMSE	.88	.92	.93	.56	.60	.71
SSE	21.93	13.44	18.91	8.60	5.49	10.51
AIC	-5.40	-1.26	-1.72	-31.47	-15.39	-13.82
F-Test	F(1)= 10.55**	F(1)= 5.02*	F(1)= 6.78*	F(2)= 33.87***	F(2)= 16.64***	F(2)= 14.22***

Notes: a. S.E. is indicated in parentheses; all parameters are z-standardized.
b. Significance levels of the models and parameters: *** significant on 0.1% level; ** significant on 1% level; * significant on 5% level; (*) significant on 10% level.

Table 17: Results of the OLS Regression on Overall, Organic and Paid Click-Through Rate (Experiment, Project II)

4.2.5 Findings

The experimental study in *Project II* aims at verifying the hypothesized impact of advertiser competition on overall, organic, and paid click-through rates. Based on the literature of consumer choice, I assume that the relationship between advertiser competition and the three different types of click-through rates is U-shaped. This postulation implies that overall, organic, and free click-through rates are highest for low levels of advertiser competition. For medium levels of advertiser competition and choice overload, the click-through rates are lowest. They improve again with increasing levels of advertiser competition and choice overload. Recent publications on consumer choice are showing negative effects (e.g., Malhotra 1982; Keller and Staelin 1987; Greenleaf and Lehmann 1995; Dhar 1997; Simonson 1999) as well as positive (e.g., Zuckerman et al. 1978; Chernev 2003; Kahn and Wansink 2004), and curvilinear relationships (Shah and Wolford 2007) between choice overload and consumer's choice. The results of the experimental study in *Project II* provide strong evidence for an

[92] It is suggested to select the model with a minimum value of the applied information criterion, here AIC (e.g., Akaike 1974; Homburg, Koschate, and Hoyer 2005; Greene 2008). The statistics are: AIC_{1a} = -5.4 and AIC_{2a} = -31.47, AIC_{1b} = -1.26, and AIC_{2b} = -15.39, respectively AIC_{1c} = -1.72, and AIC_{2c} = -13.82. The adjusted R^2 ($\overline{R}^2$) supports this finding ($\overline{R}^2_{1a}$= .25, $\overline{R}^2_{2a}$ = .69; $\overline{R}^2_{1b}$ = .19, $\overline{R}^2_{2b}$ = .65; $\overline{R}^2_{1c}$ = .20, $\overline{R}^2_{2c}$ = .53).

U-shaped relationship between advertiser competition and overall, organic (is synonymous to free CTR), and paid click-through rates. A summary of the hypothesized effects is displayed in Figure 34.

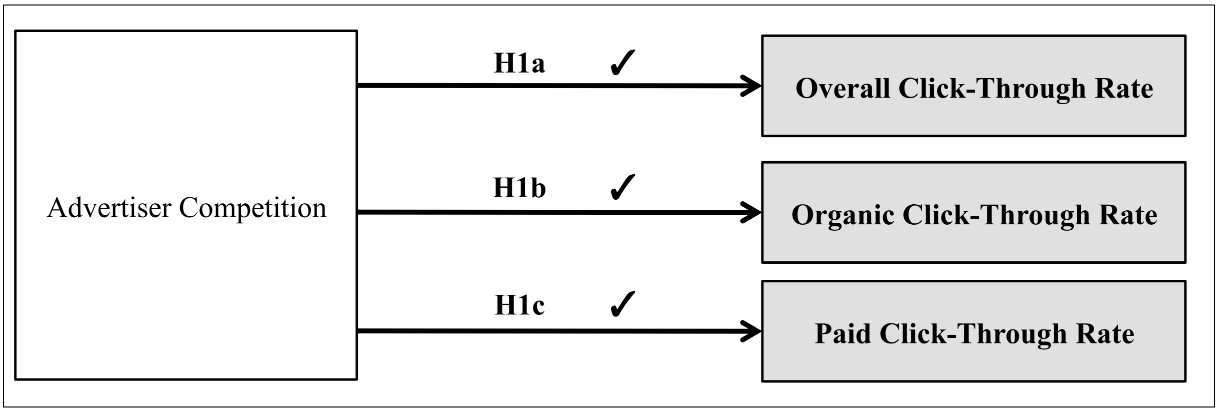

Figure 34: Summary of Hypothesized Effects (Experiment, Project II)

4.3 Field Data Study

In this descriptive study with field data, I test the applicability of the main result from the experimental investigation to a real-life context (*H1c*) and extend the analysis to conversion rate (*H2*). Finally, I test the moderating role of higher positions when the level of advertiser competition increases on click-through rate (*H3*).

4.3.1 Methodology

For analyzing the impact of advertiser competition on click-through and conversion behavior in the field setting with company data from five leading European retailers, I perform two different tests for heteroscedasticity of the proposed models for click-through rate and conversion rate analogue (see equation 4a and 4b (click-through rate) as well as 4c and 4d (conversion rate)). Therefore, the Breusch-Pagan test (Breusch and Pagan 1979) and White test (White 1980) for heteroscedasticity are applied, using PROC MODEL in SAS 9.2 for Windows. Breusch and Pagan (1979) assume that the error terms are normally distributed. Thus, the model (see equation 4a, 4b, 4c, 4d) is estimated by linear OLS. The obtained squared OLS residuals ($\hat{u}^2$) for each observation form the basis for equation five to compute the Lagrange multiplier (LM) test statistic.

$$zCTR = \beta_0 + \beta_1 zAP + \beta_2 zWord + \beta_3 zBrand + \beta_4 zRetailer + u. \quad (4a)$$
$$zCTR = \beta_0 + \beta_1 zAP + \beta_2 zWord + \beta_3 zBrand + \beta_4 zRetailer + \beta_5 zAC + \beta_6 zAC^2 + u. \quad (4b)$$
$$\mathrm{CR} = \beta_0 + \beta_1 AP + \beta_2 Word + \beta_3 Brand + \beta_4 Retailer + \beta_5 CTR + u. \quad (4c)$$
$$CR = \beta_0 + \beta_1 AP + \beta_2 Word + \beta_3 Brand + \beta_4 Retailer + \beta_5 CTR + \beta_6 AC + \beta_7 AC^2 + u. \quad (4d)$$
$$\hat{u}^2 = \delta_0 + \delta_1 zAP + \delta_2 zWord + \delta_3 zBrand + \delta_4 zRetailer + \varepsilon. \quad (5a)$$
$$\hat{u}^2 = \delta_0 + \delta_1 zAP + \delta_2 zWord + \delta_3 zBrand + \delta_4 zRetailer + \delta_5 zAC + \delta_6 zAC^2 + \varepsilon. \quad (5b)$$
$$\hat{u}^2 = \delta_0 + \delta_1 AP + \delta_2 Word + \delta_3 Brand + \delta_4 Retailer + \delta_5 CTR + \varepsilon. \quad (5a)$$
$$\hat{u}^2 = \delta_0 + \delta_1 AP + \delta_2 Word + \delta_3 Brand + \delta_4 Retailer + \delta_5 CTR + \delta_6 AC + \delta_7 AC^2 + \varepsilon. \quad (5b)$$

The White (1980) test for heteroscedasticity supplements the squares and cross products of the independent variables to equation five (see equation (6)). Adding the squares and cross products of the independent variables to the regression function, the number of regressors increases by 10 for model 3 and by 21 for model 4, for testing the LM statistic that all δ_j, except δ_0 for the intercept, are equal zero.[93]

$$\hat{u}^2 = \delta_0 + \delta_1 zAP + \delta_2 zWord + \delta_3 zBrand + \delta_4 zRetailer + \delta_5 (zAP)^2 + \delta_6 (zWord)^2 + \delta_7 (zBrand)^2 + \delta_8 (zRetailer)^2 + \delta_8 (zRetailer)^2 + \delta_9 zAP \times zWord + \delta_{10} zAP \times zBrand + \delta_{11} zAP \times zRetailer + \delta_{12} zWord \times zBrand + \delta_{13} zWord \times zRetailer + \delta_{14} zBrand \times zRetailer + \varepsilon. \quad (6a)$$

$$\hat{u}^2 = \delta_0 + \delta_1 zAP + \delta_2 zWord + \delta_3 zBrand + \delta_4 zRetailer + \delta_5 zAC + \delta_6 zAC^2 + \delta_7 (zAP)^2 + \delta_8 (zWord)^2 + \delta_9 (zBrand)^2 + \delta_{10} (zRetailer)^2 + \delta_{11} (zAC)^2 + \delta_{12} (zAC^2)^2 + \delta_{13} zAP \times zWord + \delta_{14} zAP \times zBrand + \delta_{15} zAP \times zRetailer + \delta_{16} zWord \times zBrand + \delta_{17} zWord \times zRetailer + \delta_{18} zBrand \times zRetailer + \delta_{19} zAC \times zAC^2 + \delta_{20} zAC \times zAP + \delta_{21} zAC \times zBrand + \delta_{22} zAC \times zRetailer + \delta_{23} zAC^2 \times zAP + \delta_{24} zAC^2 \times zBrand + \delta_{25} zAC^2 \times zRetailer + \varepsilon. \quad (6b)$$

For estimating click-through rate both Breusch-Pagan (model 3: LM = 3,253; df = 4; $p < .001$, and model 4: LM = 7,290; df = 6; $p < .001$) and White (model 3: LM = 5,191; df = 13; $p < .001$, and model 4: LM = 9,264; df = 25; $p < .001$) test statistic fail to reject the null hypothesis of homoscedasticity. Hence, heteroscedasticity is present. Consequently, the OLS estimator is no longer the best estimator, and heteroscedasticity-robust standard errors are first choice (see Greene 2008; Wooldridge 2009). For conversion rate, the Breusch-Pagan (model 5: LM (5) = 203.50; $p < .001$, and model 6: LM (7) = 386.80; $p < .001$) and White (model 5: LM (17) = 393.40; $p < .001$, and model 6: LM (31) = 907.90; $p < .001$) test statistic fail to reject the null hypothesis of homoscedasticity as well.

[93] The equations for the White test of heteroscedasticity for conversion rate are analogous to Equations 6a and 6b.

Furthermore, I apply the Hausman (1978) specification test procedure to indicate whether a random effects or a fixed effects model should be preferred (Greene 2008) using NLOGIT 3.0.5 for Windows. The Hausman test answers the substantive question: Are the observed explanatory variables (CTR: zAP, zWord, zBrand, zRetailer, and for model 4 additionally zAC, zAC^2; CR: AP, Word, Brand, Retailer, CTR, and for model 6 AC, AC^2), and the individual unobserved effects (a_i) correlated?[94] The results for the Hausman test for the click-through panel (model 3: $\chi^2 = 1{,}623.10$; df = 4; $p < .001$, and model 4: $\chi^2 = 814.32$; df = 6; $p < .001$) as well as for the conversion panel (model 5: χ^2 (5) = 25.44; $p < .001$, and model 6: χ^2 (7) = 42.45; $p < .001$) with a statistically significant difference between the random and fixed effects estimates can be interpreted in both cases as evidence for fixed-effects models and against random effects models (Wooldridge 2002). For that reason, I can conclude that the proposed fixed effects models are the preferred specification for the keyword panel data.

4.3.2 Data

In the empirical field validation I use a unique data set encompassing 347,571 user searches with clicks. The data contain information on paid search advertising from major European retailers (consumer electronics, direct and flagship retailing, mail order retailing, and online pharmacy) conducting paid search activities on Google. The sample period spans 17 weeks from April 1 to July 30, 2009.

The database is basically similar to those applied in prior research on click-through behavior on SERPs (e.g., Ghose and Yang 2009; Yang and Ghose 2010; Rutz and Bucklin 2011). Specifically, the data are on an individual user-level, and contain pair wise matched data on advertiser competition for each of the 17,693 keywords in the data set, extracted from the Google AdWords Keyword Tool. In more detail, the data include additional information on the advertiser, the keyword, and each user's behavior. On the advertiser side, I have more detailed information about performance. In addition to exact costs for each user's action (click or order), average cost per click and average position of the advertisement are displayed. On the keyword level, each entry in the database contains information on campaign-ID, keyword-ID, match type, search term (keyword), whether the keyword is generic or branded (re-

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[94] For the Hausman test to reveal whether the unobserved individual effects are correlated with the explanatory variables, the model equations are follows (analogous for conversion rate):

$zCTR = \beta_0 + \beta_1 zAP_i + \beta_2 zWord_i + \beta_3 zBrand_i + \beta_4 zRetailer_i + a_i + u_i$ (7a)

$zCTR = \beta_0 + \beta_1 zAP_i + \beta_2 zWord_i + \beta_3 zBrand_i + \beta_4 zRetailer_i + \beta_5 zAC_i + \beta_6 zAC^2_i + a_i + u_i$ (7b).

tailer or brand), and the corresponding level of advertiser competition for each keyword. With regard to users and their behavior, unique user-IDs are available, and each search is associated with exact information about date and time. Furthermore, whether the user clicked or clicked and purchased (conversion) is displayed, as well as the length of the search term in the number of entered words (words). For modeling the influence of a non-branded, branded or retailer-specific keyword on the paid click-through behavior, I apply a procedure similar to Yang and Ghose (2010). In the category non-branded or generic, keywords with no brand or retailer-specific details are selected (e.g., jeans or t-shirt). As branded keywords, searches with a brand name in the query are defined (e.g., Levi's jeans or Adidas t-shirt). Finally, the category retailer encompasses retailer-specific queries (e.g., Amazon or amazon.com). Therefore, dummy variables are coded to the baseline of a non-branded keyword.

To investigate the impact of increasing choice overload due to advertiser competition on click-through and conversion behavior, I requested the corresponding level of advertiser competition for each keyword. Because some keywords in the data set had no exact equivalent keyword in the Google AdWords Keyword Tool and, thus, no distinct level of advertiser competition, I omitted 1,435 keywords with 35,412 searches from further analysis.

The analysis reveals that the mean number of searches with a click on the displayed paid search advertising for a keyword of the five retailers is 2,292.53 (SD = 5,053.54). The average clicks per keyword for each retailer are 973.33 (SD = 2,605.69) for the consumer electronics retailer, 801.40 (SD = 1,669.38) for the first direct and flagship retailer, 5,347.89 (SD = 7,401.43) for the second direct and flagship retailer, 275.89 (SD = 569.75) for the pharmacy, and 145.42 (SD = 351.29) for the mail-order retailer. Across all keywords and retailers, this leads to a mean click-through rate of 10.6% (SD = 19.71). Furthermore, the mean position of the clicked search advertisements is 3.92 (SD = 4.07) on a daily level. The rankings are numbered top down on each SERP starting with 1 and continued on all subsequent SERPs. Overall, the data are based on broad (66.38%), exact (7.98%), and phrase (25.64%) match types.

Before running panel regression analysis for paid click-through and conversion rates, I needed to further adjust the data set. Therefore, I initially sorted the data set with 347,571 searches by the keyword and day of search. I then aggregated the database on a per-day basis. With this correction, I aligned the database to 108,701 cases for click-through regressions and 103,886 cases for conversion regressions so as not to overestimate the impact of keywords with more frequent searches per day. This reduction is not problematic, because I measure the relevant variables click-through rate, conversion rate, and average position on a daily level, and advertiser competition is likewise not different for various searches per keyword. Table 18 reports more detailed summary statistics.

The keyword panel (N = 17,693 keywords in the click-through rate panel and N = 10,912 keywords in the conversion rate panel) is unbalanced, because the total number of clicks and conversions per keyword and day is not uniformly distributed. The observations in the click-through rate panel spread from 2 (minimum) to 90 days (maximum) per keyword (M = 12.35, SD = 15.30) and from 2 (minimum) to 159 days (maximum) for conversion rate panel (M = 14.47, SD = 18.95) (see Greene 2008).

Variable	**N**	**Min**	**Max**	**Mean**	**SD**
			CTR Panel		
CTR overall (a day)	108,701	0	100	10.6	19.71
Average Position (a day)	108,701	1	65	5.29	4.79
Word	108,701	1	7	1.99	.87
AC	108,701	0	1	.56	.33
Brand	108,701	0	1	.28	.45
Retailer	108,701	0	1	.05	.22
Observations per Keyword	108,701	2	90	12.35	15.30
			CR Panel		
CTR overall (a day)	103,886	0	100	9.81	18.24
CR overall (a day)	103,886	0	100	2.21	11.82
Average Position (a day)	103,886	1	65	5.34	4.85
Word	103,886	1	7	1.98	.86
AC	103,886	0	1	.57	.33
Brand	103,886	0	1	.27	.45
Retailer	103,886	0	1	.06	.23
Observations per Keyword	103,886	2	159	14.47	18.95

Table 18: Detailed Summary Statistics (Field Data, Project II)

4.3.3 Results

Results Paid Click-Through Rate

To investigate the effect of advertiser competition on paid click-through rate, I test two distinct models. Model 3 includes predictors that have recently been shown to statistically significantly affect click-through behavior (control model). Therefore, I include the average position of the displayed sponsored link (zAP), the number of words (zWord), and whether the entered keyword includes information on a brand (zBrand) or a retailer (zRetailer) in model 3 (see Ghose and Yang 2009; Yang and Ghose 2010; Rutz and Bucklin 2011). For model 4, I extend the base model with the linear (zAC) and quadratic (zAC^2) predictor of advertiser competition.

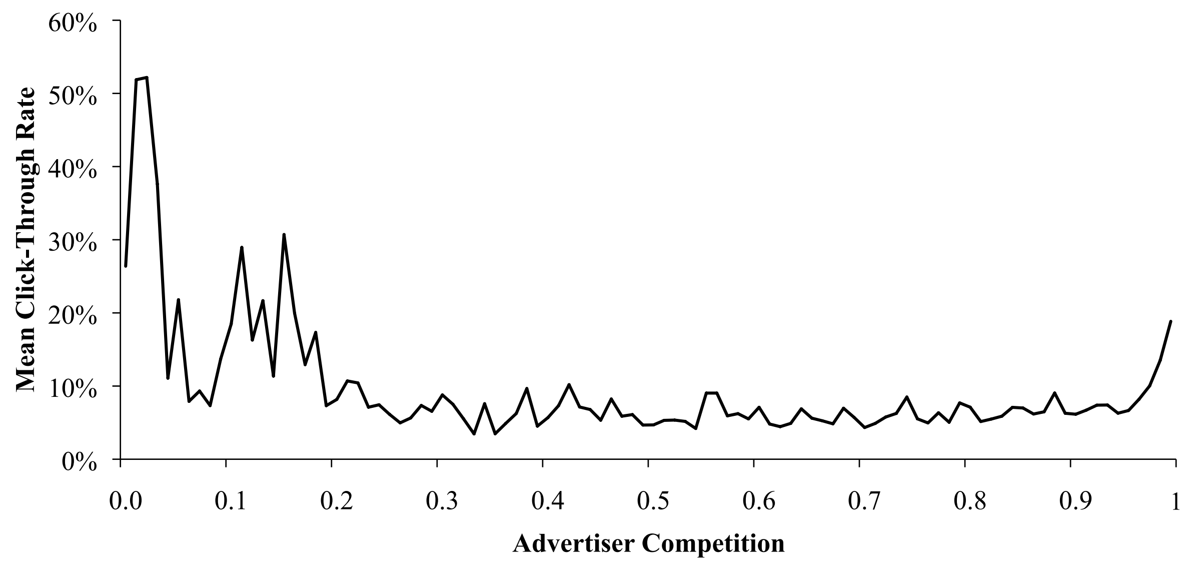


Figure 35: Paid Click-Through Rate for Different Levels of Advertiser Competition (Field Data, Project II)

I test *H1c* with a fixed effects panel regression model.[95] The results of the proposed model 4 provide strong support for *H1c* (see Figure 35). Entering the linear (zAC) and quadratic (zAC^2) terms of advertiser competition in model 4 results in statistically significant model improvement. The specified model 4 helps explain paid click-through behavior significantly better than the model with prior predictors (model 3). I can show this with a likelihood ratio chi-square test ($\chi^2(6) = 22.52$, $p < .01$). In line with this finding are the results for minimum value for sum of squares (Greene 2008).[96] In addition, the effects of zAC ($\beta_1 = -1.23$, $p < .001$) and zAC^2 ($\beta_2 = .92$, $p < .001$) are statistically significant. Therefore, the proposed curvilinear relationship between advertiser competition and paid click-through rate is supported (see Table 19). This procedure to secure the curvilinear effects is suggested by Cohen et al. (2003) and applied by Homburg, Koschate, and Hoyer (2005).

95 See *Chapter C*/4.3.1. The correlation matrix is displayed in *Appendix 10*.

96 The sums of squares are $SS_5 = 30{,}456.39$ (model 5), and $SS_6 = 30{,}450.08$ (model 6). For nested models, as I consider in this case, it is often argued that the likelihood ratio χ^2-test should be preferred (e.g., Vuong 1989; Homburg, Koschate, and Hoyer 2005).

In addition, and in line with prior studies on SERPs click-through behavior, I find a statistically significant, negative effect of average position (zAP) of a paid result on paid click-through rate. The number of words entered for a search and a retailer's name in the search term are also significant, positive predictors of paid click-through rate, whereas a brand name in the entered search has a significant, negative effect on paid click-through rate (see Table 19).

	Model 3 (Paid click-through rate)			**Model 4 (Paid click-through rate)**			**Model 7 (Paid click-through rate)**		
	Estimate	S.E.	*p*	Estimate	S.E.	*p*	Estimate	S.E.	*p*
Intercept	.30	$.68 \times 10^{-2}$	.0000	.18	$.67 \times 10^{-2}$	.0000	.18	$.67 \times 10^{-2}$	.0000
zAP	-.09	$.40 \times 10^{-2}$	.0000	-.63	$.40 \times 10^{-2}$	.0000	-.22	$.11 \times 10^{-1}$	.0000
zWord	.26	$.70 \times 10^{-2}$	.0000	.97	$.71 \times 10^{-2}$	.0000	.10	$.71 \times 10^{-2}$	.0000
zBrand	-.12	$.72 \times 10^{-2}$	.0000	-.50	$.76 \times 10^{-2}$	.0000	-.06	$.76 \times 10^{-2}$	.0000
zRetailer	.59	$.85 \times 10^{-2}$	.0000	.44	$.84 \times 10^{-2}$	.0000	.43	$.84 \times 10^{-2}$	.0000
zAC				-1.23	$.25 \times 10^{-1}$	.0000	-1.25	$.25 \times 10^{-1}$	.0000
zAC²				.92	$.26 \times 10^{-1}$	.0000	.87	$.27 \times 10^{-1}$	.0000
zAP × zAC							.19	$.13 \times 10^{-1}$	.0000
N	108,701			108,701			108,701		
Breusch-Pagan Test	LM (4) = 3,253; $p < .0001$			LM (6) = 7,290; $p < .0001$			LM (7) = 5,636; $p < .0001$		
White Test	LM (13) = 5,191; $p < .0001$			LM (25) = 9,264; $p < .0001$			LM (30) = 8,150; $p < .0001$		
Hausman Test	χ^2 (4) = 1,623.10; $p < .0001$			χ^2 (6) = 814.32; $p < .0001$			χ^2 (7) = 1017.28; $p < .0001$		
Log-Likelihood	-85,089.62			-85,078.36			-85,063.26		
Sum of Squares	30,456.39			30,450.08			30,441.62		
R^2 (variables only)	$R^2 = .23$			$R^2 = .28$			$R^2 = .28$		
R^2 (variables and group effects)	$R^2 = .78$			$R^2 = .78$			$R^2 = .78$		

Table 19: Results of Fixed Effects Regression Models for Paid CTR (Field Data, Project II)

Results Conversion Rate

To investigate the effect of advertiser competition on conversion rate,[97] I test two distinct models (see Table 20). Model 5 includes predictors that have been shown to statistically significantly affect click-through rate (control model). Therefore, I include the average position of the displayed sponsored link (AP), the number of words (Word), and whether the entered keyword includes information on a brand (Brand) or a retailer (Retailer) in model 5. Additionally, click-through rate (CTR) is added (Ghose and Yang 2009; Yang and Ghose 2010;

[97] The database provided by the five leading European retailers is limited to information on daily paid search traffic by Google AdWords, so no analyses on the traffic via organic search results are possible.

Rutz and Trusov 2011). For model 6, I extend the base model with the linear (AC) and quadratic (AC^2) predictors of advertiser competition

I test *H2* with a fixed effects panel regression model.[98] The results of the proposed model 6 provide strong support for *H2 (see* Figure 36 and Table 20). By entering the linear (AC) and quadratic (AC^2) terms of advertiser competition in model 6, both AC ($\beta_1 = -1.68$, $p < .01$) and AC^2 ($\beta_2 = 3.00$, $p < .001$) are statistically significant and support the proposed curvilinear relationship between advertiser competition and conversion rate (see Table 20). Nevertheless, I note that the U-shaped relationship for paid conversion rate is not as clear as that for paid click-through rate. The plot in Figure 36 reveals that the highest mean conversion rate is not realized for the lowest levels of advertiser competition between 0% and 10% but rather for low levels between 10% and 20 %. However, the specified model 6 helps explain paid conversion behavior better than the model with prior predictors (model 5). I can show this with the results for minimum value for sum of squares (model 5 SS_5 = 12,188,403.49; model 6 SS_6 = 12,187,497.65).

Parameter	**Model 5 (Paid conversion rate)**			**Model 6 (Paid conversion rate)**		
	Estimate	S.E.	*p*	Estimate	S.E.	*p*
Intercept	2.89	.15	.0000	2.55	.21	.0000
AP	$-.26 \times 10^{-1}$	$.11 \times 10^{-1}$	.0128	$-.38 \times 10^{-1}$	$.11 \times 10^{-1}$	.0003
Word	-.23	$.63 \times 10^{-1}$	.0003	-.28	$.66 \times 10^{-1}$	.0000
Brand	-.81	.13	.0000	-.36	.14	.0000
Retailer	1.19	.29	.0000	1.65	.29	.0000
CTR	$-.11 \times 10^{-1}$	$.26 \times 10^{-2}$	.0000	-.11	$.26 \times 10^{-2}$	.0001
AC				-1.68	.64	.0084
AC^2				3.00	.21	.0000
N	103,886			103,886		
Breusch-Pagan Test	LM (5) = 203.50; $p < .0001$			LM (7) = 386.80; $p < .0001$		
White Test	LM (17) = 393.40; $p < .0001$			LM (31) = 907.90; $p < .0001$		
Hausman Test	χ^2 (5) = 25.44; $p < .001$			χ^2 (7) = 42.45; $p < .0001$		
Log-Likelihood	-394,913.44			-394,909.58		
Sum of Squares	12,188,403.49			12,187,497.65		
R^2 (variables only)	$R^2 = .00$			$R^2 = .01$		
R^2 (variables and group effects)	$R^2 = .16$			$R^2 = .16$		

Table 20: Results of Fixed Effects Regression for Conversion Rate (Field Data, Project II)

[98] See *Chapter C*/4.3.1. The correlation matrix is displayed in *Appendix 10*.

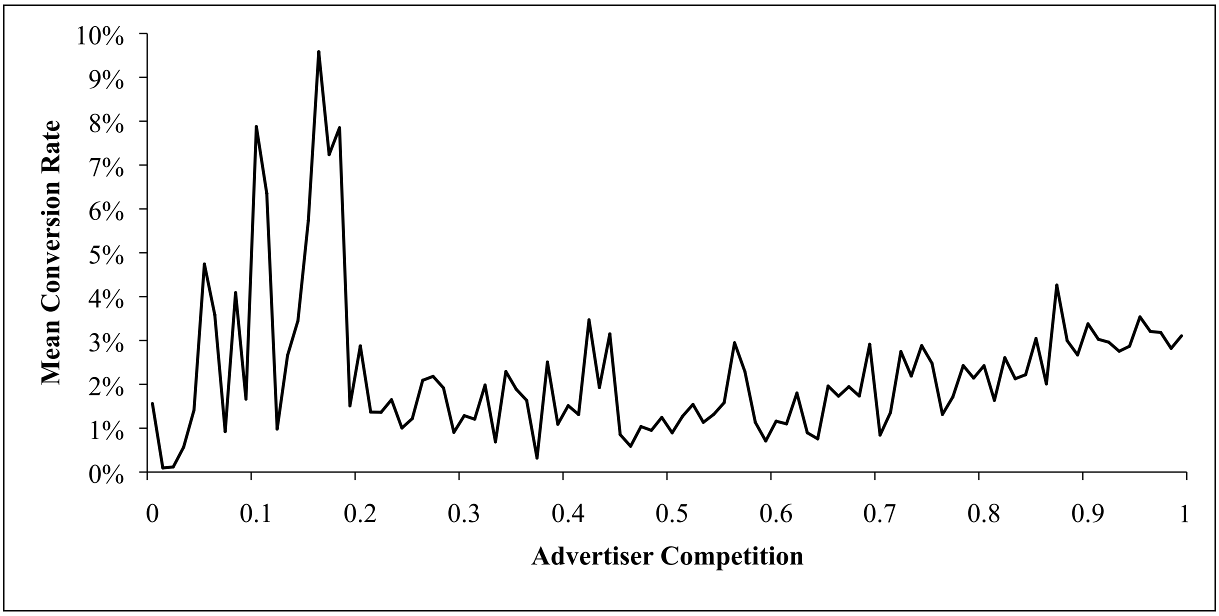


Figure 36: Conversion Rate for Different Levels of Advertiser Competition (Field Data, Project II)

In addition, I find a statistically significant, negative effect of average position (AP) of a paid result on conversion rate. The number of words entered for a search and a brand name in the search term are also significant, positive predictors of conversion rate, whereas a retailer name in the entered search has a significant, negative effect on conversion rate. Moreover, paid click-through rate negatively and statistically significantly influences conversion rate.

Interaction Average Position and Advertiser Competition

As for testing *H1* and *H2*, *H3* is also tested with a fixed-effects regression analysis. Therefore, the interaction term of average position and advertiser competition is included in model 7. In doing this, I can show two results. First, the regression results demonstrate that the impact of the interaction between average position and advertiser competition on click-through rate is positive (β = .19, p < .001).[99] Thus, *H3* is not supported. Additional post hoc probing also contradicts *H3* by revealing a significant interaction effect against the proposed direction. The applied post hoc probing procedure is similar to those suggested by Aiken and West (1991), Cohen et al. (2003), Tabachnick and Fidell (2005), and Wooldridge (2009). The calculated beta coefficients of zAP for three levels of advertiser competition (zAC mean: β_{zAP} = -.22, t = -238.90, p < .005, df = 108,697; zAC one standard deviation above mean:

99 Model 7 contributes significantly more to explain paid click-through behavior than does model 4. This can be shown with a likelihood ratio χ^2-test (χ^2 (7) = 30.20; p < .001) and SS_4 = 30,450.08 (model 4), and SS_7 = 30,441.62 (model 7).

β_{zAP} = -.03, t = -7.07, p < .005, df = 108,697; zAC one standard deviation below mean: β_{zAP} = -.41, t = -96.67, p < .005, df = 108,697) show that beta coefficients are weaker (less negative) for higher advertiser competition. Thus, a higher position on a SERP (i.e., a lower ranking number) attracts less click-through rate with higher advertiser competition. Consequently, choice overload evoked by increasing levels of advertiser competition leads to a greater impact of lower-ranked paid search results on paid click-through rate. Second, the U-shaped effect of advertiser competition still holds for this model extension (compare Table 19).

4.3.4 Findings

The descriptive study with proprietary company data from five leading European retailers advertising on Google extends the results of the experimental study to purchase behavior. In addition, the relationship between advertiser competition and click-through behavior is replicated and the statistical interaction *advertiser competition* × *average position* is extended with these field data. Underlying this statistical interaction is the theoretical framework that increasing assortments of similar search results are connected with high cognitive efforts of consumers to evaluate search results (e.g., Mogilner, Rudnick, and Iyengar 2008; Reutskaja and Hogarth 2009). To reduce associated search costs, consumers apply simple decision heuristics (e.g., Anderson, Taylor, and Holloway 1966; Gigerenzer, Todd, and ABC Research Group 1999). As such, both strategies (first option exceeding aspired level and consideration set) suggest that consumers prefer higher ranked paid search results with increasing levels of advertiser competition.

As in the case of click behavior, the relationship between advertiser competition and purchase behavior is assumed to be U-shaped. The results of this descriptive study with proprietary company data in *Project II* provide strong evidence for an U-shaped relationship between advertiser competition and paid click-through rate, and between advertiser competition and paid conversion rate. In addition, the results of the interaction *advertiser competition* × *average position* show that consumers' preference for higher-ranked search results are not enhanced with increasing levels of advertiser competition. A summary of the hypothesized effects is displayed in Figure 37.

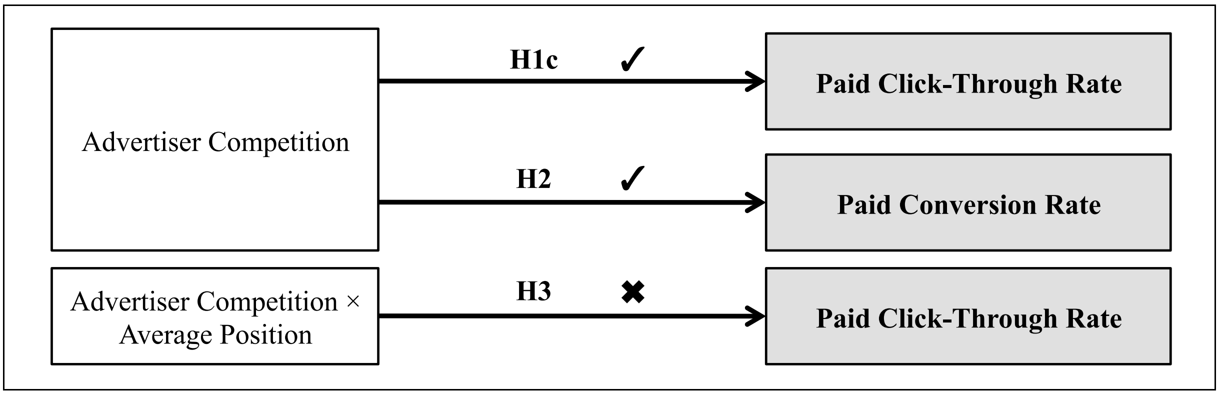


Figure 37: Summary of Hypothesized Effects (Field Data, Project II)

4.4 Discussion

Although search engine marketing has become an essential component in companies' online marketing mix, marketing academics have just recently begun to recognize the relevance of advertiser competition as a critical factor of consumer click-through and conversion behavior (Yang and Ghose 2010). Prior findings have suggested that increasing levels of advertiser competition lead to decreasing paid click-through rates (Rutz and Trusov 2011). What still remains unexplained however, drawing from consumer choice literature (e.g., Shah and Wolford 2007; Reutskaja and Hogarth 2009), is whether the influence of advertiser competition on overall, organic, and paid click-through and conversion rates is simply negative or curvilinear. Also unresolved is the question whether choice overload due to high levels of advertiser competition and extensive assortments of search results leads to clicks on higher-ranked search results to reduce search costs or cognitive effort.

As a first step to close this gap, this empirical study applies a controlled experimental online investigation and field data of five leading retailers conducting paid search activities on Google. Using OLS regressions and fixed effect panel regressions, I can find strong evidence for a U-shaped effect of advertiser competition on overall, organic, and paid click-through rates and on conversion rate. Notably, I find that consumers do not prefer to click on higher-ranked paid search results with increasing levels of advertiser competition to reduce search costs and cognitive effort. A summary on the results of the empirical analysis in this *Project II* is displayed in Figure 38. Thus, to expose the consequences resulting from this experimental and field data study for management and further research, the discussion addresses managerial and theoretical implications divided into three sections.

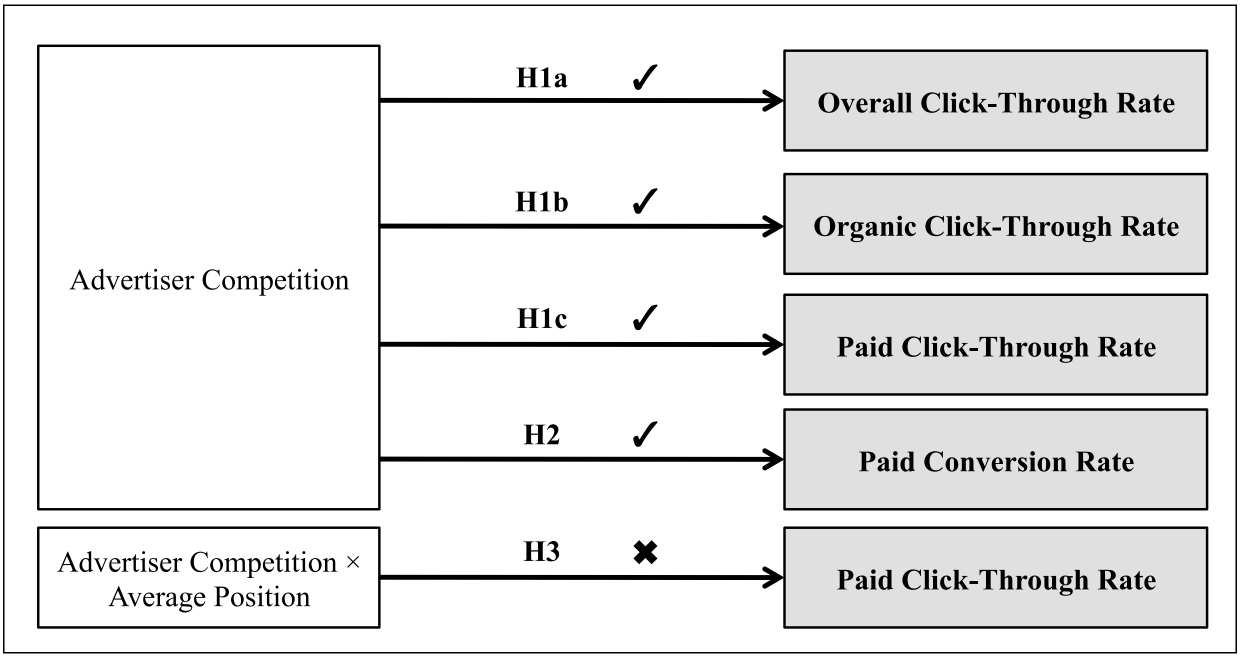


Figure 38: Summary of Hypothesized Effects (Project II)

4.4.1 Managerial Implications

Deciding in Which Keywords to Invest for Search Engine Marketing

In general, a decision to invest in organic search or paid search keywords should begin with a detailed consideration of the goals of the search engine marketing activities. For example, more traffic, a higher number of conversions, or lower costs per conversion could be the targeted goal of a search campaign.

When companies want a higher click-through rate, the results of the controlled experimental online investigation suggest that they should invest in low (AC = 0%) or high (AC = 100%) levels of advertiser competition. The results from the experiment shed further light on how this effect differs for overall, organic, and paid click-through rates by controlling for different realistic situations on SERPs. On the one hand, I show that overall click-through rate is the highest if an organic result at the first position and a corresponding paid top result at the first position are displayed and the lowest for a paid side result in the first position. On the other hand, if companies want to increase their traffic through clicks on an organic search result, the U-shaped effect is confirmed. With this goal in mind, a single organic result in the first position nearly always performs best. Finally, if a paid click-through rate is desirable, a single paid top result in the first position performs best. In general, paid side results in the first position are inferior, regardless of whether they are displayed with or without an additional organic result.

For companies that want to attract more traffic, the results of the empirical investigation with proprietary company data confirm the results of the experimental design for paid click-through rates. Specifically, companies should invest in keywords with advertiser competition levels between 0% and 19% to attract high click-through rates. In such cases, if there are no appropriate keywords in these levels of advertiser competition for the advertised product or service, keywords with the highest level of advertiser competition between 90% and 99% should be preferred to levels between 20% and 89%. At this point, the U-shaped impact of advertiser competition on paid click-through rate takes effect.

If companies conduct paid search campaigns with the goal to enhance their sales, the U-shaped influence of advertiser competition on conversion rate is also reflected. The only difference is that for lower levels of advertiser competition (lower than 10%), the conversion rate is inferior to levels between 10% and 19% of advertiser competition. Thus, in a first step, managers should invest in keywords with advertiser competition between 10% and 19% or greater than 80%. In a second step, other than the pure consideration of conversion rate, managers should account for the costs per conversion to reduce acquisition costs. Across all the different levels of advertiser competition, M = 75.5 paid clicks (SD = 128.60) are necessary to attain one conversion. Thus, the average cost per conversion is M = 9.89 Euro (SD = 7.04).

As Table 21 and Figure 39 show, the average costs per conversion are highest for advertiser competition ranging from 1% to 9%. This is a remarkable finding for managers because such levels of advertiser competition promise the highest click-through rate. Moreover, the cost per conversion is far lower for medium or highly competitive keywords with lower average click-through rate. Because the average costs per conversion are generally higher for lower to medium levels of advertiser competition (ranging from 20% to 49%), managers should invest in keywords with higher levels of advertiser competition (50% to 89%). Although the highest levels of advertiser competition from 90% to 99% are connected with relatively high costs per conversion (M = 11.09, SD = 2.11), the costs are still lower than for advertiser competition levels between 1% and 9% and between 30% and 49%. All in all, cost per conversion is the lowest for advertiser competition levels between 10% and 19%, followed by 0% of advertiser competition. Thus, managers should invest in keywords for paid search activities for these levels of advertiser competition.

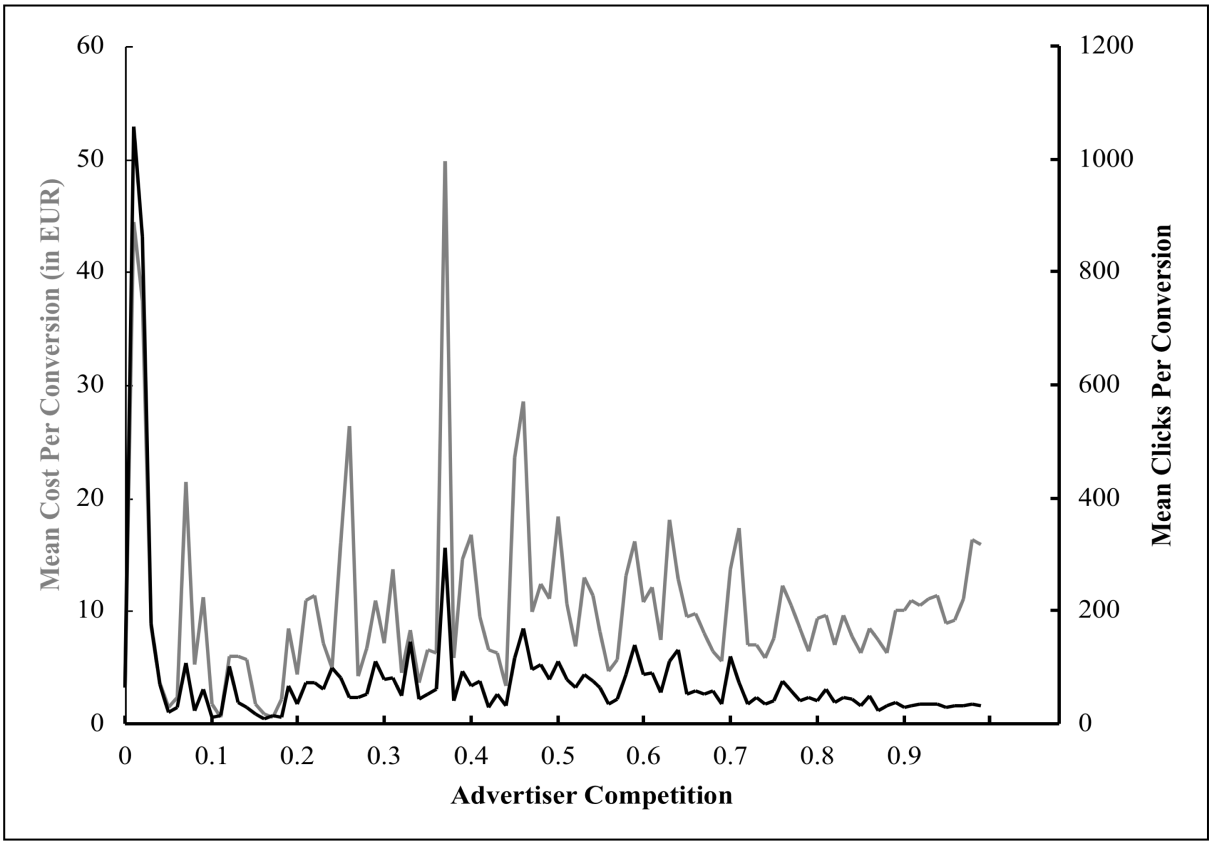


Figure 39: Mean Costs per Conversion and Mean Clicks per Conversion (Project II)

AC	Variable	N	Min	Max	Mean	SD
0%	*CTR (in %)*	*11,642*	*0*	*100*	*22.31*	*29.21*
	CR	*11,642*	*.02*	*.02*	*.02*	*.00*
	Clicks per Conversion	*11.642*	*63.95*	*63.95*	*63.95*	*.00*
	Cost per Conversion	*11.642*	*3.40*	*3.40*	*3.40*	*.00*
1-9%	*CTR (in %)*	3.643	*0*	*100*	*35.55*	*31.03*
	CR	3.643	*.00*	*.05*	*.01*	*.02*
	Clicks per Conversion	3.643	*21.08*	*1058.00*	*549.09*	*451.70*
	Cost per Conversion	3.643	*1.50*	*44.47*	*25.41*	*17.60*
10-19%	*CTR (in %)*	4.099	*0*	*100*	*21.28*	*23.14*
	CR	4.099	*.01*	*.10*	*.06*	*.03*
	Clicks per Conversion	4.099	*10.43*	*102.00*	*25.11*	*23.04*
	Cost per Conversion	4.099	*.57*	*8.49*	*2.82*	*2.47*
20-29%	*CTR (in %)*	4.290	*0*	*100*	*6.86*	*15.72*
	CR	4.290	*.01*	*.03*	*.02*	*.01*
	Clicks per Conversion	4.290	*34.75*	*110.45*	*67.51*	*22.74*
	Cost per Conversion	4.290	*4.26*	*26.33*	*11.08*	*7.02*
30-39%	*CTR (in %)*	6.121	*0*	*100*	*5.22*	*11.69*
	CR	6.121	*.00*	*.03*	*.01*	*.01*
	Clicks per Conversion	6.121	*39.87*	*313.44*	*101.90*	*79.23*
	Cost per Conversion	6.121	*3.64*	*49.78*	*12.20*	*13.24*
40-49%	*CTR (in %)*	8.495	*0*	*100*	*6.18*	*12.43*
	CR	8.495	*.06*	*.03*	*.02*	*.01*
	Clicks per Conversion	8.495	*28.80*	*170.04*	*81.69*	*39.17*
	Cost per Conversion	8.495	*3.37*	*28.52*	*12.45*	*7.34*
50-59%	*CTR (in %)*	9.355	*0*	*100*	*5.31*	*11.61*
	CR	9.355	*.01*	*.03*	*.01*	*.01*
	Clicks per Conversion	9.355	*33.91*	*141.09*	*81.42*	*28.31*
	Cost per Conversion	9.355	*4.64*	*18.35*	*10.96*	*4.04*
60-69%	*CTR (in %)*	9.829	*0*	*100*	*5.36*	*11.24*
	CR	9.829	*.01*	*.03*	*.02*	*.01*
	Clicks per Conversion	9.829	*34.32*	*132.00*	*73.15*	*30.59*
	Cost per Conversion	9.829	*5.55*	*18.06*	*9.83*	*3.36*
70-79%	*CTR (in %)*	10.728	*0*	*100*	*5.67*	*11.88*
	CR	10.728	*.01*	*.03*	*.02*	*.01*
	Clicks per Conversion	10.728	*34.68*	*118.73*	*57.91*	*25.70*
	Cost per Conversion	10.728	*5.76*	*17.36*	*9.52*	*3.25*
80-89%	*CTR (in %)*	13.976	*0*	*100*	*6.35*	*12.16*
	CR	13.976	*.02*	*.04*	*.03*	*.01*
	Clicks per Conversion	13.976	*23.46*	*61.18*	*41.46*	*10.02*
	Cost per Conversion	13.976	*6.21*	*10.09*	*8.14*	*1.39*
90-99%	*CTR (in %)*	21.708	*0*	*100*	*8.17*	*13.23*
	CR	21.708	*.03*	*.04*	*.03*	*.00*
	Clicks per Conversion	21.708	*28.25*	*36.30*	*32.58*	*2.60*
	Cost per Conversion	21.708	*8.83*	*16.29*	*11.09*	*2.11*

Table 21: Detailed Summary Statistics of the Field Data for Advertising Decision (Project II)

4.4.2 Theoretical Implications

A Behavioral Perspective of Advertiser Competition

Further research in the field of search engine marketing should include theory development. I take a step in this direction by mixing experimental and field data and by confirming hypotheses grounded in consumer choice literature. I show that the relationship between advertiser competition, as a proxy for increasing assortment, and overall, organic, and paid click-through rates and conversion rates is U-shaped. In addition, the integration of the linear and quadratic factors of advertiser competition leads to a significant improvement in paid click-through rates compared with previous studies (Ghose and Yang 2009; Yang and Ghose 2010; Rutz and Bucklin 2011).

In recent empirical studies, Shah and Wolford (2007) and Reutskaja and Hogarth (2009) find an inverted U-shaped function between the number of choices and the proportion of purchases. Scheibehenne, Greifeneder, and Todd (2010) control this curvilinear effect by increasing assortment size in their meta-analysis. The statistical validation of the curvilinear function reveals that the empirical data from Shah and Wolford (2007) and Reutskaja and Hogarth (2009) cannot support their postulated findings. Nevertheless, by investigating the relationship between increasing assortment (measured with advertiser competition) and click-through and conversion behavior in a search engine context, I show a curvilinear relationship. In contrast with Shah and Wolford's (2007) and Reutskaja and Hogarth's (2009) findings, I show that the U-shaped function for overall, organic, and paid click-through rates and paid conversion rates is not inverted. This U-shaped connection suggests that click-through and conversion rates are the highest for low levels of advertiser competition. Then, these rates decrease for medium levels of advertiser competition and again increase for higher levels of competition.

I also show that consumers do not typically reduce their search costs and cognitive effort by applying simple decision heuristics with increasing choice and choice overload. In addition, it seems that consumers are better informed and experience more dissonance reduction when higher advertiser competition is present and larger assortments of search results are displayed (Anderson, Taylor, and Holloway 1966; Eaton and Lipsey 1979; Kahn 1995). In such cases, consumers prefer to select and purchase from these displayed results. Therefore, a search result with a lower ranking in the paid results is not necessarily a bad thing.

Together, these main findings offer new perspectives for investigating the following central but unresolved questions: How does choice overload affect click-through and conversion behavior? Furthermore, how does increasing assortment influence simple decision heuristics? Building on consumer choice literature, further studies in the field of search engine marketing could attain a broad basis for research propositions and hypothesis development to test decision strategies, search result assortments, and choice overload.

4.4.3 Further Research and Managerial Activities

A more diverse inspection of traffic from SERPs can open new perspectives both in research and in managerial practice. Prior empirical research studies have tended to investigate the channels in search engine marketing separately, with a strong focus on paid search advertising. To my knowledge, only Yang and Ghose's (2010) empirical study combines paid and organic search activities and the generated traffic, though they are still unable to differentiate paid top from paid side search results. As the results from the experimental investigation reveal, the performance in those two areas of paid search activities strongly varies. Thus, these channels need to be differentiated to achieve deeper insights into paid search advertising performance.

Nevertheless, the sparse investigation of overall, organic, and paid search performance in marketing and retailing research stems from the limitations in proprietary company data provided for managerial decision making as well as research projects. In managerial practice, paid search advertising and search engine optimization are treated as isolated channels. Consequently, the tasks of tracking user activities and undertaking performance analysis and budget allocation are performed separately. To reveal interdependencies and synergies in search engine marketing campaigns, subsuming paid search as well as optimization activities, a comprehensive data recording of the traffic through organic search results is first necessary. In a second step, these data should be integrated with the broad data recorded from paid search activities.

Furthermore, knowledge from customer relationship management should be included in search engine marketing research and managerial practice. For example, customer centricity, a relational rather than transactional perspective (see Shah et al. 2006; Abhishek, Hosanagar, and Fader 2011), and the monetary value added by organic and paid search channel (see Neslin and Shankar 2009) all should be evaluated. This can be achieved by integrating data from search engine marketing activities into the customer database.

5 Project III: Does Paid Search Advertising Really Pay Off? The Impact of Order and Exposure Effects on Click-Through Rate

The research priorities of the Marketing Science Institute (2010) suggest that further marketing research should focus on gaining insights into how offline and online marketing activities influence consumers on their path to conversion. The impact of search engine marketing activities thus gains considerable importance, because they play a central role for customer acquisition (e.g., Klein and Ford 2003; Bughin et al. 2011; Rutz and Trusov 2011).

In *Chapter C*/2, I identified the fundamentals of recent research in the field of search engine marketing activities. Despite this range of research projects, some fundamental questions remain mostly neglected in recent scientific studies—such as the influence of order effects and double exposure on consumer click-through behavior. This lack of research comes as a surprise, because arguments from order effect and mere exposure literature suggest that theoretical contributions for a deeper understanding of the impact of search engine marketing on consumer behavior are overdue.

In the course of these broad theoretical frameworks of order effects and exposure, Yang and Ghose (2010) reveal that a simultaneous display of paid and organic search result influences click-through behavior. Their results suggest that parallel exposures of paid and organic search results, which I define as double exposure, increase overall click-through rates in comparison with a single displayed organic result (single organic exposure). However, Yang and Ghose (2010) cannot control for whether this effect exists for additional paid top and paid side results. This distinction between paid top and paid side search results is crucial because earlier results from research on banner advertising suggest the central role of the ordering or positioning of advertisements on lateral or upper areas (e.g., Briggs and Hollis 1997; Benway 1998). Together, these results demand further investigations on order effects and double exposure.

Recent research does not control for the effect of double exposure through simultaneous display of paid and organic search results on different types of click-through (paid side, paid top, organic). As a supplementary conclusion to the results of the experimental investigation in *Project II*, the distinction of clicks on paid results and organic results is necessary for three reasons. First, companies do not have to pay per ‘free click’ on organic search results. Therefore, it is a way to generate cheap traffic. Second, clicks on paid links are more dependent on constantly changing positions in paid listings and budget restrictions. Third, and perhaps most interesting, is the question about the effects of paid search advertising other than clicks on the link itself (e.g., positive effects on clicks on organic results).

In addition, *Project II* reveals that advertiser competition is a critical factor involved in consumer click-through and purchase behavior. I can show that choice overload via increasing levels of advertiser competition does not necessarily lead to more consumer click-through on higher ranked (paid) search results. Consumer decision heuristics to reduce search costs and cognitive efforts are not of such importance in consumer search and click-through behavior. *Project III* builds on these findings and investigates the role of double exposure for click-through behavior with increasing levels of advertiser competition.

To answer the research questions (How does message order affect click-through behavior? and How does double exposure through simultaneous display of paid and organic search result affect click-through behavior?) *Project III* proceeds as follows: First, I introduce a mixed-method research approach for investigating the impact of order effects, double exposure, and the interaction between advertiser competition and double exposure on click-through behavior. Second, an observational study is conducted to reveal first coherences in the wide field of order and exposure effects on search engine result pages. Third, a first experimental investigation controls for the impact of order effects and double exposure on click-through behavior. Fourth, a second experimental study generalizes the causal inference of order effects and double exposure from the first experimental study on a broader empirical basis. The statistical interaction between advertiser competition and double exposure effects on overall and free click-through behavior also is tested in this study. Fifth, I close *Project III* by discussing theoretical and managerial implications.

5.1 Conceptual Basis

The goal of this study is to shed light on the widely unexplored impact of order and exposure effects on click-through behavior. The applied empirical research design mixes an observational study with two experimental investigations for causal inferences. This sequential mixed-method research design starts with an observational study to explore the general phenomenon. Specifically, the observational study serves as the first stage to explore the relevance of order and exposure effects on click-through behavior. The major findings of this observational stage then can be extended to develop order effect and double exposure hypothesis for the experimental settings. An experimental research phase follows. Both experimental studies are closely connected, because the second experiment is based on the findings of the first experiment. In *Experiment 1*, the basic appropriateness of the theoretical approaches (order effects and double exposure) is tested in a 3 (top-listed paid, side-listed paid, no paid result) × 2 (relevant organic, no relevant organic result) between-subjects design with five random sampling groups. In a last step, these findings are extended and replicated in a counterbalanced design with six different scenarios (Campbell and Stanley 1963). In each experimental condition, I apply a 3 (top-listed paid, side-listed paid, no paid result) × 2 (relevant organic, no relevant organic result) between-subjects design with five random sampling groups. Altogether, this approach enables a straight connection of the initial observational results to both quantitative stages of the proposed research setting. Therefore, it is self-evident to base the interpretation of the results on the observational and experimental studies (Creswell and Plano Clark 2007).

5.2 Observational Study

5.2.1 Methodology

This descriptive and exploratory study (e.g., Marshall and Rossman 2006) applies a combination of data collection methods, including screen recording (e.g., Ahmed, McKnight, and Oppenheim 2004), think-aloud protocol (e.g., Ericsson and Simon 1993), and questionnaire. The descriptive and exploratory observational study serves two main purposes: First, I want to better understand whether the order of the search results and a simultaneous display of paid and organic search results influences consumer click-through behavior. Second, I want to gain first insights into how message order effects and double exposure through paid and organic search results influence consumer click-through behavior. The results of the observational study enable initial insights into the wide fields of order effects and double exposure in the context of search engine marketing.

The participants of this study were invited to a test lab to complete different transactional, navigational, and informational search tasks (e.g., Broder 2002). The structure of the recorded data enables matching the screened search and click behavior to the verbalization of the cognitive processes. To verify and enrich the screen-recorded behavior, I checked, using think-aloud protocols, for explanations of the observed search and click-through behavior. Consequently, the observational study with qualitative content analysis methodology, according to Mayring (2003) and Kassarjian (1977), is well suited as additional research methodology in this mixed-method study (Brewer and Hunter 1989; Kolbe and Burnett 1991; Creswell and Plano Clark 2007).

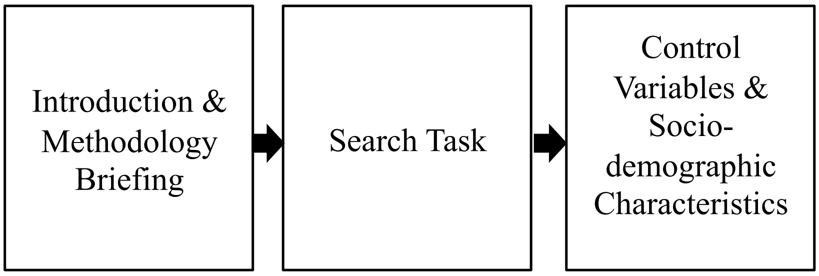


Figure 40: Observational Procedure (Project III)

The observational study was conducted in two stages, from June 2010 to August 2010 and then in December 2010, with participants from Germany.[100] Figure 40 displays the general procedure for the observational study. In a first step, the participants were introduced to the general purpose of this study. The research methodology with think-aloud protocol and screen recordings also were detailed. Before the main part of the observational study started, one rehearsal was conducted to address unclear points and situations. In a second step, 12 different search tasks were accomplished step by step, until the participants were satisfied with the results of their search task. The human–computer interaction (search behavior) and think-aloud protocol were recorded with Microsoft Windows Media Encoder 9.[101] In a third step, after completing the 12 search tasks, the participants were asked to complete a questionnaire about their Internet and search engine usage behavior, their experience in different search tasks, and some personal information. In general, confidentiality and anonymity was guaranteed to all participants.

Overall, I obtained verbal and screen data from 480 search tasks for a period of 28 hours and 20 minutes of recorded information. The observational tasks lasted between 20 and 82 minutes. These data were coded and analyzed with QSR NVIVO 7. I enriched the observations with objective details from the screen recording. Specifically, I supplemented with details about each search term entered in search engines (keywords and advertiser competition), the displayed results (single or mere exposure, exact position on the search engine result page), and the performed action (paid or free click, new search) from screen recording.

[100] The process of data collection and transcription of the verbal protocols was generously supported by Dipl.-Sportwiss. Maximilian Born and Philipp Hoffmann in the first inquiry period and Andreas Bauer, Magdalena Weiss, and Anasthasia Westphal in the second inquiry period.

[101] The search tasks in the first and second phases of the data collection differed partly due to seasonal adjustments (see Appendix 11). Search tasks were for instance: "Please find an adventure pool to your taste" and "Please prepare to buy the current Spiegel-bestseller (paperback) in the category of non-fiction books".

5.2.2 Sample Description

The sample of the observational study (N = 40) encompasses Internet users of different ages and Internet usage behaviors. These participants were recruited by both advertisements in a leading German newspaper and personal recommendations. The age set spanned between 14 and 72 years (M = 34.13 years), with 43.3% women. Their educational level is diverse: 30% completed higher education entrance qualifications, another 30% completed their academic studies, and 12.5% each had high-school diplomas or had completed vocational training. The Internet usage patterns are split as follows: 10% use the Internet several times a week, 20% daily, and 70% use the Internet several times a day. Their search engine usage behavior, compared with Internet usage, differs more, spreading from 7.5% with monthly usage, 15% with weekly usage, 22.5% with daily usage, and 55% with repeatedly daily usage. For a better description of the sample characteristic, I measured search engine expertise (SEE), using a four-item seven-point semantic differential with a numeric format, adjusted from Mishra, Umesh, and Stem (1993).[102] The reliability of the scale is good, with Cronbach's α = .91. Overall, search engine expertise is medium (M_{SEE} = 4.77, SD_{SEE} = 1.21). Appendix 12 displays the individual characteristics of the participants in the observational study.

5.2.3 Results

The major themes emerging from the verbalization of the cognitive processes and the screened behavior form the basis for a conceptual framework to understand factors that influence users' click-through behavior. This framework depicts the grouping of relevant factors that influence consumer click-through behavior, observed from human–computer interactions and enriched with verbalizations of the cognitive processes. These groups of themes represent the major findings from the analysis of the observational data.

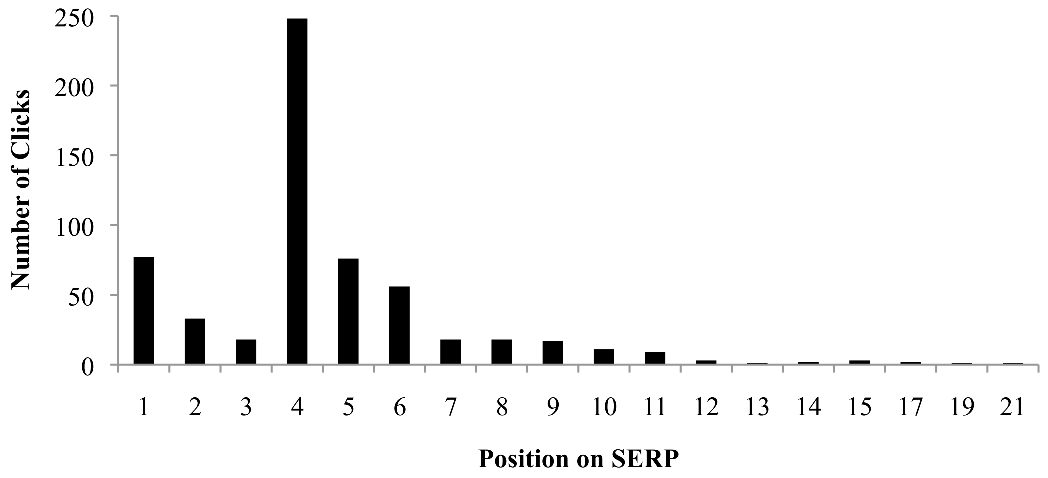
The Role of Order Effects

To examine the relevance of order effects on click-through behavior, I consider two aspects. First, I note the observed click pattern on the displayed search engine result pages. Second, I supplement these observations with statements for clicks on organic, paid top, and paid side search results. To investigate the click patterns and the relevance of order effects, it is necessary to consider which areas on a search engine result page are clicked most often (e.g.,

[102] The items and the corresponding poles were: (1) "I know very little about"/"I know very much about", (2) "Inexperienced"/"Experienced", (3) "Uninformed"/"Informed", and (4) "Novice Searcher"/"Expert Searcher". The second and fourth items were inverted from the original scale by Mishra, Umesh, and Stem (1993).

Briggs and Hollis 1997; Benway 1998; Schroeder 1998; Drèze and Hussherr 2003; Ghose and Yang 2009). Therefore, clicks on organic search results, clicks on paid top results, and clicks on paid side results are distinguished.

Answering the first relevant question in the context of this project, regarding which position on the search engine result page receives the most clicks, the observational study reveals that the first organic position (fourth position in Figure 41) received the highest proportion of all conducted clicks (N = 248; 41.75%). The first paid top position (first position in Figure 41; N = 77; 12.96%) and second organic position (fifth position in Figure 41; N = 76; 12.79%) follow with almost equal click frequencies. The screen recording of click-through behavior furthermore discloses that only 13 clicks were conducted on all displayed paid side results (on SERP position 12–21), which is equal to 2.19% of all clicks. Figure 41 displays the number of clicks on each position of a SERP in the observational study.



Notes: a. The positions 1–3 in the bar chart symbolize the clicks on paid top positions.
b. The positions 4–11 in the bar chart symbolize the clicks on organic positions.
c. The positions 12–21 in the bar chart symbolize the clicks on paid side positions.

Figure 41: Click-Through on Different SERP Positions (Observational Study, Project III)

In a second step, I build explanations for observed click patterns on the think-aloud protocols, combined with the screen-recorded click-through behavior. Therefore, I discuss reasons for clicks on organic search results, clicks on paid top search results, and clicks on paid side search results.

Clicks on organic search results

The results show that the majority of the observed clicks are on organic results (76.26%, N = 453). I could not find clear statements why clicks were performed on organic results. Rather, the content analysis discloses arguments for clicks on organic search results that frequently connected to statements against clicks on the displayed paid search results. A 51-year-old, male energy adviser (P 28)[103] argued, while clicking on the first organic search result, that he perceives the offers for products or services advertised on sponsored search links to be more expensive.[104] A hint of general avoidance behavior toward paid search results is a statement of a 20-year-old, female trainee (P 38). She argues that she never clicks on sponsored links because she tries to avoid being directly affected by advertisements in her click-through behavior. Instead, she clicks on the first organic search result.[105] This avoidance behavior—not to click on sponsored search results but rather on organic results—is supported by the explication of a 26-year-old, female flight attendant (P 16),[106] who offered additional reasons why the first organic position is so popular: It is the initial position after the ignored sponsored links. She explicated another reason against sponsored links, besides perceived higher prices, too. In her opinion, ads on search engines might be misleading, such that they would not lead to appropriate hits on the linked websites. Her apprehension that paid top results would not lead to satisfactory forwarding but rather would impede the search process was also endorsed by a 30-year-old, male photographer (P 11).[107]

Clicks on paid top search results

The section with the second most clicks was paid top results. This observational research setting showed that 21.55% (N = 128) of the clicks were on the three paid top positions for the different SERPs. Prior explanations for clicks on organic search results revealed reasons to avoid paid click-through, but consumer click-through behavior nevertheless was affected by paid top search results.

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[103] In this section, the references to the participants are shortened, and P refers to the participant number denoted in Appendix 12.

[104] “The prices for offers of the colored search results are generally more expensive with fixed price. Therefore I choose the first non-colored link [clicking on the first organic result]“ (P 28).

[105] “[….] I never click on the results in the colored box [paid links] because [….], I don’t know, that is for me like regular advertising [click on the first organic position]“ (P 38).

[106] “And now here, in first [paid top] position typical Amazon advertising. I would never click on that. I always proceed with the next […] I don’t know why, but they [paid top results] are always unlikeable. Therewith, I always have the feeling not to find the right things [click on the first organic position]” (P 16).

[107] “Yes, Amazon appears on first position and is colored. I don’t feel like it, because I don’t know whether they really have Spiegel Bestseller list [click on the third organic position]” (P 11).

With his statement, an 18-year-old, male student (P 37) encapsulated the latent ambiguity underlying clicks on sponsored top links: On the one hand, he disclosed that his click-through behavior usually neglected paid clicks. On the other hand, the argument against paid clicks seemed not very strong, such that sponsored links do not affect his behavior in general. In some situations, his actual search task and the displayed search engine result page also led him to click on the first paid top position.[108] An additional argument for clicks on paid top results, in addition to avoidance behavior, was lack of knowledge of paid results versus organic results. A 51-year-old, female office administrator (P 28) and her search engine expertise offered some explanation: She explicitly stated that advertising on search engine result pages annoys her, and she therefore did not focus on paid side results but on results in the center of the SERP. Thus, she revealed the importance of knowledge about the positions of paid results on search engine result pages. She was not aware that paid results also could be displayed in a centered position above the organic results and unwittingly clicked on the first paid top result.[109]

Additional motives for clicks on the paid top results manifested in the observational study, and proved by verbal explanations, included the following: lack of knowledge in search tasks and distinctiveness of the displayed search results for a given keyword. Addressing the lack of knowledge as a reason for clicks on paid top results, the verbal description of a 20-year-old, male student (P 33) is exemplary. He argued for systematically opening the search results top down if he lacked prior experience in the particular search task.[110] An example of the motive of distinctiveness came from the statement of a 51-year-old, male energy adviser (P 26). He could not see differences among or a selection criterion for the displayed search results from the entered search term, so he started by clicking the first displayed search result. In the explained case, it was the first paid top position.[111]

[108] "Ok, I will click on the uppermost [link to a] website, although I normally won't do this, because I think this are somehow bought offerings. Which are in general not so good. But now, I will check this [click on the first paid top position]" (P 37).

[109] "But what I notice is, that the advertisements bother me [….] Because I don't want to be distracted from the ads on Google, I focus on what is mentioned in the center and not on the right [click on the first paid top position]" (P 28).

[110] "I will click on the first three links because I have no clue [click on the first, second, and third paid top positions]" (P 33).

[111] "Let's start from the top because there is no concrete difference, no selection criterion identifiable [click on the first paid top position]" (P 26).

Clicks on paid side search results

Prior research on lateral banner ads reveals banner blindness (e.g., Drèze and Hussherr 2003). This observational study can support this finding, because only 2.19% (n = 13) of the clicks were on paid side results. To explain her click on a paid side result, a 55-year-old, female qualified designer (P 35) asserted, in the context of a general cluelessness, that the paid side results should be taken in consideration. Then she takes this contemplation into account and clicked on the third paid side result, instead of proceeding to a second search engine result page.[112]

The Role of Exposure

Investigating the relevance of exposure for click-through behavior, I again consider the observed click pattern on the displayed search engine results, supplemented with statements to explain clicks in different exposure scenarios. To examine the click pattern and thus the relevance of exposure, four main scenarios for a click can be observed: one setting is with a single exposure and three settings are with double exposures.

I detect 302 clicks (50.84%) when no additional organic or paid result is displayed. That is, the clicked result appears only once (single exposure) on a certain SERP. Furthermore, 66 clicks (11.11%) are conducted on an organic search result with an additional corresponding paid result, and 181 clicks (30.47%) occurred on an organic result with additional organic results matching to the clicked organic result. Finally, the observational design reveals only few clicks on a paid top result with additional organic exposure (N = 45; 7.58%). Figure 42 displays the number of clicks in each of the four exposure scenarios in the observational study.

[112] "Now, I will have a look at what is offered on the rightmost [paid side links] [click on the third paid side position]" (P 35).

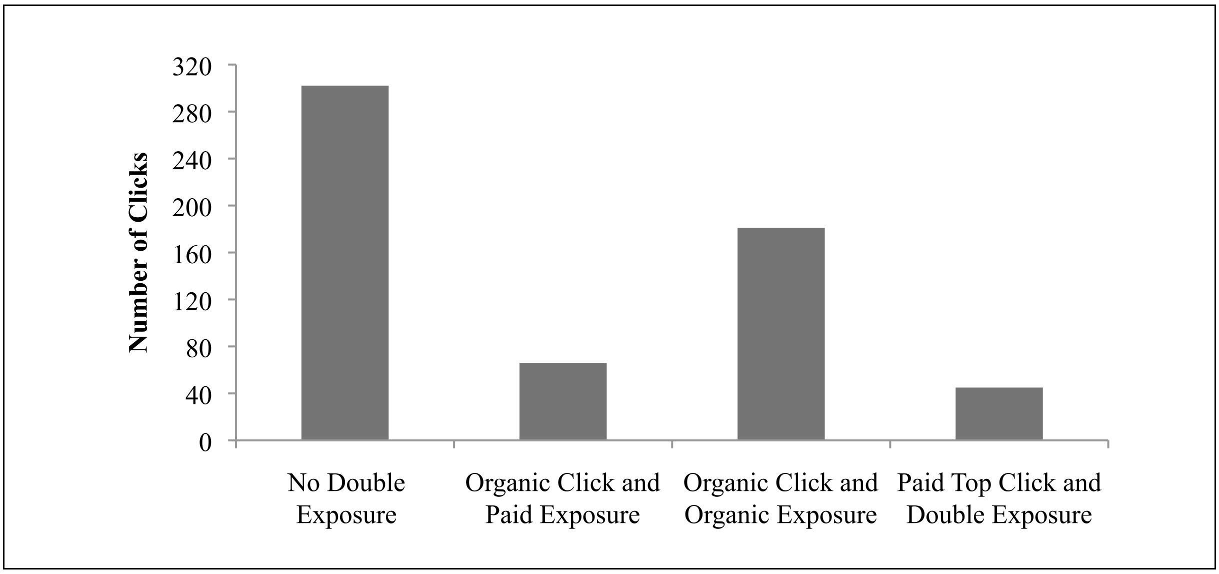

Figure 42: Number of Clicks for Different Exposure Scenarios (Observational Study, Project III)

These results from observed click-through behavior suggest that exposure effects on a search engine result page influence consumer click-through behavior. In detail, the content analysis of the think-aloud protocols reveals two different sorts of exposure effects: cross-media exposure, and double exposure on a search engine result page.

First, cross-media exposures affect consumer click-through behavior on search engines.[113] The statements of the think-aloud protocols show that offline advertising exposure influences consumer search and click-through behavior in a search engine context. The verbal explanations of the participants' perceptions reveal two distinct influences of cross-media mere exposure on click-through behavior. On the one hand, I find evidence of a direct influence on search and consequently click behavior. A 25-year-old, male journalist (P 9) stated that, when searching for a relevant result on a displayed search engine result page, he externally searched for something familiar to him.[114] Furthermore, he explicated searching for something he knew from commercials he had seen. Finally, he clicked on a search result in the top sponsored links, well known from advertisements.[115] On the other hand, the verbalization of a 25-year-old, male student (P2) and a 30-year-old, male photographer (P11) revealed that cross-media mere exposure also influenced internal consumer information search and click-

[113] Naik and Peters (2009) and Stammerjohan et al. (2005) show synergies across media.
[114] For external information search, see Beatty and Smith (1987) and Schmidt and Spreng (1996).
[115] Searching on a SERP for the search term "cheap all-inclusive holiday caribic" for a result to click. "I am searching for something familiar. Maybe there is something I already know from commercials [click on the second paid top result Billigflieger]. Billigflieger, that is something I know from commercials" (P 9).

through behavior.[116] Their click-through behavior is not affected in a way that they explicitly search for something familiar from advertising, but prior exposure to advertising stimuli led to their consciousness for a certain displayed search result and finally a click.[117]

Second, and more interesting for search engine settings, is an observation of 292 (49.16%) clicks happening in settings with additional corresponding paid or organic search result(s), which I will denote as double exposure. Despite the rarity of matching statements—suggesting a rather subliminal or unconscious impact of double exposure on a SERP—this observational study hints at the effect through a statement from the think-aloud. A 25-year-old, male journalist (P9) verbalized, after clicking on a link for a certain employment law expert, that this search result attracted his attention on a given SERP more than once.[118]

5.2.4 Findings

This observational study delivers unique insights, because it is the first study of its type to focus on determinants of click-through behavior. The combination of pure observation and verbal protocols identifies not only click-through patterns, but also deeper insights into the cognitive processes influencing click-through behavior. Based on the think-aloud protocols and observed behavior, I have identified a conceptual framework of determinants of click-through behavior in search contexts (see Figure 43). Sequence or order effects influence click-through behavior. That is, primacy rather than recency effects emerge in the click-behavior and the cognitive processes.

[116] For internal information search, see Schmidt and Spreng (1996) and Klein and Ford (2003).

[117] "Ab-in-den-Urlaub I have recently heard in commercials. That is new. Let's see whether I can find out something about the prices [click on the second organic result Ab-in-den-Urlaub.de]" (P 2). "This is what this guy from RTL Saturday Night advertises for: Expedia.de. This is the first real search result after the sponsored links [click on the first organic result Expedia.de, on a SERP with an additional paid side result in second position]" (P 11).

[118] On a SERP with two organic search results for an employment law expert, after clicking on the second organic result: "But this one has now once in a while attracted my attention" (P 9).

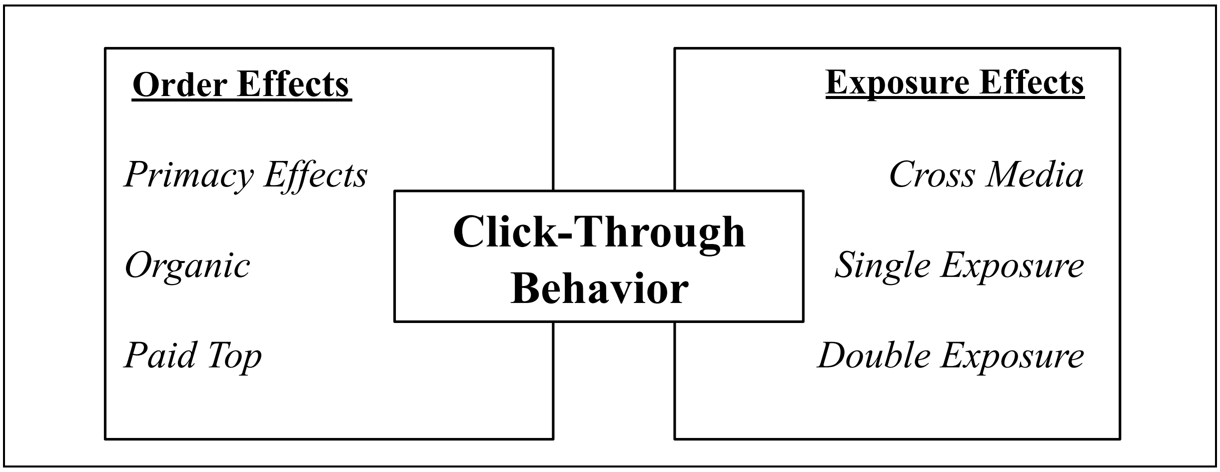

Figure 43: Exposure and Order Effects Influencing Click-Through Behavior

In addition, the observational study shows that paid top positions 1–3, and organic positions 1–3 together receive 508 clicks in the 12 different search tasks. Thus, one-third of the clicked positions, respectively ranks, receive as much as 85.52% of the clicks. This observation suggests that order effects influence consumer click-through behavior. Primacy effects dominate the click-through pattern in the observational study for both paid top and organic search results. These primacy effects are common when prior knowledge according to a search task is minimal. Generally, clicks on paid side results are less frequent, due to banner avoidance behavior.

Furthermore, this observational study discovers three exposure conditions. First, 50.84% of the clicks occur in single-exposure situations. Second, 30.47% of the clicks are on organic search results, with a second organic search result of the listed company available close to the clicked link (double organic exposure). Third, double exposure scenarios on a single search engine result page comprise 18.69% of clicks. In addition to this observed exposure click pattern, traditional mere exposure is a cognitive process influencing click-through behavior.

These general results of the observational study strongly suggest drawing from the theoretical background of order effects and exposure to develop hypotheses for the experimental studies. Therefore, the observational study not only locates observed click-through behavior and cognitive processes in a theoretical framework but also can make the experimental research setting more understandable and expand robust descriptions and interpretations (see Huff 2009).

5.3 Theoretical Basis

In *Chapter C*/5.2, I identified the relevance of order effects and exposure effects as determinants of consumer click-through behavior, though they have been widely neglected in prior research. This lack of research and the findings from the observational setting influence the theoretical foundation for experimental investigations in search engine marketing.[119]

Arguments from order and exposure literature suggest that new theoretical contributions for a deeper understanding of the impact of search engine marketing on consumer behavior are overdue. It is therefore of great concern to build on seminal theories to explain the causes of click-through on search engine result pages. In the experimental studies, I therefore build on the theoretical underpinnings of the primacy–recency and mere exposure paradigms to investigate the causal effects of order and double exposure on consumer click-through behavior. Figure 44 displays these causes and effects schematically.

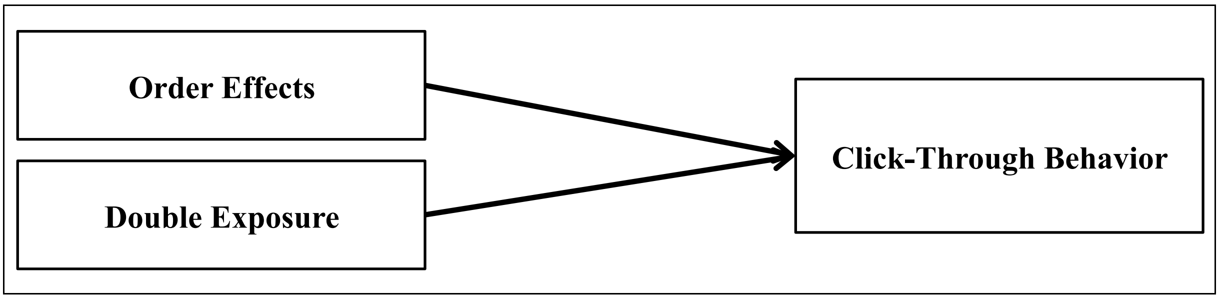

Figure 44: Research Model (Experimental Studies, Project III)

5.3.1 Order Effects

The effects of message order on persuasion or attitudinal change have been widely demonstrated in psychology and marketing in the past 85 years. Lund (1925) was the first to demonstrate that in a sequence of discussions, the first message has considerable influence on the final position or attitude of a subject. This phenomenon is also known as the *law of primacy in persuasion* (Lund 1925) or later the *primacy–recency paradigm* (Hovland and Mandell 1957).[120] The latter contrasts two opposing order effects: primacy and recency.

[119] Though the approach for testing the impact of search engine marketing in *Project III* based on exposure and order effects for hypothesis development, is partly based on classical approaches to explain how advertising works, an overview of the exhaustive literature on the modes of action of advertising is not given here. For a detailed overview, see Vakratsas and Ambler (1999).

[120] Literature on message order effects distinguishes two main aspects. Research according to Hovland and Mandell (1957) focus on whether the first message or subsequent messages have greater effects. Or, research according to McGuire (1957) focus instead on whether the first or a following argument in a single message has greater effect.

Primacy effects emerge in situations when subjects form judgments on a certain topic that are consistent with the first delivered message; recency effects exist if judgments are more consistent with the final message (e.g., Hovland, Campbell, and Brock 1957). Findings from cognitive psychology show that information that appears first in a list of information has advantages. This primacy effect can be explained because the initial information has less competition from rival information for scarce memory capacity of subjects (e.g., Waugh and Norman 1965; Poltrock and MacLeod 1977).

In marketing research, along with advertising and consumer research, order effects have been confirmed in product presentation (e.g., Buda and Zhang 2000), TV commercial presentation (e.g., Zhao 1997), print advertising (e.g., Hanssens and Weitz 1980; Lohse 1997; Brunel and Nelson 2003), and online marketing (e.g., Hoque and Lohse 1999; Ansari and Mela 2003; Drèze and Zufryden 2004; Hofacker and Murphy 2005; Murphy, Hofacker, and Mizerski 2006), among other settings. All these studies highlight primacy effects. Current research on Internet advertising also suggests that clicks on banner advertising are more likely if the ads are placed on the entry of the page (e.g., Chatterjee, Hoffman, and Novak 2003). This higher positioning of online ads enhances click-through (e.g., Ansari and Mela 2003; Ahmed, McKnight, and Oppenheim 2004; Brynjolfsson, Dick, and Smith 2004; Drèze and Zufryden 2004). Recent research on paid search advertising also shows that higher ranks of organic and paid search results have positive impacts on click-through and conversion rates (e.g., Brooks 2004; Baye et al. 2009; Ghose and Yang 2009). Hence, I conclude to compare single paid top and single organic search results with *H1*:

Hypothesis 1 (H1):	*The overall click-through for single top exposure is higher than for single organic exposure.*

Yao and Mela (2011) demonstrate the importance of focusing on order effects in the context of consumer click-through behavior on paid search results by showing that consumers attach more importance to the positions of the sponsored search results. Furthermore, recent analyses of eye movement on search engines suggest, that users mostly view search engine result pages from a left-centered triangular perspective (see Appendix 13). Hence, paid top positions above the organic results and the organic results gain the most fixation time (e.g., commercial studies: Hotchkiss, Alston, and Edwards 2005; Hotchkiss 2006; scientific studies: Granka, Joachims, and Gay 2004; Pan et al. 2004; Joachims et al. 2005; Radlinski and Joachims 2005; Granka, Hembrooke, and Gay 2006). In addition to order effects, traditional banner advertising, mainly placed along the lateral (vertical) of a website, is perceived as being annoying. Thus, consumers learn to avoid looking at the ads (e.g., Briggs and Hollis 1997; Benway 1998; Schroeder 1998; Drèze and Hussherr 2003; Ghose and Yang 2009). Because paid side results, unlike paid top results (which are below the search field and hardly separated from organic results), are similar to traditional banner advertising and thus more perceived as being advertisings, consumers ignore and do not click on lateral results. These results of consumer avoidance behavior against paid side results are also reflected in the results of the observational study in *Project III*. Therefore, I predict for single paid top and single paid side results:

Hypothesis 2 (H2):	*The overall click-through for single top exposure is higher than for single side exposure.*

5.3.2 Double Exposure

In an influential work, Zajonc (1968) introduces the effect of mere exposure to suggest that familiarity through (conscious or unconscious) simple, repeated exposures leads to an increased link with a certain stimulus. In more detail, Zajonc (1968, p. 1) defines the mere exposure effect as the observation that "mere repeated exposure of the individual to a stimulus is a sufficient condition for the enhancement of his attitude toward it. By 'mere exposure' is meant a condition which just makes the given stimulus accessible to be individual's perception." Further evidence for the phenomenon of increased exposure leading to more positive affect toward a certain stimulus appears in social interaction research (e.g., Bovard 1951; Festinger 1951; Homans 1968).

Because exposures on a typical search engine result page within one search process are not repeated in a time sequence with longer time lags, as the general idea of Zajonc (1968) suggests, I adapt the proposition of exposure effects to search engine marketing. In the case of simultaneous displayed paid and organic results, I argue that mere exposure similar situations arise through eye movement patterns (e.g., Granka, Joachims, and Gay 2004; Pan et al. 2004; Joachims et al. 2005; Radlinski and Joachims 2005; Granka, Hembrooke, and Gay 2006). Consumers' eye movement patterns follow a triangular path from the left upper level of the website to the right upper level, and then to the upper center. From the upper center of the page, the eye movement proceeds diagonally to the left end of the page (see Appendix 13). Thus, I define search engine exposition situations with organic and paid result, on the foundation of mere exposure theory, as double exposure. Double exposure is present if the paid (either top or side) search result is displayed in addition to an organic search result on the same search engine result page.

The mere exposure effect, a pure affects model in advertising research, shows that it is not necessary for a subject to be aware of certain advertisements or stimuli (see Vakratsas and Ambler 1999). Therefore, it is not surprising that previous research on consumer behavior shows that supplementary exposures to logos or brand names can cause more positive attitudes or evaluations (e.g., Janiszewski 1993). Furthermore, studies on banner advertising show that repeated exposures to banner advertising increase click-through and click-through probabilities (e.g., Ilfeld and Winer 2002; Chatterjee, Hoffman, and Novak 2003; Drèze and Hussherr 2003; Manchanda et al. 2006). A search engine result page with double top exposure through the simultaneous display of organic and paid top result thus positively influences consumers' click-through probabilities and overall or free (on organic results) click-through rates. So I suggest for *H3*:

Hypothesis 3 (H3):	*The (a) overall and (b) free click-through for double top exposure is higher than for single organic exposure.*

The hypothesis for the combination of paid side and organic result, specified as double side exposure, has the same direction as that for the combination of paid top and organic result. This is the fact because paid side results are equally, at least to some extent, (un)consciously perceived, even if consumers try to avoid knowingly looking at these paid side results (see *Chapter C*/5.2.3). Hence, for the comparison of double side exposure situations versus situations with only one stimulus in the organic result, I predict:

Hypothesis 4 (H4):	*The (a) overall and (b) free click-through for double side exposure is higher than for single organic exposure.*

In investigating the influence of advertiser competition on the relevance of double exposition to attract high levels of overall and free click-through rate, the influence of choice overload must be considered. Higher levels of advertiser competition are associated with larger assortments of similar search results,[121] and thus higher cognitive efforts for finding the appropriate search result. Hence, consumers aim to reduce search costs (e.g., Gigerenzer, Todd, and ABC Research Group 1999; Mogilner, Rudnick, and Iyengar 2008; Reutskaja and Hogarth 2009). The impact of double exposure situations on click-through behavior thus

[121] See footnote 85.

should increase with choice overload, because double exposure leads to increased awareness and thereby lowers search costs, which leads to higher click-through rates (e.g., Ilfeld and Winer 2002; Chatterjee, Hoffman, and Novak 2003; Drèze and Hussherr 2003; Manchanda et al. 2006). Therefore, I argue:

Hypothesis 5 (H5):	*The marginal effect of double exposure on (a) overall and (b) free click-through rate increases with growing levels of advertiser competition.*

5.4 First Experimental Study

This first experimental study serves as an initial test of the hypotheses, based on the results from the observational and theoretical preliminary considerations. Therefore, the general applicability of order and exposure effects is tested with a focus on demonstrating the relevance of subdivided examinations of paid top and paid side search results, as well as overall and free click-through behavior.

5.4.1 Methodology

In this first experimental online study, consumers' behavioral reactions to paid search advertising exposure are investigated using one experimental scenario. More precisely, I conduct an experimental study with a 3 (top-listed paid, side-listed paid, and no paid result) × 2 (relevant organic and no relevant organic result) between-subjects design with five random sampling groups.

This online experiment included three general steps (see Figure 45). In a first step, after a brief introduction to the purpose of this empirical investigation, the search scenario description (booking a flight from Munich to Berlin online) was presented to the participants. A vignette (see Appendix 14) was given to frame the respondents' search task (Alexander and Becker 1978; McFadden et al. 2005). Then a manipulated input screen from Google appeared. Each participant was asked to enter his or her preferred search term or keyword(s) for the described search scenario in order to present a more realistic search situation.

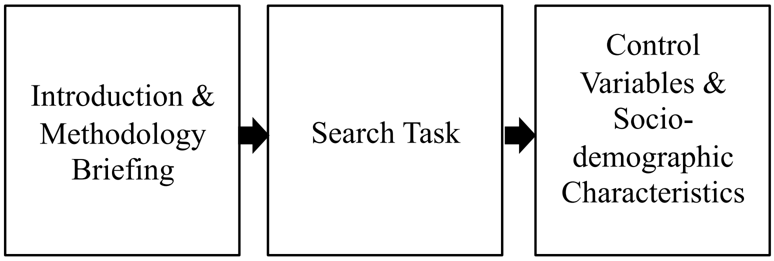

Figure 45: Experimental Procedure (Experiment 1, Project III)

In a second step, the participants were randomly assigned to one of the following five groups: (1) double top exposure (paid top and organic result), (2) double side exposure (paid side and organic result), (3) single organic exposure (organic result), (4) single top exposure (paid top result), or (5) single side exposure (paid side result). The "no relevant organic result", "top-listed, side-listed, and organic result", and "top-listed, side-listed, and no relevant organic result" scenarios are not realistic combinations in search engine marketing, so they are not included in this experimental research design (see Table 22).

Organic Exposure	**Paid Search Exposure**		
	Paid Top	**Paid Side**	**No**
Yes	N = 82	N = 80	N = 81
No	N = 79	N = 81	n.a.

Table 22: Cell Sizes (Experiment 1, Project III)

On the search engine result page in each randomly assigned experimental group, a manipulated original search engine result page for the keyword "Flug München Berlin" from Google[122] was displayed, and respondents could select one link to click. In the third step, control variables and socio-demographic characteristics of each participant were requested to determine the sample characteristics.

5.4.2 Sample

A convenience sampling method was applied. Despite the criticism of Ferber (1977), convenience sampling is not problematic for this study because respondents are frequently in the situation of searching for products, services, or other relevant information on search engines, and are therefore of peculiar interest for this research setting. The participants were invited

[122] Depending on the assignment to one of the five different groups, the SERP included manipulated single organic, top, or side, as well as double top, or double side exposures. The manipulated positions appear with frames in Appendix 15.

during February–April 2010 through direct mailing, banner advertising in a large German social network for undergraduate students (www.studivz.de), and banner advertising in a large German social network (www.meinvz.de) to join the online experiment. Entering a lottery to win one of ten EUR 15 coupons for the online retailer Amazon.com incentivized the participants. Each participant entered the free drawing and provided his or her e-mail address at the end of the experiment to be contacted if he or she won.

The final sample included N = 403 participants with an average age of 26 years and 8 months (median: 25 years; minimum: 18 years; maximum 58 years). Of the participants, 56.1% were men. The overall educational level was high: 40.4% had completed academic studies and 56.3% had higher education entrance qualifications. Their Internet and search engine usage also was high: 92.4% used the Internet and 70% used search engines several times a day. Attitude toward paid search, measured with four seven-point semantic differential scale items by Allen and Janiszewski (1989) with a numeric format (ATPSA: $M_{ATPSA} = 3.55$; $SD_{ATPSA} = 1.46$), was low in general, in unison with their high Internet search skill (ISSA: $M_{ISSA} = 5.75$; $SD_{ATPSA} = 1.31$),[123] measured by three seven-point Likert-type items from Mathwick and Rigdon (2004).

To evaluate the proposed influences of order effect and double exposure, I compared the click-through behavior of the different experimental groups: double top, double side, single organic, single top, and single side. To show the effectiveness of paid search advertising on a SERP, this study employs multiple chi-square tests with a procedure equal to Sprowls (1964). First insights for click-through pattern derived from comparing the CTR for each position of the five search engine result pages (see Figure 46). Of the 403 clicks, the first paid top position received highest CTR at 17.87%. The second paid top position received 15.88%, and the fifth organic position, with 14.64%, was next. Thus the third paid top position (6.70%) received a smaller click-through rate than the first (12.66%), second (7.20%), and fourth (10.92%) organic position. The CTR for paid side positions are quite low, ranging from 1.24% for the fourth paid side position to .25% for the second, fifth, sixth, and seventh.

[123] The tests for the reliability and validity of the applied multi-item measurements and details on the applied single-item measurements in Experiment 1 of *Project III* are reported in detail in Appendix 16.

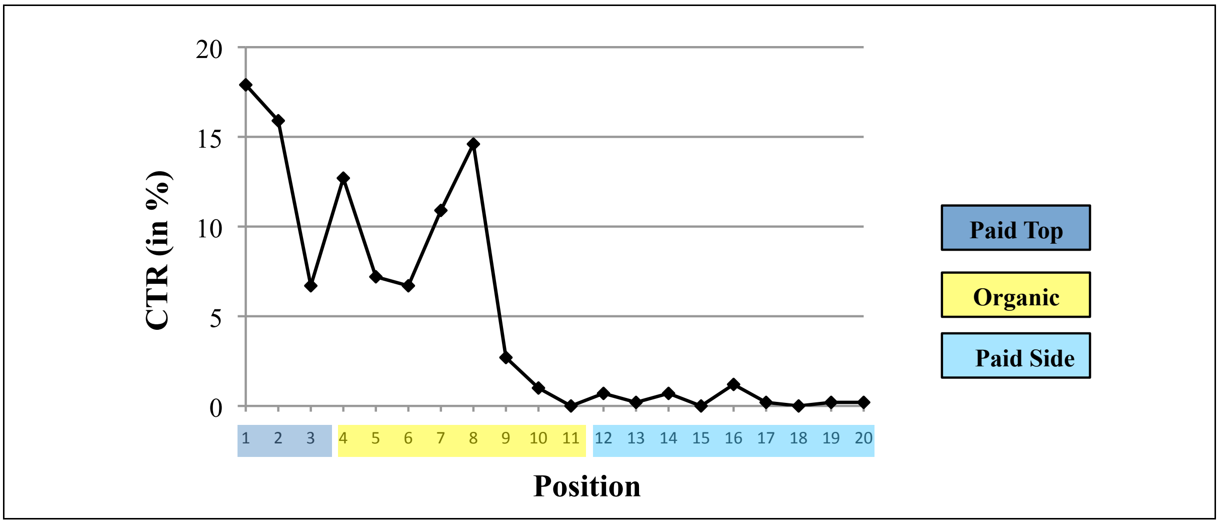

Figure 46: CTR for Different SERP Positions (Experiment 1, Project III)

The overall and free click-through statistics, displayed in Table 23 provided the basis for subsequent chi-square tests. In total, I analyzed 403 clicks on five search engine result pages: 82 clicks on a SERP with a double top exposure scenario (paid top and organic result), 80 clicks on a SERP with a double side exposure scenario (paid side and organic result), 81 clicks on a SERP with single organic exposure, 79 clicks on a SERP with single top exposure, and 81 clicks on a SERP with single side exposure. Table 23 displays the overall and free click-through, which form the basis for the following statistical analysis.

Experimental Group		**Overall**		**Free**	
	N	**CT**	**CTR**	**CT**	**CTR**
Double Top	82	20	24.39%	13	15.85%
Double Side	80	13	16.25%	13	16.25%
Single Organic	81	14	17.28%	14	17.28%
Single Top	79	12	15.19%	0	0.00%
Single Side	81	2	2.47%	0	0.00%
Total	403	61	15.14%	40	9.93%

Notes: a. CT is the abbreviation for number of clicks (click-through).
b. CTR denotes click-through rate.

Table 23: Overall and Free Click-Through (Experiment 1, Project III)

5.4.3 Results

To explain consumer click-through behavior, I also draw from literature on primacy and recency. Deducing from this stream of literature, I expect that the overall click-through for single top exposure should be significantly higher than for single organic exposure (*H1*). The results do not show that the overall click-through for single top exposure is significantly higher than for single organic exposure. The click-through is not significant but lower for paid top than for organic results ($\chi^2(1) = .13$, $p = .72$).[124] Thus, *H1* cannot be confirmed. In addition, I supposed that the overall click-through for single top exposure is significantly higher than for single side exposure *(H2)*. The number of clicks is significantly higher for single top than for single side exposure ($\chi^2(1) = 8.11$, $p < .01$),[125] which is in support of *H2*.

To verify the revealed effects of *H1* and *H2*, I additionally control for three supplementary effects (*Supplement 1–3*). First, I compared the overall click-through for single organic exposure with single side exposure. The click-through on single organic exposure is significantly higher than on the single side exposure on the general level ($\chi^2(1) = 9.99$, $p < .01$; *Supplement 1*). Second, I compared the overall click-through for double top exposure to double side exposure. Combining the evaluated primacy effects, the comparison of overall click-through for paid top and organic to paid side and organic did not indicate significant effects. The number of clicks for double top exposure was not statistically significantly higher than the double side exposure ($\chi^2(1) = 1.65$, $p = .20$; *Supplement 2*). Third, this comparison, transferred to free click-through behavior, reveals through the chi-square test statistic that the number of free clicks for double top exposure was not significantly higher than that for double side exposure ($\chi^2(1) = .01$, $p = .95$; *Supplement 3*).

Examining the hypothesis for double exposure effects, namely, that overall click-through for double top exposure is significantly higher than for single organic exposure *(H3a)*, the chi-square analysis suggested no significant effects of an additional paid top search result ($\chi^2(1) = 1.25$, $p = .26$; RR = 1.50). Consequently, *H3a* cannot be confirmed. Testing the hypothesis for the double side exposure versus single organic exposure, the results were similar ($\chi^2(1) = .03$, $p = .86$; RR = .94). Thus, *H4a* cannot be supported. In contrast with double top exposure, the overall CTR for double side exposure (16.25%) was, if only slightly, lower than that for single organic exposure (17.28%).

To investigate the impact of simultaneous displays of paid and organic search results on free click-through behavior, the cases with a single side or top exposure are not considered. Free clicks can only occur when an organic result is displayed. Therefore, search engine result pages with double top exposure, double side exposure, and single organic exposure form the basis of these analyses. In *H3b* I argued that the free click-through for double top exposure

[124] The chance (relative risks [RR] according to Agresti 1996) of an overall click-through on single top exposure compared to single organic exposure was RR = .88.

[125] The chances were RR = 6.07.

would be significantly higher than for single organic exposure. Controlling for this relationship resulted in no significant positive effects ($\chi^2(1) = .06$, $p = .81$; RR = .92). As a result, *H3b* cannot be proved. The free click-through rate (fCTR) in the double top exposure scenario was lower than in the single organic exposure scenario (see Table 23). Finally, I argued that the free click-through for double side exposure would be significantly higher than that for single organic exposure *(H4b)*. This first experimental study cannot support this hypothesis ($\chi^2(1) = .03$, $p = .86$; RR = .94): The empirical investigation revealed a decreasing fCTR (see Table 23).

5.4.4 Findings

The results of this experimental study show the impacts of order effects and double exposures on consumers' overall and free click-through behavior on search engine result pages. A summary of the results of the hypothesized effects investigated in the first experimental study is displayed in Figure 47.[126]

The first experimental study indicated that the distinction between paid top and paid side results stands to reason; for *H2*, the overall clicks on paid top results were significantly higher than for paid side results. This has two reasons: First because of the positioning of the results and second because of a general avoidance behavior of paid side results. Moreover, double exposure did not have a significant effect on overall or free click-through behavior per se. Even more, this has offered the first evidence that double exposure on search engine result pages cannibalizes free click-through behavior. Further investigations are necessary to gain additional proof of these preliminary findings.

[126] Appendix 29 summarizes the contingency tables for the χ^2-test statistics for H1–H4 and additional supplements.

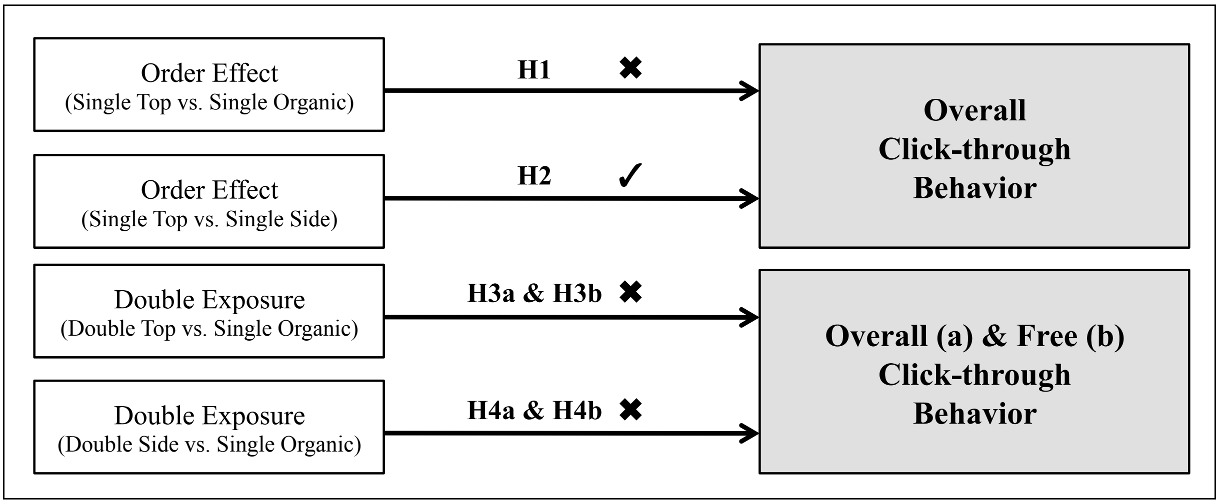

Figure 47: Summary of Hypothesized Effects (Experiment 1, Project III)

5.5 Second Experimental Study

This second experimental study of *Project III* aims to validate and generalize the causal inference of order effects and double exposure in six different scenarios, as well as test *H5* regarding the statistical interaction between advertiser competition and double exposure. This multi-scenario experimental study is obvious; the results of the observational and first experimental study hint at an (positive respectively negative) influence of these effects on overall and free click-through behavior. Additionally, Yang and Ghose (2010) suggest controlling for different search scenarios and levels of advertiser competition. Therefore, I conduct a second experimental study with six different search scenarios to gain further insights into causal inferences on overall and free click-through behavior.

This second experimental online study proceeds as follows: First, I outline the methodology and the experimental procedure. Second, I offer further details about the sample and ecological validity, before concluding with the results of the hypothesis tests and interim findings.

5.5.1 Methodology

Consumers' behavioral reaction to search engine marketing can be investigated using an additional online experimental study. Therefore, the same experimental investigation is applied as in the experimental study of *Project II* (see *Chapter C*/4.2.1). However, the main emphasis differs somewhat, so I explain the methodology again. To avoid order effects in performing the experimental conditions, I conducted a counterbalanced design with six different experimental scenarios (Campbell and Stanley 1963). In each experimental condition I apply a 3 (top-listed paid, side-listed paid, and no paid result) × 2 (relevant organic, and no relevant organic result) between-subjects design with five random sampling groups to investigate the impact of order effects, double exposure, and the interaction between double exposure and advertiser competition on overall and free click-through rates.[127]

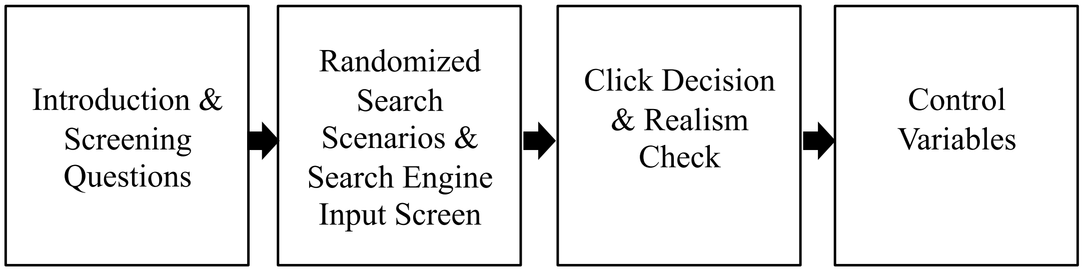

Figure 48: Experimental Procedure (Experiment 2, Project III)

Figure 48 presents the experimental procedure applied in this study. First, after a brief introduction, screening questions asked about socio-demographic factors such as age group, gender, educational level, and Nielsen areas. The representativeness of the sample for the German online population thus is secured. In a second step, the six experimental scenarios were processed in random order. In each of the experimental conditions, each participant was randomly assigned to one of the following five groups: double top (paid top and organic result), double side (paid side and organic result), single organic (organic result), single top (paid top result), or single side (paid side result). For the cell sizes, see Table 24.

AC	Organic Exposure	Paid Search Exposure		
		Paid Top	**Paid Side**	**No**
Scenario 1 (AC = 0)	*Yes*	N = 149	N = 152	N = 155
	No	N = 134	N = 154	n.a.
Scenario 2 (AC = .2)	*Yes*	N = 149	N = 154	N = 145
	No	N = 146	N = 150	n.a.
Scenario 3 (AC = .4)	*Yes*	N = 147	N = 162	N = 148
	No	N = 141	N = 146	n.a.
Scenario 4 (AC = .6)	*Yes*	N = 152	N = 152	N = 148
	No	N = 149	N = 143	n.a.
Scenario 5 (AC = .8)	*Yes*	N = 152	N = 160	N = 144
	No	N = 143	N = 145	n.a.
Scenario 6 (AC = 1)	*Yes*	N = 146	N = 144	N = 154
	No	N = 153	N = 147	n.a.

Table 24: Cell Sizes (Experiment 2, Project III)

The search scenarios and intended keywords were carefully selected (procedure see *Chapter C*/4.2.1). The final keywords for the six experimental conditions were as follows: (scenario 1;

[127] The "no relevant organic result", "top-listed, side-listed, and organic result", and "top-listed, side-listed, and no relevant organic result" scenarios are not realistic combinations in search engine marketing and thus not included in the experimental research design.

advertiser competition [AC] = .0) specialty wine from a gourmet store, (scenario 2; AC = .2) rental Frankfurt central station, (scenario 3; AC = .4) soccer shirt national team, (scenario 4; AC = .6) a magazine subscription, (scenario 5; AC = .8) individual photo calendars, and (scenario 6; AC = 1) price comparison.

As in the first experimental study, the original search engine result pages from the search engine Google provided the basis for the manipulation. These original SERPs for each of the six different keywords were manipulated in the first paid top, first paid side, or first organic position. The displayed search results for each keyword thus vary only in terms of the manipulated first top, first side, or first organic positions. All other search results were similar across the five different groups, which isolated the manipulation of the search engine result page.[128]

Each experimental scenario included a vignette to frame the search task (e.g., Alexander and Becker 1978; McFadden et al. 2005; see Appendix 8). Then a manipulated input screen from Google appeared. Each participant was asked to enter his or her preferred search term or keyword(s) for the described search scenario. Then, the manipulated search engine result page appeared, where the participant could click on the link they would choose in the described search scenario. Subsequent to their click decision, the respondents assessed the realism of the presented search engine result page with a one-item, seven-point Likert-type measurement, according to Williams and Drolet (2005). This procedure was repeated for each search scenario.

Finally, additional control variables were assessed to guarantee a more detailed sample description: Internet search skill according to Mathwick and Rigdon (2004), search engine expertise adjusted from Mishra, Umesh, and Stem (1993), modified attitudes toward paid search by Edwards, Li, and Lee (2002), attitude toward Google adapted from Sengupta and Johar (2002) and a single-item measure of satisfaction by Lemon and von Wangenheim (2009). For the operationalization of the applied measurements, see Appendix 9.

The dichotomous dependent variables (overall click, no overall click; free click, no free click) called for statistics of qualitative or binary choice (e.g., Agresti 2007; Train 2009). The chi-square tests exposed the effectiveness of the order effects and double exposure across the six different search scenarios. The foundations for all subsequent analysis were the free clicks and overall clicks on manipulated organic and paid search results, as displayed in Table 25.

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[128] Appendix 7 displays screenshots of the manipulated search engine result page for AC = 1.

5.5.2 Sample

The data were collected in August 2010 by inviting participants from a European market research panel. The respondents were incentivized when successfully completing the experimental online survey according to the common practices and conditions of the panel. The final sample of 744 respondents was representative of the German online population in terms of age group, gender, educational level, and Nielsen areas (see Appendix 5). Furthermore, their Internet usage was very high with 79.2% of the sample using the Internet several times a day and 14.7% using once per day. Almost half the sample (49.7%) used search engines several times a day. Another 12.6% indicated daily usage, and 27.0% used them several times per week. In addition, the Internet search skills (M_{ISS} = 5.63, SD_{ISS} = 1.08) were high.[129]

To learn more about respondents' search engine usage pattern, I asked to name the most often used search engines, with an open question. The most often-used search engine by far is Google (94.22%), followed by Yahoo, with 1.21%. The general preference for Google as a search engine is reflected in a high attitude toward (M_{ATG} = 6.01, SD_{ATG} = 1.05) and high overall satisfaction with (M_{SAT} = 5.88, SD_{SAT} = 1.24) Google. The level of both measures is surprising considering a simultaneous public dispute in Germany about Google Street View, and general privacy topics during the period of the study (August 2010). In the course of this debate, Google exposed its business model in a big advertising campaign in the major German newspapers and newsmagazines (Fischer and Bell 2010).

The sparseness of knowledge about paid search advertising thus seemed a little surprising. The participants were asked: "Does advertising on Google's search engine result pages (in the form of placements respectively paid search results) exist in your opinion?"[130] In response, 61.4% (N = 457) stated that paid search advertising existed, 25.4% (N = 189) thought it did not exist, and 13.2% (N = 98) had no knowledge on this topic. In more detail, the participants stating that paid search advertising existed selected, in four yes/no choice questions, that (1) the paid links were denoted as advertisements (28.4%), (2) the ads were displayed on the right side of the search results with a white background (48.1%), (3) the ads were displayed above the search results with a white background (51.2%), and (4) the ads were displayed within the search results with a white background (15.1%). Thus, even though this representative sample is skilled using the Internet and search engines, their detailed knowl-

[129] The reliability and validity tests of the applied multi-item measurements and details on the applied single-item measurements in Experiment 2 of *Project III* are reported in detail in Appendix 9.
[130] Possible answers were "yes", "no", and "do not know".

edge about paid search advertising on search engine result pages is sparse. The results also reveal low attitudes toward paid search (with knowledge that it was displayed [APSA]: M_{APSA} = 3.83; SD_{APSA} = 1.32; without knowledge that it was displayed [APSU]: M_{APSU} = 2.87; SD_{APSU} = 1.33).

In total, I analyzed 4,464 clicks on 30 search engine result pages: 895 clicks on a SERP with double top, 924 clicks on a SERP double side, 894 clicks on a SERP with single organic, 866 clicks on a SERP with single top, and 885 clicks with single side exposure. For all clicks, the results can show that the fist paid top position received the highest CTR with 20.14%. The second paid top position, with 18.64% CTR, and the first organic position, with 14.27%, were next. The third paid top position (7.24%) received less CTR than the second (9.14%) and third (7.68%) organic positions. The CTR for paid side positions were very low, ranging from 1.79% for the first side position to .13% for the third and the fourth paid side positions (see Figure 49).

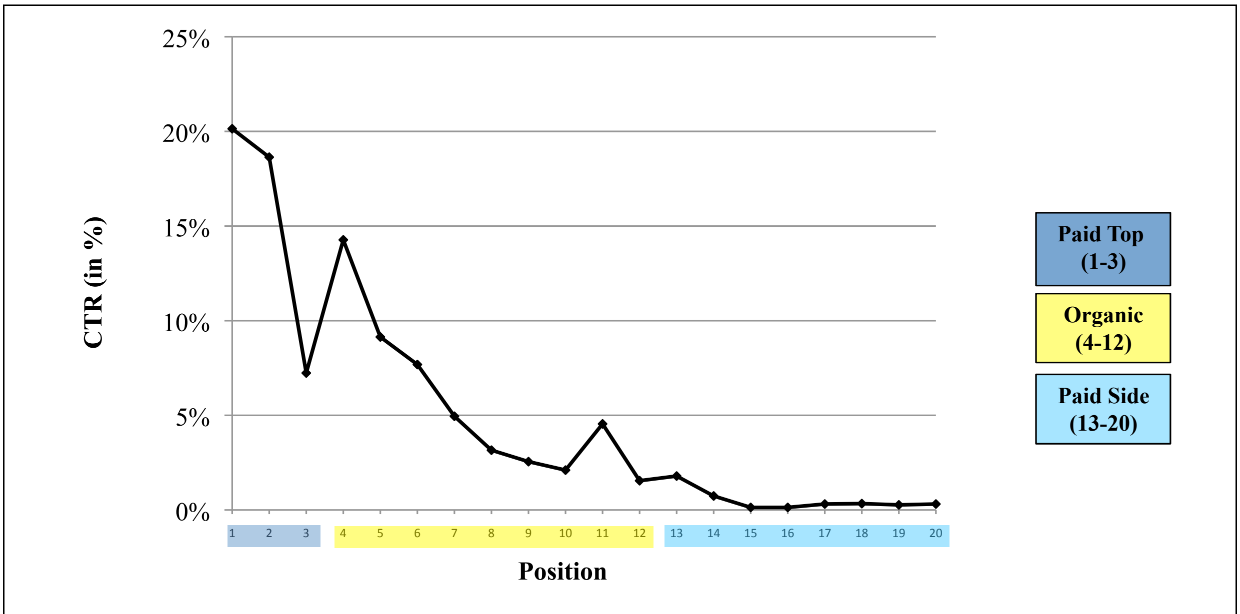

Figure 49: Overall CTR for Different Positions on a SERP (Experiment 2 Project III)

5.5.3 Ecological Validity

To test the ecological validity, as "the applicability of the results of laboratory analogues to non-laboratory, real life settings" (McKechnie 1977, p. 169), I controlled the realism of the applied keywords and the manipulated search engine result pages. First, regarding the ecological validity of the default keywords, each participant was asked to enter a search term or keyword(s) of preference into the search engine input screen after the vignette was presented. A content analysis of the used search terms showed a strong accordance between the entered search term, the scenario description, and the keyword for the manipulated search engine result page.[131]

Second, to test whether the manipulation of the search engine result pages inadvertently changed the realism of the displayed result pages, I performed six realism checks (see Darley and Lim 1993; Shimp, Hyatt, and Snyder 1993) using analysis of variance (ANOVA), I recorded the effectiveness of the manipulation of search engine result page group—(1) double top, (2) double side, (3) single organic, (4) single top, and (5) single side—with one item measured on seven-point Likert-type scale (1 = ”I strongly disagree“; 7 = ”I strongly agree“), adapted from Williams and Drolet (2005).[132] The ANOVA for each search task supported the effectiveness of the manipulated search engine result pages with no significant effects (scenario 1: $F(4, 739) = 1.13$, $p > .10$; scenario 2: $F(4, 739) = .31$, $p > .10$; scenario 3: $F(4, 739) = 1.76$, $p > .10$; scenario 4: $F(4, 739) = 2.27$, $p > .10$; scenario 5: $F(4, 739) = .45$, $p > .10$; scenario 6: $F(4, 739) = .98$, $p > .10$). The mean values of the realism check were relatively high, with means between 5.62 and 6.26, reflecting the aim to display real search engine result pages, manipulated only in terms of the position and appearance of the relevant paid or organic link.[133] The high values thus were not surprising (see Appendix 17).

5.5.4 Results

To assess the proposed effects of order effects and double exposure through displayed paid and organic search results, I compared the five groups (double top, double side, single organic, single top, and single side) for each experimental scenario. Table 25 outlines the overall and free CTR underlying the statistical analyses in this experimental study. The influence of order effects on overall and free click-through behavior is examined, before testing the hypotheses on double exposure effects (for an overview of the results see Appendix 18). Then, the statistical interaction of advertiser competition and double exposure is examined.

The Role of Order Effects

To assess the proposed effect of message order on search engine result pages, the click-through behavior for single top exposure, single side exposure, single organic exposure,

[131] See footnote 90.

[132] The one-item measure, adapted from Williams and Drolet (2005), was: “The displayed search engine result page for the search term (“Price comparison”; “Individual photo calendars”; “Subscription Welt der Wunder”; “Football shirt national team”; “Rental Frankfurt central station”; “Dallmayr wine Auslese”) is realistic.”

[133] The manipulation of the search engine result pages, as in all other experimental studies, was conducted using original search engine results pages from Google (see Appendix 15).

double top exposure, and double side exposure were compared. Building on primacy effects, I assume that the overall click-through for a single top exposure is significantly higher than for a single organic exposure *(H1)*. This assumption cannot be supported ($\chi^2(1) = 1.85$, $p > .05$; see Appendix 19), because no significant positive effect emerged. A single organic result attracted more clicks than a single top result. Except for scenario 4 ($\chi^2(1) = 1.85$, $p > .05$), the results showed higher, though not significantly, click-through for the single organic exposure than the single top exposure (scenario 1: $\chi^2(1) = .34$, $p > .05$; scenario 3: $\chi^2(1) = 1.23$, $p > .05$; scenario 5: $\chi^2(1) = .26$, $p > .05$; scenario 6: $\chi^2(1) = .11$, $p > .05$). The click-through is only significantly higher for a single organic exposure in scenario 2 ($\chi^2(1) = 4.25$, $p < .05$). Thus, *H1* is not supported.[134]

I further hypothesize that the click-through for single top exposure is significantly higher than single side exposure *(H2)*. This assumption is met in both cases. Over all levels of advertiser competition this hypothesis is supported ($\chi^2(1) = 66.01$, $p < .001$; see Appendix 20). Taking all scenarios separately into account confirms the assumption that a single top exposure receives significantly more clicks than a single side exposure (scenario 1: $\chi^2(1) = 16.37$, $p < .001$; scenario 2: $\chi^2(1) = 15.99$, $p < .001$; scenario 3: $\chi^2(1) = 13.22$, $p < .001$; scenario 4: $\chi^2(1) = 17.15$, $p < .001$; scenario 5: $\chi^2(1) = 15.41$, $p < .001$; scenario 6: $\chi^2(1) = 30.80$, $p < .001$),[135] in support of *H2*.

[134] Appendix 19 summarizes the contingency tables for the χ^2-test statistics of *H1*. The chances for a click in the single top scenario compared with a single organic scenario range from $RR_{S2} = .65$ to $RR_{S4} = 1.42$. The relative risk values for *H1* are (1) $RR_{S1} = .97$; (2) $RR_{S2} = .65$; (3) $RR_{S3} = .74$; (4) $RR_{S4} = 1.42$; (5) $RR_{S5} = .86$; (6) $RR_{S6} = .95$.

[135] Appendix 20 summarizes the contingency tables for the χ^2-test statistics of *H2*. The probabilities for a paid top click range from $RR_{S1} = 1.38$ to $RR_{S5} = 17.24$. The relative risks for *H2* are: (1) $RR_{S1} = 1.38$; (2) $RR_{S2} = 4.26$; (3) $RR_{S3} = 6.56$; (4) $RR_{S4} = 4.80$; (5) $RR_{S5} = 17.24$; (6) $RR_{S6} = 5.52$.

Experimental Condition	Experimental Group		Overall		Free	
		N	CT	CTR	CT	CTR
Scenario 1	**Double Top**	149	134	89.93%	51	34.23%
	Double Side	152	129	84.87%	87	57.42%
	Single Organic	155	129	83.23%	129	83.23%
	Single Top	134	108	80.60%	n.a.	n.a.
	Single Side	154	90	58.44%	n.a.	n.a.
	Total	*744*	*590*	*79.30%*	*267*	*35.89%*
Scenario 2	**Double Top**	149	48	32.21%	27	18.12%
	Double Side	154	25	16.23%	23	14.94%
	Single Organic	145	44	30.34%	44	30.34%
	Single Top	146	29	19.86%	n.a.	n.a.
	Single Side	150	7	4.67%	n.a.	n.a.
	Total	*744*	*153*	*20.56%*	*94*	*12.63%*
Scenario 3	**Double Top**	147	42	28.57%	30	20.41%
	Double Side	162	34	20.99%	31	19.14%
	Single Organic	148	27	18.24%	27	18.24%
	Single Top	141	19	13.48%	n.a.	n.a.
	Single Side	146	3	2.05%	n.a.	n.a.
	Total	*744*	*115*	*15.46%*	*78*	*10.48%*
Scenario 4	**Double Top**	152	42	27.63%	11	7.24%
	Double Side	152	29	19.08%	27	17.76%
	Single Organic	148	21	14.19%	21	14.19%
	Single Top	149	30	20.13%	n.a.	n.a.
	Single Side	143	6	4.20%	n.a.	n.a.
	Total	744	*128*	17.20%	*59*	7.93%
Scenario 5	**Double Top**	152	45	29.61%	17	11.18%
	Double Side	160	27	16.88%	25	15.63%
	Single Organic	144	20	13.89%	20	13.89%
	Single Top	143	17	11.89%	n.a.	n.a.
	Single Side	145	1	0.69%	n.a.	n.a.
	Total	*744*	*110*	*14.78%*	*62*	*8.33%*
Scenario 6	**Double Top**	146	74	50.68%	39	26.71%
	Double Side	144	41	28.47%	38	26.39%
	Single Organic	154	49	31.82%	49	31.82%
	Single Top	153	46	30.07%	n.a.	n.a.
	Single Side	147	8	5.44%	n.a.	n.a.
	Total	*744*	*218*	*29.30%*	*126*	*16.94%*

Notes: a. CT is the abbreviation for number of clicks (click-through).
b. CTR denotes click-through rate.

Table 25: Overall and Free Click-Through (Experiment 2, Project III)

The Role of Double Exposure

In *Chapter C*/5.3.2, I assume that the overall click-through (CT) for double top exposure is significantly higher than for single organic exposure *(H3a)*. The chi-square test statistic in Appendix 21 shows for all the different scenarios that the overall CT of double top exposure is significantly higher ($\chi^2(1) = 21.30$, $p < .001$). Thus, *H3a* is supported on the general level. To gain further insights into the levels of advertiser competition by which a double top exposure leads to significantly more overall click-through, I calculated additional chi-square tests. An additional paid top result leads to significant increases in overall click-through behavior for scenarios 1 and 3–6 (scenario 1: $\chi^2(1) = 2.93$, $p < .10$; scenario 3: $\chi^2(1) = 4.39$, $p < .05$; scenario 4: $\chi^2(1) = 8.17$, $p < .01$; scenario 5: $\chi^2(1) = 10.66$, $p < .01$; scenario 6: $\chi^2(1) = 11.03$,

$p < .01$). In contrast, for scenario 2, double exposure with an additionally displayed paid top search result does not significantly increase overall click-through compared with a single organic exposure (scenario 2: $\chi^2(1) = .12$, $p > .10$).[136]

I also have predicted that the overall click-through performance for double side exposure is significantly higher than for single organic exposure *(H4a)*. This contention is not supported for the different keywords though ($\chi^2(1) = .53$, $p > .10$; see Appendix 22). Therefore, *H4a* is not supported. The empirical validation statistically shows only non-significant, higher overall click-through in the case of scenarios 1, 3, 4, and 5 (scenario 1: $\chi^2(1) = .15$, $p > .10$; scenario 3: $\chi^2(1) = .37$, $p > .10$; scenario 4: $\chi^2(1) = 1.29$, $p > .10$; scenario 5: $\chi^2(1) = .55$, $p > .10$). An additional paid side result can lead to significant lower overall click-through (scenario 2: $\chi^2(1) = 8.38$, $p < .01$) and lower overall click-through (scenario 1: $\chi^2(1) = .4$, $p > .05$).[137]

To investigate the impact of double exposure scenarios on free click-through behavior, the cases single organic and organic with additional paid side or paid top result can be differentiated. Taking into account the search engine result pages with double top, double side, and single organic exposure, I test the prediction in *H3b* that the free click-through for double top exposure would be significantly higher than for single organic exposure. Testing this relationship shows no significant positive effect of double top exposure on free click-through. Instead, the analyses reveal statistically significantly decreasing free click-through with a supplemental paid top search result ($\chi^2(1) = 38.60$, $p < .001$; see Appendix 23) over all keyword scenarios. Consequently, *H3b* is not supported. Only for scenario 3 does free click-through behavior increase, though not significantly (scenario 3: $\chi^2(1) = .22$, $p > .10$). For all other scenarios, free click-through behavior in a double top exposure scenario leads to a decrease in free click-through (scenario 1: $\chi^2(1) = 75.52$, $p < .001$; scenario 2: $\chi^2(1) = 6.00$, $p < .05$; scenario 4: $\chi^2(1) = 3.80$, $p < .10$; scenario 5: $\chi^2(1) = .50$, $p > .10$;

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136 Appendix 21 summarizes the contingency tables for the χ^2-test statistics of *H3a*. I can show that the chances of an overall click are higher for all scenarios in a double top exposure than in a single organic exposure, spreading from $RR_{S2} = 1.06$ to $RR_{S6} = 2.13$. The relative risks for *H3a* are (1) $RR_{S1} = 1.08$; (2) $RR_{S2} = 1.06$; (3) $RR_{S3} = 1.57$; (4) $RR_{S4} = 1.95$; (5) $RR_{S5} = 2.13$; (6) $RR_{S6} = 1.59$.

137 Appendix 22 summarizes the contingency tables for the χ^2-test statistics for *H4a.* All in all, the chances for a click in a double side exposure condition compared with a single organic exposure spread widely, from $RR_{S2} = .53$ to $RR_{S4} = 1.34$. The relative risks for *H4a* are (1) $RR_{S1} = 1.02$; (2) $RR_{S2} = .53$; (3) $RR_{S3} = 1.15$; (4) $RR_{S4} = 1.34$; (5) $RR_{S5} = 1.22$; (6) $RR_{S6} = .89$.

scenario 6: $\chi^2(1) = .94$, $p > .10$).[138]

Moreover, I have argued that the free click-through for a double side exposure scenario should be significantly higher than for a single organic exposure scenario *(H4b)*. Analyzing this relationship does not show a significant positive effect of double exposure across the different scenarios due to an additional paid side result on free click-through, but instead a again significant negative effect ($\chi^2(1) = 12.30$, $p < .001$; see Appendix 24). Accordingly, *H4b* is not supported. In detail, the analyses disclose declining free click-through behavior for scenario 1, 2, and 6 (scenario 1: $\chi^2(1) = 24.85$, $p < .001$; scenario 2: $\chi^2(1) = 10.20$, $p < .01$; scenario 6: $\chi^2(1) = 1.06$, $p > .10$). For the other scenarios, free click-through increases statistically insignificantly (scenario 3: $\chi^2(1) = .04$, $p > .10$; scenario 4: $\chi^2(1) = .71$, $p > .10$; scenario 5: $\chi^2(1) = .18$, $p > .10$).[139] Building on the test of *H3b* and *H4b*, further main emphasis in the theoretical and managerial implications (*Chapter* C/5.6.1 and 5.6.2) will be stressed on these cannibalizing effects of double exposure scenarios on free click-through behavior.

Additional analyses reveal statistically significant, higher overall click-through for single organic compared with single side exposure ($\chi^2(1) = 95.63$, $p < .001$; *Supplement 1*), double top compared with double side exposure ($\chi^2(1) = 28.95$, $p < .001$; *Supplement 2*), and significantly more free click-through for double side compared with double top exposure ($\chi^2(1) = 7.78$, $p < .01$; *Supplement 3*). More details on these additional analyses are in Appendix 25.

Interaction of Double Exposure and Advertiser Competition

Finally, *H5* proposes that the marginal effect of double exposure on overall as well as free click-through rates is increasing at higher levels of advertiser competition. To test the hypothesized relationships, I perform two ordinary least square (OLS) regression models similar to those in *Chapter C*/4.2.4. Because *Project II* reveals a U-shaped connection of advertiser competition and CTR, the linear main effect for advertiser competition (AC) and the

[138] Appendix 23 summarizes the contingency tables for the χ^2-test statistics of *H3b*. The chances for a click on the organic search result are, with one exception, lower when both results are displayed and fall between $RR_{S1} = .41$ and $RR_{S3} = 1.12$. The relative risks for *H3b* are (1) $RR_{S1} = .41$; (2) $RR_{S2} = .60$; (3) $RR_{S3} = 1.12$; (4) $RR_{S4} = .51$; (5) $RR_{S5} = .81$; (6) $RR_{S6} = .84$.

[139] Appendix 24 summarizes the contingency tables for the χ^2-test statistics of *H4b*. The chances for a click on the organic search result are lower for scenarios 1, 2, and 6, but higher for scenario 3, 4, and 5 when a double side exposure is displayed with a range from $RR_{S2} = .49$, and $RR_{S4} = 1.25$. The relative risks for *H4b* are (1) $RR_{S1} = .69$; (2) $RR_{S2} = .49$; (3) $RR_{S3} = 1.05$; (4) $RR_{S4} = 1.25$; (5) $RR_{S5} = 1.13$; (6) $RR_{S6} = .83$.

quadratic effect (AC^2) are included in the regression models.[140] As revealed in the results of the regression analysis in models 1a and 1b of Table 26, the curvilinear relationship between advertiser competition and overall or organic CTR is robust, despite the addition of different exposure scenarios in the regression models. This point also is reflected in the graphs in Figure 50, which offer first hints of an increasing marginal effect of double top exposure on free click-through rate, whereas the marginal effects of double top on the overall and the marginal effects of the double side on overall and free click-through rates are barely visible.

The results of models 2a and 2b in Table 26 support these observations, revealing only a statistically significant interaction of double top exposure and advertiser competition on free click-through rate ($\beta = .60$; $p < .05$). Additional post hoc probing tests (see Aiken and West 1991) clarify this interaction effect. The results reveal less negative betas of double top exposure for higher advertiser competition levels.[141] Because the main effect of double exposure on free CTR is negative, the positive interaction effect of *AC × Double Top* leads to a decreasing absolute effect, but increasing marginal effect of double top exposure. This supports the proposed assumption. The interaction effects of *AC × Double Top* on overall CTR ($\beta = .15$; $p > .10$) and *AC × Double Side* on overall CTR ($\beta = .04$; $p > .10$) and on free CTR ($\beta = .39$; $p > .10$) are statistically not significant. That is, *H5a* is not supported, and *H5b* is only partially supported. Additionally, the results of the regression analysis in Table 26 reveal statistically significant negative effects of single side exposure on overall CTR ($\beta = -.35$; $p < .10$), as well as double top ($\beta = -.65$; $p < .01$) and double side on free CTR ($\beta = -.10$; $p < .10$).

[140] As in *Chapter C*/4.2.4, the individual click-through data were aggregated on two dimensions. First, each observation was matched with five randomly assigned groups (double top, double side, single organic, single top, and single side), an assignment repeated for each of the six levels of advertiser competition. Second, the dataset includes 30 aggregated observations with corresponding click-through rates.

[141] The beta coefficients are: zAC mean: $\beta_{\text{double top}} = -.65$, t = -2.00, $p < .05$, df = 14; zAC one standard deviation above mean: $\beta_{\text{double top}} = -.05$, t = -.19, $p > .10$, df = 14; zAC one standard deviation below mean: $\beta_{\text{double top}} = -1.25$, t = -4.79, $p < .005$, df = 14.

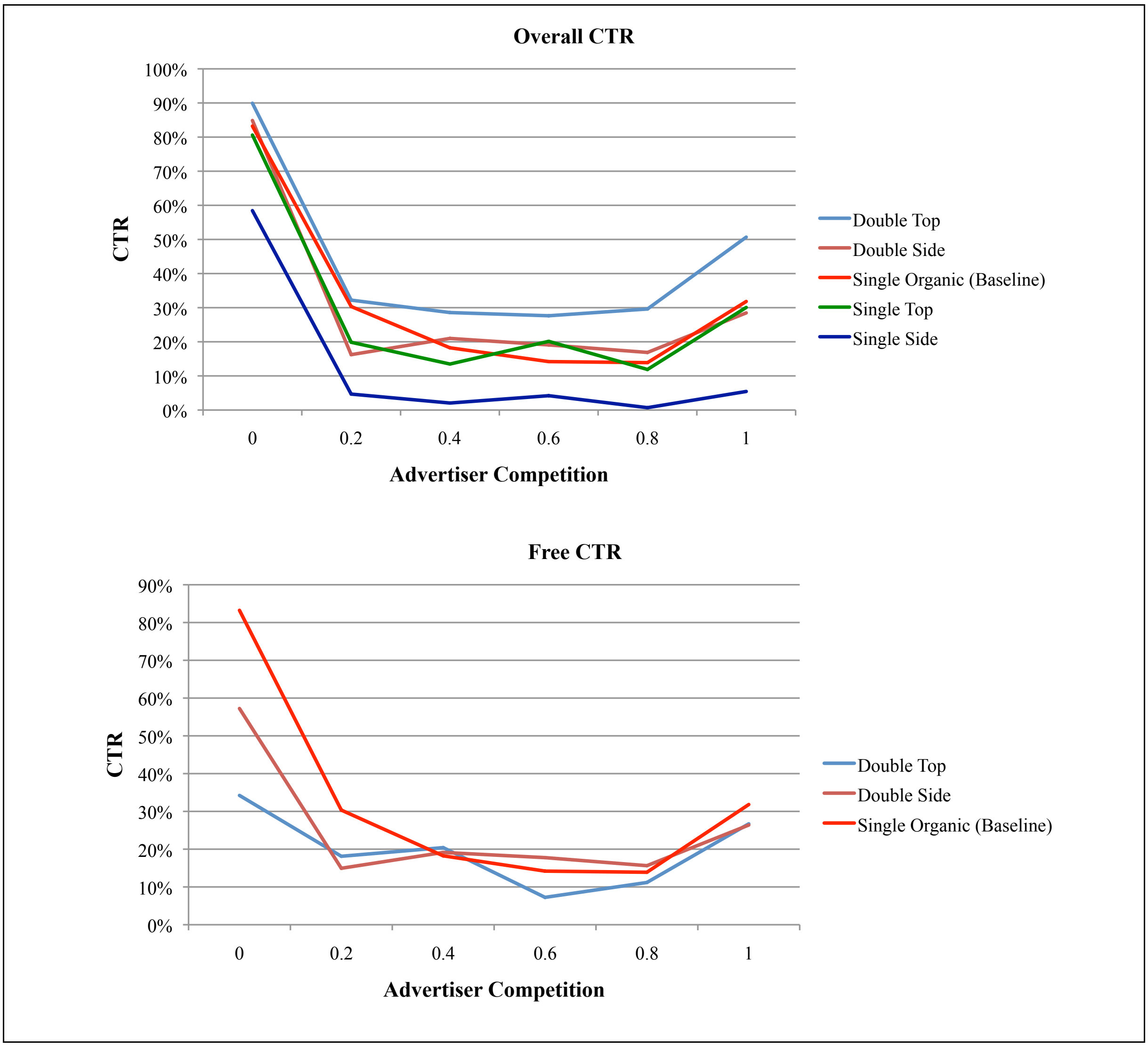


Figure 50: Interaction Between Advertiser Competition and Exposure (Experiment 2, Project III)

	Model 1a (Overall CTR)	Model 1b (Free CTR)	Model 2a (Overall CTR)	Model 2b (Free CTR)
Intercept	.86 x 10^{-4} (.08)	.13 (.15)	.24 x 10^{-3} (.08)	.34 (.17)$^{(*)}$
AC	-2.81 (.27)***	-2.76 (.47)***	-2.89 (.34)***	-3.12 (.46)***
AC^2	2.38 (.27)***	2.37 (.47)***	2.38 (.29)***	2.37 (.42)***
Double Top	.18 (.10)$^{(*)}$	-.27 (.13)$^{(*)}$	.06 (.18)	-.65 (.21)**
Double Side	-.01 (.10)	-.15 (.13)	-.05 (.19)	-.40 (.21)$^{(*)}$
Single Top	-.04 (.10)		-.09 (.18)	
Single Side	-.31 (.10)**		-.35 (.18)$^{(*)}$	
AC × Double Top			.15 (.19)	.60 (.27)*
AC × Double Side			.04 (.19)	.39 (.27)
AC × Single Top			.06 (.19)	
AC × Single Side			.05 (.19)	
N	30	18	30	18
R^2	.87	.77	.87	.84
Adjusted R^2	.83	.70	.81	.76
RMSE	.42	.56	.45	.50
SSE	3.98	4.08	3.85	2.79
AIC	-46.57	-16.70	-39.63	-19.56
F-Test	F(6)= 25.22***	F(4)= 10.81***	F(10)= 13.02***	F(6)= 9.77***

Notes: a. The standard error is indicated in parentheses; all parameters are z-standardized.
b. Significance levels of the models and parameters: *** significant on 0.1% level; ** significant on 1% level; * significant on 5% level; (*) significant on 10% level.
c. The baseline for models 3a, 3b, 4a, and 4b is organic.

Table 26: Results of the Extended OLS Regression on Overall and Free Click-Through Rate (Experiment 2, Project III)

5.5.5 Findings

The results of this second experimental study show the impact of order effects, double exposure, and the interaction of advertiser competition and double exposure on consumer overall and free click-through behavior on search engine result pages. A summary of the results of the hypothesized effects investigated in the second experimental study is displayed in Figure 51.

The experimental investigation of the influence of order effects on click-through behavior reveals that a single top exposure does not attract significantly more clicks than a single organic exposure (*H1*). As in the first experiment in *Project III*, the single top exposures (*H2*) and single organic exposures (*Supplement 1*) bring about significantly higher click-through than the single side exposures. This finding applies on the general level as well as on the level of each keyword scenario. In contrast, this second experimental study reveals a statistically significant effect for *Supplement 2* (double top versus double side for overall CTR) on the overall evaluation. In contrast with the expectable direction, a double side exposure leads to significantly more free click-through than a double top exposure (*Supplement 3*).

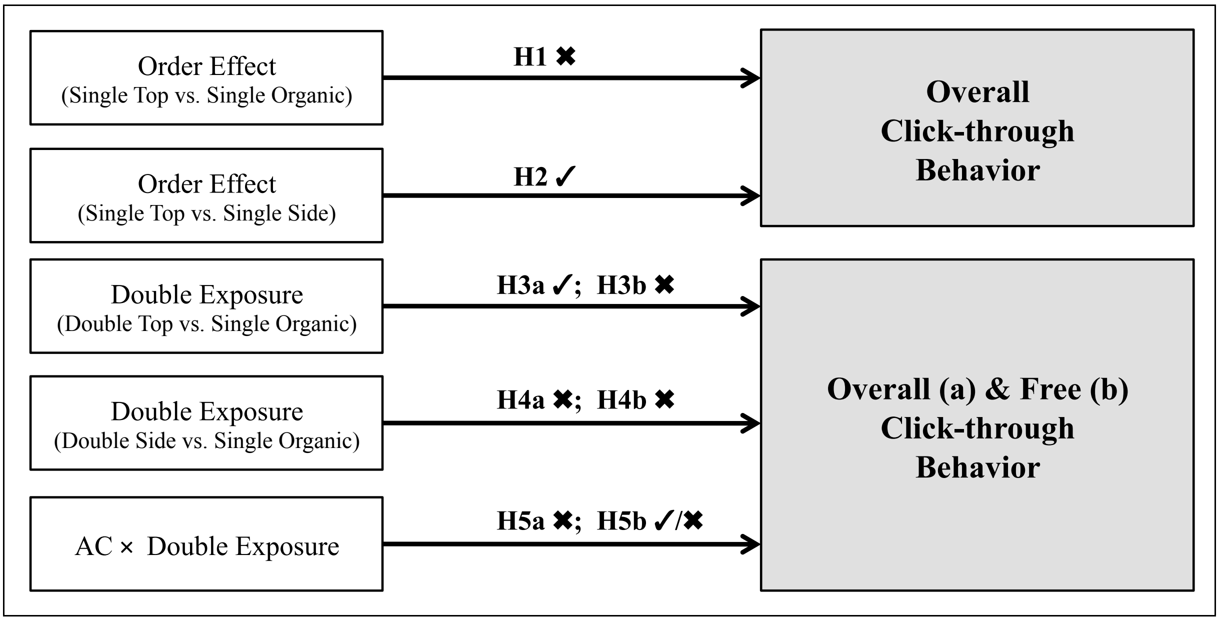


Figure 51: Summary of the Hypothesized Effects (Experiment 2, Project III)

The first experimental study provided evidence that double exposure does not have a significant effect on overall and free click-through behavior. This reproduction of the experimental setting with six different keyword scenarios with increasing levels of advertiser competition provides more diverse results. On the one hand, a double top exposure leads in general to significantly higher overall click-through than a single organic exposure (*H3a*). Although double side exposure does not lead to significantly higher overall click-through than single organic exposure (*H4a*) in general, four of six scenarios reveal at least statistically non-significant higher overall click-through. On the other hand, a double top exposure leads in general to significantly lower free click-through compared with a single organic exposure. This finding contradicts the hypothesized direction in *H3b*. A consideration of the effect of the double top exposure on free click-through behavior on an individual keyword level only reveals statistically insignificant increases in free click-through in the case of scenario 3. For all the other keyword scenarios, the effects are partly negative, though not significantly in all cases. Again, a double side exposure attracts significantly less free click-through than a single organic exposure. The hypothesized direction of *H4b* thus is not proven. On an individual level in the keyword scenarios, the results are diverse, ranging from non-significant increases to significant decreases. Appendix 29 summarizes the results of the χ^2-test statistics and contingency tables for *H1–H4*, and the additional *Supplements.*

Regarding the statistical interaction between advertiser competition and double exposure, the results show that the marginal effect of double exposure on the overall click-through rate is not significantly increasing at higher levels of advertiser competition *(H5a*). Otherwise, the marginal effect on the free click-through rate is significantly increasing with higher levels of advertiser competition for double top exposures, whereas the effect is statistically insignificant for double side exposures *(H5b*).

5.6 Discussion

The results of this comprehensive project provide insights into the effectiveness of order effects and double exposure on consumer overall and free click-through behavior in a search engine marketing context. Furthermore, the statistical interaction of advertiser competition and double exposure indicates the impact of double top or double side exposure with increasing levels of advertiser competition on overall and free click-through behavior. This project, with its mixed-method research design, offers strong evidence that double exposure does not significantly and positively affect click-through behavior in general. The impact of order effects can be supported in particular. Combining both exposure and order effects, the experimental studies show that the direct effect, generating further overall clicks with additional paid exposure, is stronger for double top than double side exposures. This finding provides evidence of primacy effects on overall click-through behavior. The effect is inverted for the indirect effect of additional paid search exposures on free clicks. In these cases, double side exposure leads to significantly more free clicks than double top exposure. Thus, recency effects are obvious in the free click-through behavior. Even more, double exposition leads to diminishing numbers of clicks on organic search results—that is, the cannibalization of free click-through rate exists when additional paid search results are displayed. Therefore, additional paid side results likely lead to lower levels of cannibalization than paid top results.

Regarding the statistical interaction between advertiser competition and double exposure, the results show that the marginal effect of double exposure on overall click-through rate does not increase significantly with higher levels of advertiser competition. Otherwise, the marginal effect of the free click-through rate increases significantly with higher levels of advertiser competition for double top exposure, whereas the effect is statistically not significant for double side exposure. This finding provides additional knowledge about the impact of advertiser competition in search engine marketing.

The following discussion thus concentrates on the theoretical implications, managerial implications, and implications for further research derived from these studies. In each section, I use the following structure: First, I present the impact of order effects on click-through behavior. Second, I discuss the relevance of double exposure effects for overall and free click-through behavior. Third, the cannibalizing effect of double exposure for different levels of advertiser competition is detailed. Fourth, I outline the interaction between advertiser competition and double exposure.

5.6.1 Theoretical Implications

The Impact of Order Effects on Click-Through Behavior

The experimental analyses of message order effects in a search engine context are based on the broad foundation of the primacy–recency paradigm (Hovland and Mandell 1957). On search engine result pages, arguments for primacy and recency effects in all three studies of the mixed-method research approach have been disclosed. Not only do the studies provide support for the relevance of higher positions on search engine result pages (e.g., Ghose and Yang 2009; Ghose and Yang 2010; Ji, Rui, and Hansheng 2010; Animesh, Viswanathan, and Agarwal 2011; Rutz and Trusov 2011), but they also document the importance of distinguishing paid top and paid side positions in further studies. Prior research on banner advertising suggests a distinction between banner ads on top of a webpage and those laterally displayed (e.g., Briggs and Hollis 1997; Benway 1998; Schroeder 1998; Drèze and Hussherr 2003), but this project, to the best of my knowledge, is the first project to reveal the empirical proof of the importance of such a differentiation in paid search advertising. Therefore, the focus is not predominantly on the impact of the pure rank of the result on the search engine result page, but also and even more on the section that displays the results—that is, whether the result appears in organic search results, paid top search results, or paid side search results.
In the *observational study*, the examination of the positions of the clicked search results reveal a general preference of the Internet users to click on organic search results and avoid paid side search results. Amongst the paid top and organic search results, a tendency to primacy effects is visible. Especially in search tasks, when Internet users have little prior information, they tend to click the highest ranked search results.

The *experimental studies* reveal recency and primacy effects. Investigating the impact of order effects on overall click-through behavior exposes primacy effects in particular. In both experiments, the primacy effects are strong and statistically significant in the comparison of single top and single organic exposure with single side exposures. This finding points to the relevance of distinct investigations of the three areas for search engine marketing activities in research conceptualizations; it also provides theoretical implications. In double exposure situations (double top and double side), a weak, statistically non-significant, primacy effect emerges in the first experiment, whereas the second experiment shows primacy effects.

The Impact of Double Exposure on Click-Through Behavior

Although the topic of interdependency effects between paid and organic links on search engine result pages has just recently found its way into empirical research projects on search engine marketing, a theoretical foundation for this phenomenon is still lacking (Yang and Ghose 2010). These experimental analyses therefore are based on the seminal foundation of mere exposure effects by Zajonc (1968). Because double exposure situations of paid top and organic, as well as paid side and organic search results on one search engine result page are not the general idea, this project applies the proposition of mere exposure effects to search engine marketing. With the concept of double exposure, search engine result pages with a simultaneously display of organic and paid (top or side) result on one search engine result page can be subsumed.

Investigating the impact of double exposure on overall and free click-through behavior, this study addresses a general problem with clickstream data research. The recently introduced possibility to track impressions and click-through rates for each position on the search engine result page has not found its way into research yet. Hence, no detailed insights can be gained regarding click-through behavior in double exposure scenarios, because the data sovereignty of such click-through data long had been disclosed to search engine providers. Therefore, this perspective has been neglected in recent publications on paid search with field data. The results of this mixed-method research design instead open a new theoretical field, investigating the reciprocal relationship between double exposition and both overall and free click-through behavior, thus supplementing and extending the work by Yang and Ghose (2010). The results from the hypotheses tests pertaining to double exposure in the experimental studies suggest a limitation in Yang and Ghose (2010), which suffered from field data and less distinctive details on the keyword level (different categories, type of search, classification of keyword, and market offering) and search engine result page level (arrangement of paid top, paid side, and organic results). The findings from this mixed-method research approach are more exact in explaining the cases in which double exposure can lead to growth in overall and free click-through.

In detail, the *observational study* identifies three different exposure conditions: single exposure, double paid exposure,[142] and double organic exposure. The analysis of the verbalization of the cognitive processes reveals that classical mere exposure and double exposure on search engine result pages influence consumer click-through behavior. In the *experimental studies*, the causal effect of double exposure on click-through behavior is diverse. In the *first* experiment, double exposure does not significantly impact click-through behavior. In contrast, the *second* experimental study shows significant effects for three of four double exposure scenarios. These significant effects are partly unexpected. In a double top exposure situation, when a paid top result is displayed in addition to an organic result, a significantly higher overall number of clicks can be detected, as expected in *H3a*. But the picture differs regarding the effect of an additional paid top or paid side result on consumer free click-through behavior. In both cases, a double exposure scenario leads to significantly decreasing clicks for double top and double side exposure compared with a single organic exposure. This effect of additional paid search advertising on click behavior is interesting from not only theoretical but also managerial points of view. For a deeper understanding of the effect of double exposure on free click-through rates, this study considers free click-through rates (fCTR) for double top exposure, double side exposure, and single organic exposure.

Free Click-Through Cannibalization

Although, many websites and weblogs host debates about the existence of the cannibalizing or synergy effects of paid search results on free clicks, little empirical attention, managerial guidance, or even more theoretical considerations have focused on this highly relevant point. From both theoretical and managerial perspectives, the cannibalizing effects revealed in this project offer new opportunities for theory improvement, as well as for the development of managerial heuristics. Hence, I will focus on these two perspectives of cannibalization or synergy in search engine marketing, through increases or losses of clicks on organic results in double exposure compared with single organic exposure, due to the additional display of a paid result. For implications in the theoretical and managerial perspectives, a cannibalization quotient (ΔfCTR) is developed.

[142] Double paid exposure indicates observed organic clicks with an additional paid exposure and paid clicks with an additional organic exposure.

Although synergies or cannibalizations across, say, product line extensions, new product developments, multi-brand strategies, or distribution channels are well recognized in scientific publications (e.g., Copulsky 1976; Kerin et al. 1978; Mason, Mason, and Milne 1994; Chandy and Tellis 1998; Deleersnyder et al. 2002; Falk et al. 2007; Pauwels and Neslin 2008), sparse research focuses on synergies and cannibalization between paid and organic search results in the context of search engine marketing. Yang and Ghose (2010) were the first to focus on interdependencies between paid and organic search results. Nevertheless, their empirical analysis are only illuminating the effect of additional paid search results on overall click-through behavior. Revealing cannibalizing effects from additional paid search exposure on free clicks in this project thus represents a vital component for a better understanding of the causal effects of search engine marketing activities. This has considerable importance, because it provides a more diverse picture of double exposition on search engine result pages.

The theoretical contribution of the model specification of the cannibalization quotient (ΔfCTR) aims at providing a marketing decision model (Leeflang 2008), stressing issues of simplicity and completeness (Little 1970), for three reasons. First, Reibstein, Day, and Wind (2009) urge marketing academics to find more relevant implications for managerial practice in marketing departments of companies. Second, authors such as Verhoef et al. (2003) reveal that simple managerial heuristics are widely applied by practitioners. Third, managerial decision making heuristics perform at least as well as complex statistical models on managerially relevant topics (Wübben and von Wangenheim 2008). Therefore, the differences in free clicks for double exposure scenarios with paid top or paid side result can be compared with single organic exposure scenarios. A simple measurement heuristic, the cannibalization quotient (ΔfCTR), thus enables a deeper understanding of spillover and cannibalization of the free click-through rates (fCTR).

$$\Delta fCTR_i = \frac{\Delta fCT_i}{\left(\frac{fCT_{i,organic}}{N_{i,organic}} \times 100\right)} \quad , \tag{8}$$

$$\text{with} \quad \Delta fCT_i = \left(\frac{fCT_{i,double\,exposure}}{N_{i,double\,exposure}} \times 100\right) - \left(\frac{fCT_{i,organic}}{N_{i,organic}} \times 100\right) \quad , \tag{9}$$

where for any keyword i, $fCT_{i,organic}$ is the free click-through in single organic exposure situations. The number of page views (impressions) is included with $N_{i,organic}$. The measures $fCT_{i,double\ exposure}$ and $N_{i,\ double\ exposure}$ are analogous for double exposure scenarios. The difference ΔfCT_i is the scaled difference in free click-through. Equation 8 builds the cannibalization quotient ΔfCTR and specifies the percentage change in fCTR resulting from spillover (positive quotient) or cannibalization (negative quotient) due to an additional paid result. Therefore, the difference in the free click-through rate, evoked by a double exposure scenario, is divided by the fCTR for the single organic exposure. Accordingly, ΔfCTR can be taken in account to calculate the expected additional costs (cannibalization) or savings (spillover) caused by a double exposure situation on a search engine result page. With this indicator, it is possible to balance pros and cons for paid search activities, beyond organic listings, by calculating the loss or increase in click-performance over organic search results. Furthermore, especially from a theoretical perspective, a new field of research in paid search advertising is established.

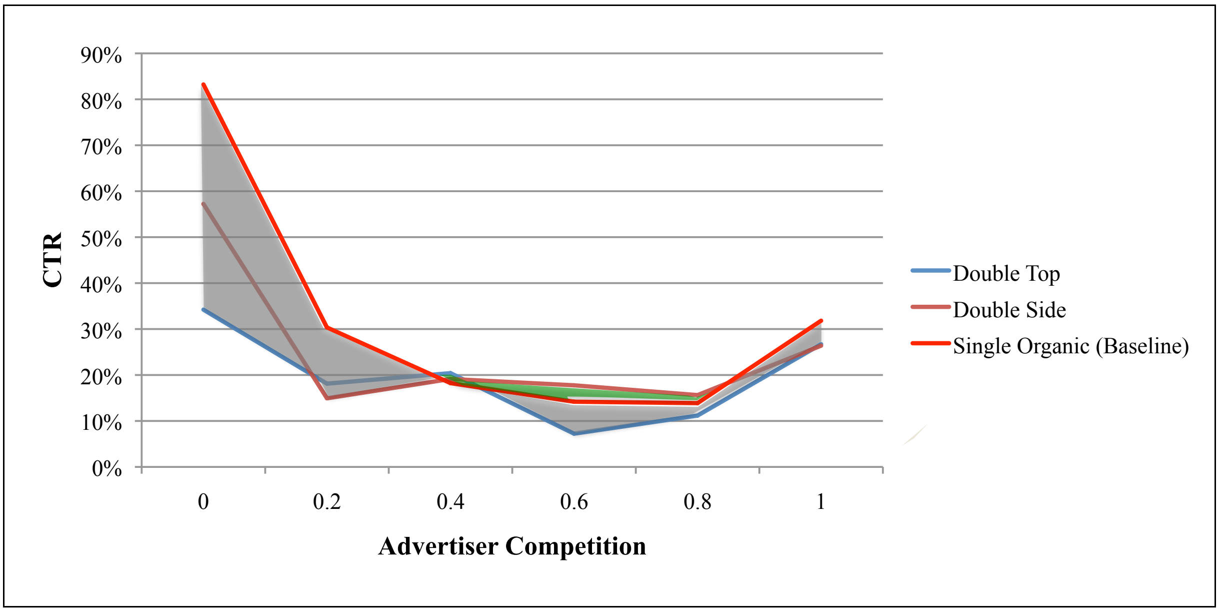
Measuring the effect of double exposure scenarios on the free click-through rate reveals an average overall loss for all different keyword scenarios of ΔfCTR = -19.02%. Dividing the impact of additional paid results on free click-through behavior further, I find that a double exposure scenario with paid side result leads to a cannibalization of 9.42% of the free click-through rate, whereas an additional paid top result cannibalizes by 28.63%. Table 27 summarizes ΔfCTR for double side exposure and double top exposure for each scenario, revealing both spillover and cannibalization. Spillover on free click-through, caused by an additional paid top result, is possible, as the ΔfCTR in double top exposure for scenario three, with an increase of 11.87% shows.

Yet, this experimental investigation reveals predominantly free click cannibalization in double top exposure scenarios, unlike the double side exposure conditions. An additional paid side result leads to positive ΔfCTR (ranging from 4.89% to 25.19%) or spillover for scenario 3, 4, and 5. Figure 52 graphs the cannibalizing and spillover effects of double exposure for increasing levels of advertiser competition.

Scenario	*Double Exposure*	$\left(\frac{fCT_{i,double\ exposure}}{N_{i,double\ exposure}} \times 100\right)$	$\left(\frac{fCT_{i,organic}}{N_{i,organic}} \times 100\right)$	*ΔfCTR*
1	*Double Top*	34.23%	83.23%	-58.87%
	Double Side	57.24%	83.23%	-31.22%
2	*Double Top*	18.12%	30.34%	-40.28%
	Double Side	14.94%	30.34%	-50.78%
3	*Double Top*	20.41%	18.24%	11.87%
	Double Side	19.14%	18.24%	4.89%
4	*Double Top*	7.24%	14.19%	-49.00%
	Double Side	17.76%	14.19%	25.19%
5	*Double Top*	11.18%	13.89%	-19.47%
	Double Side	15.63%	13.89%	12.50%
6	*Double Top*	26.71%	31.82%	-16.05%
	Double Side	16.39%	31.82%	-17.06%

Notes: The baseline for the ΔfCTR is a single organic exposure condition. The losses or gains in fCTR are always compared with each single organic exposure for each keyword scenario.

Table 27: ΔfCTR for Each Scenario (Experiment 2, Project III)



Notes: Grey area marks negative values of ΔfCTR; green area marks positive values of ΔfCTR.

Figure 52: Free Click-Through Rate Cannibalization (Experiment 2, Project III)

The results of a study published in July 2011 by the research department of the industry giant Google indirectly support the general finding of cannibalizing effects of double exposure scenarios. Chan et al. (2011) show that 89% of the traffic generated by a paid result in a double exposure scenario is not replaced by traffic by an organic result in a single organic exposure scenario (incremental clicks). Highlighting this effect, they neglect the far more interesting point—from an advertiser's, not the search engine's, perspective—of positive or negative effects of additional paid results in double exposure scenarios on the free click-through rate. The cannibalization index ΔfCTR can be assessed approximately by remodeling the underlying formula for incremental clicks *(Equation 10)* as in *Equation 11*. Chan et al. (2011) measure the incremental clicks (IAC) with a quotient of the difference between overall click-through in double exposure scenarios (O_D) and overall click-through in single organic exposure scenarios (i.e., free click-through O_S), divided by the difference of paid click-through in double exposure scenarios (P_D) and paid click-through in single organic exposure scenarios (P_S). Equation 11 and ΔIAC report the percentage of total paid clicks in a double exposure scenario by which the free click-through (single organic exposure) is reduced.

$$IAC = \frac{O_D - O_S}{P_D - P_S} \quad . \tag{10}$$

$$\Delta IAC = 1 - IAC \quad . \tag{11}$$

Consider the following situational analogue to Chan et al. (2011): In a double exposure scenario, the overall number of click-through (O_D), or the sum of paid clicks ($P_D = 300$) and free clicks ($F_D = 400$), equals $O_D = 700$. The corresponding overall clicks in a single organic exposure scenario are $O_S = F_S = 500$. Therefore, P_D equals 300, and by definition, $P_S = 0$. Thus, 200 ($O_D - O_S = 700 - 500$) additional clicks are attracted in a double exposure scenario: IAC = (700 – 500) / (300 – 0) = 0.667. Of these 300 additional paid clicks, 100 free clicks in the single organic exposure are removed ($F_S - F_D = 500 - 400$), which corresponds to ΔIAC = 1 – .667 = .133 of paid clicks. That is, 13.3% of paid clicks are cannibalized from free clicks. Transferring this calculated example to the results in Chan et al. (2011), 11% (ΔIAC = 1 – .89 = .11) of the paid clicks are cannibalized from the free clicks. Unfortunately, the values for ΔIAC of the study by Chan et al. (2011) are not directly comparable to the values of ΔfCTR of this project, because the dividends do not correspond. However, both indexes reveal a cannibalizing effect of double exposure scenarios on free click-through behavior.

The Effect of Double Exposure with Increasing Advertiser Competition

Companies from different industries and contexts try to signal their major relevance for specific keywords on a search engine result page to increase click-through rates. Therefore, prior research has suggested, among other things, that double exposure situations lead to significant increases in overall CTR in comparison with single organic exposure (Yang and Ghose 2010). This study adds additional theoretical contributions to the work by Yang and Ghose (2010). Embedding double exposure effects in the framework of the relationship between advertiser competition and click-through behavior reveals relevant empirical and theoretical findings.

As increasing levels of advertiser competition lead to the assimilation of displayed (paid and organic) search results for certain keywords, the recognition heuristic (Goldstein and Gigerenzer 2002) can help explain the impact of double exposition with increasing levels of advertiser competition on overall and free click-through behavior. I argue that the impact of double exposure situations on click-through behavior increases, because double exposition creates increased awareness and thus acts as an instrument to lower search costs, which leads to higher CTR (e.g., Ilfeld and Winer 2002; Chatterjee, Hoffman, and Novak 2003; Drèze and Hussherr 2003; Manchanda et al. 2006). Consequently, this project assumes that the marginal effect of double exposure on overall and free click-through rates increases with growing levels of advertiser competition. This effect can be statistically verified in the case of double top exposition and free click-through behavior. By means of the recognition heuristic, this partial verification can be explained. The recognition heuristic, according to Goldstein and Gigerenzer (2002), suggests that the search process ends as soon as the individual recognizes an object. An effect that becomes more complicated with increasing levels of advertiser competition, which in turn strengthens the influence of the recognition heuristic. In the original framework of the ecological rationality of the recognition heuristic, the relevance of the search result for the specific keyword (hidden criterion) is reflected by the double exposure situation, which in turn influences the probability of recognition and thus click-through (see Goldstein and Gigerenzer 2002). Because double exposure is associated with double appearances in paid and organic search results, the organic result, which is second in a typical eye-movement pattern on a search engine result page, is recognized and finally clicked with a higher probability. This effect does not exist for double side exposure, because eye-movement studies suggest that paid side results are not necessarily perceived before the organic search results are viewed (e.g., Joachims et al. 2005; Granka, Hembrooke, and Gay 2006).

The results of this project indicate that the effect of double exposition on click-through behavior only increases for additional paid top and free click-through behavior with increasing advertiser competition. In the case of double side exposition on overall and free click-through behavior, just as for double top exposure and overall click-through rate, a double exposure does not become more critical for click-through behavior. In this sense, search engine marketing activities, to achieve double top exposure situations, should be conducted only to increase the effect on the free click-through rate. Firms should be particularly careful with double exposition, which can lead to significant negative effects on the free click-through rate, despite the revealed results of this statistical interaction of double top exposure and advertiser competition.

5.6.2 Managerial Implications

To derive managerial implications of the order effects, double exposure, and the interaction of double exposure and advertiser competition, the theoretical implications are relevant. Altogether, considering the order effects' influence on click-through behavior, organic listings outperform paid top and paid side positions, but paid side listings are far inferior to the other two possibilities. Therefore, the goal from a managerial perspective should be to achieve top organic listings. These positions are not easy to achieve, especially within a narrow time frame, so managers should invest in paid top positions in the short-run. This effort can boost overall click-through rates, and hence traffic on companies' websites. Adopting this strategy should not distract attention from the fact that top organic listings need to be obtained. If nothing else, it can be traced to the fragility of paid listings. Paid search results are subject to two restrictions: positions in paid listings are constantly changing, and budget restrictions are constantly an issue.

The overall negative effect of double top and double side exposures on free click-through behavior, as mentioned in the theoretical implications of double exposure in *Chapter C*/5.6.1, also raises an interesting question. Is the cost per click (CPC) metric, designed to measure the effective costs of paid search activities, the right metric? Or do we need a true cost per click perspective that includes the loss of free click-through, when additionally displayed paid search results are in place? Comparing the free click-through rates, the experimental scenarios show that the average ΔfCTR over all different keywords is -19.02%. Distinguishing the results show ΔfCTR for additional paid side results of -9.42% and ΔfCTR for additional paid top results of -28.63%. These results suggest at a general level of abstraction that double exposure leads to cannibalization of clicks on organic search results. This cannibalizing effect on the free click-through rate is stronger for paid top positions than for paid side positions. The true costs per click on paid search results increase because of the decreasing free click-through rate. Therefore, I suggest calculating true campaign costs by incorporating the surcharges on paid search advertising spending of 9.42% for paid side positions and 28.63% for paid top positions in the campaign–cost–calculations. The ΔfCTR thus offers an a priori measurement of the true cost per click. To determine if double exposure scenarios are still economical, a combination of additional costs and additional profits stands to reason. The (true) cost per click metric enables a better estimation of expected costs, so a more comprehensive picture of double exposure can be achieved through the integration of expected benefits. If expected benefits exceed expected costs, double exposure on a search engine result page pays off, despite the cannibalizing effects on free clicks. In fact, this needs to be extensively evaluated. Especially for low levels of advertiser competition, the effect of double exposition on free click-through behavior is predominantly negative. Therefore, low levels of advertiser competition should not be targets for double exposures.

5.6.3 Further Research and Managerial Activities

The results of this project on order effects, double exposure, and the interaction of double exposure and advertiser competition shed light on a more diverse success measurement, from both managerial and research perspectives. These developments should focus on relational instead of transactional success measures. Therefore, a primary topic for further research and managerial perspectives should be the integration of search engine marketing into the analytical structure of customer relationship management. This effort could address the limitations of transactional success measurements (e.g., clicks, leads, sales). Even more, customer relationship management could enrich online and search engine marketing analytics to measure and predict the breadth, depth, and length of the relationship with each individual customer. A first step in this direction has been taken by the research project "Fre(E)S – Service Productivity of free E-Services," which spun off the first general framework of this thesis and has been funded by the Federal Ministry of Education and Research (BMBF: Bundesministerium für Bildung und Forschung; FKZ 01FL10038 / 01FL10039; http://www.frees-online.de).

A measure of the true impact of search engine marketing activities on companies' overall success, customer lifetime value, defined as the "net present value of profit streams a customer generates over the average customer lifetime" (Reichheld and Sasser 1990, p. 109), is gaining considerable attention in such a framework. This approach, on the individual customer level, can transform managerial and research approaches in online and search engine marketing from a transactional perspective on clicks, leads, and sales into measures of a relational evaluation of costs and benefits. In a second step, this approach would enable estimates of the overall success of search engine marketing activities on a company level, with the customer equity metric used as the discounted cash flows of actual and future customers (e.g., Rust, Lemon, and Zeithaml 2004).

From an empirical point of view, future research should compare the relevance of primacy versus recency effects in further experimental studies. Doing so would enable a more granular perspective on the effects of both opposing concepts in a framework of search engine marketing. Furthermore, more research activities should focus on the effect sizes of order effects and double exposure in experimental investigations, to compare the influence of these distinct theoretical concepts. This demand calls for experimental field studies. Even more, the influence of different ranks of the search results on the search engine result page and their effect on the impact of double exposition could be examined, testing different combinations of paid and organic search result positions (e.g., double exposure with the first paid top and fifth organic search result versus double exposure with the fifth paid side result and first organic result). This investigation would have considerable importance, in that the results of possible experimental field studies could validate the cannibalization index developed in this study. Furthermore, the influence of the position of the search result and advertiser competition on cannibalizing effects could be further investigated, with regard to double exposure scenarios.

D. Concluding Remarks

The Internet has become a central driver of economic growth, as well as of reduced search and transaction costs (e.g., Klein and Ford 2003; Bughin et al. 2011; Pélissié du Rausas et al. 2011). These fundamental changes are possible not only because of the continuous improvements to the technological infrastructure but also because of newly emerging business models. Associated with these fundamental developments on the Internet, more and more channels for customer acquisition, distribution, and interaction are emerging (e.g., Hennig-Thurau et al. 2010; van Bruggen et al. 2010). The literature reviews at the beginning of *Chapter B* on customer-initiated channel migration and *Chapter C* on search engine marketing show that the field of research on the Internet has developed considerably, and a plethora of studies has contributed to a better understanding of the role of the Internet. Nevertheless, extensive reviews on customer channel migration and search engine marketing research also identify considerable gaps in the literature, which form the basis for the research questions answered in the empirical projects of this thesis.

This chapter offers concluding remarks on the research questions of the three empirical projects and is structured as follows: The major findings and major contributions of the three empirical research projects are presented first. These results form the basis of the concluding remarks for two reasons: First, they open the field to future research. Second, this future research demands for discussions on privacy concerns on the Internet and discussion on empirical research designs. Thus, I discuss privacy concerns on the Internet and their implications for further research and research designs for customer channel migration and search engine marketing. Finally, the concluding remarks end with new issues for further research.

1 Conclusions

1.1 Project I

Project I implements a 2 (direct vs. indirect) × 2 (online vs. offline) channel matrix with the dimensions of intermediation (direct and indirect channels; e.g., Bolton, Lemon, and Verhoef 2004; von Wangenheim 2006) and service distribution (online vs. offline; e.g., Hitt and Frei 2002; Campbell and Frei 2010). Building on this general conceptual framework and additionally on transaction cost and switching cost theory, on results from empirical research on direct, indirect, online, and offline channels, and on channel migration, hypotheses about the behavioral consequences of customer-initiated channel migration (CICM) are investigated.

Therefore, *Project I* focuses on the causal effects of three types of CICM on relationship breadth and depth: CICM from indirect to direct channels, CICM from offline to online channels, and CICM from indirect offline to direct online channels. The key findings of the quasi-experimental analyses with proprietary company data on these three types of customer-initiated channel migration can be summarized as follows:

1. *CICM from indirect to direct channels* on the dimension of intermediation reveals that migration from indirect to direct channels leads to negative causal effects on relationship breadth and depth. Bolton, Lemon, and Verhoef (2004) and von Wangenheim's (2006) results suggest that using and enabling direct customer–company communications has positive effects on the relationship. The causal effects of *Project I* lead to the conclusion that the empirical generalization that direct channel usage enhances company knowledge, relationship intensity, and future usage behavior of the customer (e.g., Frazier 1999; Bolton, Lemon, and Verhoef 2004; Achabal et al. 2005; von Wangenheim 2006) should be reconsidered or revised, due to the increasing strength and relevance of intermediaries for communicating and distributing services in the digital age.
2. *CICM from offline to online channels* on the dimension of service distribution reveals that migration from offline to online channels leads to positive effects on relationship breadth and depth unlike, for instance, Brynjolfsson and Smith's (2000) and Ansari, Mela, and Neslin's (2008) results suggest. The finding in *Project I* of my thesis contributes to a better understanding of Hitt and Frei's (2002), Campbell and Frei's (2004), and Xue, Hitt, and Chen's (2011) research projects on Internet channel adoption. These works reveal that the customer segment of Internet channel adopters is more profitable. However, these studies in a banking context suffer considerable limitations, because the customer segment of adopters is a priori more profitable before adopting the Internet channel. My findings support and broaden these results from the banking sector, because my quasi-experimental design with a Mahalanobis-metric matching procedure and the conditional difference-in-differences estimation controls for prior differences between the treatment and control groups in relationship breadth and depth.
3. *CICM from indirect offline to direct online channels* combines the effects of the dimensions of intermediation and service distribution. My results reveal that migration from indirect offline to direct online channels leads to positive causal effects on sales

and cross-buying, whereas the effect on revenue is negative. These results disclose that the causal effect on the dimension of service distribution is stronger than the causal effect on the dimension of intermediation on sales and cross-buying. This general finding contributes to understanding of the findings of Gensler, Leeflang, and Skiera (2011), which revealed that the effect of online channel usage on profitability is higher than the effect of reduced serving costs.

In summary, the major findings of *Project I* contribute to a better understanding of the causal effects of customer-initiated channel migration on relationship breadth and depth. Thereby, the causal effects of CICM on the dimensions intermediation and service distribution lead to a broader understanding of the role of the Internet as a channel for distributing services. Furthermore, my results reveal the importance of reconsidering and revising prior findings on the impact of direct and indirect channels on measures of the strength of the customer–company relationship.

1.2 Project II

Search engine marketing is an essential component in companies' marketing mix (e.g., Rangaswamy, Giles, and Seres 2009; Rutz and Bucklin 2011), and competition in general is a central determinant of a company's success (e.g., Weitz 1985; Hunt and Morgan 1995). Nevertheless, research has just begun acknowledging the relevance of advertiser competition for search engine marketing (e.g., Yang and Ghose 2010; Rutz and Trusov 2011). Using theory from consumer choice (e.g., Rolls et al. 1981; Iyengar and Lepper 2000), I apply six counterbalanced online experiments and test the effect of advertiser competition on overall, organic, and paid click-through behavior. By analyzing proprietary company data from five leading European retailers advertising on Google, I extend the results to purchase behavior.

The results of this experimental and descriptive study show that the relationship between advertiser competition, as an indicator of increasing assortment of choice, and overall, organic, and paid click-through rates is U-shaped. This relationship implies that overall, organic, and paid click-through rates are highest for low levels of advertiser competition, which means with limited choice. For medium levels of advertiser competition and choice overload, the click-through rates are lowest. With increasing levels of advertiser competition and higher choice complexity through assimilating search results, these click-through rates improve again. My results reveal the same U-shaped influence of advertiser competition on conversion rate, though the U-shaped relationship between advertiser competition and conversion behavior is not as distinct as that for click-through behavior. Regarding literature on consumer choice, my contribution informs the negative effects (e.g., Malhotra 1982; Keller and Staelin 1987; Greenleaf and Lehmann 1995; Dhar 1997; Simonson 1999), positive effects (e.g., Zuckerman et al. 1978; Chernev 2003; Kahn and Wansink 2004), as well as curvilinear (Shah and Wolford 2007) relationships between choice overload and consumer's choice with a U-shaped relationship. From a managerial perspective, the combined approach of click-through and conversion behavior with increasing advertiser competition offers strategic implications for selecting levels of advertiser competition with the lowest costs per conversion.

In addition, my results reveal no enhanced preference for higher-ranked search results with increasing levels of advertiser competition. This interaction between advertiser competition and average position bridges the gap between consumer choice and decision heuristics and contributes to these streams of literature. Thereby, I can show that consumers' preference for higher-ranked search results (a simple decision heuristic) does not increase with higher levels of advertiser competition. This finding is surprising because choices among more assortments demand higher cognitive efforts to make the choice (e.g., Mogilner, Rudnick, and Iyengar 2008; Reutskaja and Hogarth 2009). The conclusion thus stands to reason that consumers apply decision heuristics, such as choosing the first option that exceeds the aspired level and consideration set, to reduce their associated search costs (e.g., Simon 1955; Anderson, Taylor, and Holloway 1966; Hauser and Wernerfelt 1990; Gigerenzer, Todd, and ABC Research Group 1999; Scheibehenne, Greifeneder, and Todd 2010). Therefore, my results contribute to this body of literature by showing that a lower ranking (i.e., higher position) in the paid search results for increasing levels of choice overload and advertiser competition does not necessarily foster consumers' choice.

Additionally, my results from *Project II* also contribute to literature on search engine marketing. For the literature on search engine marketing, these contributions form a basis for a better understanding of consumer click-through and conversion behavior under the influence of advertiser competition, a market characteristic (according to the categorization of the independent variables in *Chapter C*/2.1). Furthermore, I contribute to the postulation of Yang and Ghose (2010) in extending the first results of Rutz and Trusov (2011) on the effect of advertiser competition on click-through behavior—not only, in showing the causal relationship between advertiser competition and click-through behavior and confirming this causal effect for overall, organic, and paid click-through rates, but also in extending it to paid conversion behavior.

Furthermore, the combination of experimental and descriptive research designs opens a new methodological perspective in search engine marketing research, which has so far been dominated by modeling and estimation approaches (e.g., Ghose and Yang 2009; Yang and Ghose 2010; Rutz and Trusov 2011) and seldom applied primary data or experimental designs (e.g., Dou et al. 2010). This mixed-method approach achieves the fundamental advantages of experimental research designs, such as isolation of the treatment, high internal validity, isolated testing of theory, and control for confounding factors (e.g., Shadish, Cook, and Campbell 2002). Additionally, the advantages of field data guarantee high external validity by enhancing the robustness of the experimental results (e.g., Wagner, Hennig-Thurau, and Rudolph 2009).

1.3 Project III

Project III investigates the influences of order effects, double exposure, and the interaction between advertiser competition and double exposure on overall and free click-through behavior. Initial studies in the area of search engine marketing show interdependency effects between paid and organic search results (Yang and Ghose 2010). I build on the theoretical fundaments of exposure effects and order effects for this project. With order effects, the approach of this multimethod research design integrates results of Briggs and Hollis (1997) and Benway (1998), which show that distinctions between the lateral and upper areas for placing advertisements on the Internet are necessary. In addition, consumer choice literature helps to found the interaction effect of advertiser competition and double exposure on recognition heuristics (e.g., Goldstein and Gigerenzer 2002).

The results of these observational and experimental studies of *Project III* show that order effects influence consumer click-through behavior. Thus the importance of distinguishing paid top, paid side, and organic search results for further research on search engine marketing is highlighted. Regarding this distinction, the analysis of the impact of order effects reveals, based on the primacy–recency paradigm by Hovland and Mandell (1957), that primacy effects are present in the comparison of the click-through rates of single top and single organic to single side exposures. Furthermore, the investigations of the influences of double exposure (based on Zajonc 1968) in a simultaneous display of paid and organic search results on click-through behavior disclose positive and negative effects. Double exposures of paid top and organic search results positively affect overall click-through behavior. This effect changes for double exposure scenarios with negative effects on free click-through behavior. My results in

Project III reveal that double side and double top exposure situations lead, altogether, to a cannibalizing effect on free click-through rate. Thus, I develop and apply a cannibalization quotient for free click-through behavior. The results of my calculation of the cannibalization indexes are confirmed when converting the results of Chan et al.'s (2011) study to the same purpose. Finally, the marginal effect of double exposure for increasing levels of advertiser competition on click-through behavior only increases for the interaction of double top exposure and advertiser competition on free click-through behavior.

The findings of *Project III* of this thesis contribute to different streams of literature and managerial practice. This empirical project introduces the theoretical fundament of order effects and double exposure effects to search engine marketing research, suggests further developments to consumer choice literature, and introduces a quotient to measure the effects of double exposure on free click-through behavior:

1. My results extend the search engine marketing literature by building on a theoretical framework and applying mixed-method research designs instead of pure modeling and estimation approaches. The widely recognized paradigms of primacy–recency (Hovland and Mandell 1957) for order effects and the adaptation of mere exposure (Zajonc 1968) for double exposure thus are shown to contribute extensively to a better understanding of the effects of search engine marketing. Furthermore, the investigation of order and exposure effects contributes to search engine marketing literature in two additional manners. First, from a methodological perspective, the comprehensive research design consists of observational and experimental components. It combines the advantages of high validity of data from the think-aloud protocol and screen recording with the advantages of isolated treatment, isolated testing of theory, high levels of internal validity, and the control over confounding factors in the experimental research approach (e.g., Fisher 1935; Campbell and Stanley 1963; Ericsson and Simon 1980). Second, from a theoretical and conceptual perspective, my results can show the causal effects of order and double exposure on overall, free, and paid click-through behavior (see search engine result page characteristics in the categorization of the independent variables in *Chapter C*/2.1).
2. *Project III* supports further developments in consumer choice literature. The interpretation of the results of the interaction between advertiser competition and double exposure on free click-through behavior suggests that recognition heuristics (e.g., Goldstein and Gigerenzer 2002) are relevant for top and organic search results, but

this does not apply to paid side results (see Joachims et al. 2005; Granka, Hembrooke, and Gay 2006). The results of *Project III* thus limit the effectiveness of recognition heuristics to stimuli (here: search results) that gain considerable attention from consumers. Peripheral perceptions of information (here: paid side results) are not adequate for influencing consumers' recognition heuristics.

3. Finally, the results contribute to the development of marketing decision models for evaluating search engine marketing activities. In this matter, *Project III* again contributes to both managerial and scientific perspectives. For managers, the cannibalization coefficient and application to click-through data from a controlled experimental environment not only show its necessity for managerial decision making but also shed light on a more diverse evaluation of the success of paid search advertising activities. Through validation with a transformation of the results of Google's research study by Chan et al. (2011), the external validity of these results is confirmed. From a scientific perspective, the development of the cannibalization quotient is a further step in improving recently applied online marketing metrics and introducing more managerial relevance in the scientific development process of marketing decision models (e.g., Bughin, Shenkan, and Singer 2008; Wübben and von Wangenheim 2008; Reibstein, Day, and Wind 2009; Jaworski 2011).

In summary, the results of *Project III* contribute to a better understanding of the causal effects of order and double exposure, of cannibalizing effects on free click-through behavior evoked by double exposure situations, and the effectiveness of double exposure with increasing levels of advertiser competition.

2 Privacy Concerns on the Internet

Research and managerial activities on customer channel migration and search engine marketing share high levels of dependence on usage data. Further developments in managerial practice and research in these two highly interesting fields require the agreement of companies and customers to use their data and data sources. Thus, I adopt the costumers' point of view in these reflections on the challenges and potentials of privacy concerns for further research and management.

Consumers' privacy concerns are more than justified; customers and users on the Internet have almost no secrets. Anecdotal evidence of privacy violations appear increasingly in diverse Internet technology–enabled applications by different companies worldwide (e.g., Karjoth, Schunter, and Waidner 2003; Boulding et al. 2005). The directive of the European Union (EU) on data protection in the electronic communication sector sets essential parameters how personal data can be gathered on the Internet (European Union 2009). Thereby the EU imposes legal parameters that are judged as strict (Baumer, Earp, and Poindexter 2004), but also reduce the effectiveness of targeted display advertising, more so than in other regions of the world (Goldfarb and Tucker 2011). These regulations do not only affect targeted online banner advertising but also search engine marketing activities (Jakobs 2009).

One central component of the directive of the European Union (2009) is the implementation of a general "opt-in" condition. Under this restriction, cookies, which are little packages of data that transfer a transcript of users' activities to a provider or advertiser (e.g., Bucklin and Sismeiro 2009), cannot be stored on the user's hardware without prior agreement. Certainly, even though these privacy regulations protect the sphere of personal privacy to a considerable extent from a technological perspective, users of diverse offerings on the Internet also need to adapt their behavior to protect their own privacy. In this respect, Acquisti and Gross (2009) reveal that publicly accessible information on the Internet can predict highly personal information, such as the Social Security numbers of U.S. citizens.

Because clickstream data, as applied in most scientific publications on search engine marketing with proprietary company data (e.g., Ghose and Yang 2009; Chen, Chiang, and Storey 2010; Yang and Ghose 2010; Rutz and Trusov 2011; *Project II* of this thesis) underlie these restrictions, the highest sensitivity is required when handling clickstream data. More awareness of the sensitivity of these data is needed in the scientific community and among practitioners. It is especially necessary in the next step in analyzing consumer behavior on the Internet: the path to conversion, as the Marketing Science Institute prioritizes (Marketing Science Institute 2010). Possible paths to conversion analysis include tracking the whole journey of the users and customers on the Internet to a final conversion with cookie-based clickstream data (e.g., Patrzek 2008; Galagate and Jank 2011; Lourenco and Belo 2011). The application of these data to customer relationship management, through the integration of clickstream data in the customer database of the companies, is a logical next step (e.g., Chen, Chiang, and Storey 2010). Thus, click-path and recorded Internet usage behavior would be matched to customers who are known by name in the customer database.

Various different scandals have made the problem of accessible records of companies' customer databases evident, including Deutsche Telekom (e.g., Spiegel Online 2008), REWE (e.g., Zeit Online 2011), Sony (e.g., Schiesel 2011), and diverse others (e.g., Helft 2011;

Süddeutsche Zeitung 2011). Scientific and managerial practice in customer relationship management increasingly pays attention to privacy issues. For example, Boulding et al. (2005, p. 159) propose that a "successful implementation of CRM requires that firms carefully consider issues of consumer trust and privacy." Deighton (2004) outlined the relevance of customers' trust in companies' handling of personal data well before the debates on privacy issues emerged, noting "consumer agrees to disclose transaction and demographic data in exchange for discounts and superior service" (Deighton 2004, p. 16). This underlying principle of reciprocity is a central component of any customer loyalty program (e.g., Kumar and Shah 2004; Berman 2006; Nunes and Dreze 2006; Blattberg, Kim, and Neslin 2009), as was the case with the data provided for *Project I* of this thesis.

Nevertheless, this principal of reciprocity between advertising companies and their customers has not found its way into the Internet environment. Some might argue that reciprocity exists between Internet users and providers of free applications on the Internet, such as newspaper websites, social networks, search engines, and price comparison websites, where firms place advertising (e.g., Hoffman and Novak 1996; Hoffman and Novak 2000; Parasuraman and Zinkhan 2002; Pauwels and Weiss 2008). These might be arguments for displaying advertisements to finance costless applications on the Internet, but they do not apply to the extensive use of data about transactional and customer characteristics. The challenge on the Internet thus is ensuring the willingness of customers to disclose transaction, click-path, and demographic data by building an environment that fosters the principle of reciprocity among advertising companies, providers of Internet applications, and customers. Especially in the context of search engine marketing, the unbalance actually favors companies. To change the status quo and achieve a fairer relationship between customers' willingness to disclose personal and transactional data and companies' intent to analyze these data, firms should take a proactive approach. Companies should not wait until legal frameworks, such as additional EU directives about data protection in the electronic communication sector, block operations. Moreover, they should take a reciprocal approach in customer loyalty programs as a starting point for developing programs that support their industry's purposes. In recent years, consumers have learned that not all information on the Internet is free (e.g., Gupta and Mela 2008; Pauwels and Weiss 2008)—the same should apply to companies on the Internet.

The advantages derived from such a reciprocal framework might create new opportunities for all parties, as well as for research and management. Increased willingness to provide personal data might enable more regular surveys that would disclose further customer characteristics, customer behavior, and determinants of customer behavior, as established in customer loyalty programs (e.g., Lemon and von Wangenheim 2009). A combination of insights from survey research, clickstream data, and purchase behavior also could be obtained with the permission of users and customers. This combination would enhance the quality of the scientific approaches and conclusions, as well as the implications for management.

3 Research Designs for Investigating the Role of the Internet

The three empirical projects in this thesis demonstrate the importance of experimental, quasi-experimental, and mixed-method research designs for investigating the role of the Internet from a theoretical, not just a modeling, perspective. Although research into multichannel customer management and customer channel migration have been dominated by descriptive and modeling research approaches, both experimental (e.g., Konus, Trampe, and Verhoef 2009) and quasi-experimental research (e.g., Böhm 2008; Campbell and Frei 2010; Gensler, Leeflang, and Skiera 2011) designs have been taken into account too. That is, beyond data-driven research, theoretical and phenomenological approaches are appearing. For search engine marketing research, theory development and theory testing does not currently play a central role. However, experimental investigations and mixed-method research designs are gaining in importance, not only because of the results of *Projects II* and *III* of this thesis but because increasingly complex research questions demand several sources of data for testing theories.

If integrated frameworks with survey research, clickstream data, and data on the purchase behavior are not possible, due to systematic imbalances (see *Chapter D*/2) or technological restrictions, mixed-method research designs are a good answer to investigating complex issues. These research designs can clarify complex issues that cannot be discerned from a single source of data. From a methodological perspective, the mixed-method research designs in *Projects II* and *III* prove that combinations of observational and experimental, as well as experimental and descriptive, research approaches are capable of delivering profound contributions to research on the Internet and in the context of search engine marketing.

Undoubtedly, search engine clickstream data offer tremendous amounts of information about, for example, click-path and conversion behavior (e.g., Bucklin and Sismeiro 2009; Ghose and Yang 2009; Yang and Ghose 2010; Rutz and Trusov 2011). The structure of these data reveals considerable weaknesses. Aggregated data, as mostly applied in recent search engine marketing publications, cannot control for consumer heterogeneity as individual consumer–

level data can (e.g., Yang and Ghose 2010). Moreover, search engine clickstream data predominantly come from single companies advertising on search engines, so only one part of the picture can be investigated. Holistic approaches and generalizable results are thus virtually impossible. Search engine clickstream data also are established on a cookie level, rather than an individual consumer level. Thus inferences can be drawn on the cookie-level but not, as mostly intended, individually (e.g., Rangaswamy, Giles, and Seres 2009). Psychometric measures such as perceptions, attitudes, skills, and intentions of search engine users cannot be investigated with these kind of data either, as would be possible with mixed-method research designs or experimental designs (e.g., Dou et al. 2010). Finally, mixed-method research designs with experimental and observational or descriptive research designs enable insights, theory development, and theory testing into search engine usage patterns and search engine marketing modes of action, which cannot be revealed through purely statistical or modeling research approaches with clickstream data.

Although there are good reasons to apply secondary search engine clickstream data, there are equally good reasons for primary data collection through qualitative, observational, experimental, or mixed-method research designs. Some reasons emerge from efforts to address the shortcomings listed in previous sections. In more detail, an observational method, mixing think-aloud protocol with screen recording (*Project III*) can enrich observed click-through patterns of each subject with verbalized attitudes, intentions, expertise, and skills (e.g., Ericsson and Simon 1980; Benbunan-Fich 2001). Pure quantitative or modeling research approaches clearly would be able to reveal certain click-through patterns, but they struggle to demonstrate the reasons for inconsistent consumer behavior, which could be grounded in a lack of expertise or skills. By combining think-aloud protocols and screen recording, observational behavior and deeper insights from consumer perceptions and knowledge merge, ultimately leading to revealing explanations for inconsistent behavior.

Experimental designs provide a further approach for collecting primary data in mixed-method research (with additional observational or descriptive designs with secondary data), because they can test causal hypotheses grounded in a theoretical basis (e.g., Fisher 1935). Thus, the causal generalization of manipulations (e.g., causal effect of different positions or textual effects in a SERP on click-through rate) can be investigated with random assignment conditions (e.g, Campbell and Stanley 1963), isolation of the treatment (e.g., Shadish, Cook, and Campbell 2002), control over confounding factors (e.g., Venkatesan 1967), and high internal validity (e.g., Campbell 1957). These factors not only promote increasing popularity of experimental research in the marketing discipline (e.g., Eschweiler, Evanschitzky, and Woisetschläger 2007) but also can lead to broader adaptation in research on search engine marketing (e.g., Dou et al. 2010; *Project II* and *Project III* of this thesis).

4 Further Research

I conclude this dissertation with some potential developments on the basis of the limitations of my work. These limitations should serve as starting points for further research in the fields of customer channel migration and search engine marketing. I refer to my major findings and contributions as additional basis for future research. These major findings and contributions raise new issues in the research areas of customer channel migration and search engine marketing. Thereby, I focus on some especially challenging research themes that could be addressed in further research.

The emphasis in *Project I* on the behavioral consequences of customer-initiated channel migration reveals the causal effects of channel migration on the breadth and depth of the customer–company relationship. For technical reasons and to match the treatment and control groups for the quasi-experimental research design, I chose a point in time for channel migration. Because a customer–company relationship and customer channel selection are dynamic, further research on customer channel migration should address these effects. Classical matching procedures, such as Mahalanobis-metric or propensity score matching cannot account for dynamic effects though, because they depend on a treatment at a particular time. Therefore, the application of dynamic structural models would offer possibilities for studying dynamic effects in customer channel migration (for an overview, see Chintagunta et al. 2006; Baohong 2006). Additional research in the field of customer channel migration also should consider the importance of indirect online channels. Restrictions in the database prevented me from considering the causal effects of customer-initiated channel migration to indirect online channels on relationship breadth and depth.

Project II goes into greater detail about the impact of advertiser competition, as indicator of choice overload, on consumer click-through and conversion behavior on search engines. These transactional measurements cannot reflect the effect of advertiser competition on relational measures though, such as length, breadth, and depth of the relationship or customer lifetime value. Further research might disclose two highly interesting effects of advertiser competition. First, the integration of relational measures to choice overload can be a strong enhancement to the literature stream on consumer choice. Thus, the following research question seems to suggest itself: How does advertiser competition affect the length, breadth, and depth of the customer relationship? These extensions might be explained by the relevance of search costs and cognitive efforts, connected to consumers' choice in an environment of choice overload. Second, these developments reflect the enhancements in managerial practice, where the first moves to integrate clickstream data and customer databases are made. These developments still must bear the privacy concerns in mind (see *Chapter D*/2).

The focus of *Project III* is on the causal relationship between order effects and double exposure on consumer click-through behavior. Three areas are of considerable interest for further research. First, my results show that a distinction of paid top, paid side, and organic search results is necessary. This finding suggests the need for further research on the influence of these three distinct areas for customer acquisition on search engines and their impact on relational measures. Such measures again could include length, breadth, and depth of the relationship, customer lifetime value, or a higher-order measurement of customer equity. Thus the following research questions might be of interest: How do customers, acquired via paid top, paid side, or organic search results, differ in their relationship length, breadth, and depth? Do customers acquired via organic search results have higher customer lifetime value? How does customer acquisition via paid top positions affect customer lifetime value? How does customer acquisition via paid side positions affect customer lifetime value? Second, the insights from observations of consumer click-through behavior in the observational and experimental studies strongly hint at different types of search engine users (e.g., with different attitudes toward paid search). An approach similar to that used by Konus, Verhoef, and Neslin (2008) could be applied to the search engine context, as could a mixed-method research approach similar to *Project III.* In these cases, different search types might be identified by multinomial logit analysis (see McFadden 1974; McFadden 2001). Third, my analyses of the effect of double exposure on free click-through behavior reveal considerable cannibalizing effects. Additional research into the negative effects of double exposure could provide a more sound basis for my initial results. A field experiment or a combined approach with paid and organic clickstream data would be effective. Both research approaches offer considerable advantages, but I suggest a field experiment, because it offers the promise of a random assignment of participants, isolation of the treatment effect, manipulation checks, and the ability for theory testing. Descriptive analysis can still enable further fascinating insights in this field. All in all, these areas of customer channel migration and search engine marketing research continue to offer ample opportunities for future research projects.

Appendix

Appendix 1: Results of the Regression Analysis for Matching Procedures (Project I)

Results Linear Regression Analysis for Estimating Mahalanobis Distance H1

Independent Variables	**Estimates**
Intercept	4.58×10^8 (3,286,468.06) ***
FLY (Q1–Q8)	9,774,926.44 (4,325,767.39) *
CRB (Q1–Q8)	-1,063,520.40 (3,521,493.74) n.s.
REV (Q1–Q8)	121,098.21 (4,421,086.51) n.s.
N (Cross Sections)	6,461
R^2	.00
SEE	264,200,000
F-Test	F(3) = 2.79 *

Notes: a. S.E. is indicated in parentheses; all parameters are z-standardized.
b. Significance levels of the models and parameters: *** significant on 0.1% level; ** significant on 1% level; * significant on 5% level; (*) significant on 10% level.
c. The dependent variable is customer ID. The independent variables are standardized values of booked flights (FLY), cross-buying (CRB), and revenue (REV).

Results Linear Regression Analysis for Estimating Mahalanobis Distance H2

Independent Variables	**Estimates**
Intercept	4.61×10^8 (12,662,086.19) ***
FLY (Q1–Q8)	-2,306,453.02 (17,809,398.28) n.s.
CRB (Q1–Q8)	12,233,747.97 (14,895,605.49) n.s.
REV (Q1–Q8)	-15,858,921.33 (17,405,314.71) n.s.
N (Cross Sections)	445
R^2	.00
SEE	267,100,000
F-Test	F(3) = .52 n.s.

Notes: a. S.E. is indicated in parentheses; all parameters are z-standardized.
b. Significance levels of the models and parameters: *** significant on 0.1% level; ** significant on 1% level; * significant on 5% level; (*) significant on 10% level.
c. The dependent variable is customer ID. The independent variables are standardized values of booked flights (FLY), cross-buying (CRB), and revenue (REV).

Results Linear Regression Analysis for Estimating Mahalanobis Distance H3

Independent Variables	**Estimates**
Intercept	4.58×10^8 (3,350,971.20) ***
FLY (Q1–Q8)	10,358,012.55 (4,399,998.69) n.s.
CRB (Q1–Q8)	-1,050,434.11 (3,587,858.44) n.s.
REV (Q1–Q8)	-148,303.85 (4,500,437.28) n.s.
N (Cross Sections)	6,226
R^2	.00
SEE	264,400,000
F-Test	F(3) = 2.98 *

Notes: a. S.E. is indicated in parentheses; all parameters are z-standardized.
b. Significance levels of the models and parameters: *** significant on 0.1% level; ** significant on 1% level; * significant on 5% level; (*) significant on 10% level.
c. The dependent variable is customer ID. The independent variables are standardized values of booked flights (FLY), cross-buying (CRB), and revenue (REV).

Appendix 2: Results of Difference-in-Differences Estimation for Cross Checking H1 (Project I)

Parameter	**Model 4a (flights)**			**Model 4b (revenue)**			**Model 4c (cross-buying)**		
	Estimate	S.E.	*p*	Estimate	S.E.	*p*	*Estimate*	*S.E.*	*p*
Intercept	.56	.107	< .0001	754.20	122.8	< .0001	53.94	53.19	.311
Period	.02	.01	< .05	91.58	50.71	< .10	19.06	3.89	< .0001
Treatment	-.04	.15	.770	73.40	173.7	.673	-4.74	75.22	.950
Period × Treatment	.03	.01	< .05	35.04	71.71	.625	1.25	5.05	.820
N (Cross Sections)	194			194			194		
Sum of Squares	8,937.91			962,658,171.40			1,547,983,526		
R^2	R^2 = .01			R^2 = .01			R^2 = .02		

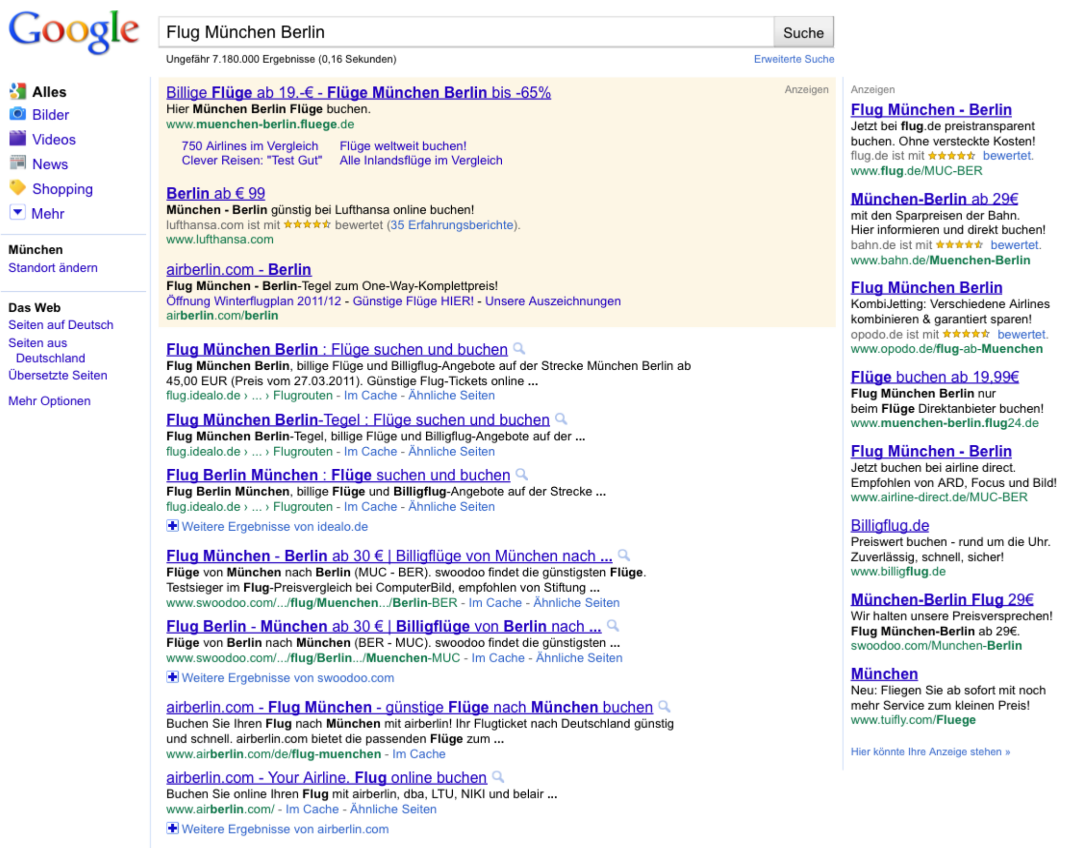
Notes: Flight (a) and cross-buying (c) are calculated with a time-series of 16 quarters and revenue (b) with an annual time-series of 4 years.

Results Linear Regression Analysis for Estimating Mahalanobis Distance (Cross Checking H1)

Independent Variables	**Estimates**
Intercept	4.66×10^8 (13,525,537.90) ***
FLY (Q1–Q8)	-10,173,160.91 (14,335,648.80) $^{n.s.}$
CRB (Q1–Q8)	4,962,244.99 (12,657,337.90) $^{n.s.}$
REV (Q1–Q8)	2,059,604.30 (13,107,476.90) $^{n.s.}$
N (Cross Sections)	654
R^2	.00
SEE	272,500,000
F-Test	F(3) = .18 $^{n.s.}$

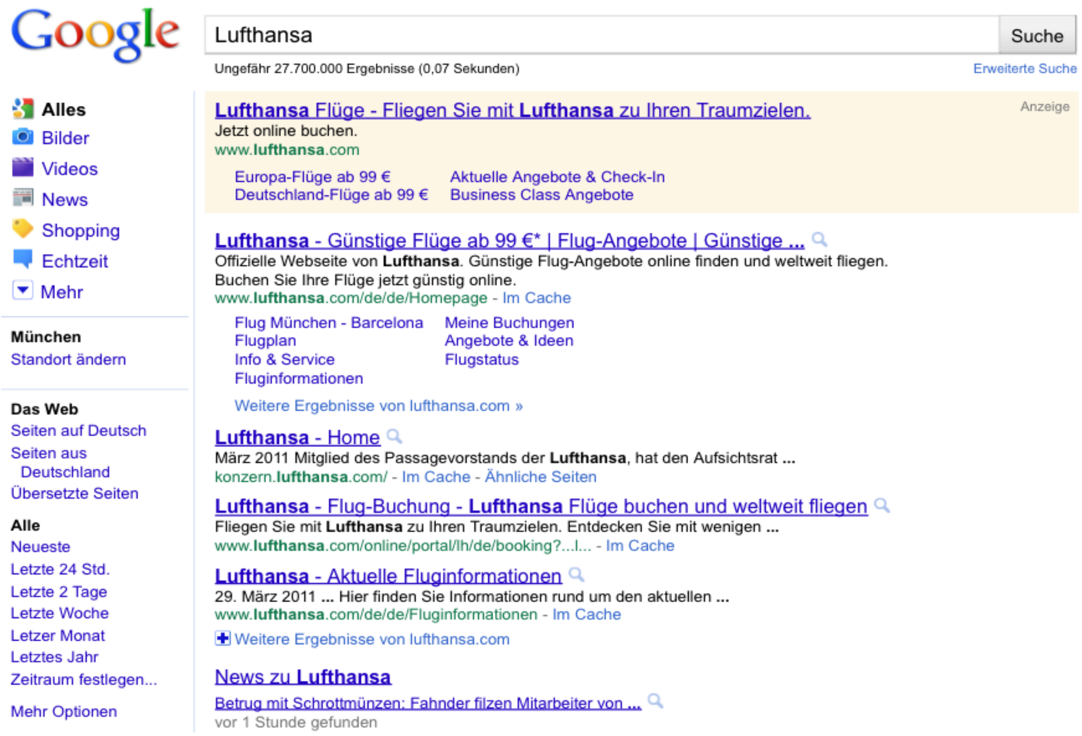
Notes: a. S.E. is indicated in parentheses; all parameters are z-standardized.
b. Significance levels of the models and parameters: *** significant on 0.1% level; ** significant on 1% level; * significant on 5% level; (*) significant on 10% level.
c. The dependent variable is customer ID. The independent variables are standardized values of booked flights (FLY), cross-buying (CRB), and revenue (REV).

Appendix 3: Exemplary Search Engine Result Page with Eleven Paid Search Results



Notes: This Google screenshot was accessed on March 31, 2011 [available at: http://www.google.de].

Appendix 4: Exemplary Search Engine Result Page with only one Paid Top Search Result Displayed

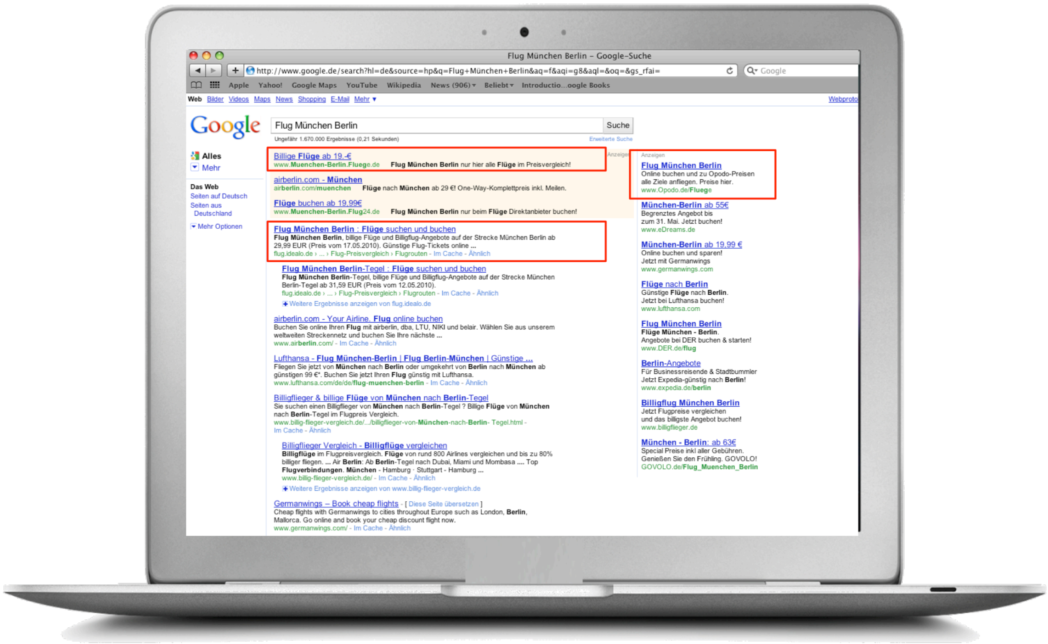


Notes: This Google screenshot was accessed on March 31, 2011 [available at: http://www.google.de].

Appendix 5: Demographics for the Representative Online Experiment (Experiment, Project II; Experiment 2, Project III)

Gender:	Male N = 379 (50.8%)				Female N = 366 (49.2%)			
Age Group:	18-24 N = 132 (17.7%)	25-34 N = 119 (16%)	35-44 N = 189 (25.4%)	45-54 N = 129 (17.3%)	55-64 N = 110 (14.8%)	65 + N = 65 (8.7%)		
Educational Level:	Higher education entrance qualification N = 126 (16.9%)	Higher education entrance qualification N = 121 (16.3%)	Secondary school leaving certificate N = 328 (44.1%)	Secondary modern school qualification N = 169 (22.7%)				
Nielsen area:	Nielsen 1 N = 129 (17.3%)	Nielsen 2 N = 171 (23%)	Nielsen 3a N = 103 (13.8%)	Nielsen 3b N = 99 (13.3%)	Nielsen 4 N = 95 (12.8%)	Nielsen 5 N = 33 (4.4%)	Nielsen 6 N = 59 (7.9%)	Nielsen 7 N = 55 (7.5%)

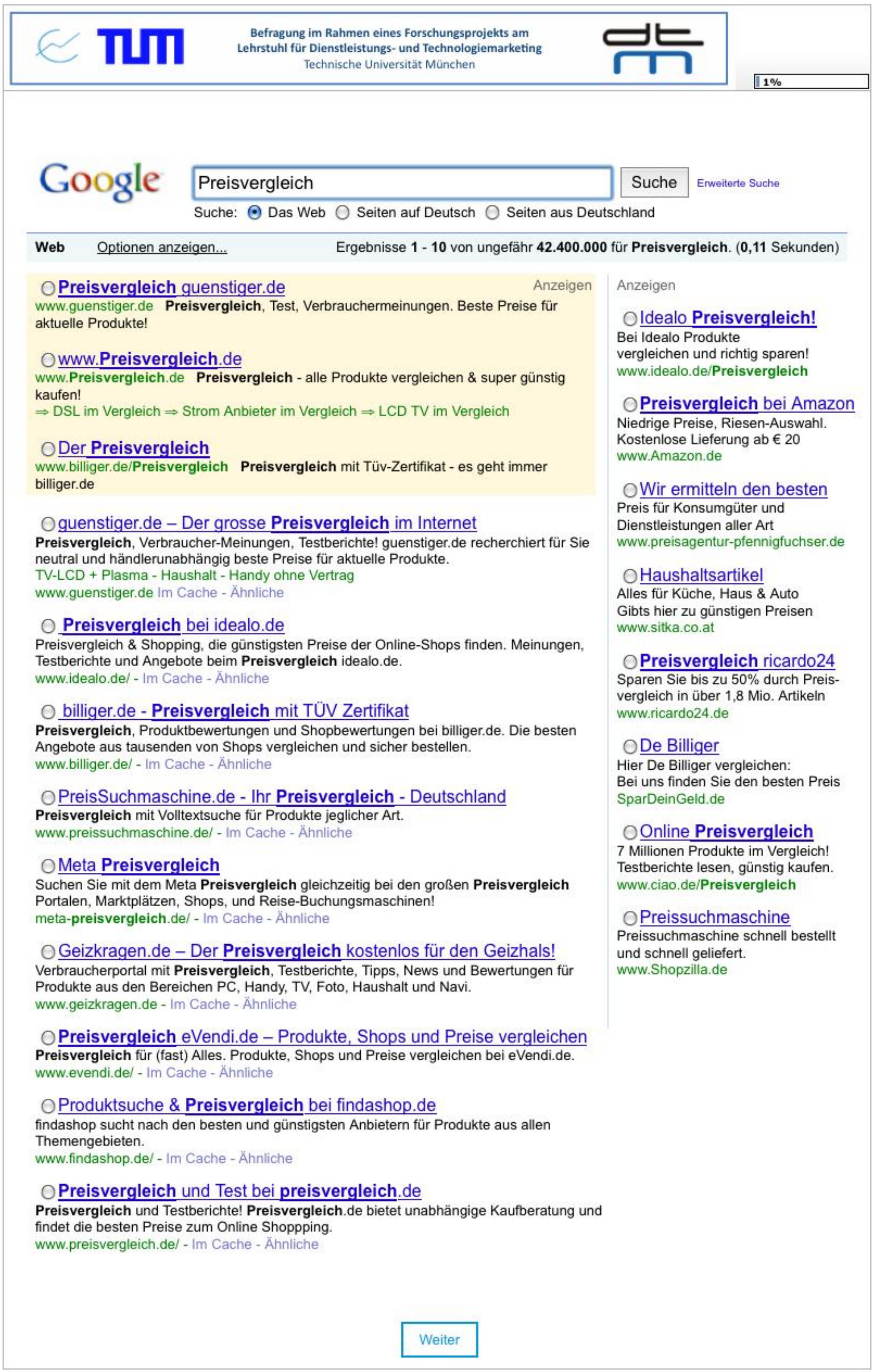
Appendix 6: Example for Manipulation of the SERP in the Experimental Studies



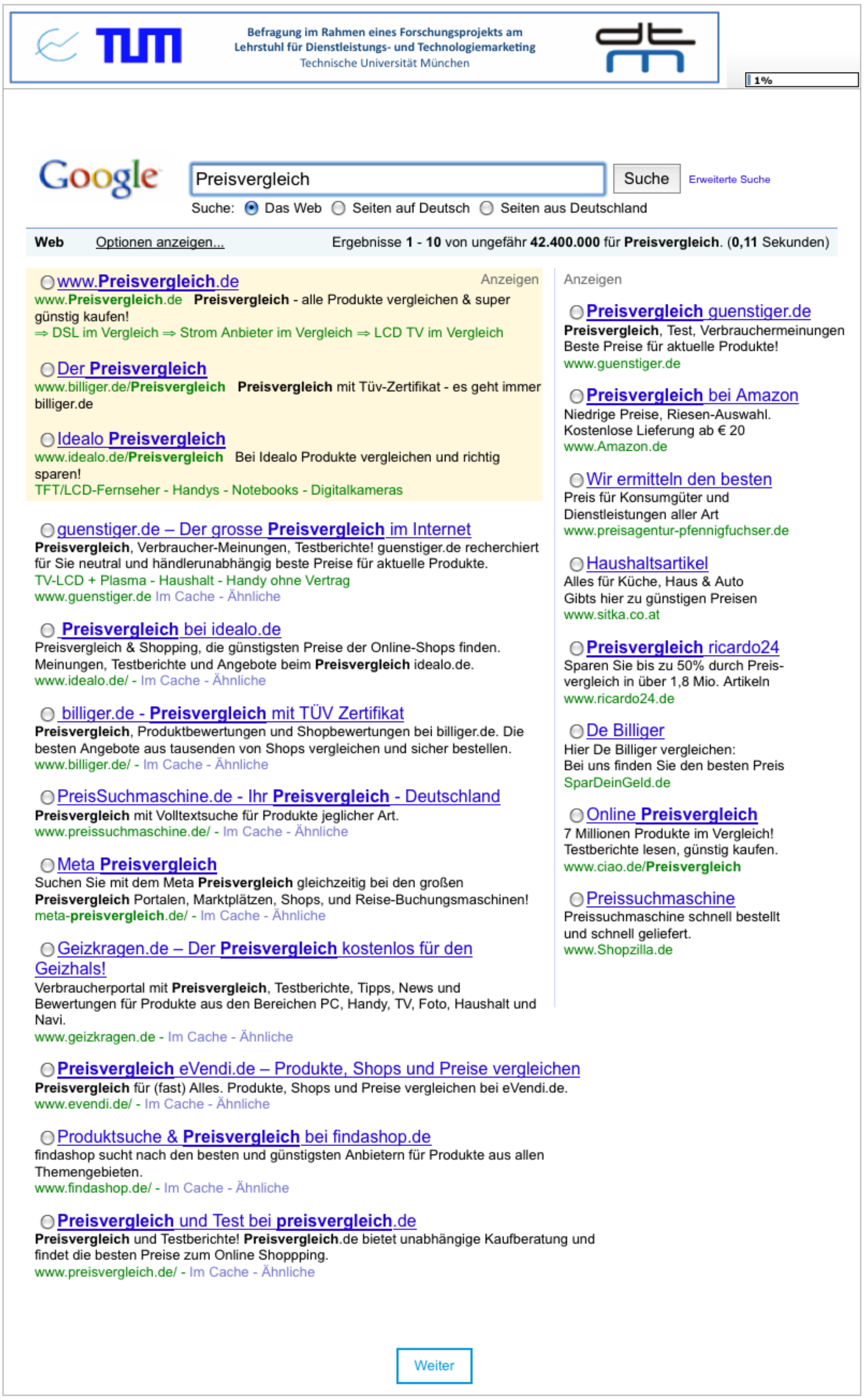
Notes: The framed search results indicate positions where a manipulation of the search results was conducted.

Appendix 7: Manipulated Search Engine Result Page (Experiment, Project II; Experiment 2, Project III)

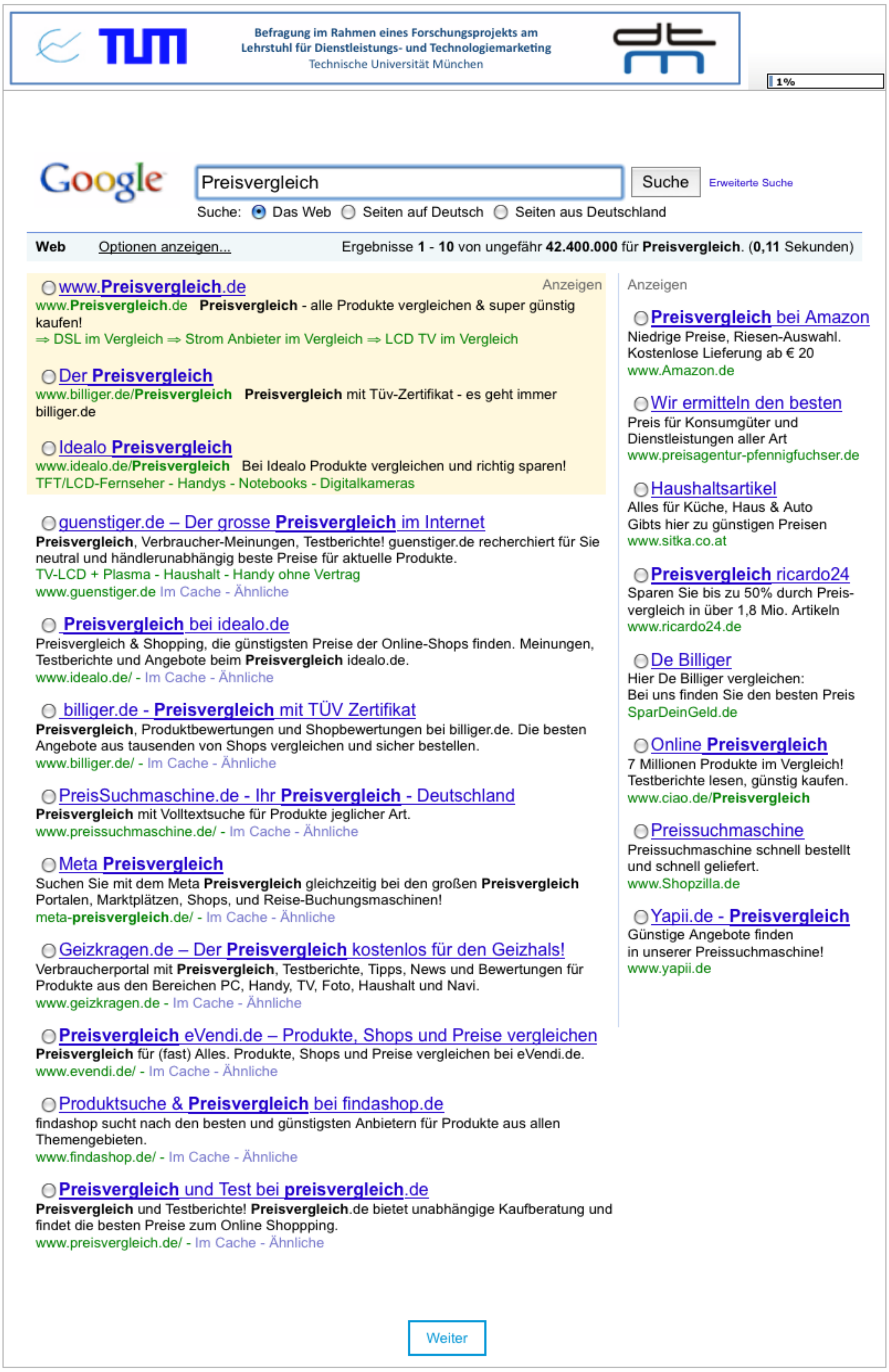
Double Top Search Engine Result Page for AC = 1 ***(Experiment, Project II; Experiment 2, Project III)***



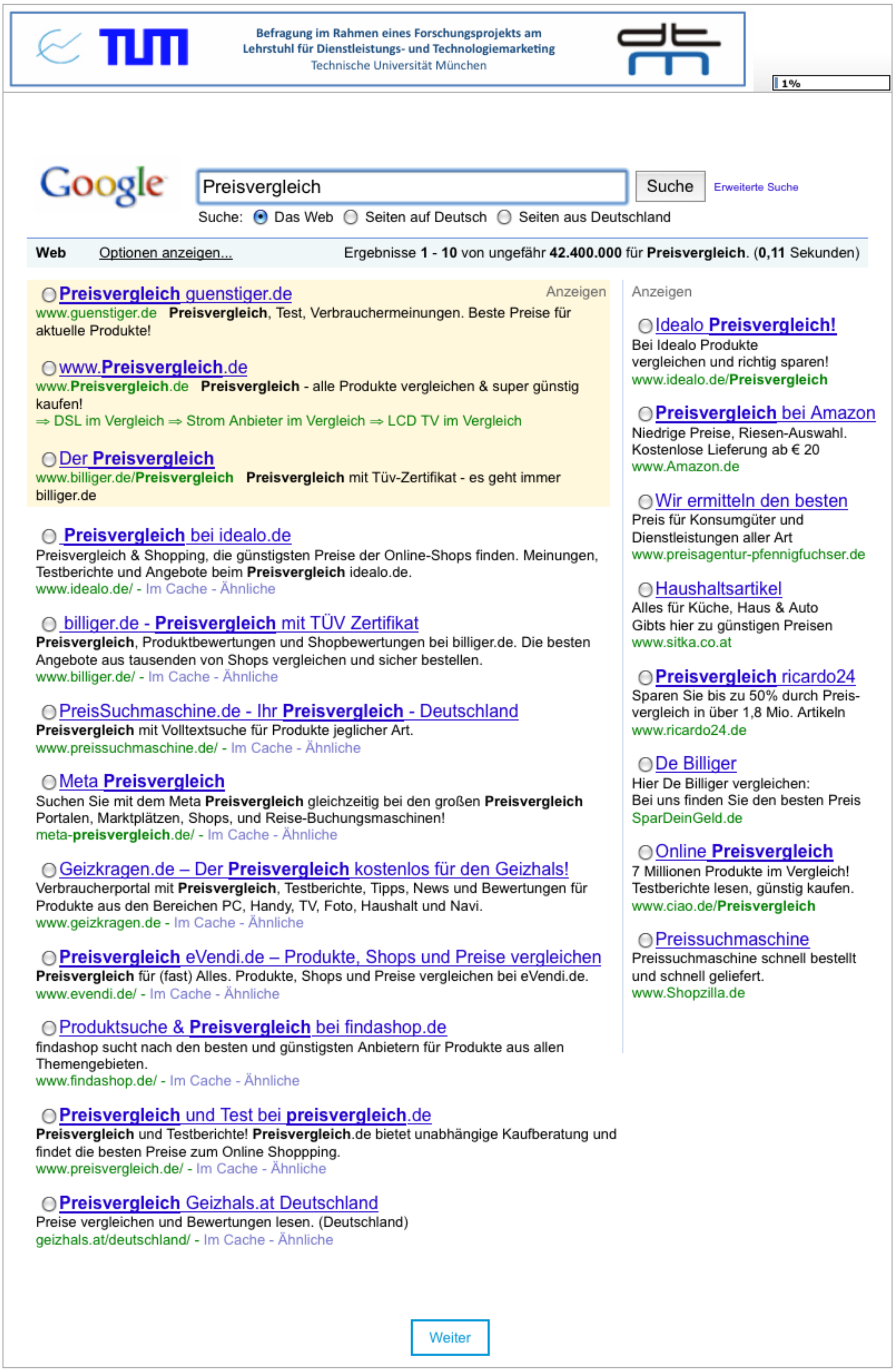
Double Side Search Engine Result Page for AC = 1 ***(Experiment, Project II; Experiment 2, Project III)***



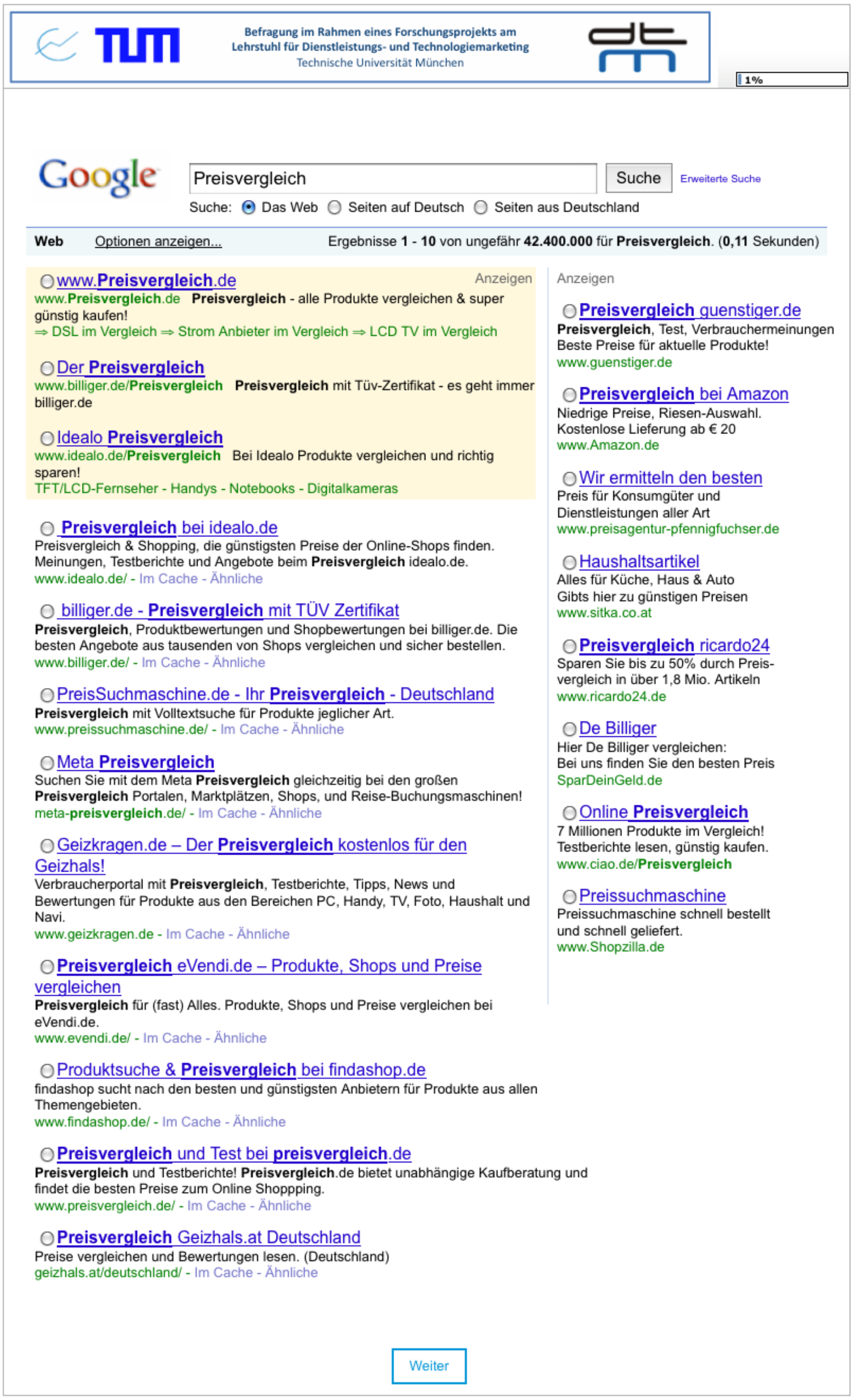
Single Organic Search Engine Result Page for AC = 1 ***(Experiment, Project II; Experiment 2, Project III)***



Single Top Search Engine Result Page for AC = 1 ***(Experiment, Project II; Experiment 2, Project III)***



Single Side Search Engine Result Page for AC = 1 *(Experiment, Project II; Experiment 2, Project III)*



Appendix 8: Scenario Description (Experiment, Project II; Experiment 2, Project III)

Scenario 1 (AC = .0): Specialty wine from a gourmet store

Stellen Sie sich vor, dass Ihre gesamte Abteilung zu einer Jubiläumsfeier bei einem Geschäftspartner eingeladen ist. Dieser Geschäftspartner ist ein ausgewiesener Weinkenner und bevorzugt deutsche Weine. Sie haben sich bereit erklärt das gemeinsame Geschenk Ihrer Abteilung, einen deutschen Qualitätswein aus der Weinabteilung von Dallmayr in München, für den Jubilar im Internet zu besorgen. Da Sie sich etwas mit Weinen auskennen, wissen Sie, dass Auslese ein Prädikat für Qualitätsweine ist. Sie beginnen Ihre Suche nach einer Bestellmöglichkeit eines Auslese Weins aus der Weinabteilung von Dallmayr bei einer Suchmaschine. Welchen Suchbegriff geben Sie in eine Suchmaschine (z.B. Google) ein, um einen Auslese Wein aus der Weinabteilung von Dallmayr zu finden?

[Instruction before the display of the manipulated SERP]

Gehen Sie im Folgenden davon aus, dass Sie den **Suchbegriff „Dallmayr Wein Auslese“** in die Suchmaschine „Google“ eingegeben und nachfolgende Suchergebnisseite erhalten haben. Bitte suchen Sie auf der folgenden Suchergebnisseite spontan <u>den Link</u> heraus, den Sie in oben genannter Situation anklicken würden, um einen Auslese Wein bei Dallmayr zu bestellen.

Scenario 2 (AC = .2): Rental Frankfurt central station

Stellen Sie sich vor, dass Sie in den nächsten Tagen von Ihrer Heimatstadt (aus privatem Anlass) mit der Bahn nach Frankfurt am Main Hauptbahnhof fahren werden. Sie möchten am Hauptbahnhof einen Mietwagen anmieten und suchen daher nach einer Möglichkeit einen Mietwagen am Hauptbahnhof zu bekommen. Sie beginnen Ihre Suche nach einem Mietwagen am Frankfurter Hauptbahnhof bei einer Suchmaschine. Welchen Suchbegriff geben Sie in eine Suchmaschine (z.B. Google) ein, um einen Mietwagen am Frankfurter Hauptbahnhof zu buchen?

[Instruction before the display of the manipulated SERP]

Gehen Sie im Folgenden davon aus, dass Sie den **Suchbegriff „Mietwagen Frankfurt Hbf“** in die Suchmaschine „Google“ eingegeben und nachfolgende Suchergebnisseite erhalten haben. Bitte suchen Sie auf der folgenden Suchergebnisseite spontan <u>den Link</u> heraus, den Sie in oben genannter Situation anklicken würden, um einen Mietwagen am Frankfurter Hauptbahnhof zu buchen.

Scenario 3 (AC = .4): Soccer shirt national team

Stellen Sie sich vor, dass Sie von den Spielen der Nationalmannschaft bei der Fußball Weltmeisterschaft in Südafrika, die erst vor wenigen Wochen zu Ende gegangen ist, sehr begeistert waren. Daher möchten Sie ein Trikot der Fußball Nationalmannschaft im Internet bestellen und beginnen Ihre Suche nach einer Bestellmöglichkeit für das Trikot der Fußball Nationalmannschaft bei einer Suchmaschine. Welchen Suchbegriff geben Sie in eine Suchmaschine (z.B. Google) ein, um ein Trikot der Fußball Nationalmannschaft zu bestellen?

[Instruction before the display of the manipulated SERP]

Gehen Sie im Folgenden davon aus, dass Sie den **Suchbegriff „Trikot Fußball Nationalmannschaft“** in die Suchmaschine „Google“ eingegeben und nachfolgende Suchergebnisseite erhalten haben. Bitte suchen Sie auf der folgenden Suchergebnisseite spontan den Link heraus, den Sie in oben genannter Situation anklicken würden, um eine Bestellung eines Trikots der Fußball Nationalmannschaft durchzuführen.

Scenario 4 (AC = .6): A magazine subscription

Stellen Sie sich vor, dass Sie ein großer Fan der wöchentlichen Wissenssendung bzw. des Infotainment-Fernsehmagazins „Welt der Wunder“ sind. Über die Fernsehsendungen hinaus sind Sie an einem Abonnement des monatlich erscheinenden Print-Magazins „Welt der Wunder“ interessiert. Sie möchten das Magazin gerne abonnieren und beginnen Ihre Suche nach einer Bestellmöglichkeit für das Abo von „Welt der Wunder“ bei einer Suchmaschine. Welchen Suchbegriff geben Sie in eine Suchmaschine (z.B. Google) ein, um ein Abo von „Welt der Wunder“ zu bestellen?

[Instruction before the display of the manipulated SERP]

Gehen Sie im Folgenden davon aus, dass Sie den **Suchbegriff „Abo Welt der Wunder“** in die Suchmaschine „Google“ eingegeben und nachfolgende Suchergebnisseite erhalten haben. Bitte suchen Sie auf der folgenden Suchergebnisseite spontan den Link heraus, den Sie in oben genannter Situation anklicken würden, um ein Abonnement der Zeitschrift „Welt der Wunder” abzuschließen.

Scenario 5 (AC = .8): Individual photo calendars

Stellen Sie sich vor, dass in den nächsten Monaten zwei Ihrer engsten Freunde runde Geburtstage feiern werden. Da Sie in den letzten Jahren viele schöne gemeinsame Erlebnisse hatten, möchten Sie für diese engen Freunde aus eigenen Bildern individuelle Fotokalender erstellen. Sie beginnen Ihre Suche nach passenden Anbietern für individuelle Fotokalender mit einer Suchanfrage bei einer Suchmaschine. Welchen Suchbegriff geben Sie in eine Suchmaschine (z.B. Google) ein, um mehr über Anbieter für die Erstellung individueller Fotokalender zu erfahren?

[Instruction before the display of the manipulated SERP]

Gehen Sie im Folgenden davon aus, dass Sie den **Suchbegriff „individuelle Fotokalender“** in die Suchmaschine „Google“ eingegeben und nachfolgende Suchergebnisseite erhalten haben. Bitte suchen Sie auf der folgenden Suchergebnisseite spontan den Link heraus, den Sie in oben genannter Situation anklicken würden, um sich über Anbieter für individuelle Fotokalender zu informieren.

Scenario 6 (AC = 1): Price comparison

Stellen Sie sich vor, Sie möchten sich über aktuelle Preise für verschiedene Produkte im Internet informieren. Wichtig ist Ihnen dabei, dass Sie nicht nur die Preise eines Produktes von unterschiedlichen Herstellern vergleichen können, sondern auch die Verkaufspreise der Produkte (z.B. Mobiltelefon, CD etc.) bei unterschiedlichen Händlern/Verkäufern. Sie beginnen Ihre Suche mit einer Suchanfrage bei einer Suchmaschine. Welchen Suchbegriff geben Sie in eine Suchmaschine (z.B. Google) ein, um einen solchen Dienst zu finden?

[Instruction before the display of the manipulated SERP]

Gehen Sie im Folgenden davon aus, dass Sie den **Suchbegriff „Preisvergleich“** in die Suchmaschine „Google“ eingegeben und nachfolgende Suchergebnisseite erhalten haben.
Bitte suchen Sie auf der folgenden Suchergebnisseite spontan den Link heraus, den Sie in oben genannter Situation anklicken würden, um sich über die aktuellen Preise von verschiedenen Produkten zu informieren.

Appendix 9: Measurement of Control Variables (Experiment, Project II; Experiment 2, Project III)

Reliability and Validity of Internet Search Skill

Internet search skill (ISS) was measured with a three item seven-point Likert-type scale by Mathwick and Rigdon (2004) (Appendix-Table 1). The three items of ISS are adequate for exploratory factor analysis respectively a principal component analysis (KMO = .72, according to Kaiser (1974), p. 35: middling; MSA ≥ .68; Bartlett's test of sphericity: χ^2 (3) = 1163.17, $p < .001$).

Internet search skill (Seven-point Likert-type: 1="I strongly disagree"; 7="I strongly agree")
Please evaluate the following statements.

Item	***Item text***	**Source, item was adapted from**
ISS_1	*"I am extremely skilled at using the Web."*	*Mathwick and Rigdon (2004)*
ISS_2	*"I consider myself knowledgeable about good search techniques on the Web."*	*Mathwick and Rigdon (2004)*
ISS_3	*"I know how to find what I am looking for on the Web."*	*Mathwick and Rigdon (2004)*

Appendix-Table 1: Operationalization of ISS

The first generation tests for the ISS construct show very good values for item-to-total correlations, explained variance, and communalities well above the cut-off borders (see Appendix-Table 2). The reliability of the scale is very good (α = .87).

	1st Generation					
	M	*SD*	*I-t-t*	*α*	*EV*	h^2
all				.87	79.64%	
ISS_1	5.69	1.18	.78			.81
ISS_2	5.31	1.33	.80			.84
ISS_3	5.89	1.13	.70			.74

Notes: M = Mean; SD = Standard deviation; I-t-t = Item-to-total correlation; α = Cronbach's α; EV = Explained Variance; h^2 = Communality.

Appendix-Table 2: 1st Generation Reliability and Validity of ISS

Reliability and Validity of Search Engine Expertise

Search engine expertise (SEE) was measured with a five-item 7-point semantic differential scale with a numeric format adjusted from Mishra, Umesh, and Stem (1993). The items two and four were inverted from the original scale and item five was additionally introduced (see Appendix-Table 3). All five items of SEE are adequate for exploratory factor analysis respectively a principal component analysis (KMO = .89, according to Kaiser (1974), p. 35: meritorious; MSA ≥ .87; Bartlett's test of sphericity: χ^2 (10) = 3073.55, p < .001).

Search engine expertise (7-point semantic differential scale with a numeric format)

Please evaluate the following statements.

Item	***Item text***	**Source, item was adapted from**
SEE_1	*"I know very little about"/ " I know very much about"*	*Mishra, Umesh, and Stem (1993)*
SEE_2	*"Inexperienced" / "Experienced"*	*Mishra, Umesh, and Stem (1993)*
SEE_3	*"Uninformed" / "Informed"*	*Mishra, Umesh, and Stem (1993)*
SEE_4	*"Novice searcher" / "Expert searcher"*	*Mishra, Umesh, and Stem (1993)*
SEE_5	*"Not familiar at all" / "Very familiar"*	*Own development*

Appendix-Table 3: Operationalization of SEE

With item-to-total correlations ranging from .77 to .87, communalities from .73 to .85, explained variance of 79%, and Cronbach's α = .93 the criteria for reliability are well above the inclusion levels (see Appendix-Table 4).

	1st Generation					
	M	*SD*	*I-t-t*	*α*	*EV*	h^2
all				.93	79 %	
SEE_1	5.51	1.07	.77			.73
SEE_2	5.70	1.09	.87			.85
SEE_3	5.63	1.15	.84			.81
SEE_4	5.33	1.08	.79			.75
SEE_5	5.69	1.06	.84			.81

Notes: M =Mean; SD = Standard deviation; I-t-t = Item-to-total correlation; α = Cronbach's α; EV = Explained Variance; h^2 = Communality.

Appendix-Table 4: 1st Generation Reliability and Validity of SEE

Reliability and Validity of Attitude Toward Paid Search Aware

Attitude toward paid search aware (APSA) was measured via a modified four-item seven-point Likert-type scale by Edwards, Li, and Lee (2002). The third item of the original scale was reversed (Appendix-Table 5). In order to assess the validity and reliability of the scale, the Items “APSA_2” and “APSA_4” were transliterated. Transliterated value for “I strongly disagree” = 7 and for ”I strongly agree“ = 1. The items of APSA were only answered in cases, when participants know that paid search advertisings can appear on Google’s search engine result pages.[143] For that reason the data set has been modified by list wise deleting non-respondents (see Byrne 2001, p. 289). Preliminary analyses show that principal component analysis can be applied to attitude toward paid search aware (KMO = .69; MSA ≥ .65; Bartlett’s test of sphericity: χ^2 (6) = 684.12, p < .001).

Attitude toward paid search (aware) (Seven-point Likert-type: 1=”I strongly disagree“; 7=”I strongly agree“)

I think advertisements (in terms of displays or sponsored links) on Google search engine result pages are:

Item	***Item text***	**Source, item was adapted from**
APSA_1	*“Helpful”*	*Edwards, Li, and Lee (2002)*
APSA_2	*“Unimportant”*	*Edwards, Li, and Lee (2002)*
APSA_3	*“Informative”*	*Edwards, Li, and Lee (2002)*
APSA_4	*“Useless”*	*Edwards, Li, and Lee (2002)*

Appendix-Table 5: Operationalization of APSA

The results for first generation are above the required levels to assess reliability (see Appendix-Table 6).

[143] Therefore, the participants were asked: “What is your opinion: Does advertising exist on Google’s search engine result pages (in form of placements respectively paid search results)?” Possible answers are: “yes”, “no”, “do not know”.

	1st Generation					
	M	*SD*	*I-t-t*	*α*	*EV*	h^2
all				.80	64.44%	
APSA_1	3.65	1.65	.69			.74
APSA_2	3.76	1.78	.53			.51
APSA_3	3.77	1.56	.59			.62
APSA_4	4.16	1.73	.63			.63

Notes: M = Mean; SD = Standard deviation; I-t-t = Item-to-total correlation; α = Cronbach's α; EV = Explained Variance; h^2 = Communality.

Appendix-Table 6: 1st Generation Reliability and Validity of APSA

Reliability and Validity of Attitude Toward Paid Search Unaware

As measured for participants expecting search results on Google search engine result pages (APSA), attitude toward paid search for unaware participants (APSU) was measured via a modified four item seven-point Likert-type scale by Edwards, Li, and Lee (2002). Again, the third item was reversed (Appendix-Table 7).

Attitude toward paid search (unaware) (Seven-point Likert-type: 1="I strongly disagree"; 7="I strongly agree")

Advertisements (in terms of displays or sponsored links) on Google search engine result pages:

Item	*Item text*	**Source, item was adapted from**
APSU_1	*"I would consider helpful."*	*Edwards, Li, and Lee (2002)*
APSU_2	*"I would consider unimportant."*	*Edwards, Li, and Lee (2002)*
APSU_3	*"I would consider informative."*	*Edwards, Li, and Lee (2002)*
APSU_4	*"I would consider useless."*	*Edwards, Li, and Lee (2002)*

Appendix-Table 7: Operationalization of APSU

The items of attitude toward paid search (unaware) were only answered in cases, when the participants do not know that paid search advertisings can appear or think that advertising does not exist on Google's search engine result pages.[144] Thus the original data set has been customized by list wise deleting non-respondents (see Byrne 2001, p. 289) for confirmatory factor analysis. In order to assess the validity and reliability of the scale, the Items "APSA_2"

[144] Compare footnote 143.

and "APSA_4" were transliterated. Transliterated value for "I strongly disagree" = 7 and for "I strongly agree" = 1. All four items are adequate for an exploratory factor analysis (KMO = .64; MSA ≥ .61; Bartlett's test of sphericity: χ^2 (10) = 305.60, p < .001) in order to asses first generation reliability. Item-to-total correlations ranging from .46 to .67, communalities from .45 to .66, explained variance of 55.66%, and Cronbach's α = .72 confirm acceptable reliability values above the cut-off criteria (see Appendix-Table 8).

	1st Generation					
	M	*SD*	*I-t-t*	*α*	*EV*	h^2
all				.72	55.66%	
APSU_1	2.38	1.54	.57			.66
APSU_2	2.95	1.97	.46			.45
APSU_3	2.85	1.72	.54			.64
APSU_4	3.32	1.94	.50			.49

Notes: M = Mean; SD = Standard deviation; I-t-t = Item-to-total correlation; α = Cronbach's α; EV = Explained Variance; h^2 = Communality.

Appendix-Table 8: 1st Generation Reliability and Validity of APSU

Reliability and Validity of Attitude Toward Google

The attitude toward Google (ATG) was measured with a three-item seven-point Likert-type scale adapted from Sengupta and Johar (2002) (Appendix-Table 9). The three items are well suited for exploratory factor analysis, (KMO = .71; MSA ≥ .65; Bartlett's test of puerility: χ^2 (3) = 1641.87, p < .001).

Attitude toward Google (Seven-point Liker-type: 1="I strongly disagree"; 7="I strongly agree")

My opinion about the company Google is:

Item	***Item text***	**Source, item was adapted from**
ATG_1	*"I think Google is a very good search engine."*	*Sengupta and Johar (2002)*
ATG_2	*"I think Google is a very useful search engine."*	*Sengupta and Johar (2002)*
ATG_3	*"My opinion of Google is very favorable."*	*Sengupta and Johar (2002)*

Appendix-Table 9: Operationalization of ATG

Principal component analysis revealed very good values for first generation reliability. Item-to-total correlations are between .73 and .85, the communalities range from .76 to .90, the explained variance is 84.24%, and the reliability (α = .88) of the scale is well above the limit (see Appendix-Table 10).

	1st Generation					
	M	*SD*	*I-t-t*	α	*EV*	h^2
all				.88	84.24%	
ATG_1	6.17	1.04	.85			.90
ATG_2	6.24	.95	.82			.87
ATG_3	5.61	1.46	.73			.76

Notes: M = Mean; SD = Standard deviation; I-t-t = Item-to-total correlation; α = Cronbach's α; EV = Explained Variance; h^2 = Communality.

Appendix-Table 10: 1st Generation Reliability and Validity of ATG

Single-Item Measurements

Although authors like Churchill (1979) and Peter (1979) argue that multi-item measures should be first choice in marketing research, recent articles invalidate these positions in some cases. The reduction of the measurement scale to one item is acceptable if the object of the construct and attribute of the construct can be imagined without problems and uniformly (Rossiter 2002, pp. 309-315).[145] This development to single-item measures is not exclusive to marketing but is also relevant in psychology (for an overview: Sackett and Larson 1990; Wanous, Reichers, and Hudy 1997; Gardner et al. 1998; Bergkvist and Rossiter 2007).

Realism (REAL) was measured using a one-item measurement and was repeated after each of the six different search tasks (Appendix-Table 11). The scale was adapted from advertising credibility by Williams and Drolet (2005) and reduced to one item.[146]

[145] In the case of objects it is "concrete singular" (Rossiter 2002, pp. 309-312) and for the attribute it is "concrete" (Rossiter 2002, pp. 303-315).

[146] The original advertising credibility items are ("The advertisement is believable", "The advertisement is realistic." and "The advertisement is credible") with the anchors 1 ("Not at all") and 7 ("Very much") (Williams and Drolet 2005, pp. 326-327).

Realism (Seven-point Likert-type: 1=”I strongly disagree“; 7=”I strongly agree“)

Please evaluate the following statement, by selecting the box reflecting your opinion best.

Item	***Item text***	**Source, item was adapted from**
REAL	*“The displayed search engine result page for the search term __________ is realistic.”*	Williams and Drolet (2005)

Appendix-Table 11: Operationalization REAL

Satisfaction (SAT) was measured using a one-item measurement for overall satisfaction with Google (Appendix-Table 12). Single-item measurements for overall satisfaction are quite often used (e.g., Bolton 1998; Mittal, Ross, and Baldasare 1998; Bolton and Lemon 1999; Ganesh, Arnold, and Reynolds 2000; Lemon and von Wangenheim 2009).

Satisfaction (Seven-point Likert-type: 1=”I strongly disagree“; 7=”I strongly agree“)

Please evaluate the following statement, by selecting the box reflecting your opinion about Google best.

Item	***Item text***	**Source, item was adapted from**
SAT	*“Overall, I am very satisfied with Google.”*	Lemon and von Wangenheim (2009)

Appendix-Table 12: Operationalization SAT

Appendix 10: Correlation Matrix of Independent Variables (Field Study, Project II)

Correlation Matrix IV CTR Models

	zAP	*zWord*	*zBrand*	*zRetailer*	*zAC*	*zAC²*	*zCTR*
zAP	1						
zWord	-.21 (.00)	1					
zBrand	-.24 (.00)	.40 (.00)	1				
zRetailer	-.21 (.00)	-.05 (.00)	-.14 (.00)	1			
zAC	.30 (.00)	-.13 (.00)	-.18 (.00)	-.36 (.00)	1		
zAC²	.28 (.00)	-.10 (.00)	-.27 (.00)	-.31 (.00)	.96 (.00)	1	
zCTR	-.27 (.00)	.08 (.00)	-.11 (.00)	.48 (.00)	-.29 (.00)	-.21 (.00)	1

Correlation Matrix IV CR Models

	AP	*CTR*	*AC*	*AC²*	*WORD*	*BRAND*	*RETAILER*	*CR*
AP	1							
CTR	-.27 (.00)	1						
AC	.30 (.00)	-.29 (.00)	1					
AC²	.28 (.00)	-.21 (.00)	.96 (.00)	1				
WORD	-.21 (.00)	.08 (.00)	-.13 (.00)	-.10 (.00)	1			
BRAND	-.24 (.00)	-.11 (.00)	-.18 (.00)	-.27 (.00)	.40 (.00)	1		
RETAILER	-.21 (.00)	.48 (.00)	-.36 (.00)	-.31 (.00)	-.05 (.00)	-.15 (.00)	1	
CR	-.01 (.00)	.02 (.00)	.03 (.00)	.03 (.00)	-.03 (.00)	-.04 (.00)	.05 (.00)	1

Notes:
a. Parentheses contain p values.
b. The correlations between the metric variables were measured with Pearson correlation coefficient; correlations between metric and dichotomous variables with point biseral correlation coefficient; correlations between dichotomous variables with Spearman's rho.

Appendix 11: Search Task Description (Observational Study, Project III)

Search Task	Search Task Description
	First Stage of the Data Collection
1	Please find an adventure pool to your taste (without think-aloud).
2	Please prepare to buy the current Spiegel-bestseller (paperback) in the category of non-fiction books (think-aloud).
3	Please watch the trailer of Alice in Wonderland by Tim Burton (without thinking aloud).
4	You want to spend an all-inclusive holiday in the Caribbean. Please find an appropriate offer (think-aloud).
5	Please prepare to book a Lufthansa flight for two persons from Munich to Hamburg on the first weekend of July (think-aloud).
6	Please find a website, where you can buy a Philips Ambilight Full HD flat screen TV (without think-aloud).
7	Please find a waterproof digital compact camera and a website where you can buy the camera (without think-aloud).
8	Please prepare to buy two tickets for the open-air concert of the band Green Day in Munich (without think-aloud).
9	You are interested in a shoe of the Nike Free assortment. Please prepare to buy a pair of theses shoes in your size (without think-aloud).
10	Please find a labor law attorney in your hometown (think-aloud).
11	You plan to visit Stockholm for a weekend in the first week of September. Please find a cheap flight between Munich and Stockholm (without think-aloud).
12	An acquaintance of yours will finish his studies at the Ludwig-Maximilians-University (LMU) Munich soon. As souvenir you plan to make him a present of a LMU hoodie in size L. Please prepare to buy the hoodie (think-aloud).
	Second Stage of the Data Collection
1	Please find an adventure pool to your taste (without think-aloud).
2	Please prepare to buy the book "Time of your Life" of Cecelia Ahern (think-aloud).
3	Please watch the trailer of Alice in Wonderland by Tim Burton (without think-aloud).
4	Please prepare to book a Lufthansa flight for two persons from Munich to Hamburg on the first weekend of July (think-aloud).
5	You want to spend an all-inclusive holiday in the Caribbean. Please find an appropriate offer (think-aloud).
6	Please find a website, where you can buy a Philips Ambilight Full HD flat screen TV (without think-aloud).
7	Please find a waterproof digital compact camera and a website where you can buy the camera (think-aloud).
8	Please prepare to buy two tickets for the "Münchner Sommernachtstraum 2011" (think-aloud).
9	You are interested in a shoe of the Nike Free assortment. Please prepare to buy a pair of theses shoes in your size (without think-aloud).
10	Please find a labor law attorney in your hometown (think-aloud).
11	You plan to visit Stockholm for a weekend in the first week of April. Please find a cheap flight between Munich and Stockholm (without think-aloud).
12	An acquaintance of yours will finish his studies at the Ludwig-Maximilians-University (LMU) Munich soon. As souvenir you plan to make him a present of a LMU hoodie in size L. Please inform about possible vendors, colors, sizes and the prize in the Internet (think-aloud).

Appendix 12: Individual Characteristics (Observational Study, Project III)

Participant	Age	Gender	Occupation	SEE	Internet Usage	Search Engine Usage
1	26	Male	Manager	6.00	Several times a day	Several times a day
2	25	Male	Student	5.75	Several times a day	Several times a day
3	25	Female	Student	5.00	Several times a day	Several times a day
4	26	Male	Student	2.25	Several times a week	Several times a month
5	27	Male	Student	4.50	Several times a day	Several times a day
6	28	Male	Deskman	5.25	Several times a day	Several times a day
7	27	Male	Deskman	5.75	Several times a day	Several times a day
8	24	Female	Physical therapist	4.00	Daily	Daily
9	25	Male	Trainee	4.00	Daily	Daily
10	24	Female	Student	4.25	Several times a day	Several times a day
11	30	Male	Photographer	5.75	Several times a day	Several times a day
12	30	Male	Consultant	3.75	Several times a day	Several times a day
13	28	Male	Student	4.50	Several times a day	Several times a day
14	27	Female	Student	4.00	Several times a day	Several times a day
15	27	Female	Stewardess	3.50	Several times a day	Daily
16	26	Female	Stewardess	4.75	Daily	Daily
17	34	Female	Caterer	4.00	Several times a day	Several times a day
18	21	Female	Paralegal	5.00	Several times a day	Daily
19	27	Female	Manager	5.25	Several times a day	Several times a day
20	27	Female	Student	3.50	Several times a day	Several times a day
21	62	Male	Clerk	5.50	Several times a day	Several times a day
22	15	Female	Student	5.75	Several times a day	Several times a day
23	55	Female	Housewife	2.50	Several times a day	Several times a week
24	68	Male	Pensioner	4.00	Several times a day	Several times a month
25	57	Female	Office Adminis-trator	5.50	Several times a day	Several times a week
26	51	Male	Energy adviser	5.00	Daily	Daily
27	55	Male	Administrative official	5.25	Daily	Several times a week
28	54	Female	Office administra-tor	1.25	Several times a week	Several times a week
29	15	Male	Student	6.75	Several times a day	Several times a day
30	52	Female	Graduate chemist	4.00	Several times a day	Several times a week
31	60	Male	Pensioner	6.00	Several times a day	Several times a day
32	72	Male	Pensioner	4.75	Several times a week	Several times a month
33	20	Male	Student	4.00	Daily	Several times a day
34	14	Male	Student	6.50	Several times a day	Daily
35	55	Female	Designer	6.75	Several times a week	Several times a week
36	17	Female	Student	5.00	Daily	Daily
37	18	Male	Student	6.00	Several times a day	Several times a day
38	20	Female	Intern	3.75	Several times a day	Daily
39	57	Male	Manager	6.00	Several times a day	Several times a day
40	14	Female	Student	5.75	Daily	Several times a day

Appendix 13: Schematic Illustration of Eye Movement Fixation and Scan Path on Search Engine Result Page

Source: Own illustration based on Granka, Joachims, and Gay (2004), Pan et al. (2004), Joachims et al. (2005) Radlinski and Joachims (2005), and Granka, Hembrooke, and Gay (2006).

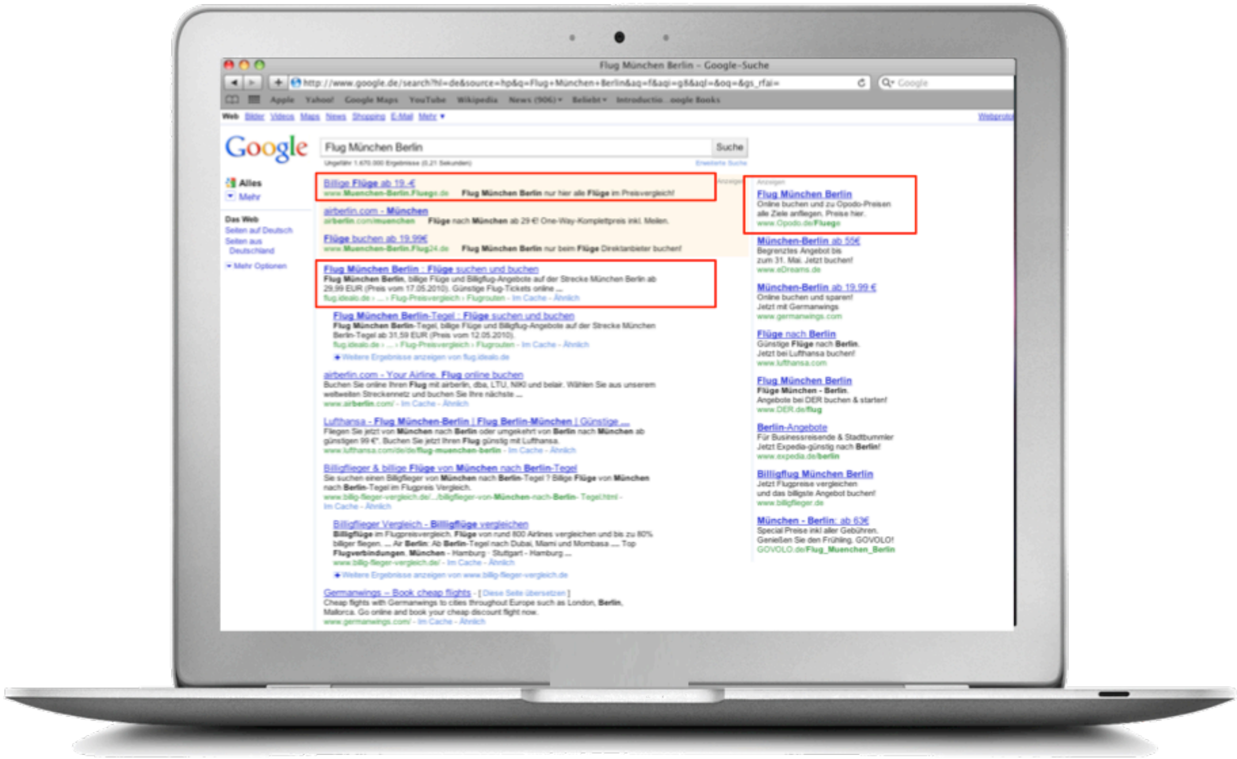
Appendix 14: Scenario Description (Experiment 1, Project III)

Stellen Sie sich vor, Sie möchten privat einen Flug von München nach Berlin im Internet buchen um in vier Wochen Bekannte in Berlin zu besuchen. Dazu werden Ihnen nun in der Folge einige Fragen gestellt, die im Zusammenhang mit einer Flugbuchung auftauchen können. Sie beginnen Ihre Suche nach einem Flug von München nach Berlin mit einer Suchmaschine (z.B. Google).

[Instruction before the display of the manipulated SERP]

Bitte suchen Sie auf der folgenden Suchergebnisseite spontan den Link heraus, den Sie in oben genannter Situation anklicken würden, um sich über die aktuellen Preise von verschiedenen Produkten zu informieren.

Appendix 15: Example for Manipulation of the SERP



Appendix 16: Measurement of Control Variables (Experiment 1, Project III)

Reliability and Validity of ATPSA

To measure the attitude toward paid search (ATPSA) the four 7-point semantic differential scale items by Allen and Janiszewski (1989) with a numeric format were adapted (see Appendix-Table 13). The Kaiser-Meyer-Olkin measure verified the sampling adequacy for the exploratory factor analysis for the four items (KMO = .86; according to Kaiser (1974), p. 35: meritorious). All KMO values for the individual items were ≥ .84, which is well above the limit of Burgers et al. (2000, p. 151) of MSA ≥ .30. Bartlett's test of sphericity, χ^2 (6) = 1477.35, p < .001 indicated that the correlations between the four items were sufficiently large enough for a principal component analysis (PCA) of the four items.

Attitude toward paid search (7-point semantic differential scale)

Please evaluate your personal attitude toward paid search, by selecting the box reflecting your attitude best.

Item	***Item text***	**Source, item was adapted from**
ATPSA_1	*"bad/good"*	*Allen and Janiszewski (1989)*
ATPSA _2	*"unpleasant/pleasant"*	*Allen and Janiszewski (1989)*
ATPSA _3	*"unlikeable/likeable"*	*Allen and Janiszewski (1989)*
ATPSA _4	*"negative/positive"*	*Allen and Janiszewski (1989)*

Appendix-Table 13: Operationalization of ATPSA

A principal component analysis was conducted on the four items with orthogonal rotation (varimax). The scale provides excellent psychometric properties (see Appendix-Table 14). All cut-off values for fist generation reliability and validity are well exceeded. The scale attitude toward paid search has high reliability with Cronbach's α = .95.

	1st Generation					
	M	*SD*	*I-t-t*	*α*	*EV*	*h^2*
all				.95	85.95%	
ATPSA_1	3.89	1.61	.85			.84
ATPSA _2	3.44	1.61	.87			.86
ATPSA _3	3.33	1.55	.87			.86
ATPSA _4	3.55	1.55	.89			.88

Notes: M = Mean; SD = Standard deviation; I-t-t = Item-to-total correlation; α = Cronbach's α; EV = Explained Variance; h^2 = Communality

Appendix-Table 14: 1st Generation Reliability and Validity ATPSA

Reliability and Validity of ISSA

Internet search skill (ISSA) was measured with a three-item seven-point Likert-type scale by Mathwick and Rigdon (2004) (see Appendix-Table 15). The Kaiser-Meyer-Olkin measure verified the sampling adequacy for the exploratory factor analysis for the three items (KMO = .75; middling (Kaiser 1974, p. 35)), along with large enough correlations between the three items for a principal component analysis (MSA ≥ .72; Bartlett's test of sphericity: χ^2 (3) = 733.50, p < .001).

Internet search skill (Seven-point Likert-type: 1="I strongly disagree"; 7="I strongly agree")

Please evaluate the following statements.

Item	*Item text*	**Source, item was adapted from**
ISSA_1	*"I am extremely skilled at using the Web."*	*Mathwick and Rigdon (2004)*
ISSA_2	*"I consider myself knowledgeable about good search techniques on the Web."*	*Mathwick and Rigdon (2004)*
ISSA_3	*"I know how to find what I am looking for on the Web."*	*Mathwick and Rigdon (2004)*

Appendix-Table 15: Operationalization of ISSA

The conducted principal component analysis revealed very good values of item-to-total correlations, explained variance, and communalities well above the limits (Appendix-Table 16). The ISSA scale has high reliability with Cronbach's α = .89.

	1st Generation					
	M	*SD*	*I-t-t*	α	*EV*	h^2
all				.89	82.90%	
ISSA_1	5.96	1.16	.77			.80
ISSA_2	5.42	1.40	.81			.84
ISSA_3	5.87	1.18	.82			.85

Notes: M = Mean; SD = Standard deviation; I-t-t = Item-to-total correlation; α = Cronbach's α; EV = Explained Variance; h^2 = Communality.

Appendix-Table 16: 1st Generation Reliability and Validity ISSA

Appendix 17: Mean Values for Realism Check ANOVA (Experiment, Project II; Experiment 2, Project III)

	Double Top	Double Side	Single Organic	Single Top	Single Side	F-Test	*p*
Scenario 1	5.91	5.88	5.80	5.90	5.62	F(4,739) =1.13	> .10
Scenario 2	6.05	6.01	6.11	6.13	6.01	F(4,739) = .31	> .10
Scenario 3	5.87	6.06	6.03	6.09	5.75	F(4,739) = 1.76	> .10
Scenario 4	6.07	5.86	5.93	5.94	5.62	F(4,739) = 2.27	> .10
Scenario 5	5.95	5.85	5.98	5.87	5.80	F(4,739) = .45	> .10
Scenario 6	6.19	6.26	6.10	6.14	6.00	F(4,739) = .98	> .10

Appendix 18: Contingency Tables and χ^2-Test H1-H4 and Supplement 1-3 (Experiment 2, Project III)

Hypothesis	Experimental Group		Click: No Click	Click: Click	Total	χ^2 *Test Statistic*
H1	Single Top	Observed	617	249	866	$\chi^2(1) = 2.81$, $p = .094$
		Expected	*600.8*	*265.2*	*866*	
	Single Organic	Observed	604	290	894	
		Expected	*620.2*	*237.8*	*894*	
	Total	*Observed*	*1221*	*539*	*1760*	
H2	Single Top	Observed	617	249	866	$\chi^2(1) = 66.01$, $p < .001$
		Expected	*686*	*180*	*866*	
	Single Side	Observed	770	115	885	
		Expected	*701*	*184*	*885*	
	Total	*Observed*	*1387*	*364*	*1751*	
H3a	Double Top	Observed	510	385	895	$\chi^2(1) = 21.30$, $p < .001$
		Expected	*557.3*	*337.7*	*895*	
	Single Organic	Observed	604	290	894	
		Expected	*556.7*	*337.3*	*894*	
	Total	*Observed*	*1114*	*675*	*1789*	
H3b	Double Top	Observed	720	175	895	$\chi^2(1) = 38.60$, $p < .001$
		Expected	*662.4*	*232.6*	*895*	
	Single Organic	Observed	604	290	894	
		Expected	*661.6*	*232.4*	*894*	
	Total	*Observed*	*1324*	*465*	*1789*	
H4a	Double Side	Observed	639	285	924	$\chi^2(1) = .53$, $p = .470$
		Expected	*631.8*	*292.2*	*924*	
	Single Organic	Observed	604	290	894	
		Expected	*611.2*	*282.8*	*894*	
	Total	*Observed*	*1243*	*575*	*1818*	
H4b	Double Side	Observed	693	231	924	*$\chi^2(1) = 12.30$, $p < .001$*
		Expected	*659.2*	*264.8*	*924*	
	Single Organic	Observed	604	290	894	
		Expected	*637.8*	*256.2*	*894*	
	Total	*Observed*	*1297*	*521*	*1818*	
Supplement 1	Single Organic	Observed	604	290	894	$\chi^2(1) = 95.63$, $p < .001$
		Expected	*690.5*	*203.5*	*894*	
	Single Side	Observed	770	115	885	
		Expected	*683.5*	*201.5*	*885*	
	Total	*Observed*	*1374*	*405*	*1779*	
Supplement 2	Double Top	Observed	*510*	385	895	$\chi^2(1) = 28.95$, $p < .001$
		Expected	*565.3*	*329.7*	*895*	
	Double Side	Observed	*639*	*285*	*924*	
		Expected	*583.7*	*340.3*	*924*	
	Total	*Observed*	*1149*	*670*	*1819*	
Supplement 3	Double Top	Observed	720	175	895	$\chi^2(1) = 7.78$, $p < .01$
		Expected	*695.2*	*199.8*	*895*	
	Double Side	Observed	693	231	924	
		Expected	*717.8*	*206.2*	*924*	
	Total	*Observed*	*1413*	*406*	*1819*	

Appendix 19: Contingency Tables and χ^2-Test H1 (Experiment 2, Project III)

Experimental Scenario	Experimental Group		Click: No Click	Click: Click	Total	χ^2 *Test Statistic*
Scenario 1	Single Organic	Observed	26	129	155	$\chi^2(1) = .34$ $p = .562$
		Expected	*27.9*	*127.1*	*15*	
	Single Top	Observed	26	108	134	
		Expected	*24.1*	*109.9*	*134*	
	Total	*Observed*	*52*	*237*	*289*	
		Expected	*52*	*237*	*289*	
Scenario 2	Single Organic	Observed	101	44	145	$\chi^2(1) = 4.25$ $p = .039$
		Expected	*108.6*	*36.4*	*145*	
	Single Top	Observed	117	29	146	
		Expected	*109.4*	*36.6*	*146*	
	Total	*Observed*	*218*	*73*	*291*	
		Expected	*218*	*73*	*291*	
Scenario 3	Single Organic	Observed	121	27	148	$\chi^2(1) = 1.23$ $p = .268$
		Expected	*124.4*	*23.6*	*148*	
	Single Top	Observed	122	19	141	
		Expected	*118.6*	*22.4*	*141*	
	Total	*Observed*	*243*	*46*	*289*	
		Expected	*243*	*46*	*289*	
Scenario 4	Single Organic	Observed	127	21	148	$\chi^2(1) = 1.85$ $p = .174$
		Expected	*122.6*	*25.4*	*148*	
	Single Top	Observed	119	30	149	
		Expected	*123.4*	*25.6*	*149*	
	Total	*Observed*	*246*	*51*	*297*	
		Expected	*246*	*51*	*297*	
Scenario 5	Single Organic	Observed	124	20	144	$\chi^2(1) = .26$ $p = .613$
		Expected	*125.4*	*18.6*	*144*	
	Single Top	Observed	126	17	143	
		Expected	*124.6*	*18.4*	*143*	
	Total	*Observed*	*250*	*37*	*287*	
		Expected	*250*	*37*	*287*	
Scenario 6	Single Organic	Observed	105	49	154	$\chi^2(1) = .11$ $p = .740$
		Expected	*106.3*	*47.7*	*154*	
	Single Top	Observed	107	46	153	
		Expected	*105.7*	*47.3*	*153*	
	Total	*Observed*	*212*	*95*	*307*	
		Expected	*212*	*95*	*307*	

Appendix 20: Contingency Tables and χ^2-Test H2 (Experiment 2, Project III)

Experimental Scenario	Experimental Group		Click: No Click	Click: Click	Total	χ^2 *Test Statistic*
Scenario 1	**Single Top**	Observed	26	108	134	$\chi^2(1) = 16.37$ $p = .000$
		Expected	*41.9*	*92.1*	*134*	
	Single Side	Observed	64	90	154	
		Expected	*48.1*	*105.9*	*15*	
	Total	*Observed*	*90*	*198*	*288*	
		Expected	*90*	*198*	*288*	
Scenario 2	**Single Top**	Observed	117	29	146	$\chi^2(1) = 15.99$ $p = .000$
		Expected	*128.2*	*17.8*	*146*	
	Single Side	Observed	143	7	150	
		Expected	*131.8*	*18.2*	*150*	
	Total	*Observed*	*260*	*36*	*296*	
		Expected	*260*	*36*	*296*	
Scenario 3	**Single Top**	Observed	122	19	141	$\chi^2(1) = 13.22$ $p = .000$
		Expected	*130.2*	*10.8*	*141*	
	Single Side	Observed	143	3	146	
		Expected	*134.8*	*11.2*	*146*	
	Total	*Observed*	*265*	*22*	*287*	
		Expected	*265*	*22*	*287*	
Scenario 4	**Single Top**	Observed	119	30	149	$\chi^2(1) = 17.15$ $p = .000$
		Expected	*130.6*	*18.4*	*149*	
	Single Side	Observed	137	6	143	
		Expected	*125.4*	*17.6*	*143*	
	Total	*Observed*	*256*	*36*	*292*	
		Expected	*256*	*36*	*292*	
Scenario 5	**Single Top**	Observed	126	17	143	$\chi^2(1) = 15.41$ $p = .000$
		Expected	*134.1*	*8.9*	*143*	
	Single Side	Observed	144	1	145	
		Expected	*135.9*	*9.1*	*145*	
	Total	*Observed*	*270*	*18*	*288*	
		Expected	*270*	*18*	*288*	
Scenario 6	**Single Top**	Observed	107	46	153	$\chi^2(1) = 30.80$ $p = .000$
		Expected	*125.5*	*27.5*	*153*	
	Single Side	Observed	139	8	147	
		Expected	*120.5*	*26.5*	*147*	
	Total	*Observed*	*246*	*54*	*300*	
		Expected	*246*	*54*	*300*	

Appendix 21: Contingency Tables and χ^2-Test H3a (Experiment 2, Project III)

Experimental Scenario	Experimental Group		Click: No Click	Click: Click	Total	χ^2 *Test Statistic*
Scenario 1	**Double Top**	Observed	15	134	149	$\chi^2(1) = 2.93$, $p = .087$
		Expected	*20.1*	*128.9*	*149*	
	Single Organic	Observed	26	129	155	
		Expected	*20.9*	*134.1*	*155*	
	Total	*Observed*	*41*	*263*	*304*	
		Expected	*41*	*263*	*304*	
Scenario 2	**Double Top**	Observed	101	48	149	$\chi^2(1) = .12$, $p = .730$
		Expected	*102.4*	*46.6*	*149*	
	Single Organic	Observed	101	44	145	
		Expected	*99.6*	*45.4*	*145*	
	Total	*Observed*	*202*	*92*	*294*	
		Expected	*202*	*92*	*294*	
Scenario 3	**Double Top**	Observed	105	42	147	$\chi^2(1) = 4.39$, $p = .036$
		Expected	*112.6*	*34.4*	*147*	
	Single Organic	Observed	121	27	148	
		Expected	*113.4*	*34.6*	*148*	
	Total	*Observed*	*226*	*69*	*295*	
		Expected	*226*	*69*	*295*	
Scenario 4	**Double Top**	Observed	110	42	152	$\chi^2(1) = 8.17$, $p = .004$
		Expected	*120.1*	*31.9*	*152*	
	Single Organic	Observed	127	21	148	
		Expected	*116.9*	*31.1*	*148*	
	Total	*Observed*	*237*	*63*	*300*	
		Expected	*227*	*63*	*300*	
Scenario 5	**Double Top**	Observed	107	45	152	$\chi^2(1) = 10.66$, $p = .001$
		Expected	*118.6*	*33.4*	*152*	
	Single Organic	Observed	124	20	144	
		Expected	*112.4*	*31.6*	*144*	
	Total	*Observed*	*231*	*65*	*296*	
		Expected	*231*	*65*	*296*	
Scenario 6	**Double Top**	Observed	72	74	146	$\chi^2(1) = 10.03$, $p = .001$
		Expected	*86.1*	*59.9*	*146*	
	Single Organic	Observed	105	49	154	
		Expected	*90.9*	*63.1*	*154*	
	Total	*Observed*	*177*	*123*	*300*	
		Expected	*177*	*123*	*300*	

Appendix 22: Contingency Tables and χ^2-Test H4a (Experiment 2, Project III)

Experimental Scenario	Experimental Group		Click: No Click	Click: Click	Total	χ^2 *Test Statistic*
Scenario 1	**Double Side**	Observed	23	129	152	$\chi^2(1) = .15$, $p = .694$
		Expected	*24.3*	*127.7*	*152*	
	Single Organic	Observed	26	129	155	
		Expected	*24.7*	*130.3*	*155*	
	Total	*Observed*	*49*	*258*	*307*	
		Expected	*49*	*258*	*307*	
Scenario 2	**Double Side**	Observed	129	25	154	$\chi^2(1) = 8.38$, $p = .004$
		Expected	*118.5*	*35.5*	*154*	
	Single Organic	Observed	101	44	145	
		Expected	*111.5*	*33.5*	*145*	
	Total	*Observed*	*230*	*69*	*299*	
		Expected	*230*	*69*	*299*	
Scenario 3	**Double Side**	Observed	128	34	162	$\chi^2(1) = .37$, $p = .544$
		Expected	*130.1*	*31.9*	*162*	
	Single Organic	Observed	121	27	148	
		Expected	*118.9*	*29.1*	*148*	
	Total	*Observed*	*249*	*61*	*310*	
		Expected	*249*	*61*	*310*	
Scenario 4	**Double Side**	Observed	123	29	152	$\chi^2(1) = 1.29$, $p = .256$
		Expected	*126.7*	*25.3*	*152*	
	Single Organic	Observed	127	21	148	
		Expected	*123.3*	*24.7*	*148*	
	Total	*Observed*	*250*	*50*	*300*	
		Expected	*250*	*50*	*300*	
Scenario 5	**Double Side**	Observed	133	27	160	$\chi^2(1) = .52$, $p = .472$
		Expected	*135.3*	*24.7*	*160*	
	Single Organic	Observed	124	20	144	
		Expected	*121.7*	*22.3*	*144*	
	Total	*Observed*	*257*	*47*	*304*	
		Expected	*257*	*47*	*304*	
Scenario 6	**Double Side**	Observed	103	41	144	$\chi^2(1) = .53$, $p = .395$
		Expected	*100.5*	*43.5*	*144*	
	Single Organic	Observed	105	49	154	
		Expected	*107.5*	*46.5*	*154*	
	Total	*Observed*	*208*	*90*	*298*	
		Expected	*208*	*90*	*298*	

Appendix 23: Contingency Tables and χ^2-Test H3b (Experiment 2, Project III)

Experimental Scenario	Experimental Group		Free Click: No Click	Free Click: Click	Total	χ^2 Test Statistic
Scenario 1	**Double Top**	Observed	98	51	149	$\chi^2(1) = 75.52$, $p = .000$
		Expected	*60.8*	*88.2*	*149*	
	Single Organic	Observed	26	129	155	
		Expected	*63.2*	*91.8*	*155*	
	Total	*Observed*	*124*	*180*	*304*	
		Expected	*124*	*180*	*304*	
Scenario 2	**Double Top**	Observed	122	27	149	$\chi^2(1) = 6.00$, $p = .014$
		Expected	*113*	*36*	*149*	
	Single Organic	Observed	101	44	145	
		Expected	*110*	*35*	*145*	
	Total	*Observed*	*223*	*71*	*294*	
		Expected	*223*	*71*	*294*	
Scenario 3	**Double Top**	Observed	117	30	147	$\chi^2(1) = .22$, $p = .638$
		Expected	*118.6*	*28.4*	*147*	
	Single Organic	Observed	121	27	148	
		Expected	*119.4*	*28.6*	*148*	
	Total	*Observed*	*238*	*57*	*295*	
		Expected	*238*	*57*	*295*	
Scenario 4	**Double Top**	Observed	141	11	152	$\chi^2(1) = 3.80$, $p = .051$
		Expected	*135.8*	*16.2*	*152*	
	Single Organic	Observed	127	21	148	
		Expected	*132.2*	*15.8*	*148*	
	Total	*Observed*	*268*	*32*	*300*	
		Expected	*268*	*32*	*300*	
Scenario 5	**Double Top**	Observed	135	17	152	$\chi^2(1) = .50$, $p = .482$
		Expected	*133*	*19*	*152*	
	Single Organic	Observed	124	20	144	
		Expected	*126*	*18*	*144*	
	Total	*Observed*	*259*	*37*	*296*	
		Expected	*259*	*37*	*296*	
Scenario 6	**Double Top**	Observed	107	39	149	$\chi^2(1) = .94$, $p = .332$
		Expected	*103.2*	*42.8*	*146*	
	Single Organic	Observed	105	49	154	
		Expected	*108.8*	*45.2*	*154*	
	Total	*Observed*	*212*	*88*	*300*	
		Expected	*212*	*88*	*300*	

Appendix 24: Contingency Tables and χ^2-Test H4b (Experiment 2, Project III)

Experimental Scenario	Experimental Group		Free Click: No Click	Free Click: Click	Total	χ^2 *Test Statistic*
Scenario 1	**Double Side**	Observed	65	87	152	$\chi^2(1) = 24.85$, $p = .000$
		Expected	*45,1*	*106,9*	*152*	
	Single Organic	Observed	26	129	155	
		Expected	*45,9*	*109,1*	*155*	
	Total	*Observed*	*91*	*216*	*307*	
		Expected	*91,0*	*216*	*307*	
Scenario 2	**Double Side**	Observed	131	23	154	$\chi^2(1) = 10.20$, $p = .001$
		Expected	*119,5*	*34,5*	*154*	
	Single Organic	Observed	101	44	145	
		Expected	*112,5*	*32,5*	*145*	
	Total	*Observed*	*232*	*67*	*299*	
		Expected	*232*	*67*	*299*	
Scenario 3	**Double Side**	Observed	131	31	162	$\chi^2(1) = .04$, $p = .840$
		Expected	*131.7*	*30.3*	*162*	
	Single Organic	Observed	121	27	148	
		Expected	*120.3*	*27.7*	*148*	
	Total	*Observed*	*252*	*58*	*310*	
		Expected	*252*	*58*	*310*	
Scenario 4	**Double Side**	Observed	125	27	152	$\chi^2(1) = .71$, $p = .399$
		Expected	*127.7*	*24.3*	*152*	
	Single Organic	Observed	127	21	148	
		Expected	*124.3*	*23.7*	*148*	
	Total	*Observed*	*252*	*48*	*300*	
		Expected	*252*	*48*	*300*	
Scenario 5	**Double Side**	Observed	135	25	160	$\chi^2(1) = .18$, $p = .670$
		Expected	*136.3*	*23.7*	*160*	
	Single Organic	Observed	124	20	144	
		Expected	*122.7*	*21.3*	*144*	
	Total	*Observed*	*259*	*45*	*304*	
		Expected	*259*	*45*	*304*	
Scenario 6	**Double Side**	Observed	106	38	144	$\chi^2(1) = 1.061$, $p = .303$
		Expected	*102*	*42*	*144*	
	Single Organic	Observed	105	49	154	
		Expected	*109*	*45*	*154*	
	Total	*Observed*	*211*	*87*	*298*	
		Expected	*211*	*87*	*298*	

Appendix 25: Additional Analysis (Experiment 2, Project III)

Drawing from the lessons learned in banner advertising research, I argue that the overall click-through for single organic exposure is significantly higher than for single side exposure because search engine users avoid looking at lateral banners on the Internet *(Supplement 1)*. The experimental research design stresses upon the inferiority of single side exposure showing significantly more click-through for single organic exposure than for single side exposure over all different keyword scenarios ($\chi^2(1) = 95.63$, $p < .001$; see Appendix 18). This result is also confirmed for each different scenario (scenario 1: $\chi^2(1) = 22.99$, $p < .001$; scenario 2: $\chi^2(1) = 34.00$, $p < .001$; scenario 3: $\chi^2(1) = 21.02$, $p < .001$; scenario 4: $\chi^2(1) = 8.63$, $p < .001$; scenario 5: $\chi^2(1) = 18.68$, $p < .001$; scenario 6: $\chi^2(1) = 34.09$, $p < .001$).[147]

Additionally, I assume that the overall click-through for double top exposure is significantly higher than for double side exposure *(Supplement 2)*. To answer the question if it is worth to invest in higher bids for a keyword to attain first paid top position instead of first paid side position in addition to a top organic listing, the analysis show that the overall click-through for double top exposure over all levels different keyword scenarios is significantly higher than for double side exposure ($\chi^2(1) = 28.95$, $p < .001$). In more detail, for scenario 2 ($\chi^2(1) = 10.58$, $p < .01$), 4 ($\chi^2(1) = 3.11$, $p < .10$), 5 ($\chi^2(1) = 7.12$, $p < .01$), and 6 ($\chi^2(1) = 14.95$, $p < .001$) these significant effects are verified. For scenario 1 ($\chi^2(1) = 1.75$, $p > .10$), and scenario 3 ($\chi^2(1) = 2.39$, $p > .10$), the clicks are higher even though not significantly. As a result, *Supplement 2* is supported on the overall level.[148] This can be partly verified on an individual keyword level.[149]

Finally, I test whether the free click-through for double top exposure is significantly higher than for double side exposure *(Supplement 3)*. This is of particular importance, since, in contrast to *Supplement 2*, the impact of an additional paid side or paid top result is analyzed on the free click-through. The results show, that a double side exposure leads to significant more free clicks than a double top exposure ($\chi^2(1) = 7.78$, $p < .01$).[150] In more detail, merely in scenario 2 ($\chi^2(1) = .56$, $p > .10$) and scenario 6 ($\chi^2(1) = .01$, $p > .10$) the free click-through is

[147] Appendix 26 summarizes the contingency tables for the χ^2-test statistics of *Supplement 1*. The relative risks for *Supplement 1* are: (1) $RR_{S1} = 1.42$; (2) $RR_{S2} = 6.50$; (3) $RR_{S3} = 8.88$; (4) $RR_{S4} = 3.38$; (5) $RR_{S5} = 20.14$; (6) $RR_{S6} = 5.85$.

[148] Appendix 27 summarizes the contingency tables for the χ^2-test statistics of *Supplement 2.*

[149] The relative risks for *Supplement 2* are: (1) $RR_{S1} = 1.06$; (2) $RR_{S2} = 1.98$; (3) $RR_{S3} = 1.36$; (4) $RR_{S4} = 1.45$; (5) $RR_{S5} = 1.74$; (6) $RR_{S6} = 1.78$.

[150] Appendix 28 summarizes the contingency tables for the χ^2-test statistics of *Supplement 3.*

higher, even though not significantly, for double top exposure than for double side exposure. In case of the keyword scenarios 1, 3, 4 and 5, the free click-through is (significantly) higher for double side exposure than for double top exposure (scenario 1: $\chi^2(1) = 16.04$, $p < .001$; scenario 3: $\chi^2(1) = .08$, $p > .10$; scenario 4: $\chi^2(1) = 7.70$, $p < .01$; scenario 5: $\chi^2(1) = 1.32$, $p > .10$).

Appendix 26: Contingency Tables and χ^2-Test Supplement 1 (Experiment 2, Project III)

Experimental Scenario	Experimental Group		Click: No Click	Click: Click	Total	χ^2 *Test Statistic*
Scenario 1	**Single Organic**	Observed	26	129	155	$\chi^2(1) = 22.99$, $p = .000$
		Expected	*45.1*	*109.9*	*155*	
	Single Side	Observed	64	90	154	
		Expected	*44.9*	*109.1*	*154*	
	Total	*Observed*	*90*	*219*	*309*	
		Expected	*90*	*219*	*309*	
Scenario 2	**Single Organic**	Observed	101	44	145	$\chi^2(1) = 34.00$, $p = .000$
		Expected	*119.9*	*25.1*	*145*	
	Single Side	Observed	143	7	150	
		Expected	*124.1*	*25.9*	*150*	
	Total	*Observed*	*244*	*51*	*295*	
		Expected	*244*	*51*	*295*	
Scenario 3	**Single Organic**	Observed	121	27	148	$\chi^2(1) = 21.02$, $p = .000$
		Expected	*132.9*	*15.1*	*148*	
	Single Side	Observed	143	3	146	
		Expected	*131.1*	*14.9*	*146*	
	Total	*Observed*	*264*	*30*	*294*	
		Expected	*264*	*30*	*294*	
Scenario 4	**Single Organic**	Observed	127	21	148	$\chi^2(1) = 8.63$, $p = .003$
		Expected	*134.3*	*13.7*	*148*	
	Single Side	Observed	137	6	143	
		Expected	*129.7*	*13.3*	*143*	
	Total	*Observed*	*264*	*27*	*291*	
		Expected	*264*	*27*	*291*	
Scenario 5	**Single Organic**	Observed	124	20	144	$\chi^2(1) = 18.68$, $p = .000$
		Expected	*133.5*	*10.5*	*144*	
	Single Side	Observed	144	1	145	
		Expected	*134.5*	*10.5*	*145*	
	Total	*Observed*	*268*	*21*	*289*	
		Expected	*268*	*21*	*289*	
Scenario 6	**Single Organic**	Observed	105	49	154	$\chi^2(1) = 34.09$, $p = .000$
		Expected	*124.8*	*29.2*	*154*	
	Single Side	Observed	139	8	147	
		Expected	*119.2*	*27.8*	*147*	
	Total	*Observed*	*244*	*57*	*301*	
		Expected	*244*	*57*	*301*	

Appendix 27: Contingency Tables and χ^2-Test Supplement 2 (Experiment 2, Project III)

Experimental Scenario	**Experimental Group**		**Click: No Click**	**Click: Click**	**Total**	***χ^2 Test Statistic***
Scenario 1	**Double Top**	Observed	15	134	149	$\chi^2(1) = 1.75$, *p* = .186
		Expected	*18.8*	*130.2*	*149*	
	Double Side	Observed	23	129	152	
		Expected	*19.2*	*132.8*	*152*	
	Total	*Observed*	*38*	*263*	*301*	
		Expected	*38*	*263*	*301*	
Scenario 2	**Double Top**	Observed	101	48	149	$\chi^2(1) = 10.58$, *p* = .001
		Expected	*113.1*	*35.9*	*149*	
	Double Side	Observed	129	25	154	
		Expected	*116.9*	*37.1*	*154*	
	Total	*Observed*	*230*	*73*	*303*	
		Expected	*230*	*73*	*303*	
Scenario 3	**Double top**	Observed	105	42	147	$\chi^2(1) = 2.39$, *p* = .122
		Expected	*110.8*	*36.2*	*147*	
	Double Side	Observed	128	34	162	
		Expected	*122.2*	*39.8*	*162*	
	Total	*Observed*	*233*	*76*	*309*	
		Expected	*233*	*76*	*309*	
Scenario 4	**Double Top**	Observed	110	42	152	$\chi^2(1) = 3.11$, *p* = .078
		Expected	*116.5*	*35.5*	*152*	
	Double Side	Observed	123	29	152	
		Expected	*116.5*	*35.5*	*152*	
	Total	*Observed*	*233*	*71*	*304*	
		Expected	*233*	*71*	*304*	
Scenario 5	**Double Top**	Observed	107	45	152	$\chi^2(1) = 7.12$, *p* = .008
		Expected	*116.9*	*35.1*	*152*	
	Double Side	Observed	133	27	160	
		Expected	*123.1*	*36.9*	*160*	
	Total	*Observed*	*240*	*72*	*312*	
		Expected	*240*	*72*	*312*	
Scenario 6	**Double Top**	Observed	72	74	146	$\chi^2(1) = 14.95$, *p* = .000
		Expected	*88.1*	*57.9*	*146*	
	Double Side	Observed	103	41	144	
		Expected	*86.9*	*57.1*	*144*	
	Total	*Observed*	*175*	*115*	*290*	
		Expected	*175*	*115*	*290*	

Appendix 28: Contingency Tables and χ^2-Test Supplement 3 (Experiment 2, Project III)

Experimental Scenario	Experimental Group		Free Click: No Click	Free Click: Click	Total	χ^2 *Test Statistic*
Scenario 1	**Double Top**	Observed	98	51	149	$\chi^2(1) = 16.04$, $p = .000$
		Expected	*80.7*	*68.3*	*149*	
	Double Side	Observed	65	87	152	
		Expected	*82.3*	*69.7*	*152*	
	Total	*Observed*	*163*	*138*	*301*	
		Expected	*163*	*138*	*301*	
Scenario 2	**Double Top**	Observed	122	27	149	$\chi^2(1) = .56$, $p = .455$
		Expected	*124.4*	*24.6*	*149*	
	Double Side	Observed	131	23	154	
		Expected	*128.6*	*25.4*	*154*	
	Total	*Observed*	*253*	*50*	*303*	
		Expected	*253*	*50*	*303*	
Scenario 3	**Double Top**	Observed	117	30	147	$\chi^2(1) = .08$, $p = .779$
		Expected	*118*	*29*	*147*	
	Double Side	Observed	131	31	162	
		Expected	*130*	*32*	*162*	
	Total	*Observed*	*248*	*61*	*309*	
		Expected	*248*	*61*	*309*	
Scenario 4	**Double Top**	Observed	141	11	152	$\chi^2(1) = 7.70$, $p = .006$
		Expected	*133*	*19*	*152*	
	Double Side	Observed	125	27	152	
		Expected	*133*	*19*	*152*	
	Total	*Observed*	*266*	*38*	*304*	
		Expected	*266*	*38*	*304*	
Scenario 5	**Double Top**	Observed	135	17	152	$\chi^2(1) = 1.32$, $p = .251$
		Expected	*131.5*	*20.5*	*152*	
	Double Side	Observed	135	25	160	
		Expected	*138.5*	*21.5*	*160*	
	Total	*Observed*	*270*	*42*	*312*	
		Expected	*270*	*42*	*312*	
Scenario 6	**Double Top**	Observed	107	39	146	$\chi^2(1) = .01$, $p = .95$
		Expected	*107.2*	*38.8*	*146*	
	Double Side	Observed	106	38	144	
		Expected	*105.8*	*38.2*	*144*	
	Total	*Observed*	*213*	*77*	*290*	
		Expected	*213*	*77*	*290*	

Appendix 29: Contingency Tables and χ^2-Test H1-H4 and Supplements (Experiment 1, Project III)

Hypothesis	Experimental Group		Click: No Click	Click: Click	Total	χ^2 *Test Statistic*
H1	**Single Top**	Observed	67	12	79	$\chi^2(1) = .13$, $p = .72$
		Expected	*66.2*	*12.8*	*79*	
	Single Organic	Observed	67	14	81	
		Expected	*67.8*	*13.2*	*81*	
	Total	*Observed*	*134*	*26*	*160*	
H2	**Single Top**	Observed	67	12	79	$\chi^2(1) = 8.11$, $p < .01$
		Expected	*72.1*	*6.9*	*79*	
	Single Side	Observed	79	2	81	
		Expected	*73.9*	*7.1*	*81*	
	Total	*Observed*	*146*	*14*	*160*	
H3a	**Double Top**	Observed	62	20	82	$\chi^2(1) = 1.25$, $p = .264$
		Expected	*64.9*	*17.1*	*82*	
	Single Organic	Observed	67	14	81	
		Expected	*64.1*	*16.9*	*81*	
	Total	*Observed*	*129*	*34*	*163*	
H3b	**Double Top**	Observed	69	13	82	$\chi^2(1) = .06$, $p = .806$
		Expected	*68.4*	*13.6*	*82*	
	Single Organic	Observed	67	14	81	
		Expected	*67.6*	*13.4*	*81*	
	Total	*Observed*	*136*	*27*	*163*	
H4a	**Double Side**	Observed	67	13	80	$\chi^2(1) = .03$, $p = .861$
		Expected	*66.6*	*13.4*	*80*	
	Single Organic	Observed	67	14	81	
		Expected	*67.4*	*13.6*	*81*	
	Total	*Observed*	*134*	*27*	*161*	
H4b	**Double Side**	Observed	67	13	80	$\chi^2(1) = .03$, $p = .861$
		Expected	*66.6*	*13.4*	*80*	
	Single Organic	Observed	67	14	81	
		Expected	*67.4*	*13.6*	*81*	
	Total	*Observed*	*134*	*27*	*161*	
Supplement 1 (S1)	**Single Organic**	Observed	67	14	81	$\chi^2(1) = 9.99$, $p < .01$
		Expected	*73*	*8*	*81*	
	Single Side	Observed	79	2	81	
		Expected	*73*	*8*	*81*	
	Total	*Observed*	*146*	*16*	*162*	
Supplement 2 (S2)	**Double Top**	Observed	62	20	82	$\chi^2(1) = 1.65$, $p = .198$
		Expected	*65.3*	*16.7*	*82*	
	Double Side	Observed	67	13	80	
		Expected	*63.7*	*16.3*	*80*	
	Total	*Observed*	*129*	*33*	*162*	
Supplement 3 (S3)	**Double Top**	Observed	69	13	82	$\chi^2(1) = .01$, $p = .945$
		Expected	*68.8*	*13.2*	*82*	
	Double Side	Observed	67	13	80	
		Expected	*67.2*	*12.8*	*80*	
	Total	*Observed*	*136*	*26*	*162*	

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