Monetization Strategies for Internet Companies

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DISSERTATION

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Foreword by Prof. Dr. Oliver Hinz

The digitization trend is one of the key challenges for firms these days. Nearly every industry gets fundamentally transformed, and new business and monetization models evolve every day. The steady change and the pace of this transformation are posing new challenges for both, practitioners and researchers. On the one hand, new and more data is available, and on the other hand, we need increasingly more analytics to gain insights out of this data.

Under my supervision, Sebastian Voigt started with this dissertation after working several years as a consultant in the area of monetization and pricing for numerous Internet companies, and as a manager in the digital gaming industry. His articles benefited from his experience in business practice and new methods he learned during his time as PhD student. This promising combination has led to an excellent cumulative dissertation with five articles published in very good journals. He conducted his research in a very target-oriented manner, and his efficiency is outstanding. Sebastian Voigt showed a lot of resilience when a paper did not initially receive the desired feedback and reasonably incorporated reviewers' feedback. This has ultimately led to this very nice result in your hands.

Mr. Voigt's good connections to several Internet companies allowed him to acquire unique and super-interesting datasets that not only helped him in his undertaking, but also the scientific community as his analysis led to a number of valuable insights. Would you for example think that on a dating platform it is revenue-optimal to have about 64% male and 36% female users (at least under the common pricing scheme that men and women have to equally pay for the service)? My gut feeling was that 50:50 would be the optimal split, but I was wrong.

All essays address important and timely research questions, and the breadth of the work is laudable: While most of his essays address very concrete business problems, he also discusses the opportunities, challenges and problems in this new digital era.

I highly recommend this book to both practitioners and scientists who are working in the area of Internet platforms, and especially in the field of sales, CRM and monetization. It delivers a lot of theoretical insights and innovative ways to deal with the new analytical challenges. I wish the author all the best with this publication, and I believe that the book will be a huge success!

Prof. Dr. Oliver Hinz, Technische Universität Darmstadt

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Table of Abbreviations

A	Buyer's share of total surplus
AR(p)	Autoregressive model of order p
ARPU	Average (daily) revenue per user
B	Bid
BDSG	Bundesdatenschutzgesetz (Federal Data Protection Act)
BKA	Bundeskriminalamt (Federal Criminal Police Office)
C	(Variable) cost
CLV	Customer lifetime value
CNE(s)	Cross-side network effect(s)
CPC	Cost per click
CPI	Cost per install
CRM	Customer relationship management
d	Discount rate
Diff.	Differentiation
DMR	Dynamic market response model
EC3	European Cybercrime Centre
FBI	Federal Bureau of Investigation
G€	Game Euro
GG	Grundgesetz (Basic Law)
Hardw.	Hardware
iAP	In-app purchase
iOS	iPhone operating system (by Apple)
IRR	Incidence rate ratio
IS	Information system

IT	Information technology
IV	Instrumental variable
Logit	Logistic (function)
m	Number of men on the platform
MMO	Massively multi-player online
n.s.	Not significant
NB	Negative binomial (regression)
NE(s)	Network effect(s)
NYOP	Name your own price
OLS	Ordinal least squares (regression)
PAYG	Pay as you go
pi / PN	Purchase instance (pi) within total number of purchases (PN)
prob	Probability
Probit	Probability unit (function)
Rev	Revenue
RFQ	Request for quotation
RiStBV	Richtlinien für das Strafverfahren und das Bußgeldverfahren (Guidelines for criminal and summary proceedings)
RP	Reservation price
SD	Standard deviation
SEM	Search engine marketing
SMS	Short message service
SNE(s)	Same-side network effect(s)
Softw.	Software
StPO	Strafprozessordnung (Code of Criminal Procedure)

SURE	Seemingly unrelated regression equations (model)
t / T	Time t in time period T
TS	Total surplus
VIP	Very important person
w	Number of women on the platform
WTP	Willingness to pay

SYNOPSIS

1. Introduction

Many Internet service companies such as providers of two-sided markets, social networks, or online games rely on the social interaction between their user base and thus capitalize from positive network effects (Gupta and Mela 2008; Katz and Shapiro 1985; Kim et al. 2008; Lin and Bhattacherjee 2008; Yang and Mai 2010). Thereby, they aim to quickly reach a critical mass of users as soon as possible. For such companies, a common strategy is to offer (basic) services for free (and thereby abolish entry barrier of a one-off or recurring price). This however can be a risky strategy, especially if companies rely their business model purely on advertising revenues with highly fluctuating prices (Clemons 2009), or on innovative pricing models such as Name-your-own-price (e.g., Spann et al. 2004; Hinz et al. 2011). The dot-com bust proved that companies who do not possess an adequate revenue model can easily fail and disappear from the landscape (Teece 2010).

Today, many more Internet service companies than few years ago charge their users directly for their services. Companies such as eBay, PayPal, LinkedIn, or Skype added paid services to their originally free business models, either via subscriptions, PAYG, or direct sales of virtual items. Their strategy how to make money and whom to bill however differs widely. In the Internet business, 'monetization' has become a frequently used buzzword for all aspects of a company's revenue strategy. According to Wikipedia (2016), the term is originally used in the context of *"converting or establishing something into legal tender"* such *as "coining of currency or the printing of banknotes by central banks"*. In the online industry however, practitioners and an increasing number of researchers use it to describe revenue strategies for digital services (e.g., Clemons 2009; Fields 2014, pp. 21-24; Jin and Feenberg 2015; Stroh 2015).

Although a clear and well-recognized definition of a monetization strategy is still missing, it includes the decision who should be billed (e.g., for a two-sided market: seller vs. buyer vs. advertisers only), with which price model (e.g., mandatory subscription vs. optional subscriptions vs. selling virtual currency or items) and price level (e.g., differentiated between user groups), and – in case of a freemium strategy (Teece 2010) – how a new (free) user can be converted most efficiently into a paying and remunerative customer (e.g., via effective CRM measures). The overarching objective of all monetization measures is to maximize the company's revenue and/or profit. eBay for example, monetizes only sellers with insertion and selling fees, while buyers can use the platform for free. Online dating platforms sell subscription models to all their users, but focus mainly on monetizing their male users. Almost the entire online gaming industry abolished subscription-based or pay-per-download models, and is now focusing on selling virtual goods to their player base which allow users, among other things, faster progress in the game. Clemons (2009) provides a classification of online different monetization strategies beyond 'classical' online advertising. We updated this classification, considering the development of new monetization strategies in the last years, as shown in Table 1.

Major category	Subcategory	Monetization models	Examples
Selling real things		Pay per item (fixed or variable prices)	Amazon
Selling virtual things	Selling content and information	Pay per view, pay per subscription	iTunes, Spotify, New York Times
	Selling experience and participation in a virtual community	Pay for software, pay per subscription, pay per transaction, NYOP	World of Warcraft, eBay, Match.com, LinkedIn, Priceline
	Selling virtual goods	Pay for additional content of an online service	Most online (free-to-play) games
Selling access to customers	Misdirection	Charge service vendors and providers for the use of key words related to their businesses	Facebook Connect, Google, Bing, Yahoo
	Evaluation, assessment and validation through community content	Use safe, trusted community content to allow consumers to assess and validate unfamiliar offerings	TripAdvisor, OpenTable, Amazon (via customer reviews)
	Social search	Provide trusted recommendations based on experience of friends and similar people, in response to specific search requests	Facebook Graph Search
	Contextual mobile advertising	Provide timely and trusted suggestions, without explicit request, based on knowledge of current location, preferences, search history, etc.	Tinder, Google AdSense

Table 1: Overall Map of Internet Monetization Strategies

Table 1 already indicates that the field of monetization offers a wide field of research opportunities, and the articles of this dissertation also cover very different aspects. The next chapter 'Research Contexts' will describe the topics been focused on, which are:

- The Name-your-own-price model (article I)
- Users' spending behavior in virtual communities (article II)
- The monetization of network effects in social networks (articles III and IV)
- The legal boundaries of social network usage (article V)

As a result, this dissertation solves a series of questions currently being worked on by practitioners and uses a wide range of methods from various disciplines such as economic, psychological, and game theory. Most of the research projects presented in this dissertation were initiated in conjunction with market-leading Internet companies searching for solutions of complex optimization problems. For example, the article 'Assessing the Economic Effects of Server Launches in Free-to-Play MMO Games' rests upon a cooperation with a globally operating online gaming company; 'Network Effects in Two-sided Markets: Why a 50/50 User Split is not Necessarily Revenue-Optimal' is based on a challenge addressed by a market-leading online dating platform; 'Making Digital Freemium Business Models a Success: Predicting Customers' Lifetime Value via Initial Purchase Information' incorporates data from three European digital service providers (two gaming companies and a dating platform). Industry-wise, three papers investigate monetization-related topics in the fast-growing online gaming industry, three studies address different kinds of social networks, and one looks at the NYOP model which is most relevant (but not solely) to retailers. The next chapter provides an introduction into the four main research topics of this dissertation.

2. Research Contexts

2.1 Name Your Own Price

Among researchers, the Name-your-own-price model is a very popular interactive monetization model (e.g., Cai et al. 2009; Fay and Laran 2009; Hinz and Spann 2008; Spann et al. 2010), however in practice it has not yet found a widespread acceptance. Several larger online platforms such as Expedia or Germanwings have experimented with it, however as of now, Priceline.com is (with $8.4bn revenues in 2014; Priceline 2015) the only 'big player' that still prevails with the model. One reason why this model may be less attractive to sellers than others (such as fixed price sales or eBay-like auctions) could be found through integrating aspects of game theory in the observation of participants' bidding behavior. So far, most research articles (e.g., Shapiro and Zillante 2009; Spann et al. 2004) assume one of the two user groups' (i.e., sellers and buyers) behavior as exogenously given and focus on optimizing the other side's behavior, neglecting interaction effects. These 'myopic' models ignore buyers' learning effects over time, which may eventually reduce sellers' surplus (Fay and Laran 2009; Spann et al. 2010), and thus a suboptimal monetization approach.

The article 'Assessing Strategic Behavior in Name-Your-Own-Price Markets' aims to close these gaps and presents a game-theoretical model that simultaneously incorporates sellers' and buyers' behavior and factors in interaction and learning effects. In a laboratory experiment with 100 subjects given an economic incentive, the study investigates both parties' price strategies over time. A realistic NYOP retail market scenario has been set up where vendors aim to sell different goods to prospective buyers. The setup is designed as a repeated one-shot game (comparable to the design used by NYOP pioneer Priceline) with different trading partners. In each round of the game, every seller sets a reservation price for a specific product that applies to all buyers, and all buyers place a bid for this product. Over 12 rounds with alternate products, we examine how sellers set their reservation prices and how buyers place their bids, and especially how both parties revise their strategies according to their previous experiences.

Overall, the results are good news for NYOP sellers who managed in the experiment to increase their profitability over time. One reason arises from buyers' risk aversion. They often sacrificed some of their surplus by bidding higher to increase their chances of obtaining a product.

2.2 Spending Behavior in Virtual Communities

Monetization is all about understanding if and why users are spending money, and to optimize this process. In the online gaming industry, a lot of research has been conducted that assesses why people are playing such games, but surprisingly little why they are spending money in free-to-play games (Guo and Barnes 2009, 2012) – and if so, they are purely theoretical without providing empirical support by applying real in-game purchase data (e.g., Lehdonvirta 2009, 2012). This knowledge however is vital for providers of free services, as the sales of additional virtual goods are the companies' most important (and in most cases: only) revenue source. The article 'Motivations to Purchase Virtual Items in Free-To-Play MMO Games' aims to fill this gap. The paper is unpublished and thus does not contribute to this dissertation. It categorizes the MMO-relevant purchase motivations, and tests their strength in terms of revenue generation, using in-game purchase data from a large selection of MMO games.

Finding the reasons why people spend money in virtual communities (with the application for MMO games) is however only one step of optimizing the monetization process. It is also vital to understand what future CLV a company can expect from its customers in order to – for example – offer the most promising users a preferred service treatment (Goldstein and Gigerenzer 2009; Kim et al. 2006; Chan and Ip 2011). Again, this aspect is even more important to industries without a subscription model and regular revenue flows, in order to cover the raising user acquisition costs on the Internet (Zhang et al. 2010).

Although the body of research on CLV is extensive and reached its peak in the 2000s (e.g., Reinartz and Kumar 2000, 2003; Malthouse and Blattberg 2005; Gupta et al. 2006), empirical studies examining Internet-specific business models' CLVs are still very scarce. The study 'Making Digital Freemium Business Models a Success: Predicting Customers' Lifetime Value via Initial Purchase Information' aims to assess the extent to which a customer's initial purchase information can be used to predict his/her future CLV in a freemium business model, and to study how paying users' purchase amounts evolve with subsequent transactions. To do so, we use three kinds of regression models (NB, OLS, and Logit) and apply them to payment data collected from three European digital service providers (two gaming companies and a dating platform) operating freemium monetization models.

Today, many companies who operate on the Internet use and capitalize on behavioral psychology, such as the ‘attraction effect’. It refers to the situation when the introduction of a third dominated alternative (the so-called decoy) into a core set of two alternatives increases the choice share of the target option (Huber et al. 1982; Huber and Puto 1983). Ariely (2008) suggested that *The Economist* can increase its average revenue per newly won subscription customer by 43% simply by introducing a third, actually irrelevant, subscription to its two subscription portfolio.

Over the past 30 years, this phenomenon has been extensively researched (see Malkoc et al. 2013 for a detailed review). An effective use of the attraction effect could significantly improve companies’ monetization tactics. However, two studies have recently challenged its relevance for business practice. The claim is that successful findings on the attraction effect are restricted to artificial choice stimuli where every product attribute is presented by abstract numerical descriptions. Using more realistic choice sets including qualitative verbal descriptions or pictorial information of the product attributes, Frederick et al. (2014) and Yang and Lynn (2014) did not find attraction effects.

The paper ‘Attraction Effect Validity in Realistic Hypothetical Settings and Field Experiments’, co-written by Katharina Kaufmann and Martin Natter from Goethe University of Frankfurt, aims at (re)gaining confidence about the robustness of the attraction effect, which includes better understanding the conditions in which the attraction effect works, the impact of customer background factors when real money is in place, and the role of decoy design. We conducted four field experiments in different business settings (i.e., retailing, services, and online gaming) and five corresponding hypothetical online studies with realistic choice sets. The study has not yet been published and is therefore not part of this dissertation.

2.3 Monetization of Network Effects

In networked services, such as the telephone, email, MMO games, or social dating, the user base may exert strong direct network effects as it is realistic to assume that many users join them to interact with other users. Every additional network member adds benefit to the community (Gupta and Mela 2008). A growing user base can improve the user experience, and eventually the willingness to pay increases (Farrell and Saloner 1985; Katz and Shapiro 1985). On the other hand, one might also expect negative effects with a larger user base, especially in services where users compete against each other (e.g., online gamers competing for limited resources, single men on an online dating platform competing for women, eBay sellers competing for buyers).

In spite of substantial theoretical and methodological work on network effects, empirical analyses are still scarce due to a lack of real-life data to properly identify the effects within and across the user groups (Wilbur 2008; Kraemer et al. 2012). Two of the articles in this dissertation employ empirical scrutiny to identify the direction and the magnitude of network effects. Moreover, these articles address very concrete business problems of the two companies we cooperated with. 'Assessing the Economic Effects of Server Launches in Free-to-Play MMO Games' determines the strength of both positive and negative network effects for a real-time strategy MMO game. This allows to develop a server start sequence that better allocates players onto different game servers (= game instances) and thus better capitalizes on network effects. 'Network Effects in Two-sided Markets: Why a 50/50 User Split is not Necessarily Revenue-Optimal' investigates an online dating platform with cross- and same-side network effects for both user groups (i.e., women and men). The result at hand allowed to calculate the revenue-optimal share of women (and men), given a fixed number of users on the platform. Both studies help the respective companies to increase their monetization tactics, and more precisely, to generate higher revenue from a given number of users.

2.4 Legal Boundaries of Social Network Usage

With 1.65 billion monthly active users as of March 31, 2015 (Facebook 2016), Facebook is the world's largest social network. Companies, celebrities as well as public authorities are using the network for their respective purposes, and Facebook capitalizes from them through boosted network activity and eventually higher advertisement revenues.

The article 'Law Enforcement 2.0 – The Potential and the (Legal) Restrictions of Facebook Data for Police Tracing and Investigation' examines the police authorities' state-of-the-art application of Facebook information and identifies two fields of usage: First, the police use Facebook to ask users for help, for example looking for witnesses of a crime. Second, the police search the social network for information, pictures or social bonds of a specific person. The study compiles recent media reports and results from a German pilot project conducted by Hanover police. Although several success cases show the potential of this new approach, new areas of conflict such as the question how to protect the privacy of prospective offenders or witnesses, are created in this way. The analysis reveals that the regulatory framework for the police work on Facebook is unclear.

Interestingly, academic literature is rather quiet on this timely and important topic, and there is only very limited academic literature which provides valuable information on the police's usage of Facebook and its restrictions. The study summarizes dozens of recent TV, radio and newspaper reports from different countries, and analyzes the results from a pilot project conducted by Hanover police, approaches from other public authorities, contributions from the European Union and the German federal government, existing laws and judiciary decisions.

3. Structure of the Dissertation and Summary of Articles

This dissertation consists of five published research articles. Table 2 provides an overview of the articles contributing to the cumulative dissertation, including their research objectives, methods, data sets, and publication status.

#	Name	Objectives	Methods	Data set(s)	Publication
I	Assessing Strategic Behavior in Name-Your-Own-Price Markets	▪ Develop model that considers learning effects and interactions in the NYOP process ▪ Assess whether NYOP can be a sustainable pricing mechanism in the long run	▪ Game theory, NYOP research ▪ Laboratory experiment ▪ Regression and descriptive analysis	▪ Experiment with 100 subjects over 12 rounds (i.e., 1,200 data points)	International Journal of Electronic Commerce (2014)
II	Making Digital Freemium Business Models a Success: Predicting Customers' Lifetime Value via Initial Purchase Information	▪ Explore to what extent initial-purchase data can be used to determine future CLVs ▪ Support online companies to better and earlier segment their customer base	▪ Theory on CLV and customer loyalty ▪ NB regression models ▪ Logistic regression analysis	▪ Data from three online service platforms selling virtual 'credits' ▪ Data sets comprise more than 1.3 million users and, 195,000 transactions	Business & Information Systems Engineering (2016)
III	Network Effects in Two-sided Markets: Why a 50/50 User Split is not Necessarily Revenue-Optimal	▪ Study network effects for a two-sided market ▪ Determine revenue-optimal share of male / female users ▪ Assess incremental revenue of new users	▪ Economic theory ▪ Regression model to empirically assess network effects	▪ Data set from European online dating platform ▪ Detailed activity and payment information for over 8,900 users ▪ Two-and-a-half-year period	Business Research (2015)
IV	Assessing the Economic Effects of Server Launches in Free-to-Play MMO Games	▪ Estimate network and server start effects for free-to-play MMO games ▪ Determine recommended timing for 20 server launches	▪ Economic and psychological theory ▪ Regression model ▪ Counterfactual simulation	▪ Unique data provided by a major European gaming company ▪ Focus on free-to-play MMO real-time strategy game ▪ Sustained 4-year user activity and payment information	Journal of Business Economics (2016)
V	Law Enforcement 2.0 – The Potential and the (Legal) Restrictions of Facebook Data for Police Tracing and Investigation	▪ Identify police application of Facebook data for tracing and investigation ▪ Provide policy makers with list of legal issues that need clarification	▪ Desk research	▪ Recent TV, radio and newspaper reports from different countries ▪ Hanover police pilot project ▪ Existing laws and judiciary decisions	21st European Conference on Information Systems (2013)

Table 2: List of Contributing Papers with Objectives, Methods, Data Sets and Publication Status

In the following, each research article is briefly summarized. Please note that the articles' style guidelines are mainly aligned throughout this dissertation, and do not necessarily follow the respective academic journals' guidelines, as they were published.

3.1 Article I: Assessing Strategic Behavior in Name-Your-Own-Price Markets

The Internet enables a plethora of interactive pricing mechanisms in which both buyers and sellers interactively influence the final price of a product by exchanging bids or messages. Thus, unlike in posted-price markets, the seller does not set the purchase price on his own (Spann et al. 2012). Interactive pricing mechanisms allow the seller to differentiate prices according to prospective buyers' willingness to pay. This can yield higher prices on average without losing customers and thereby increase the seller's profit. Moreover, interactive pricing mechanisms tend to increase the allocation efficiency of markets since low-valuation buyers who are priced out in a fixed-price scenario can be served by a lower individual price in markets that apply an interactive pricing mechanism (Bakos 1998).

Interactive pricing mechanisms on the Internet use various types of negotiations and auctions (Schwind et al. 2008). Google and Facebook both use interactive pricing mechanisms to sell advertisements. IBM, Motorola, Dell, and many more companies extensively use procurement auctions to manage their RFQs (Adomavicius et al. 2012). eBay offers an interactive pricing format ('Best offer') which allows buyers to send a bid to a seller, which he can accept or reject. The researched 'name-your-own-price' (NYOP) mechanism was introduced in 1998 by the US company Priceline, which uses this pricing mechanism to allow companies to sell airline tickets, hotel rooms and rental cars on Priceline.com. With revenues of US$8.4 billion in 2014, Priceline states that the acceptance and success of the NYOP mechanism were key to becoming a strong player in the tourism and airline industry (Priceline 2015). Several other companies have already employed NYOP in various formats, including the travel company Expedia, insurance provider Progressive Direct, software producer Ashampoo, and dedicated NYOP marketplaces such as Greentoe and Buystand.

Previous research on NYOP focused primarily on bidding behavior and the optimal design of the NYOP mechanism to make it more profitable for sellers. Most of these models (e.g., Shapiro and Zillante 2009; Spann et al. 2004) assume one side's behavior as exogenously given and focus on optimizing the other side's behavior, neglecting interaction effects. These 'myopic' models ignore buyers' learning effects over time, which may eventually reduce sellers' surplus (Fay and Laran 2009; Spann et al. 2010). Still, they suggest that game-theoretical considerations might influence participants' behavior (Cai et al. 2009; Spann et al. 2004). With this work, we aim to close these gaps and present a game-theoretical model that simultaneously incorporates sellers' and buyers' behavior and factors in interaction and learning effects.

In a laboratory experiment with 100 subjects given an economic incentive, we investigated both parties' price strategies over time. Sellers showed the expected behavior: they quickly learned to use the provided bidding information and set their reservation prices closer to their variable product costs. This resulted in a larger number of realized transactions and a greater surplus for sellers and buyers alike. We found support for our hypothesis that buyers' bids, compared to their willingness to pay, decrease over time. Buyers aimed to increase their surplus per round in the course of our experiment. We also observed that the provided (incomplete) information on the seller's variable costs had a particularly strong impact on buyers' bidding behavior. We assume the same results even if we had not provided any cost information to buyers. In that case, however, buyers might have taken longer to identify this dominant bidding strategy.

Despite overall lower bids, the sellers in our experiment managed to increase their profitability over time. One reason arises from buyers' varying bidding behavior: following an unsuccessful bid, buyers raised their bids in the next round by 8% on average; when a bid was accepted, the subsequent one was on average 3% lower. This indicates that negative feelings from not closing a deal and the fear of doing so again have a stronger effect on the buyer's reaction in the next round than positive feelings from closing a deal.

We can conclude that the buyers in our experiment tended to be risk-averse. They sacrificed some of their surplus to increase their chances of obtaining the product. This is an important finding and good news for NYOP providers or companies thinking about selling products via NYOP. The buyers in our experiment preferred to buy a product at a higher price than to risk not getting it. In most NYOP setups, a large number of sellers and buyers come together, and buyers' experience with one seller does not allow them to easily predict a reservation price set by another. The buyers in our experiment were provided with a specific cost range – information that many consumers in the real world do not have. Nevertheless, the sellers realized the larger share of the total surplus in each of the 12 rounds. In common NYOP marketplaces, the buyers' information base is usually not as good, and sellers on Priceline or other platforms have significantly more information about prospective buyers than vice versa. Thus, our experiment provides evidence that sellers can use their information advantage to collectively steer buyers' bidding behavior. Adaptive reservation prices (Hinz et al. 2011) can help sellers to reduce the buyers' chances of accurately predicting the reservation price and to make NYOP a sustainable pricing mechanism – even in the long run.

Overall, the results presented in this study should help to deliver a better understanding of seller and buyer behavior in NYOP. Additional interesting studies under alternate conditions remain to be conducted.

The paper has been published as: Voigt S, Hinz O (2014). Assessing Strategic Behavior in Name-Your-Own-Price Markets. International Journal of Electronic Commerce 18(3):103-124

3.2 Article II: Making Digital Freemium Business Models a Success: Predicting Customers' Lifetime Value via Initial Purchase Information

The growth of the Internet presents myriad opportunities for digital business models, along with intensified competition and an accelerated pace of technological change (Veit et al. 2014). These digital business models differ fundamentally from conventional ones, and are particularly challenging with regard to business operations and revenue generation (Amit and Zott 2001; Teece 2010; Veit et al. 2014). In this context, the freemium pricing model (also known as 'free to play' in the gaming industry) has gained increasing attention.

Freemium has become the dominant pricing strategy for software, games, and social network apps (Lehdonvirta 2009; Lehmann and Buxmann 2009). Users can access such services for free, and usually use them as long as they like at no cost. Among these, we find large heterogeneity in terms of total revenue spent. The earliest possible identification of high-value customers is a prerequisite for differentiating more profitable from less profitable customers (Kim et al. 2006; Chan and Ip 2011) and for treating the 'best' customers in such a way that they continue paying for the service (Reinartz and Kumar 2003; Malthouse and Blattberg 2005).

The 'customer lifetime value' (CLV) is used as a key metric to assess the return on investment of management decisions (Gupta et al. 2006; Gneiser 2010) and marketing measures (Rosset et al. 2003; Zhang et al. 2010). It represents a customer's present value in terms of expected benefits less the burdens and plays a key role in customer acquisition decisions (Dwyer 1997). (Freemium) companies that can accurately predict if a given new customer generates future revenue or not will be able to optimize profitability (Jain and Singh 2002; Malthouse and Blattberg 2005). Therefore, Shaw et al. (2001) propose that companies should develop IS-based support systems that create customer profiles and compute CLVs in order to make better marketing decisions, such as developing VIP programs for promising customers (Zhang et al. 2010) or setting up differentiated direct marketing campaigns.

In our study, we aim to assess the extent to which a customer's initial purchase information can be used to predict his/her future CLV in a freemium business model, and to study how paying users' purchase amounts evolve with subsequent transactions. To do so, we use three kinds of regression models (NB, OLS, and Logit) and apply them to payment data collected from three European digital service providers (two gaming companies and a dating platform) operating freemium business models. Combined, they have more than 1.3 million registered users, approx. 57,000 of whom are paying customers, spending more than €3 million in more than 195,000 credit purchases.

Our results show that digital companies operating a freemium business model can expect a higher future CLV from users who …

1. … become paying customers early after their registration,
2. … spend a large amount on their initial purchase, and
3. … use specific payment methods (especially credit cards).

Our results are consistent for the two rather distinct business types (gaming and dating) examined; we therefore believe the findings can be applied to other digital freemium business models, as well.

The paper has published as: Voigt S, Hinz O (2016). Making Digital Freemium Business Models a Success: Predicting Customers' Lifetime Value via Initial Purchase Information. Business & Information Systems Engineering 58(2):107-118. http://link.springer.com/article/10.1007/s12599-015-0395-z

3.3 Article III: Network Effects in Two-sided Markets: Why a 50/50 User Split is not Necessarily Revenue-Optimal

In two-sided markets, an intermediary provides a platform enabling two different user groups to interact, for instance to make a transaction in order to satisfy their interdependent demands (Bakos and Katsamakas 2008; Eisenmann et al. 2006; Ellison and Ellison 2005; Rochet and Tirole 2003, 2006). eBay, for example, brings together sellers and prospective buyers of different kinds of goods, Google advertisers and web users, and Prosper lenders and borrowers of private loans (Berger and Gleisner 2009). Eisenmann et al. (2006) provide a comprehensive list of examples for online and offline two-sided markets. Often, a neutral third party manages the platform (Yoo et al. 2002, 2007) with the commercial objective to maximize its own profits by optimally monetizing one or both user groups.

Previous research on two-sided markets indicates that the two user groups exhibit different kinds of network effects (Katz and Shapiro 1985; Liebowitz and Margolis 1994). Users may derive positive cross-side network effects (CNEs) from the participation of members on the other side of the market, which means the larger the installed user base on one side of the platform, the more attractive the service for the opposite side's users (Armstrong 2006; Li et al. 2010; Tucker and Zhang 2010). Network effects can also emerge within one user group, known as same-side network effects (SNEs).

Utilizing positive network effects and mitigating negative ones is an important challenge for providers of two-sided markets. In recent years, the number of scientific studies which empirically assess such effects has been rapidly increasing (Chu and Manchanda 2013). Yoo et al. (2002, 2007) highlight the importance of identifying the magnitude of the network effects for both user groups, and state that it is difficult to estimate these effects. Knowledge of the direction and the magnitude of network effects can be used to support customer acquisition, pricing, monetization, and IT investment strategies for two-sided markets (Bakos and Katsamakas 2008; Kraemer et al. 2012; Malthouse and Blattberg 2005; Borle et al. 2008).

For the paper at hand, we cooperate with a leading online dating platform and analyze its user activity and payment data over a period of two and a half years. The data sample covers 8,923 users who spent approximately €90,000 by subscribing to one of the premium packages offered by the platform provider. Prior to our research, between 35 and 41% of the users on the platform in question were women, and the intermediary aimed to reach a 50/50 split in the near future. Naturally, one might think that equal numbers of men and women on such a platform yields the best user experience (then, every woman matches with a man) and thus the highest revenue per user for the platform intermediary. However, this does not take into consideration the differences in the user groups' willingness to pay and how CNEs and SNEs impact user behavior (Katz and Shapiro 1985).

In our paper, we propose an approach to determine the revenue-optimal ratio of men to women on the platform in light of the aforementioned various existing network effects. We show that the online dating platform in question can significantly increase its revenue with the proper balance of male and female users. We observed that both user groups (i.e., male and female users) exert positive CNEs with regard to revenue and user enrollment of the other group; however, the positive CNEs women exert on revenue generation per man are stronger than vice versa. Moreover, we identified negative SNEs which lead to lower revenue per user and an increased churn rate on a market side, when that side exclusively grows. Additionally, we found that men are more willing to pay for dating services than women (if the installed base of women is sufficiently large), and almost generate 90% of the platform's total revenue. As a result, the platform maximizes its revenue with a female proportion of the user base of only 36.2%. This share yields 17.2% more revenue than a 50/50 split for the same total number of users.

Our model is transferrable not only to other online dating platforms, but to all kinds of two-sided markets with network effects. Platform intermediaries can use the results from this optimization problem to develop more efficient user acquisition and monetization strategies.

The paper has published as: Voigt S, Hinz O (2015). Network Effects in Two-sided Markets: Why a 50/50 User Split is not Necessarily Revenue-Optimal. Business Research 8(1):139-170. http://link.springer.com/article/10.1007/s40685-015-0018-z

3.4 Article IV: Assessing the Economic Effects of Server Launches in Free-to-Play MMO Games

Nowadays, video gaming revenues clearly exceed those of the global film box industry, and are to grow furthermore within the next years. In MMO games, players are simultaneously interconnected, taking part in the same game world. Social interaction with others plays a key role.

Many researchers (e.g., Bonardi and Durand 2003; Lin and Kulatilaka 2006; Venkatraman and Lee 2004) name video gaming as a typical industry where network effects occur. In MMO games, the user base may exert strong direct network effects that can be both positive and/or negative. A growing user base can improve the game experience, and eventually the players' willingness to pay increases (Farrell and Saloner 1985; Katz and Shapiro 1985). On the other hand, one might also expect negative effects with a larger user base, especially in games where competition between players is central to the game experience: if players consider beating a disproportionate number of users as unrealistic, they might cease playing the game or being willing to pay for it (Lin and Sun 2011; Locke and Latham 1994).

To utilize the positive effects stemming from the user base and to mitigate negative ones, gaming companies often distribute their users on different ‘game servers’. In our paper, we use the term ‘game server’ synonymous to game instance, and not to hardware performing computational tasks. Gaming companies create new servers on a regular basis to produce new impulses for the user base and to distribute players more effectively on the game servers. If different game servers exist, a new player signing up can choose on which server he wants to play. Based on his decision, he co-plays only with the other users on this game server and usually has no interaction with players on any other game server.

Optimally distributing the user base has become an increasingly important monetization challenge, however companies lack sophisticated models how to forecast the revenue impact of such server launches. In practice, determining the timing when to launch a new server is typically based on gut feeling and previous experience, and the outcomes may thus not be optimal. Our study investigates in an MMO gaming context if and how server launches can be used to generate extra revenues. We theoretically and empirically assess to what extent the user base, a server’s lifetime, and other parameters impact players’ spending behavior in the game. To ensure robust results, we use a high-quality and unique data set provided by a major European gaming company, comprising more than four years of data on user activity and payment information for a leading free-to-play MMO real-time strategy game.

In our work, we find a positive linear and a negative quadratic influence of the number of users on a game server’s revenue. The positive effects come from the players’ extended possibilities to interact with other users, resulting in a better game experience. However, if a server grows beyond a certain number of users, the game becomes excessively unbalanced and new players have little chance to compete with players who joined earlier than them. A deterioration of the game experience eventually leads to lower absolute revenues. In our case, the absolute revenue maximum per server is reached at 10,409 users, decreasing with additional users.

In a counterfactual simulation that forecasts the revenue per server on a daily basis, we examine for 20 cases whether or not starting a new server can lead to higher revenues during the subsequent 180 days. In all cases, we find that starting an additional server within 180 days could be more beneficial than not doing so. The right timing for the respective server start is however vital to generating extra revenue. Our simulation shows that the optimal strategy in the game's infancy is to start new servers in very quick succession, and more slowly later on. We suggest practitioners to follow our rule of thumb 'at the beginning, start new servers very quickly, later on every 90 to 120 days'. Still, to determine the optimal timing for a specific case, one also needs to consider other game-specific factors like the number of existing servers, the size of the user base, and the lifetime of the game. Promotions may amplify the revenue peak on the first day(s) of a new server and are worth testing soon after a server launch. In our analysis, applying the best point in time to start a new server yiels an average of 9.4% higher revenues than the respective worst case.

The challenge of assessing the optimal size and configuration of the user base is not only interesting in the MMO real-time strategy gaming context, but also for different game types (Henderson and Bhatti 2001) or other online services such as peer-to-peer networks, online communities, online dating, and classifieds marketplaces (Asvanund et al. 2003, 2004; Bapna and Umyarov 2012; Butler 2001). Our model can be applied to these similar markets, which possess the ability to create a new instance of their platform. For example, a classifieds marketplace that reaches a sensible user limit could split into more regional offerings, or a peer-to-peer network could divide into multiple, more efficient ones (e.g., servers with special content such as movies, music, or software).

The paper has been published as: Voigt S, Hinz O (2016). Assessing the Economic Effects of Server Launches in Free-to-Play MMO Games. Journal of Business Economics, DOI: 10.1007/s11573-016-0825-5, http://link.springer.com/article/10.1007/s11573-016-0825-5

3.5 Article V: Law Enforcement 2.0 – The Potential and the (Legal) Restrictions of Facebook Data for Police Tracing and Investigation

Since the 2001 terrorist attacks in New York, security concerns have increased world-wide. Not only intelligence agencies intensified the collection and analysis of information to investigate terrorists' activities, but also local law enforcement agencies put more effort into modern information technologies (Chen et al. 2003; Custers 2012) which allow new approaches for public authorities to prevent crime and prosecute criminals, such as data mining (e.g., Abbasi and Chen 2005), Policeware (e.g., Nabbali and Perry 2004; Diffie and Landau 2009), intelligent camera tracking (e.g., Lee et al. 2012), mobile phone and computer surveillance (e.g., Nettleton and Watts 2006; COM 2010).

For a few years, police authorities use social networks such as Facebook for tracing and investigation purposes. In a simple case of an online tracing, the police may ask Facebook users for help, for example if they are looking for eye witnesses of a crime or the whereabouts of a missing person. In our study dated from June 2013, we find 14 local police authorities in Germany who regularly post requests for information on Facebook and more examples in the UK and the US. Besides, the police use the social network to collect information about a person. With more than one billion monthly active users sharing their pictures, social activities or interests, Facebook may be a useful source of information for the police.

Our work on the police's state-of-the-art usage of Facebook data provides an overview on technological, societal and legal issues and the new areas of conflict created hereby. While the police may wish to use information gathered via Facebook most effectively, they must consider existing laws and regulations that protect the privacy of prospective offenders or witnesses. However, the existing regulatory framework may not always be as precise as needed. Our review has three main objectives: First, as it is (to our knowledge) the first scientific paper exploring police work on Facebook, we review how police authorities use Facebook today for tracing and investigation, and assess the potential of this new approach. Second, we study if the legislation in Germany provides a clear regulatory framework for the police work on Facebook. We identify legal ‘gray areas’ and advise policy makers to focus on these existing legal issues. Third, we compile hypotheses that aim at stimulating researchers to conduct additional studies.

Interestingly, academic literature is rather quiet on this timely and important topic. To receive valuable information on the police’s usage of Facebook and its restrictions, we compiled dozens of recent TV, radio and newspaper reports from different countries. Additionally, we looked into the results from a pilot project conducted by Hanover police, approaches from other public authorities, contributions from the European Union and the German federal government, existing laws and judiciary decisions. We selectively spoke with police staff specialized in the field of Internet crime to verify our findings.

We found that the main objective of the police’s Facebook use is to collect information that helps them to trace criminals and to solve cases or prevent criminal offences. Facebook data can be used by the police, for instance to track the location of a suspect, get access to recent pictures or to interact with possible witnesses. However, the development of new information technologies, including social networks such as Facebook, is often much faster than the passage of appropriate laws. We found that the exploitation of Facebook information can interfere with (innocent) people’s privacy and their right for informational self-determination. Creating a legal framework that protects personal rights, but enables the police to use Facebook information to prevent and solve crimes is a critical challenge that remains to be addressed by the respective working group of the ministry of justice. To achieve this, we have three concrete recommendations for policy makers: first, to develop a legislative framework and a consistent national information policy that controls Facebook tracings in Germany; second, to find a solution to simplify the collaboration between Facebook and European authorities; and third to update German data policies to boost the efficiency of the police’s Facebook usage.

The paper has been presented and published as: Voigt S, Jansen N, Hinz O (2013). Law Enforcement 2.0 – The Potential and the (Legal) Restrictions of Facebook Data for Police Tracing and Investigation. In: 21st European Conference on Information Systems, Utrecht, June 6-8, 2013

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Article I: ASSESSING STRATEGIC BEHAVIOR IN NAME-YOUR-OWN-PRICE MARKETS

Abstract

Name-your-own-price (NYOP) is an interactive pricing mechanism in electronic commerce that lets both buyers and sellers influence the selling price of a product. Until now, research has focused mainly on optimizing either the buyer's or the seller's strategy, without considering learning effects or interactions between the two sides in the process. However, these aspects are vital: if participants behaved as game theory suggests (i.e., anticipating their counterpart's actions), buyers would place their bids very close to their assumption of the seller costs. In the long run, this may lead to deals at low prices, leaving sellers little surplus and thus no incentive to sell via NYOP. In this paper, we present a game-theoretical model that incorporates interactions between buyers and sellers as well as learning effects. We assess its applicability in a laboratory experiment simulating a common NYOP design. We find that sellers quickly learn to set lower reservation prices, which ultimately increases the total surplus. Buyers, realizing that they can close deals at lower prices, place lower bids over time. Their bids are based mainly on their knowledge of the seller's costs, not on their own willingness to pay. However, buyers are risk-averse in that they prefer to settle a deal than break it off. This is good news for NYOP sellers and shows that NYOP can be a sustainable pricing mechanism even in the long run.

Key words: Name-your-own-price; Reverse pricing; Game theory; Strategic bidding behavior; Laboratory experiment

1. Introduction

The Internet enables a plethora of interactive pricing mechanisms in which both buyers and sellers interactively influence the final price of a product by exchanging bids or messages. Thus, unlike in posted-price markets, the seller does not set the purchase price on his own (Spann et al. 2012). Interactive pricing mechanisms allow the seller to differentiate prices according to prospective buyers' willingness to pay. This can yield higher prices on average without losing customers and thereby increase the seller's profit. Moreover, interactive pricing mechanisms tend to increase the allocation efficiency of markets since low-valuation buyers who are priced out in a fixed-price scenario can be served by a lower individual price in markets that apply an interactive pricing mechanism (Bakos 1998).

Interactive pricing mechanisms on the Internet use various types of negotiations and auctions (Schwind et al. 2008). Google and Facebook both use interactive pricing mechanisms to sell advertisements. IBM, Motorola, Dell, and many more companies extensively use procurement auctions to manage their RFQs (Adomavicius et al. 2012). eBay offers an interactive pricing format which allows buyers to send a bid to a seller, which he can accept or reject. This feature is called 'Best offer' (eBay 2013) and is closely related to the mechanism that literature calls 'name-your-own-price' (NYOP) or 'reverse pricing'. NYOP was introduced in 1998 by the US company Priceline, which uses this pricing mechanism to allow companies to sell airline tickets, hotel rooms and rental cars on Priceline.com. With revenues of US$5.3 billion in 2012, Priceline states that the acceptance and success of the NYOP mechanism were key to becoming a strong player in the tourism and airline industry (Priceline 2013). Several other companies have already employed NYOP in various formats, including the travel company Expedia, insurance provider Progressive Direct, software producer Ashampoo, and dedicated NYOP marketplaces such as Greentoe and Buystand.

Previous research on NYOP focused primarily on bidding behavior and the optimal design of the NYOP mechanism to make it more profitable for sellers. Most of these models (e.g., Shapiro and Zillante 2009; Spann et al. 2004) assume one side's behavior as exogenously given and focus on optimizing the other side's behavior, neglecting interaction effects. These 'myopic' models ignore buyers' learning effects over time, which may eventually reduce sellers' surplus (Fay and Laran 2009; Spann et al. 2010). Still, they suggest that game-theoretical considerations might influence participants' behavior (Cai et al. 2009; Spann et al. 2004). With this work, we aim to close these gaps and present a game-theoretical model that simultaneously incorporates sellers' and buyers' behavior and factors in interaction and learning effects.

In a laboratory experiment with 100 subjects given an economic incentive, we investigate both parties' price strategies over time. We set up a realistic NYOP retail market scenario where vendors aim to sell different goods to prospective buyers. The setup is designed as a repeated one-shot game (comparable to the design used by NYOP pioneer Priceline) with different trading partners. In each round of the game, every seller sets a reservation price for a specific product that applies to all buyers, and all buyers place exactly one bid for this product. Over 12 rounds with alternate products, we examine how sellers set their reservation prices and how buyers place their bids, and especially how both parties revise their strategies according to their previous experiences.

2. Name-Your-Own-Price Auctions

As an interactive pricing mechanism, NYOP enables both sellers and buyers to influence the final price of a transaction. First, the seller sets a reservation price (also known as the 'price threshold') indicating the minimum price he is willing to sell a given product for. This reservation price is not communicated to potential buyers at any time. They can submit bids for the product. A bid is accepted if it hits or surpasses the seller's reservation price, and then denotes the selling price.

Figure 1 depicts the bargaining zone if a transaction is realized, with a bid $B \geq$ the seller's reservation price RP. The seller faces variable costs C for the product he offers. He usually sets RP to a price above or equal to his costs (Spann and Tellis 2006). This ensures that any effected transaction does not result in a loss for the seller.

The buyer has a certain willingness to pay *WTP* that establishes the value of the product to him. We term the difference between a successful bid *B* and *WTP* the buyer surplus. Buyer and seller surplus add up to the total surplus. The buyer and seller aim to maximize their own surplus. The buyer tries to place his bid as close as possible to the seller's reservation price while the seller wants the buyer to significantly overbid. If the buyer's bid is below the seller's reservation price, the transaction will not be realized, and everyone's surplus is equal to 0.

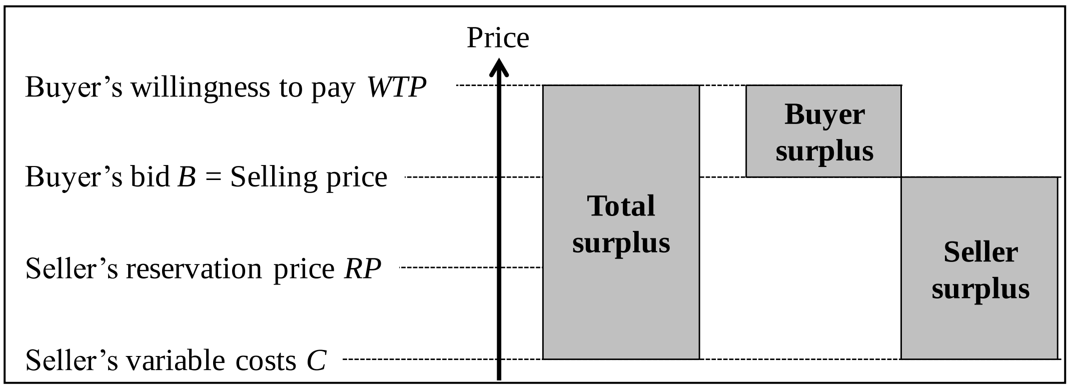

Figure 1: Zone of Bargaining in NYOP if $B \geq RP$

With NYOP, sellers can simultaneously sell a large number of identical products at differentiated prices with just one offer. In contrast to other auction mechanisms, competition between buyers does not directly influence the selling price or a bid's probability of success. Any buyer has solely to overbid the seller's reservation price, even in the common case of limited product capacity. Products are sold to successful bidders on the first-come, first-served principle. When all products are sold, the offer ends. This is a major difference to typical eBay auctions where customers compete against each other and directly influence the selling price until the specified end time of the auction (Ku et al. 2005; Zeithammer 2006).

One of the characteristic features of NYOP is information asymmetry: the seller does not know the buyer's exact willingness to pay, and the buyer does not know the seller's costs and reservation price. A seller usually knows his product's exact variable costs *C*, but he can only estimate the buyer's willingness to pay for the product on the interval $[WTP_L, WTP_H]$ from the lowest possible to the highest possible willingness to pay. The buyer is aware of his exact *WTP*, which is capped to a known posted price for the product, if such exists (Shapiro and Zillante 2009). He can only assess the seller's variable costs on $[C_L, C_H]$ and his reservation price on $[RP_L, RP_H]$. Thereby, $RP_L \geq C_L$ and $RP_H \geq C_H$ must hold since the seller would not sell below his variable costs (Hinz 2007; Spann and Tellis 2006). In line with Ding et al. (2005), Hann and Terwiesch (2003) and Spann et al. (2004), we assume that the probability distribution of willingness to pay, costs and reservation price is equally distributed within each interval. Whereas sellers learn about the bids placed by buyers, the seller's reservation price usually remains hidden throughout the bidding process (Spann et al. 2012; Wolk and Spann 2008).

The NYOP platform operator, which is either the seller himself or an intermediary, can influence the process and its outcome by choosing appropriate design variables. Most existing research on designing the NYOP mechanism aims to make it more profitable for the seller. Researched design features include price elicitation formats (i.e., the design of the bidder-seller interaction; Chernev 2003; Cai et al. 2009; Spann et al. 2012; Wolk and Spann 2008) such as anchor prices (e.g., 'last successful bid was at $52'), price options (e.g., 'you can bid between $50 and $100'; Chernev 2003; Spann et al. 2012), or posted-price benchmarks (e.g., 'median retail price is $189'; Shapiro and Zillante 2009). Other design variables include the number of allowed bids (Cai et al . 2009; Fay 2004; Spann et al. 2004), the application of bidding fees (Bernhardt and Spann 2010; Spann et al. 2010), and adaptive reservation prices (Fay and Laran 2009; Hinz et al. 2011). Priceline and other sellers of travel services conceal certain 'opaque' product information. For instance, buyers can bid for a stay in a four-star hotel in New York, but are not told the hotel's brand or exact location until after their bid has been accepted (Shapiro and Zillante 2009).

3. Explaining Behavior in NYOP Markets

Several recent papers aim to better understand buyers' bidding behavior and determine their optimal strategy in a given NYOP market. They focus on the influence of emotions (Ding et al. 2005), risk aversion (Abbas and Hann 2010), or haggling attitude (Joo et al. 2012) on buyers' bidding strategy, or study behavior in repeated bidding models (Hann and Terwiesch 2003; Terwiesch et al. 2005). Most of the models assume one side's actions as exogenously given and do not consider interaction effects between buyer and seller in a repeated one-shot game over time. Fay and Laran (2009) provide buyers with the expected variability in the reservation price set by the seller and analytically determine the optimal bidding strategy (to maximize customer surplus). However, they do not observe how sellers react to the buyers' bids over time. Shapiro and Zillante (2009) study the profitability of different NYOP design options, but do not assess the possibility that buyers can learn and bid more strategically over time. Spann et al. (2004) determine a buyer's optimal bid B^*_{myopic} in a single-bid model as a function of the willingness to pay *WTP* and the buyer's beliefs about the lower threshold of the reservation price distribution RP_L.

$$B^*_{myopic} = \frac{WTP + RP_L}{2}$$

Assuming such myopic bidding behavior from a buyer, a seller maximizes his surplus if he sets the reservation price at cost level. In this way, he can realize all transactions at a price of B^*_{myopic} with $B^*_{myopic} \geq C$ that grant him a positive surplus for every transaction.

In real markets, where sellers interact with buyers more than just once, they would strategically take buyers' behavior into account. Similarly, the buyers would anticipate the sellers' considerations. Some studies have already assessed such learning effects (Vragov et al. 2010; Wilcox 2000) and used game theory to model seller and buyer strategies in selected interactive pricing mechanisms (e.g., Caldentey and Vulcano 2007; Gallien and Gupta 2007; Mathews 2004; Wilcox 2000), but none of them applied their model to an NYOP design. Our study aims to close this research gap.

We model the decision-making process as a normal-form game where the two players $I = \{buyer, seller\}$ set their strategies without knowledge of the strategy of their counterpart. Thereby, the game can be modeled as a Nash game with or without complete information, depending on the NYOP setup. Both players bargain over the total surplus $TS = WTP - C$, assuming $WTP \geq C$, otherwise, the two sides would never reach an agreement. Each player's part of the total surplus depends on the bargaining outcome. If the buyer bids high, the seller receives the larger part. If the buyer bids low and the bid surpasses the seller's reservation price, he collects a large part whereas the seller receives only a small part. If the bid is too low, it will be rejected and both players receive a surplus of 0.

In the game, we face a limited set of possible strategies and depict it as a table. To outline the mechanism, we assume that buyer and seller each have a set of three possible strategies, which are known to both players. The buyer can bid low *(B_L)*, which – assuming a successful transaction – would leave him with a large share of the total surplus *(A_H)*, or he can place a medium bid *(B_M)* to achieve a medium share *(A_M)* or a high bid *(B_H)* to receive a small share *(A_L)*. The seller can set a low reservation price (RP_L, i.e., close to his variable costs), a medium reservation price *(RP_M)* or a high reservation price *(RP_H)*. $0 < A_L < A_M < A_H < 1$ and $TS \geq 0$ must hold. Table 3 shows the generalized payoff matrix with the buyer surplus (left) and seller surplus (right).

		Seller's reservation price setting options		
		RP_L Low reservation price	RP_M Med. reservation price	RP_H High reservation price
Buyer's bidding options	B_L Low bid	$TS\ (A_H; 1 - A_H)$	0; 0	0; 0
	B_M Med. bid	$TS\ (A_M; 1 - A_M)$	$TS\ (A_M; 1 - A_M)$	0; 0
	B_H High bid	$TS\ (A_L; 1 - A_L)$	$TS\ (A_L; 1 - A_L)$	$TS\ (A_L; 1 - A_L)$

Table 3: General Payoff Matrix for Three Strategies

By conducting an iterative elimination of weakly dominated strategies (see Appendix for the detailed approach), we obtain a weakly dominant strategy equilibrium in *(B_L, RP_L)*. The number of strategies can be extended arbitrarily for both buyer and seller (proof by induction); we will always observe equilibrium in the upper-left corner of our payoff matrix. This means that a seller will always set his reservation price as close as possible to his variable costs. New and inexperienced sellers may not instantly realize this dominant strategy, but they may learn it over time. If so, they would place their reservation price closer to the variable product costs in order to realize more transactions and increase their surplus.

This line of argumentation is supported by Hayek's theoretical argument that private information (i.e., the seller's costs *C*, his reservation price *RP*, and the buyer's willingness to pay *WTP*) does not need to be shared publicly on market exchanges or platforms to find the equilibrium price (Hayek 1945). In his experiments, Smith (1982a) found strong support for the ‘Hayek hypothesis’ and showed that economic agents that were only given selected private information quickly converged on the theoretical equilibrium price. Therefore, we hypothesize as follows:

Hypothesis 1 (Reservation price approaches seller costs). The difference between a seller’s reservation price and the variable costs declines over time.

If the buyers anticipate that sellers will change their strategy over time, they will aim to increase their surplus even further. When buyers learn that setting reservation prices at cost level (or slightly above) is the dominant strategy for sellers, they will realize that they can close a deal at a lower price. Buyers will therefore consider lowering their bids (i.e., bidding lower than their willingness to pay over time), trying to increase their buyer surplus.

Hypothesis 2 (A buyer’s bid level approaches WTP). A buyer’s bid level, compared to his willingness to pay, decreases over time.

Strategic buyers will anticipate that sellers set reservation prices very close to their products’ variable costs. This reduces a strategically acting buyer’s decision on his bid level to a guess of the seller’s variable costs *C*, which he assumes to be within the continuous range $[C_L,\ C_H]$. Assuming that a seller sets his reservation price close to his variable costs, the buyer’s optimal strategic bid B^*_{game} is determined only by his belief about the seller’s variable costs.

$$B^*_{game} = \frac{C_L + C_H}{2}$$

$$s.t.\ WTP\ \geq C_L$$

We believe that the optimal bid B^*_{game}, which is based purely on the seller’s costs, is sufficient to forecast the bid level – presuming that buyers possess certain (or complete) information about costs. In practice, consumers struggle to estimate the variable costs of certain services (e.g., airline tickets and hotel rooms), but we assume that they possess rough knowledge of costs and seller margins for retail items (e.g., consumer electronics) they are interested in buying.

Hypothesis 3 (Buyer's assumptions on a seller's costs determine bid level). If available, a buyer's assumptions on the seller's variable costs are sufficient to predict the level of his bid for a certain product. His willingness to pay is then not required to predict his bid.

So far, our model implies rational bidding behavior without accounting for a buyer's excitement or frustration after a played round. Ding et al. (2005) have shown that buyers revise their bids if their emotional state changes due to the outcome of the previous bid. The applied NYOP design in their experiment comprised several rounds of single bids on the same product with fixed success probabilities. They showed that (frustrated) buyers are likely to increase their bid if they did not surpass the seller's reservation price in the previous round, and lower their bid after a successful transaction. In our setup (without fixed success probabilities), changing bid levels do not necessarily have to be associated with the buyers' emotional state, but can also be attributed to learning effects. For example, if a buyer's bid is declined, he might assume that it will be declined again if he does not increase it in the next round. Kahneman and Tversky (1979) found that consumers do not always rationally choose those options that promise the highest utility, but often overweight the risk of losing. If the frustration of losing was stronger than the excitement of closing a deal, it would also have a larger impact on buyers' bidding behavior in the next round.

Hypothesis 4 (Previous round's results affect bidding behavior in next round). Buyers who failed to realize a transaction in the previous round are more likely to increase their next bid, while buyers who realized a transaction are more likely to lower their bid in the next round. The reactions to unsuccessful bids are stronger than those to successful bids.

Our hypothesis 4 aims to replicate the results by Ding et al. (2005) in a different NYOP setup, but the hypotheses 1, 2 and 3 have never been tested before and will deliver new insights into buyers' and sellers' bidding strategies and learning behavior in NYOP markets.

4. Experiment Design

The aim of this laboratory study is to understand the degree of strategic behavior and learning effects in a realistic NYOP retail environment. 100 subjects took part in our study: 65 students (a mix of graduates and undergraduates) and 35 non-students. They were recruited at a large European university, either through direct contact or notices posted on campus. The experiment took part in a seminar room at the university. An instructor (a graduate student) was present throughout to explain and guide the study, and to answer any questions arising.

At the beginning of the experiment, the instructor explained the NYOP setup to all subjects and assigned them a role, buyer or seller, which they kept for the entire study. Our experiment ran for 12 rounds. The bidding process of each round was as follows: first of all, sellers and buyers were assigned a product. In every round, a seller offered one random product out of 12 possible options. Sellers and buyers never played the same product in more than one round. Participants were given an information sheet that described the product very generically, without brand or quality details that might influence their behavior. It also included buyer-specific or seller-specific information on the product's variable costs and resale value. 'Resale value' means that a buyer could resell the product at this price at once if he bought it from a seller (the seller did not have this option). It induces the buyer's maximum willingness to pay (we will use the terms 'resale value' and 'willingness to pay' synonymously). In a successful bid, the difference between the resale value and the buyer's bid is the buyer surplus. Smith (1982b) proposes using resale values so participants behave in an economically rational manner. In NYOP experiments (e.g., Amaldoss and Jain 2008; Fay 2009; Hinz et al. 2008), resale values are often the same for all buyers, which equals common value auctions (Goeree and Offerman 2003; Milgrom and Weber 1982). This dramatically simplifies the analysis without essentially affecting results (Fay 2009) and gives all participants the same chance of achieving a decent payoff. The instructor explained the term to the subjects by using a common example: *"A mother asks her daughter/son to buy something on the Internet and gives her/him €100. If the daughter/son is able to get the product more* *cheaply, s/he can keep the rest. If s/he is not able to get the product, s/he has to return the money to her/his mother."*

In the simulated retail environment, one can expect sellers and buyers to have incomplete information about their counterparts' variable costs or willingness to pay, respectively. The aforementioned product information sheet was therefore tailored to sellers and buyers: sellers were told their exact product costs and only a range of resale values, while buyers were shown their exact resale value but only a range of estimated variable product costs. This reflects the fact that sellers possess limited information on buyers' willingness to pay and that buyers have rough cost knowledge of the products they are interested in (such as laptops, microwave ovens and DVD players). The product's resale value and its costs were randomly generated from the uniformly distributed ranges (with the constraint that a product's resale value exceeded its costs) so that the subjects could not see any pattern, and were the same for all participants. Figure 2 shows an example product information sheet for the sellers (left) and the buyers (right). Sellers and buyers could use this information to set their reservation prices and place their bids.

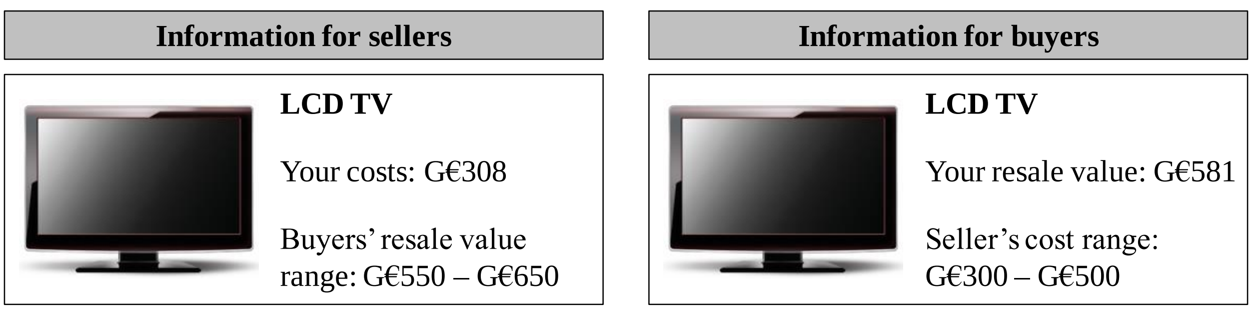

Figure 2: Example Product Information Sheets for Sellers (Left) and Buyers (Right)

In each round, every seller set one reservation price applicable to all his buyers. Then, four buyers were randomly assigned to a seller, and every buyer placed exactly one bid for the product. In our setup, we wanted to avoid two single subjects consecutively playing against each other and influencing each other's future play with their behavior so that the natural benchmark solution is that of equilibrium in the repeated game (Fudenberg and Levine 2007). Such equilibrium is not applicable in most NYOP markets. For example, on Priceline.com, a large number of companies aim to sell flight tickets, rental cars or hotel rooms to an even larger number of potential buyers who are unknown to the sellers. Thus, in every new round of our experiment, we randomly assigned buyers to sellers to replicate common NYOP markets.

The aim of all subjects was to maximize their own payoff in the course of 12 rounds. To ensure subjects acted accordingly, a proportion of the surplus they made was paid out to them, serving as a monetary incentive (Smith 1982b). In addition to a show-up fee of €5 for all subjects, buyers received a variable amount that was 1% of the realized surplus (i.e., resale value – realized price) after 12 rounds; sellers received 0.25% of their surplus (i.e., realized price – variable costs). This means that neither selling below variable costs nor bidding above the resale value made economic sense because it would result in negative payoffs. Also, setting too high reservation prices or placing too low bids would result in not closing the deal and therefore no payoff at all for the seller or the buyer. The monetary incentive was the same for all 12 rounds, so the subjects were rewarded for behaving rationally at any time.

At the end of each round, the instructor informed the buyers individually whether their bids had been successful. The sellers' reservation prices were not communicated to the buyers. Sellers learned how much the buyers had bid for their products, the number of the realized transactions and their selling prices. With this information, buyers and sellers were able to calculate the payoffs they had earned. After each round, there was a short break that allowed sellers and buyers to reflect and learn from their observations (Wilcox 2000).

All cost and price-related information was declared in euros. In this paper we call the in-game currency 'Game Euro' (G€) and distinguish it from the 'real' euro amount paid out to the subjects at the end of the experiment.

Figure 3 summarizes the steps of the laboratory study. After 12 rounds, the session closed with the payoff of the realized surpluses. The experiment instructions, which all subjects received before the first round, can be found in the Appendix of this paper.

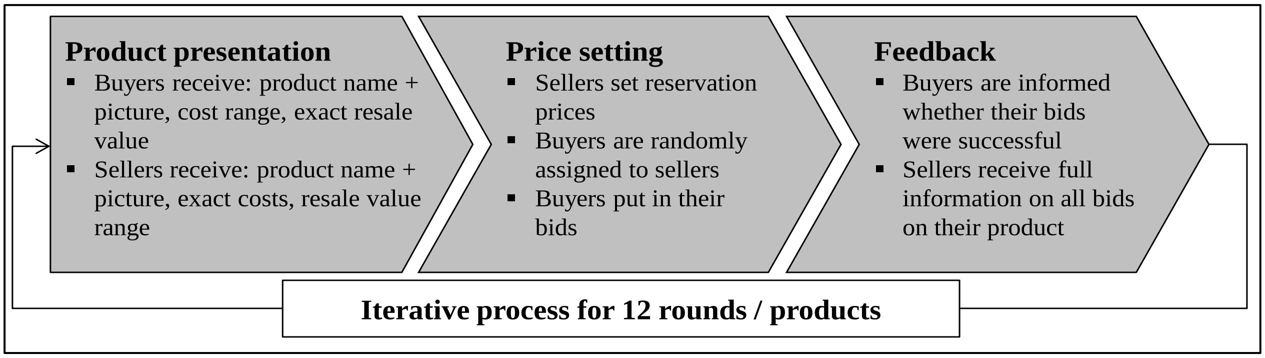

Figure 3: Experiment Process per Round and Product

5. Hypothesis Testing

Descriptives. With 100 subjects and 12 rounds, we collected 1,200 data points: 240 reservation prices set by sellers and 960 bids placed by buyers. Out of 960 possible transactions, 714 were realized (i.e., 74.4%). On average, a buyer purchased 8.9 out of 12 possible products, achieving an average total surplus per buyer of G€576.96. On average, a seller closed 35.7 out of 48 possible transactions with an average total surplus per seller of G€3,294.08. This means an average surplus per bid of G€48.08 for buyers and of G€68.83 for sellers. Taking into consideration that the surplus is 0 for both the buyer and the seller if no deal is concluded, these numbers indicate that buyers were more willing to sacrifice some of their potential surplus in order to increase the probability of closing the deal. Apparently, sellers used their information advantage from receiving full information on four bids per round to skim a larger share of the total surplus. Table 4 shows an overview of the most important descriptive results.

Sample	Subjects	100 (80 buyers, 20 sellers)		
	Profession	65% students, 35% non-students		
	Avg. age	26.2 years		
Bids	Number of bids placed	960 (80 buyers × 12 rounds)		
	Number of reservation prices set	240 (20 sellers × 12 rounds)		
	Realized transactions	714 (i.e., 74.4% of all bids)		
Surplus		Max.	Avg.	Min.
	Buyer surplus	G€1,028.00	G€576.96	G€0.00
	Seller surplus	G€4,161.20	G€3,294.08	G€758.00
Payoff (incl. show-up fee of €5)	Buyer payoff	G€15.28	€10.77	€5.00
	Seller payoff	G€15.40	€13.24	€6.90

Table 4: Overview of Descriptive Results

Basic behavioral tests. To assess the validity of our experiment's results, we checked to what extent sellers or buyers violated the basic rationality rules of the NYOP setup. We identified four possible irrational activities. If a subject acted in such a way and their counterparts behaved rationally, they would either realize no deal (1 and 3), or close the deal with a negative surplus (2 and 4; in such cases, the surplus was set to 0 to avoid negative payoffs).

Table 5 provides a breakdown of the occurrences of irrational behavior. We find that the number of violations was very low. We therefore believe that the subjects fully understood the experimental setup. Nobody made the same mistake again in any subsequent round. In the last three rounds combined, we found only one case of irrational behavior, and could not detect any irrational last-minute strategy changes (comparable to the frequently observed last-minute bidding in second-price Internet auctions; Ku et al. 2005; Ockenfels and Roth 2006; Wilcox 2000).

Violation	Description	# of observations	% of violations observed
(1) $RP > WTP_H$	Sellers setting the reservation price above the upper end of the buyers' resale value range	240	0.4%
(2) $RP<C$	Sellers setting the reservation price below costs	240	0.4%
(3) $B < C_L$	Buyers bidding below the lower end of the cost range	960	0.0%
(4) $B \geq WTP$	Buyers bidding equal to and higher than the resale value	960	0.4%

Table 5: Violations of Rational Behavior

Seller behavior. In the game-theoretical model, setting the reservation price closely above variable costs is the dominant strategy for a seller. We hypothesized that the sellers (none of whom had experience with NYOP before the experiment) would learn this in the course of the experiment and place their reservation prices closer to the product costs.

As different products at different costs were randomly sold in the experiment, we calculated the mark-up in percentage between costs and the set reservation price. Example: if the seller had a product with costs of G€100, and he set the reservation price at G€120, the ratio between reservation price and costs would be G€120 / 100 = 1.2. We expected a ratio of 1 to be the minimum as it implies that sellers set their product reservation prices at cost level.

Figure 4 shows how the average reservation price mark-up developed during the 12 rounds of the experiment. As expected, the difference between the sellers' reservation prices and their costs declined over time. The median per round for all sellers went down from 1.43 in round 1 to 1.16 in round 12, as the linear trend line in Figure 4 indicates. Table 6 shows the results from a linear regression with the round and the average of the buyers' resale value as the independent variables and the reservation price divided by variable costs as the dependent variable. We see that the round had a highly significant, negative impact ($p<0.01$) on the reservation price mark-up. On average, sellers reduced the reservation price by 1.9% in every round. This result supports our first hypothesis that sellers learned to put the reservation price closer to their costs over time. We did not observe any correlation between the buyer's expected willingness to pay and the reservation price set by the seller.

Result for hypothesis 1 (Reservation price approaches seller costs). The difference between a seller's reservation price and the product costs declines over time.

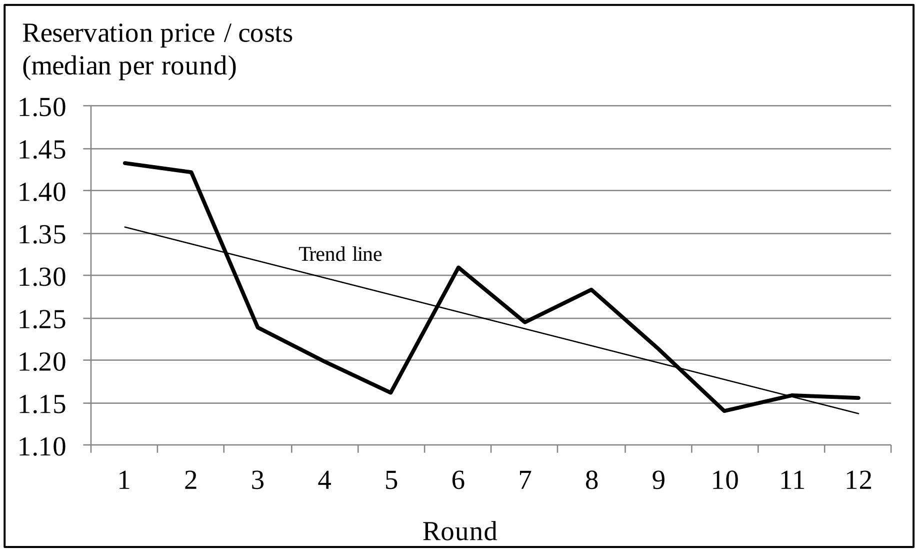

Figure 4: Development of the *RP / C* Ratio over Time

	Unstandardized coefficients		Standardized coefficients	T	Significance
	B	Standard error	Beta		
Constant	1.411	0.020		69.001	0.000
Round	-0.019	0.002	-0.251	-7.968	0.000
$\frac{WTP_L + WTP_H}{2}$	0.000	0.000	0.002	0.053	0.957
Dep. variable	Reservation price / costs ratio				
R^2	0.063				
Number of observations	240				

Table 6: Influence of Rounds Played on the *RP / C* Ratio

Buyer behavior. We found support for our first hypothesis that sellers learn to set their reservation prices closer to their costs, and now we investigate whether buyers anticipated the sellers' observed behavior when placing their bids. If so, the buyers' bids would decline over time.

Since buyers were consecutively offered different products from alternate sellers, we normalized the absolute bid values by calculating the ratio between the observed bid *B* and the resale value *WTP* in each round. Example: in round 1, the buyers' resale value *WTP* for product A was equal to G€200. A certain buyer bid G€160, so the *B / WTP* ratio was 0.8. In the next round, *WTP* was G€300, and the buyer placed a bid of G€150. Then, the *B / WTP* ratio was 0.5, which means the buyer placed a lower bid than in the previous round. Please note that we did not use the exact product costs in this analysis since they were not observed by buyers.

As shown in Figure 5, we can observe that the gap between the buyers' bids and their willingness to pay slowly increased over time. The regression results in Table 7 show a significant negative impact of rounds played ($p<0.1$), although the effect of -0.2% per round is not as strong as previously seen on the sellers' side. We also find a highly significant impact of the expected costs (i.e., the mean cost range) on the *B / WTP* ratio. This supports our second hypothesis: buyers learned that sellers set lower reservation prices, and thus placed lower bids, trying to realize deals at lower prices and to maximize their surplus.

Result for hypothesis 2 (A buyer's bid level approaches WTP). A buyer's bid level, compared to his willingness to pay, decreases over time.

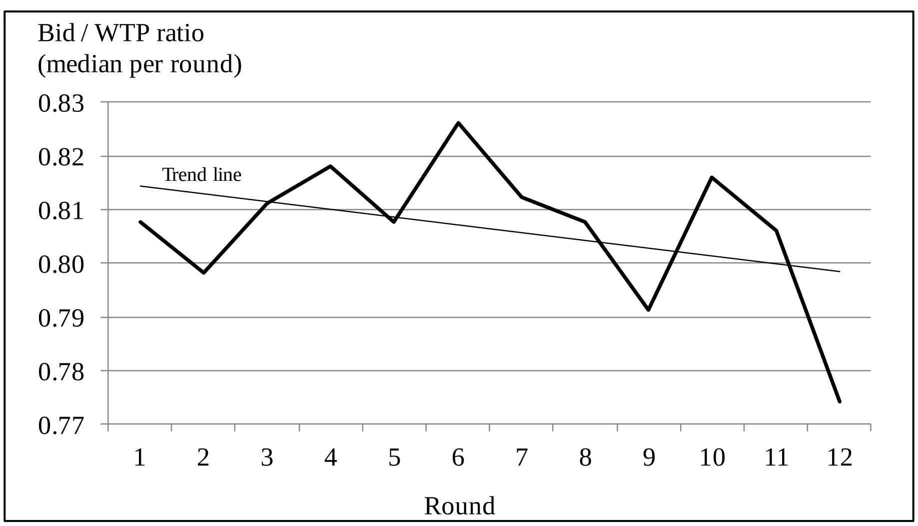

Figure 5: Development of the *B / WTP* Ratio over Time

	Unstandardized coefficients		Standardized coefficients	T	Significance
	B	Standard error	Beta		
Constant	0.706	0.007		105.103	0.000
Round	-0.002	0.001	-0.058	-1.879	0.061
$\frac{C_L + C_H}{2}$	0.000	0.000	0.295	9.519	0.000
Dep. variable	Bid / willingness to pay ratio				
R^2	0.087				
Number of observations	960				

Table 7: Influence of Rounds Played on the *B / WTP* Ratio

Our game-theoretical model showed that the buyer's optimal bid is based solely on his belief of the seller's variable costs. Our third hypothesis investigates the extent to which the provided (incomplete) cost information can be used to predict a buyer's actual bid, without considering his willingness to pay. The regression in Table 8 shows that 97.3% of the variance in buyers' observed bidding behavior is captured by $B^*_{game} = (C_L + C_H) / 2$ (p<0.001). The results provide support for hypothesis 3 that a cost-based bid B^*_{game} is a strong predictor for *B*.

Result for hypothesis 3 (Buyer's assumptions on seller's costs determine bid level). A buyer's assumptions of the sellers' costs are sufficient to predict his bid for a certain product. A buyer's willingness to pay is not necessarily required to predict his bid.

	Unstandardized coefficients		Standardized coefficients	T	Significance
	B	Standard error	Beta		
Constant	11.001	1.961		5.609	0.000
B^*_{game}	1.246	0.007	0.986	185.166	0.000
Dep. variable	Bid *B*				
R^2	0.973				
Number of observations	960				

Table 8: Influence of the Optimal Bid B_{game}* on the Actual Bid *B*

Impact of emotions on bidding behavior. Hypothesis 4 postulates that buyers do not act purely rationally when placing bids. The emotional state of a buyer resulting from the outcome of the previous bid may affect his next bid (Ding et al. 2005), and buyers may overweight the risk of losing (Kahneman and Tversky 1979).

To test our hypothesis, we calculated the ratio between the observed bid *B* and the resale value *WTP* to assess the level of a bid. Table 9 shows that buyers reacted quickly to the success of the previous round. We find that the amount of the subsequent bid depended on whether the previous bid was successful (i.e., whether it led to a transaction). If a bid was accepted in the previous round, 33% of the buyers kept their bids at the same level in the next round (within a range of +/- 5%), and 43% lowered their bids. If a bid was not accepted, 69% of the buyers raised it the next time. The corresponding Chi-square tests are highly significant (p<0.01) for both scenarios. These results show that buyers were heavily influenced by the result of the previous round: they changed their strategy, even though they were assigned to a different seller in the next round.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="4">Next bid</td></tr>
<tr><td>Next bid is higher</td><td>Next bid is at the same level (within 5% range)</td><td>Next bid is lower</td><td>Sample</td></tr>
<tr><td rowspan="2">Previous bid</td><td>Previous bid was successful</td><td>159 (25%)</td><td>211 (33%)</td><td>277 (43%)</td><td>647 (100%)</td></tr>
<tr><td>Previous bid was unsuccessful</td><td>161 (69%)</td><td>38 (16%)</td><td>34 (15%)</td><td>233 (100%)</td></tr>
</table>

Table 9: Bidding Strategy Change Depending on the Outcome of the Previous Bid

Buyers reacted more strongly to unsuccessful bids than to successful bids. On average, buyers raised their next bid by 8.0% after an unsuccessful bid and lowered it by only 3.1% after a successful bid. Our results indicate that the frustration of not concluding a deal had a stronger effect on the next bid than the excitement of closing a deal, and that buyers can be considered risk-averse in that they want to realize a deal even if they have to sacrifice some surplus to do so.

Result for hypothesis 4 (Previous round's results affect bidding behavior in next round). The success of the previous round's bid affects the bid level in the next round. A buyer who failed to make a transaction is likely to sharply raise their next bid, while a buyer who succeeded is likely to slightly reduce his next bid.

Impact on surplus. The behavior changes over time led to increased surplus. In the first two rounds, only 48% and 41% of the bids were successful, but in the last four rounds, each bid showed a success rate of over 80%. As Figure 6 shows, this led to a substantial increase in surplus per round for sellers and buyers (with product costs being standardized to 1). Sellers' absolute (normalized) surplus in round 12 was 163% higher than in round 1, and buyers' surplus increased by as much as 246%. This can be primarily attributed to the sellers changing their behavior by setting lower reservation prices in the course of the experiment. Interestingly, the sellers' absolute surplus was larger than the buyers' share in every round.

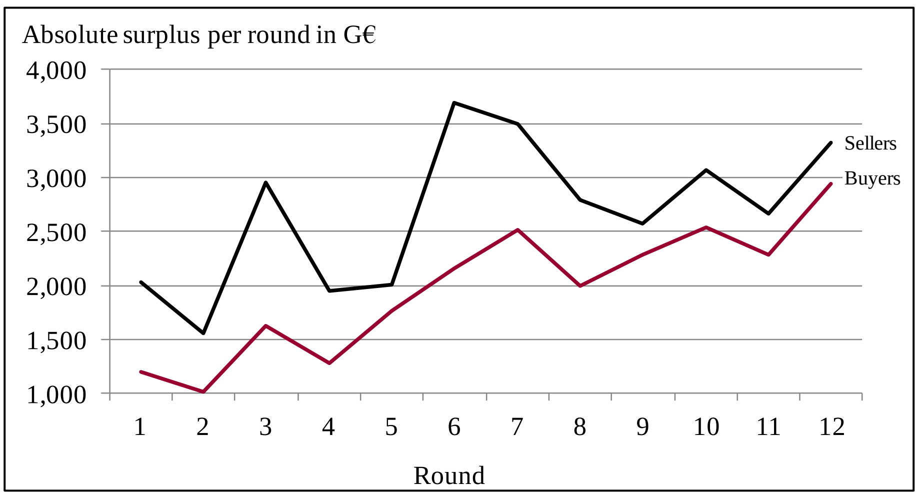

Figure 6: Sellers' and Buyers' Absolute (Normalized) Surplus per Round

6. Discussion and Conclusion

This work's objective was to investigate strategic behavior in an NYOP market and its impact on surplus distribution. Based on the developed game-theoretical model, we set up four hypotheses and tested them in a laboratory experiment with 100 subjects given an economic incentive.

In our experiment, sellers showed the expected behavior: they quickly learned to use the provided bidding information and set their reservation prices closer to their variable product costs. This resulted in a larger number of realized transactions and a greater surplus for sellers and buyers alike. We found support for our hypothesis that buyers' bids, compared to their willingness to pay, decrease over time. Buyers aimed to increase their surplus per round in the course of our experiment. We also observed that the provided (incomplete) information on the seller's variable costs had a particularly strong impact on buyers' bidding behavior. We assume the same results even if we had not provided any cost information to buyers. In that case, however, buyers might have taken longer to identify this dominant bidding strategy.

Despite overall lower bids, the sellers in our experiment managed to increase their profitability over time. One reason arises from buyers' varying bidding behavior: following an unsuccessful bid, buyers raised their bids in the next round by 8% on average; when a bid was accepted, the subsequent one was on average 3% lower. This indicates that negative feelings from not closing a deal and the fear of doing so again have a stronger effect on the buyer's reaction in the next round than positive feelings from closing a deal.

We can conclude that the buyers in our experiment tended to be risk-averse. They sacrificed some of their surplus to increase their chances of obtaining the product. This is an important finding and good news for NYOP providers or companies thinking about selling products via NYOP. The buyers in our experiment preferred to buy a product at a higher price than to risk not getting it. In most NYOP setups, a large number of sellers and buyers come together, and buyers' experience with one seller does not allow them to easily predict a reservation price set by another. The buyers in our experiment were provided with a specific cost range – information that many consumers in the real world do not have. Nevertheless, the sellers realized the larger share of the total surplus in each of the 12 rounds. In common NYOP marketplaces, the buyers' information base is usually not as good, and sellers on Priceline or other platforms have significantly more information about prospective buyers than vice versa. Thus, our experiment provides evidence that sellers can use their information advantage to collectively steer buyers' bidding behavior. Adaptive reservation prices (Hinz et al. 2011) can help sellers to reduce the buyers' chances of accurately predicting the reservation price and to make NYOP a sustainable pricing mechanism – even in the long run.

Our study has a number of limitations that provide avenues for further research. First, the buyers in our study had reasonable information available on sellers' costs and used it to place bids. In practice, however, depending on the product category or service sold, this knowledge might be vaguer. For example, consumers will certainly struggle to estimate the variable costs of services such as air fares or hotel accommodations. If buyers do not have this information, their bidding decision may be based on other factors. Adomavicius et al. (2012) showed that the amount of information a buyer possesses when placing a bid has implications on both parties' surplus. Lower cost transparency may eventually lead to more differentiated bids and higher seller profits. A study that assesses the impact of consumers' cost knowledge on their bidding behavior may identify product types that are more suitable than others for NYOP. Also, depending on the sellers' business model, their costs could have been alternatively conceptualized as fixed sunk costs, for example if unsold goods have no value to the seller. This may apply to those NYOP sellers who purchase or produce products or services in bulk (e.g., a number of TV sets or air fares) and then aim to recoup the costs as quickly as possible.

Second, the instructions for our experiment used some academic terminology to explain the NYOP method which was new to all subjects. This may have impacted the subjects' behavior, especially in the first rounds. However, since most of the participants were well-educated university students, we believe the terminology did not bias the results of the experiments to a large extent.

Third, we could not test long-term effects in our study. Reservation prices and bids may not have found their equilibrium by the end of the experiment, if such equilibrium exists. A longitudinal study, possibly with real bidding data, could uncover longer-term learning effects. Our findings may also have varied with a different NYOP design, for instance by allowing multiple bids per buyer for the same product, charging bidding fees, applying adaptive reservation prices or providing competitor price information to buyers. Moreover, our experimental NYOP setup did not entail competition among buyers, and all bids were placed at the same time. In practice, often only a limited number of items is available for the given reservation price. Prospective buyers who bid first are served first. Product scarceness and buyer competition might therefore influence buyers' bidding behavior.

Overall, the results presented in this study should help to deliver a better understanding of seller and buyer behavior in NYOP. Additional interesting studies under alternate conditions remain to be conducted.

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Appendix

Determining the Strategy Equilibrium (Numeric Example)

We conduct an iterative elimination of weakly dominated strategies to determine the strategy equilibrium. For reasons of comprehensibility, we use typical values (A_L = 0.1; A_M = 0.5; A_H = 0.9 and *TS* = 1) in the initial payoff matrix in Table 10.

		Seller's reservation price setting options		
		RP_L Low reservation price	RP_M Med. reservation price	RP_H High reservation price
Buyer's bidding options	B_L Low bid	90%; 10%	0; 0	0; 0
	B_M Med. bid	50%; 50%	50%; 50%	0; 0
	B_H High bid	10%; 90%	10%; 90%	10%; 90%

Table 10: Initial Payoff Matrix of the Evaluated Game

Looking at the payoff matrix, we observe that the seller's strategy RP_H is weakly dominated by RP_M: if the buyer bids B_L or B_H, the seller's payoff is identical for RP_M and RP_H. However, if the buyer picks strategy B_M, RP_M generates a larger seller surplus (50%) than RP_H (0). A seller would therefore never play the high-price strategy RP_H. We therefore eliminate this option and produce Table 11.

		Seller's reservation price setting options	
		RP_L Low reservation price	RP_M Med. reservation price
Buyer's bidding options	B_L Low bid	90%; 10%	0; 0
	B_M Med. bid	50%; 50%	50%; 50%
	B_H High bid	10%; 90%	10%; 90%

Table 11: Payoff Matrix after Elimination of Strategy RP_H

An anticipating buyer would now consider the high-bid strategy B_H as unattractive, since strategy B_M strictly dominates strategy B_H (50% payoff for B_M versus 10% for $B_{H,}$ independent of the seller's choice between RP_L and RP_M). Therefore, we eliminate strategy B_H, which results in Table 12.

		Seller's reservation price setting options	
		RP_L Low reservation price	RP_M Med. reservation price
Buyer's bidding options	B_L Low bid	90%; 10%	0; 0
	B_M Med. bid	50%; 50%	50%; 50%

Table 12: Payoff Matrix after Elimination of Strategy B_H

A seller could now take the described buyer's considerations into account and regard this strategy RP_L as weakly dominant since the seller receives 10% if the buyer plays strategy B_L whereas there is no change (still 50%) if the buyer plays B_M. In Table 13, we eliminate seller strategy RP_M.

		Seller's reservation price setting options
		RP_L Low reservation price
Buyer's bidding options	B_L Low bid	90%; 10%
	B_M Med. bid	50%; 50%

Table 13: Payoff Matrix after Elimination of Strategy RP_M

Finally, we obtain a weakly dominant strategy equilibrium in *(B_L, RP_L)* by eliminating B_M since the buyer can realize 90% by playing B_L compared to 50% by playing B_M.

Experiment Instructions

Handout given to all subjects at the beginning of the experiment (translated from German):

The setting. In this experiment, you are a buyer or a seller. Your role will be set at the start and remain the same throughout. You aim to buy or sell products in a name-your-own-price (NYOP) setting. The NYOP design we use works as follows: the seller of a product sets a secret minimum price threshold that is not communicated to the buyers. Afterwards, buyers place bids for this product. If a bid is at least as high as the threshold set by the seller, a transaction becomes effective at the bid price. If a bid is below the price threshold, no transaction takes place. A product can be sold multiple times, depending on the number of bids above the thresholds. This means buyers do not compete against each other for a specific product because the other buyers' bids are not relevant for the realization of their deal.

The process. The experiment runs for 12 rounds. A new product is sold in each round. The round proceeds as follows: first, you receive a sheet with basic product information. Buyers receive the resale value of this product and a range of estimated costs. Sellers receive the exact product costs and a resale value range. 'Resale value' means that a buyer can sell the product at this price after buying it from a seller. You may use this information to place your bid (if you are a buyer) or to set your price threshold (if you are a seller).

At the start of each round, all sellers set their secret price thresholds. Then, the prospective buyers are anonymously assigned to the sellers. The assignment of buyers to sellers changes every round. By making transactions, sellers and buyers can generate benefits. In this case, the surplus for a buyer is the difference between the resale value and the buyer's bid (i.e., the selling price); the surplus for a seller is the difference between a buyer's bid (i.e., the selling price) and the product costs. If a buyer buys a product below the resale value, or if the seller sells below cost, they make a loss. If a buyer places a bid below the price threshold, no deal is closed and both parties earn 0. You should therefore ensure that you close some deals – without making a loss. Note: sellers can sell an unlimited number of products each round.

At the end of each round, buyers are told whether their bid was successful. Sellers receive information on all bids, and on how many deals were closed in that round. The sellers' price thresholds are not communicated to buyers.

The payoff. For taking part in this experiment, you will receive a fixed amount of €5 plus a variable amount depending on the surplus you make in the 12 rounds. The variable amount is 1% of the total surplus for buyers and 0.25% for sellers.

Article II: MAKING DIGITAL FREEMIUM BUSINESS MODELS A SUCCESS: PREDICTING CUSTOMERS' LIFETIME VALUE VIA INITIAL PURCHASE INFORMATION

Abstract

In digital freemium business models such as those of online games or social apps, a large share of overall revenue derives from a small portion of the user base. Companies operating in these and similar businesses are increasingly constructing forecasting models with which to identify potential heavy users as early as possible and create special retention measures to suit those users' needs. In our study, we observe three digital freemium companies selling virtual credits and investigate to what extent initial purchase information can be used to determine a given customer's lifetime value. We find that customers represent higher future lifetime values if they a) make a purchase early after registration, b) spend a significant amount on their initial purchase, and c) use credit cards to purchase credits. In addition, we see that users tend to spend increasing amounts on subsequent purchases.

Key words: Freemium; Digital business models; Online gaming; CLV forecasting

1. Introduction

The growth of the Internet presents myriad opportunities for digital business models, along with intensified competition and an accelerated pace of technological change (Veit et al. 2014). These digital business models are highly relevant to IS researchers as they differ fundamentally from conventional ones, and are particularly challenging with regard to business operations and revenue generation (Amit and Zott 2001; Teece 2010; Veit et al. 2014). In this context, the freemium pricing model (also known as 'free to play' in the gaming industry) has gained increasing attention.

In recent years, freemium has become the dominant pricing strategy for software, games, and social network apps (Guo and Barnes 2009; Lehdonvirta 2009; Lehmann and Buxmann 2009). Users can access such services for free, and usually use them as long as they like at no cost. Wagner et al. (2014) describe the freemium business model as a promising solution for content providers to earn money from users who have a ‘for free’ mentality. It allows companies to suppress entry barriers and thus to attract a much larger audience than paid services do. However, only a minority of such users actually become paying customers. Among these, we find large heterogeneity in terms of total revenue spent. The earliest possible identification of high-value customers is a key customer relationship management (CRM) challenge (Goldstein and Gigerenzer 2009). It is a prerequisite for differentiating more profitable from less profitable customers (Kim et al. 2006; Chan and Ip 2011) and for treating the ‘best’ customers in such a way that they continue paying for the service (Reinartz and Kumar 2003; Malthouse and Blattberg 2005).

CRM has emerged as an important field at the intersection of marketing and IS (Gneiser 2010). Within CRM, customer lifetime value (CLV) is used as a key metric to assess the return on investment of management decisions (Gupta et al. 2006; Gneiser 2010) and marketing measures (Rosset et al. 2003; Zhang et al. 2010), and to optimize long-term customer profitability (Rust et al. 2010; Chan and Ip 2011). CLV represents a customer’s present value in terms of expected benefits less the burdens and plays a key role in customer acquisition decisions (Dwyer 1997). (Freemium) companies that can accurately predict if a given new customer generates future revenue or not will be able to optimize profitability (Jain and Singh 2002; Malthouse and Blattberg 2005). Therefore, Shaw et al. (2001) propose that companies should develop IS-based support systems that create customer profiles and compute CLVs in order to make better marketing decisions, such as developing VIP programs for promising customers (Zhang et al. 2010) or setting up differentiated direct marketing campaigns.

Especially for digital companies utilizing a freemium model, it is increasingly important to forecast the revenue they can expect from new users which should at least cover acquisition costs (Zhang et al. 2010). Several online blogs recently report a steep increase in user acquisition costs. For example, Hochman (2015) mentions an average CPC (cost per click) increase from $0.38 in 2005 to $0.92 in 2013 (i.e., an average annual increase of 11.7%). Likewise, search engine marketers estimate an annual 'Google CPC inflation' of 5-12% per year (Pretorius 2013). Companies without proper CLV-predicting models risk to acquire unprofitable customers.

Developing forecasting models has been subject of extensive recent research within the IS community (e.g., Ngai et al. 2009; Lessmann and Voß 2010; Chan and Ip 2011; Gerlach et al. 2013; Cleophas and Ehmke 2014). To predict a customer's future value, digital companies can use various sources of information, among them demographic information, acquisition channel, or stated preferences. The most frequently used input for CLV models is information on customers' past purchases (Rosset et al. 2003; Malthouse and Blattberg 2005; Wübben and Wangenheim 2008; Zhang et al. 2010; Chan and Ip 2011). Kim et al. (2006) state that using a CLV calculation based on socio-demographic information and purchase history is more meaningful for segmenting the customer base than all other mentioned methods. Schmittlein and Peterson (1994) point out that past purchase behavior generally outpredicts geo-demographic information.

Although the body of research on CLV is extensive and reached its peak in the 2000s (e.g., Reinartz and Kumar 2000, 2003; Malthouse and Blattberg 2005; Gupta et al. 2006), empirical studies examining Internet-specific business models are still very scarce. In our study, we aim to assess the extent to which a customer's initial purchase information can be used to predict his/her future CLV in a freemium business model, and to study how paying users' purchase amounts evolve with subsequent transactions. To do so, we use three kinds of regression models (NB, OLS, and Logit) and apply them to payment data collected from three European digital service providers (two gaming companies and a dating platform) operating freemium business models. Combined, they have more than 1.3 million registered users, approx. 57,000 of whom are paying customers, spending more than €3 million in more than 195,000 credit purchases. Investigating varied digital businesses allows us to generalize our results.

The remainder of this paper is organized as follows. In Section 2, we propose an analytical CLV model specific to digital freemium business models. Section 3 provides a description of the three data sets analyzed for the purposes of our study. Section 4 delineates the different regression models used for empirical analysis. The results of said analysis are addressed in Section 5, including CLV prediction and purchase amount development over time. In Section 6, we discuss the implications of our results for theory and practice; we also propose future research topics. Finally, the paper closes with a summary.

2. Analytical Model Depicting CLVs for Digital Freemium Business Models

CLV can be calculated in numerous ways, depending on the relevant company's industry and price model (Berger and Nasr 1998; Gupta et al. 2006). Jain and Singh (2002) propose the following basic CLV model, which includes the absolute sum of all customer-related, discounted cash flows:

$$(1)\quad CLV = \sum_{t=1}^{T} \frac{(Rev_t - C_t)}{(1+d)^{t-0.5}}$$

with t = the period of cash flow (with t=1 as the day of the initial purchase);

T = the total number of periods of projected life for the customer under consideration;

Rev_t = the revenue from the customer in period t;

C_t = the marginal cost of generating the revenue Rev_t in period t;

d = the discount rate.

Literature distinguishes between CLV definitions for contractual and non-contractual products or services. Contractual products possess continuous cash flow – for instance, insurance policies, mortgages, and cell phone contracts (Rosset et al. 2003; Venkatesan and Kumar 2004; Fader and Hardie 2007). Non-contractual customer relationships, like those of freemium businesses selling virtual credits, are not governed by a membership or contract (Reinartz and Kumar 2003). As such, companies do not observe an explicit customer defection. Purchase timing and amount are not continuous or transparent, and can only be predicted probabilistically (Reinartz and Kumar 2000, 2003; Fader et al. 2005; Borle et al. 2008).

Based on the CLV model discussed above, we propose an adapted model that fits the non-contractual freemium context. First, we refrain from including marginal costs in the CLV equation. For digital businesses, fixed overhead costs such as development, server maintenance, and personnel are more relevant than marginal costs of reproducing and distributing services over the Internet (Lehmann and Buxmann 2009). We therefore set marginal costs at 0 and focus our CLV assessment purely on revenue, as many analytical CLV models do (Borle et al. 2008).

Second, we need to consider that in a freemium business model, a customer can make multiple purchases on the same day. To calculate the expected future CLV at a specific point in time (e.g., at the initial purchase), it does not suffice to look only at a day-by-day basis, so we include the purchase instance $pi = \{1, \ldots, PN\}$ as a variable to facilitate correct ordering of intra-day purchases. Furthermore, the relationship does not start with the customer's first purchase, as in retail businesses, but with his/her registration to the (free) service, and ends with his/her final login.

Third, customer lifetime cycles vary depending on the nature of the business and the profile of its customers (Jain and Singh 2002). Naturally, discount rates are considered in businesses with long-lasting customer relationships. Older studies (Kim et al. 1995; Berger and Nasr 1998; Reinartz and Kumar 2000, 2003) use annual discount rates in the range of 12% to 20%. In online games and dating, the average user does not stay with the service for very long. In our data sets, between 40% and 55% of newly registered users log in only once and then never return, and only 1-2% of all users still generate revenue more than a year after their registration. Blattberg et al. (2009) state that discount rates do not make *"much of a difference"* for such short time spans, especially given today's low interest rates. Accordingly, we use no discount rates in our CLV model.

With these three adaptations to the original CLV model, the CLV formula for non-contractual freemium business models is as follows:

$$(2)\ CLV_{freemium} = (\sum_{t=1}^{T} \sum_{pi=1}^{PN} Rev_{t,\, pn})$$

with t = the period of cash flow (with t = 1 as the day of customer's registration);

T = the total customer lifetime of the customer under consideration;

pi = the customer's purchase instance;

PN = the total number of purchases the customer makes within T;

Rev_t = the revenue from purchase pi in period t.

3. Data Description

For our empirical study, we use customer and purchase data from three European digital businesses that sell a virtual currency in a non-contractual freemium model. A data confidentiality agreement with the companies prevents us from disclosing their names. Working with multiple data sets allows us to see whether our results can be applied broadly rather than being specific to one platform. The three data sets come from two online real-time strategy games (data sets 1 and 2), and an online dating platform (data set 3).

The services can be used via Internet browsers and dedicated mobile apps. They feature a shop where users can buy credits that provide them with access to additional in-app features compared to non-paying users, such as extra resources for constructing cities or armies more quickly (gaming), or the ability to send messages to other users (dating).

The selection of the gaming and dating software industries for our study covers the most in-demand digital service applications and provides us with highly relevant data. A look at the top-grossing apps for iPhone (AppAnnie 2015) in the US, Japan and Germany shows that games constitute by far the most popular apps (in terms of generated revenue), followed by social apps (i.e., networking and dating). We find in Table 14 that on average, 94% of the top-grossing apps are free to download, leaving only 6% that require an upfront payment. 97% of all apps allow in-app purchases (iAP).

Country	Genre	Free	Paid	Have iAP
US Top 100	Gaming	82	4	83
	Social / Dating	8	1	9
	Other	4	1	4
Japan Top 100	Gaming	85	0	85
	Social / Dating	14	0	14
	Other	1	0	1
Germany Top 100	Gaming	68	3	69
	Social / Dating	8	3	10
	Other	12	6	16
Share of all apps		94%	6%	97%

Table 14: Top-Grossing iPhone Apps in Apple's AppStore – January 4, 2015

When registering for one of the two online games in the study, users must provide no more than a nickname and an email address. Additional demographics are only very rarely revealed; as a result, the companies' knowledge of their user base is very limited. On the dating platform (data set 3), users usually share profile pictures, gender, age, place of residence and other personal details; however, this information is – according to the platform provider – inaccurate or incomplete for the majority of the new registrations.

When buying credits on any of these platforms, users choose a purchase amount (e.g., €5, €10, €20) and a payment method (e.g., credit card, PayPal, prepaid card). The available amounts differ by payment method. Payment methods are available for data sets 1 and 2, but not for data set 3. We excluded all incomplete purchases, such as chargebacks and free promotions (with a revenue of €0) from our samples.

For each user we consider all purchases he/she makes within the first 365 days after his/her registration as CLV. This one-year window is in line with previous CLV studies (e.g., Najar and Rajan 2005; Rust and Verhoef 2005). For data set 3, which is the smallest, we reduce the CLV calculation window to 180 days in favor of expanding the observation timeframe to compensate for the disparity in user count. On average, the paying users in data set 3 make their last purchase 39.3 days after registration (SD: 48.3 days), so only negligible revenue is lost through our adjustment.

Table 15 shows that in our data sets, only 3.3% to 6.1% of registering users become paying users (that is, purchase credits at least once). A business with >90% free users sharing little to no demographic information makes it difficult to predict a user's future value to the company. Since the goal of our paper is to predict CLV using paying customers' initial purchase information, we exclude free users (whose CLV is always 0) from our data set for all analyses (same approach as Fader et al. 2005).

		Data set 1	Data set 2	Data set 3
Observation timeframe (for users to register)		January 1, 2009 to October 31, 2010	January 1, 2009 to October 31, 2010	September 25, 2011 to July 4, 2012
Newly registered users within timeframe		831,617	444,934	52,200
Timeframe for CLV calculation (after registration)		365 days	365 days	180 days
Share of newly registered users becoming paying users		3.3%	6.1%	4.8%
Sample size	Credit purchases	104,659	87,230	3,639
	Paying users	27,707	27,236	2,500
	Revenue	€1.3m	€845k	€138k
CLV per paying user	Min	€2.99	€2.99	€9.99
	Max	€10,932.76	€1,102.29	€1,697.00
	Mean	€47.01	€31.01	€55.25
	Median	€10.97	€10.98	€29.00
	SD	€124.39	€52.08	€73.20
Credit purchases per paying user	Min	1	1	1
	Max	224	96	23
	Mean	3.78	3.20	1.46
	Median	2	2	1
	SD	6.84	4.58	1.29
Avg. purchase amount	All purchases	€12.45	€9.68	€37.96
	Initial purchases	€9.46	€9.08	€34.81
	Non-initial purchases	€13.52	€9.96	€44.87

Table 15: Data Set Descriptives

All three data sets show significant heterogeneity among paying users. In the paying user base, average CLV varies from €31.01 (data set 2) to €55.25 (data set 3), with standard deviations between €52.08 (data set 2) and €124.39 (data set 1). In data set 1, 20% of the paying customers with the highest CLV contribute up to 75.6% of total revenue. When we consider all users (including non-paying), we see that the top 1% of users contribute up to 84.6% (data set 1), 60.5% (data 2), and 53.6% (data set 3) of total revenue. The numbers indicate how important it is for freemium companies to identify high-value customers expediently in order to design proper CRM measures that suit varied customer segments.

Despite operating similar business models, freemium gaming and dating platforms are quite distinct from a user perspective. For example, whereas a 'successful' gamer is likely to keep playing (Choi and Kim 2004), a 'successful' dater is likely to quit the service after finding a partner. It will be interesting to see if these conflicting user objectives affect CLV or if we find consistent results for both businesses.

4. Methodology and Empirical Model Description

We estimate a negative binomial (NB) regression model to assess how past purchase information impacts a paying user's future CLV at the time of his/her initial credit purchase (i.e., $pi = 1$ in our CLV model). As a user's demographic information is often incomplete or incorrect for non-contractual online services, we focus purely on past purchase behavior to predict users' future CLV. Following our previous argumentation, we use three input variables:

- *Time until initial purchase (in days)*: Equals a user's past customer lifetime (in days) elapsed before he/she makes his/her initial purchase.
- *Initial purchase amount (in €)*: Equals the chosen virtual currency package (e.g., €10, €20, and €50) for a user's initial purchase.
- *Payment method used for initial purchase*: Equals the chosen payment method (see Table 19 in the Appendix for a detailed description) when purchasing credits for the first time. The payment methods are coded as dummy variables. Each is set at 1 if used, and 0 if not.

Wübben and Wangenheim (2008) describe NB models as the state-of-the-art approach in determining the future activity and purchase levels of a customer. Based on the work of Schmittlein et al. (1987) and Schmittlein and Peterson (1994), these kinds of models have been employed in several studies (Reinartz and Kumar 2000, 2003; Fader et al. 2005; Glady et al. 2009; Zhang et al. 2010). NB models are attractive because they (1) forecast individuals' future purchase levels and (2) operate on past transaction behavior. They operate solely on the frequency and recency of a customer's past purchase behavior (Wübben and Wangenheim 2008), and are thus well-suited to forecasting CLV in a freemium business model.

Gupta et al. (2006) summarize frequently-used alternative modeling approaches that aim to predict CLV, among them probability, econometric, persistence, computer science, and diffusion/growth models. Goldstein and Gigerenzer (2009) name studies (such as Venkatesan and Kumar 2004) in which linear regression models fit to predict future 'best' customers and their purchase activity. Jain and Singh (2002) recommend such regression models and Bayesian approaches (as applied by Borle et al. 2008) to assess which individuals in the customer group most likely represent active and inactive customers, and what level of transactions the company can expect from them in the future, both individually and collectively.

In all of our data sets, the standard deviation exceeds the mean in terms of CLV per paying user (see Table 15 above). Such customer heterogeneity is accepted when predicting CLV (Reinartz and Kumar 2003). NB models possess an extra parameter to accommodate such overdispersion (STATA 2015; UCLA 2015) and are thus especially useful for discrete, overdispersed data, where a Poisson distribution is unsuitable. This also allows us to use discrete data as dependent variables, such as purchase amounts in € which depend on the chosen payment method.

In the second part of our empirical work (in section 5.2), we assess if and how a user's purchase amounts change over time, in the case that he/she makes multiple credit purchases. We apply a standard OLS regression with *Purchase amount* of a given transaction (in €) as dependent variable, while a user's *Purchase instance* (i.e., whether it was his/her first, second etc. transaction) and *Payment method used for initial purchase* serve as predictive variables.

Finally, we apply a logistic regression to assess the probability of a customer's purchase amount changing over time. Logit models are non-linear estimation techniques with a binary outcome (Zhang et al.

2010), which solve the problem of unboundedness of OLS. Alternatively, a Probit model could be used, but both models usually yield very similar results (Freedman 2009, pp. 121-129). The dependent dummy variable *Same amount as previous purchase* equals 1 if a purchase amount is identical to the previous purchase, and 0 if it is higher or lower. The *Payment method used* (also coded as a dummy variable) for the purchase in question is included as a control variable.

To address the challenges that outliers pose for some statistical models, we use the Huber-White sandwich estimators (Huber 1967; White 1980) in all three regression models, thereby obviating minor concerns about the potential failure to meet assumptions, such as normality, heteroskedasticity, or observations that exhibit large residuals, leverage, or influence. For all regression models and data sets, we check the correlation matrices to identify potential multicollinearity issues. For all (non-dummy) independent variables, the off-diagonal correlation values are all clearly below the common threshold of 0.4, which would indicate multicollinearity problems (Fickel 2001, p. 41).

5. Empirical Results

5.1 CLV Prediction Using Initial Purchase Information

For our first analysis, we check the influence of the information available at the initial credit purchase upon a customer's (remaining) CLV. We estimate several NB models to ensure the robustness of our results. We first consider only *Initial purchase amount* as independent variable and successively include *Time until initial purchase* and *Payment method used for the initial purchase*, which results in our final model shown in Table 16. We detect no change of algebraic signs at the significant variables from one model to another and thus believe our model to be robust. The reported incidence rate ratios (IRRs) are the exponential equivalent to regular regression coefficients.

		Data set 1	Data set 2	Data set 3
Time until initial purchase (in days)		.9956***	.9960***	.98550***
Initial purchase amount (in €)		1.0354***	1.0269***	1.0119***
Payment method used for initial purchase	*Bank transfer*	.9017	.7109***	
	Credit card	1.2206***	1.0487	
	Direct debit	.9987	.7943***	
	Phone	.7013***	.8781***	
	Cell phone	.7987*	.8552	
	Prepaid card	.9478	.7974***	
	SMS	.5522***	.7098	
	Wallet	(omitted)	(omitted)	
Constant		40.46722***	24.2738***	17.3975***

Table 16: Results from NB Regression (Dependent Variable: *CLV in €*)

Investigating the *Time until initial purchase (in days)*, we see that the IRRs are less than 1 in all three data sets. This means that the earlier a new user buys credits for the first time (after registration), the higher his/her remaining CLV. Conversely, this means that users who decide to purchase credits later than others usually have a lower future CLV.

Result 1: The length of time between a user's registration and his/her initial credit purchase is negatively correlated to that user's remaining CLV.

Moreover, we can see in three data sets (with each $p<.01$) that the *Initial purchase amount* is positively correlated to remaining CLV. The effect is more pronounced in the two online games than in the dating platform. These results show that even in settings with usually short customer relationships, customers spending large amounts in their initial purchase promise higher future revenues than those spending less.

Result 2: The higher the customer's initial credit purchase, the higher his/her remaining CLV.

Data sets 1 and 2 offer eight payment methods each. We can see that in both cases, using a credit card for the first purchase has the highest positive impact on the remaining CLV (data set 1: 1.2206, $p<.01$; data set 2: 1.0487, n.s.), followed by online wallets (omitted variable with an IRR set to 1). SMS payments promise the lowest remaining CLV (data set 1: .5522, $p<.01$; data set 2: .7098, n.s.). Overall, four out of seven payment methods show significant results in each of the data sets (excl. the omitted Wallet method).

Result 3: The payment method of the initial purchase is a significant predictor of remaining CLV. Credit card users promise higher CLVs than all other paying customers.

5.2 Development of Purchase Amounts in Subsequent Purchases

We now assess to what extent a user's purchase amounts develop over subsequent transactions. The last row in Table 15 shows that the average amount (in €) of all users' initial purchases is lower than the amount of each subsequent purchase. On average, the amount of any subsequent purchase is 42.9% (data set 1), 9.7% (data set 2), and 28.9% (data set 3) larger than the initial purchase.

Figure 7 illustrates how average purchase amounts develop for all three data sets. We indexed the average amount spent on the initial purchase at 1 (e.g., €9.46 for data set 1). For all platforms, we can see that the average purchase amount increases with the second and third purchases, and more or less flattens after that. For example, the average amount spent in the tenth purchase is 57% higher for data set 1, 5% higher for data set 2, and 41% higher for data set 3 than in the initial purchase. The results of the OLS regression in Table 17 confirm an increase of the average *Purchase amount in €* with subsequent purchases.

Result 4: The average revenue per purchase increases with the number of purchases a customer makes.

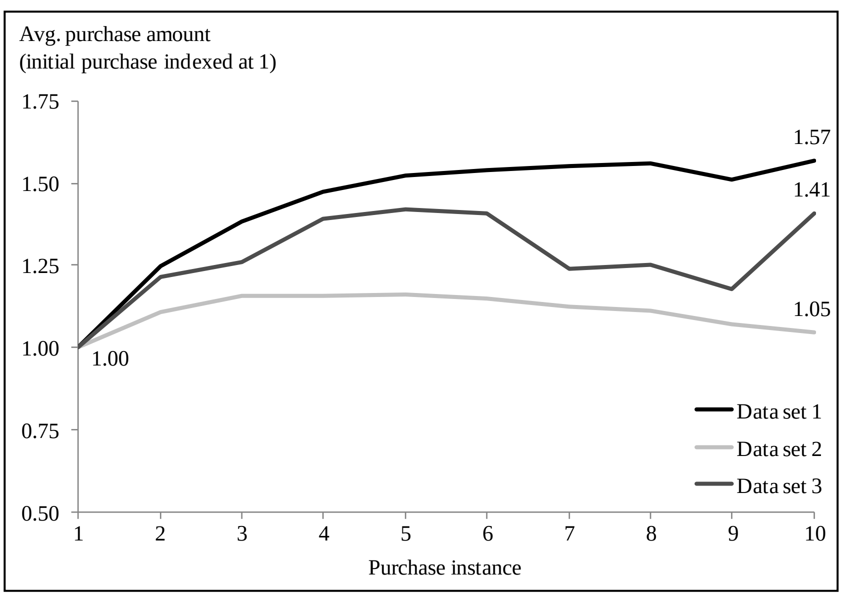

Figure 7: Average Purchase Amount Depending on Purchase Instance

		Data set 1	Data set 2	Data set 3
Number of observations		104,659	87,230	3,639
Prob > F		.0000	.0000	.0000
R-square		.2483	.2443	.0444
Root MSE		11.445	8.6473	23.022
		Coeff.	Coeff.	Coeff.
Purchase instance		.0544***	.0480***	2.4477***
Payment method used for initial purchase	*Bank transfer*	(omitted)	(omitted)	
	Credit card	4.9880***	.7887	
	Direct debit	.0613	-3.4678***	
	Phone	-11.9071***	-11.8921***	
	Cell phone	-9.8883***	-11.7784***	
	Prepaid card	-4.4203***	-6.6812***	
	SMS	-14.8287***	-14.9902***	
	Wallet	-1.9824***	-4.6504***	
Constant		21.6124***	20.9884***	33.5591***

Table 17: Results from OLS Regression (Dependent Variable: *Purchase Amount in €*)

**p*<.1; ***p*<.05; ****p*<.01

Finally, we aim to assess the probability of a change in purchase amount for a customer's subsequent purchases. We first compare how the purchase amount develops from one purchase to another. If a customer decides to make a purchase beyond the first one, he/she has three options: 1) purchase credits for the same amount as in the previous purchase, 2) spend more than previously, or 3) spend less. Figure 8 illustrates how often each of the cases occurs in the three data sets. In data set 1, for example, we see that from all customers making a second purchase, 59.6% spent the same amount in the second purchase as in the first, 28.1% spent more, and 12.3% spent less. We find a consistent picture across all three data sets: the more purchases a customer has made, the less likely he/she is to spend more than in his/her previous purchase. However, this is still more likely than a drop in the purchase amount.

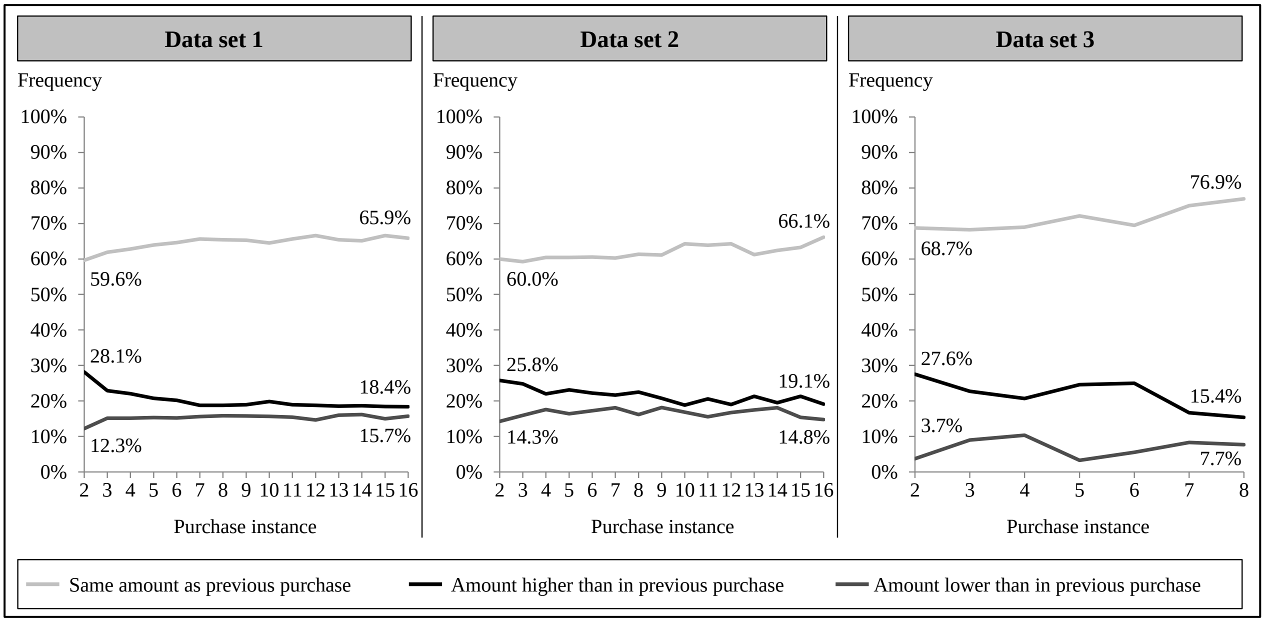

Figure 8: Probability of a Purchase Amount Change Depending on Purchase Instance

To check if the descriptive results from Figure 8 are statistically significant, we conduct a logistic regression. In Table 18, we can see that *Purchase instance* has a positive and highly significant impact on the probability that the per-instance purchase amount remains stable. The likelihood of a purchase amount change reduces with every purchase. For data set 3, the coefficient is also positive but the results are not statistically significant. Changing the dependent variable into *Higher/lower amount than previous purchase*, we see that the *Purchase instance* has a negative impact on both the likelihood of the user choosing a higher (data sets 1 and 2: $p<.01$; data set 3: $p<.1$) or a lower purchase amount (data set 1: $p<.01$; data sets 2 and 3: n.s.).

		Data set 1	Data set 2	Data set 3
Purchase instance		.0096***	.0068***	.0265
Payment method used	*Bank transfer*	-.2383***	-.5393***	
	Credit card	-.1275***	-.2972***	
	Direct debit	-.0984**	-.1025*	
	Phone	-.1316***	-.1065***	
	Cell phone	-.8938***	-.5677***	
	Prepaid card	-.2102***	-.3215***	
	SMS	.1273***	.1989***	
	Wallet	(omitted)	(omitted)	
Constant		.4810***	.3486***	.7201***

Table 18: Results from Logistic Regression (Dep. Dummy Variable: *Same Amount as Previous Purchase*)

**p*<.1; ***p*<.05; ****p*<.01

Result 5: With each subsequent purchase, the purchase amount becomes less likely to change (compared to the previous purchase).

6. Discussion

6.1 Theoretical Contributions

Our empirical analysis produces five key results, which are consistent for two quite distinct businesses: online gaming and dating (except result 3, for which data for the dating platform is unavailable). We thus believe that the results may also apply to other freemium business models.

First, the sooner a user becomes a payer, the higher his/her remaining CLV. This result agrees with existing theory from traditional businesses which incur an upfront payment. Early adopters of a product or service also tend to be heavy users (Taylor 1977) and less price-sensitive than late adopters (Goldsmith and Newell 1997). In the case of freemium business models, users who decide to move from being free users to paying customers very quickly can be considered early adopters of the paid part of the service. According to our results, they are likely to take the service more seriously than those who make the transition later, and thus are likely to spend more money in total.

Second, we find that the higher a customer's initial purchase amount, the higher his/her remaining CLV. That this holds true in all three cases is particularly interesting, as Malthouse and Blattberg (2005) describe a contradictory situation in which customers with exceptional spending in a given instance often converge to a lower true mean spending over the course of future transactions. One can expect a similar effect with freemium services that do not exhibit sufficient incentives and features on which to spend credits. Various studies support our findings, however. Reinartz and Kumar (2003) find positive relationships between previous spending levels and customer lifetime. Venkatesan and Kumar (2004) show that revenue generated by a certain customer in the past is positively correlated to – and thus a good predictor of – his/her future spending. Blattberg et al. (2009) discover that historical profitability is usually closely correlated with future CLV estimates. Our results are remarkable in the context of online dating, as one could have expected that paying users invest their credits, and either leave the service happily (having found a partner) or unhappily (having found no partner despite having bought credits). We assume that the experience for paying users is good enough to keep them engaged and induce them to buy credits again.

Third, we find that the payment method of the initial purchase significantly impacts a user's remaining CLV. Although the results are only partially statistically significant, they indicate that credit card users tend to have the highest CLV, followed by users of e-wallets (such as PayPal), direct debit and bank transfer, prepaid cards, and finally cell phone and SMS payment. The fact that credit card users have a higher willingness to pay (as shown by Feinberg 1986; Prelec and Simester 2001; Soman 2001) does not come as a surprise. For digital business models however, surprisingly little research has been conducted to date on the effects of payment method on a consumer's future behavior.

Fourth, we see that average revenue per purchase increases with the number of purchases a customer makes. This comports with the findings of Reichheld (2001), who attributes the acceleration in customers' revenues over time to (among other things) an increased use of the product and a higher willingness to pay. Some studies (e.g., Reinartz and Kumar 2003; Liu 2007) provide support that the amount spent per purchase is positively correlated to customer loyalty. Fader et al. (2005) analyze the customer base of an online music site and discover a positive correlation between the average purchase amount and the number of purchases.

In our empirical study, we examined online gaming and dating platforms. Characteristics of such services' users may have led or supported the results. Many games are competitive, and those who continue playing a specific game for a long time are highly motivated to attain a certain in-game status and/or achieve a high or the highest possible score or rank (Bostan 2009), which positively influences their willingness to pay for credits. In addition, gaming and dating platforms are social networks that exhibit positive network effects which eventually increase users' willingness to pay (Farrell and Saloner 1985; Bapna and Umyarov 2012). The longer a customer uses the service, the more social contacts he/she may come to know, and the stronger the network effects. This could mean that freemium business models that exert weaker network effects may see lower progressive revenue per transaction.

Fifth and last, our data shows that a customer's purchase amount becomes less likely to change with each subsequent purchase. Digital services such as software, gaming, or dating services are experiential goods whose actual value customers can assess only after their usage or purchase (Lehmann and Buxmann 2009), as are credit purchases. Users who decide to make another credit purchase are likely to have been satisfied with their previous buying decision. According to Latham and Locke (1991), consumers who realize that their purchase behavior is instrumental to achieving a positive outcome (e.g., building a stronger base in an online game or getting in touch with other people on a dating website) will be more likely to engage in this behavior, and therefore make repeated purchases out of habit (Aarts et al. 1998). Still, our results are somewhat limited because the companies we investigated offered only a selected range of credit packages; this limits the customer's ability to increase his/her amount per purchase indefinitely.

6.2 Practical Contributions

Our five main findings allow us to derive several recommendations for operators of digital freemium businesses. Before we propose these, we would like to stress that our research deals only in correlations; we are not able to draw explicit conclusions of causality between initial purchase information and future CLV. For example, we see that credit card users have on average higher CLVs than any other users. However, this does not mean that moving all customers to credit card payments is necessarily profitable (see Takac et al. 2011 for a longer discussion on this ‘causality challenge’).

In our three data sets, we see that up to 84.6% of the total revenues derive from a mere 1% of users. This represents a clear call to action for companies operating a freemium model to identify potential heavy spenders early on and to cater to them as best as possible. We find that payment information at the time of the initial purchase can be used to identify high-value users: customers tend to generate higher future CLVs if they a) become paying customers early after their registration, b) spend a large amount on their initial purchase, and c) use specific payment methods (especially credit cards). These findings can be used in an information system that segments the customer base by forecasted CLV (Rust et al. 2010), executes appropriate CRM measures (Chan and Ip 2011), and evaluates these measures’ effectiveness in CLV increase (Zhang et al. 2010).

An appropriate CLV prediction can support freemium businesses’ acquisition, retention, and monetization strategies. As freemium companies pay customer acquisition costs despite not knowing if they will ever generate revenues with a given user, it is important that they align these costs with their CLV forecasts to assess whether a certain customer group is likely to generate enough future revenues to be profitable (Zhang et al. 2010). Regarding retention, identified high potential-value customers should be treated with special care – for example, with a (VIP-like) retention program with dedicated services (such as guaranteed response time to service tickets or unique platform content) to reduce their churn risk (Rosset et al. 2003). Observing users’ previous purchase amounts and CLV potential also allows freemium companies to apply differentiated monetization strategies for up- and cross-selling. This includes tactics to take payers to the next highest spender bracket (e.g., from a €10 credit package to a €20 package). Overall, we find that a thorough CLV forecast can support and inform a large range of CRM applications.

6.3 Limitations

Our study is the first to predict CLV and purchase amount development over time within the context of digital freemium business models, and leaves room for improvement and future research. The initial-purchase information we used should be available to all freemium companies and thus serves as a sensible starting point. A logical extension would be to update the CLV prediction over time, for example, after the second or third purchase (Borle et al. 2008), or to assess CLV right after a user's registration. This, however, requires additional information on the user such as user demographics (e.g., sex, age, place of residence), and acquisition channel (e.g., SEM, online ads, partner websites). Also, on-site activity (e.g., number of logins, time on platform in the last week) would be interesting input data to explore (Alves et al. 2014). Chan and Ip (2011) indicate that today, no information system that forecasts CLV takes all key areas into account at the same time. If a system did so, a CLV model could create a clearly better picture as to which users promise the highest future CLV (Glady et al. 2009).

In accordance with our definition of CLV, we looked solely at the revenue a user generates directly during his/her relationship with the company. However, a user may also generate extra value indirectly, for example by referring the service to other users (and thus reducing the acquisition costs for those users; Hinz et al. 2011), or by exerting network effects that positively influence other users' willingness to pay (Farrell and Saloner 1985). An expansion of the model may be helpful to assess the CLV more holistically.

As mentioned above, our results indicate only correlations, as it is hard to draw causal conclusions based solely on transactional data (Takac et al. 2011). For future research, it would be fruitful to conduct A/B field experiments (e.g., discounting credit packages for users who just registered to see if an earlier payer conversion drives CLV, or excluding certain payment methods to see if shifting customers to other methods increases their CLV), which would ultimately allow causal claims to be made.

7. Summary

This study had two main objectives: First, to assess how information that is available to digital freemium companies at a customer's initial purchase impacts his/her future CLV, and second, to measure how paying customers' purchase amounts develop with subsequent purchases. For that purpose, we collected registration and purchase data from three digital companies (two online strategy games and a dating platform) operating a non-contractual freemium business model. Combined, our three data sets comprised more than 1.3 million user registrations, of which about 57,000 became paying customers. These users processed more than 195,000 credit purchases and spent about €3 million on the services in question.

We used three kinds of regression models (NB, OLS, and Logit) for our empirical analysis. Our results show that digital companies operating a freemium business model can expect a higher future CLV from users who …

- … become paying customers early after their registration,
- … spend a large amount on their initial purchase, and
- … use specific payment methods (especially credit cards).

Our results are consistent for the two rather distinct business types (gaming and dating) examined; we therefore believe the findings can be applied to other digital freemium business models, as well.

Beyond predicting CLV at an early stage, we saw that users tend to spend an increasing amount in subsequent purchases. However, the likelihood of the purchase amount increasing (or dropping) compared to the last purchase decreases with each additional purchase. We believe that many new users are uncertain about the true value of the credits when they buy them for the first time, and that this uncertainty is dissolved when they decide to make another purchase.

Our data has shown that digital freemium businesses operate in an environment with very heterogeneous users: in one case, 1% of the user base accounted for almost 85% of total revenues. This makes clear how important it is to identify high-potential customers as soon as possible and to give them preferential treatment. Freemium companies can integrate our CLV prediction model into their CRM system to adapt their customer acquisition, retention and monetization strategies accordingly. Changes in CLV should be carefully monitored and used to improve the effectiveness of these strategies.

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Appendix

Payment Method Description

The payment process differs slightly between the two gaming platforms (i.e., data sets 1 and 2), but both include three main steps. First, the user chooses the amount of credits he wants to purchase. Second, he chooses his/her preferred payment method, which then determines the price for the selected credit package. Lastly, the customer confirms his/her choice. He is then directed to the selected payment provider or shown instructions on how to make the purchase. This last step is described in the table below.

Payment method	Description	Available purchase amounts (in €)	Frequency (% of all purchases)	
			Data set 1	Data set 2
Bank transfer	The user is shown the company's bank account number and a reason for payment. The user can use this information to transfer the money.	4.99 - 99.99	5,714 (3.7%)	4,024 (2.5%)
Credit card	The user enters his/her credit card details. The purchase amount is then debited from his/her credit card account.	4.99 - 99.99	8,568 (5.5%)	5,654 (3.5%)
Direct debit	The user enters his/her debit card details. The purchase amount is then debited from his/her bank account.	4.99 - 99.99	5,942 (3.8%)	5,550 (3.4%)
Phone	To process the purchase, the user calls a service phone number from a landline and enters a purchase code. The purchase amount appears on the user's next telephone bill or is debited from his/her prepaid credit balance.	4.99 - 19.99	19,364 (12.5%)	20,552 (12.7%)
Cell phone	Similar to *Phone*, the only difference being the use of a cell phone instead of a landline phone.	4.99 - 19.99	1,420 (0.9%)	1,921 (1.2%)
Prepaid card	The user can purchase prepaid gaming cards which are available from numerous providers at different amounts. After entering the prepaid card's code, the credits are booked.	Mostly 10.00 - 50.00	14,340 (9.3%)	9,391 (5.8%)
SMS	The company sends an SMS with a purchase code to the user's cell phone. Entering this code into the payment screen triggers the purchase. The purchase amount appears on the user's next telephone bill or is debited from his/her prepaid credit balance.	2.99 - 9.99	69,956 (45.2%)	88,917 (54.9%)
Wallet	The user is transferred to an online payment provider (e.g., PayPal) where he/she processes the purchase.	4.99 - 99.99	29,502 (19.1%)	25,995 (16.0%)

Table 19: Detailed Payment Method Description and Frequency in Data Sets 1 and 2

Article III: NETWORK EFFECTS IN TWO-SIDED MARKETS: WHY A 50/50 USER SPLIT IS NOT NECESSARILY REVENUE-OPTIMAL

Abstract

Our study applies empirical scrutiny to the network effects of a leading European online dating platform. While one might expect equal gender representation on such a platform to yield the best user experience and the highest revenue per user, our analysis shows that the platform requires only 36.2% of its user base to be female in order to maximize revenue, primarily because women exert stronger positive cross-side network effects on men than vice versa; this optimum results in 17.2% higher sales than a 50/50 split. Intermediaries of two-sided markets can use our model to improve user acquisition strategies.

Key words: Network effects; Two-sided markets; Online dating; Willingness to pay; Revenue optimization

1. Introduction

In two-sided markets, an intermediary provides a platform enabling two different user groups to interact, for instance to make a transaction in order to satisfy their interdependent demands (Bakos and Katsamakas 2008; Ellison and Ellison 2005; Rochet and Tirole 2003, 2006). Some two-sided online markets have expanded at a furious pace in recent years (Tucker and Zhang 2010). eBay, for example, brings together sellers and prospective buyers of different kinds of goods, Google advertisers and web users, and Prosper lenders and borrowers of private loans (Berger and Gleisner 2009). Eisenmann et al. (2006) provide a comprehensive list of examples for online and offline two-sided markets. Often, a neutral third party manages the platform (Yoo et al. 2002, 2007) with the commercial objective to maximize its own profits by optimally monetizing one or both user groups.

Previous research on two-sided markets indicates that the two user groups exhibit different kinds of network effects (Katz and Shapiro 1985; Liebowitz and Margolis 1994). Users may derive positive cross-side network effects (CNEs) from the participation of members on the other side of the market, which means the larger the installed user base on one side of the platform, the more attractive the service for the opposite side's users (Armstrong 2006; Li et al. 2010; Tucker and Zhang 2010). Network effects can also emerge within one user group, known as same-side network effects (SNEs). For example, a new eBay seller can have a negative effect on other sellers because he or she increases competition between sellers and may snatch away potential buyers (Kraemer et al. 2012; Li et al. 2010).

Utilizing positive network effects and mitigating negative ones is an important challenge for providers of two-sided markets. In recent years, the number of scientific studies which empirically assess such effects has been rapidly increasing (Chu and Manchanda 2013). Yoo et al. (2002, 2007) highlight the importance of identifying the magnitude of the network effects for both user groups, and state that it is difficult to estimate these effects. Knowledge of the direction and the magnitude of network effects can be used to support customer acquisition, pricing, monetization, and IT investment strategies for two-sided markets (Bakos and Katsamakas 2008; Kraemer et al. 2012; Sridhar et al. 2011).

Our empirical study examines a leading European online dating platform. Although online dating is one of the example industries in literature on two-sided markets and seems theoretically very promising for identifying network effects (Armstrong 2006; Caillaud and Jullien 2003; Ellison and Ellison 2005; Rochet and Tirole 2003, 2006), this paper is the first to examine this industry empirically. In our case, the two user groups are heterosexual men and women. The platform enables them to search for each other, to communicate and to initiate real-life dates.

For an intermediary of a two-sided market, it is of interest to know how much future revenue and/or profit can be expected from a given user group; this data informs effective and efficient use of limited budgets (Malthouse and Blattberg 2005; Borle et al. 2008). Prior to our research, between 35 and 41% of the users on the platform in question were women, and the intermediary aimed to reach a 50/50 split in the near future. Naturally, one might think that equal numbers of men and women on such a platform yields the best user experience (then, every woman matches with a man) and thus the highest revenue per user for the platform intermediary. However, this does not take into consideration the differences in the user groups' willingness to pay and how CNEs and SNEs impact user behavior.

Our research aims to determine the direction and the magnitude of the different kinds of network effects on the platform and their impact on revenue, both in aggregate and of each user group individually. In addition to this empirical validation of existing theory, we propose an approach to determine the revenue-optimal ratio of men to women on the platform in light of the various existing network effects. We show that the online dating platform in question can significantly increase its revenue with the proper balance of male and female users.

2. Network Effects in Two-Sided Markets

2.1 Previous Research

Katz and Shapiro (1985) state that for many technologies, users may benefit from a growing user base. Services such as the telephone, e-mail and social networks exhibit positive network effects. These occur if two or more individuals are able to interact within this network, changing their utility of the network.

Two-sided markets have two different user groups. The intermediary provides a platform for the interaction between these groups (Berger and Gleisner 2009; Kraemer et al. 2012; Yoo et al. 2002, 2007). Usually, a user interacts only with participants from the other user group. For example, a retailer aims to sell his or her products on eBay to a certain consumer (not to another retailer), and a heterosexual man looks only for a potential female partner on Match.com.

Such two-sided markets possess network effects across user groups (CNEs) and within a single user group (SNEs). CNEs exist if the number of users on one market side influences the utility of the opposite group's users. On eBay, for example, an increased number of sellers improves the product selection and makes the platform more attractive to buyers. Similarly, having more buyers increases sellers' chance of successfully selling their items, thereby making the platform more attractive to them. SNEs exist if a user's utility is affected by the installed user base of his or her own user group (Armstrong 2006; Eisenmann et al.

2006). For example, more eBay sellers competing for a given number of potential buyers reduce each other's chances of transacting with a buyer. Depending on the investigated market, SNEs can possess either a negative effect (Dai and Kauffman 2006; Villanueva et al. 2008; Yoo et al. 2002, 2007) or a positive one (Bakos and Katsamakas 2008; Eisenmann et al. 2006) on users' utility.

To date, the literature on two-sided online markets has concentrated mainly on two research paths. The first path focuses on pricing considerations that are specific to two-sided markets experiencing network effects and examines which price structure to apply at which price level, and which user group to charge for using the services provided (Armstrong 2006; Chao and Derdenger 2013; Eisenmann et al. 2006; Jullien 2005; Parker and Van Alstyne 2005; Rochet and Tirole 2003, 2006; Rysman 2009). In the case of eBay, the platform may charge sellers, buyers, or both user groups for using the platform.

The second research path investigates the effectiveness of the intermediary's investment decisions and is more closely related to our work. Bakos and Katsamakas (2008) analyze design choices and investments such as the quality of technology, the services offered to each side, and the rules of interaction between the two user groups that create network effects in two-sided markets. Yoo et al. (2002, 2007) offer different strategies to optimize the intermediary's revenue, depending on the ownership model of the platform. Kraemer et al. (2012) find asymmetric network effects on an eBay-like platform and assess the effectiveness of various IT and design investment features in increasing the platform value. Tucker and Zhang (2010) examine the impact of advertising the size of the user base on further participation of buyers and sellers in two-sided markets.

While these studies aim to find the intermediary's optimal strategy (e.g., in terms of revenue or platform value) to invest in IT improvements, quality, or marketing strategies, our paper searches for the revenue-optimal split between the two user groups, after empirically proving all corresponding directions of network effects, considering fixed user fees. In spite of substantial theoretical and methodological work on network effects, Wilbur (2008) as well as Kraemer et al. (2012) state that empirical analyses are still scarce due to a lack of real-life data to properly identify the effects within and across the user groups. Table 20 summarizes the results of these empirical studies and highlights the research gap and the contribution of our paper.

Author(s)	Main research topic(s)	Data gen.	Analysis method(s)	Industry / data set(s)	Economic dependent variable(s)	Considers	
						CNE	SNE
Ackerberg and Gowrisankaran (2006)	NEs for banks and customers	T	Max. likelihood	ACH banking	Number of transactions	Yes	No
Brynjolfsson and Kemerer (1996)	User base on price	M	Semi-log, OLS	Spreadsheet software	Prices	Yes	No
Chacko and Mitchell (1998)	User base on company growth	M	OLS	3 technology sectors	Corporate growth rate	Yes	No
Chao and Derdenger (2013)	NEs on revenue-opt. price structure	M	Regression with IV	Portable game consoles	Associated prices	Yes	No
Chen and Xie (2007)	Implications of customer loyalty	M	Regression	Newspaper	Advertising rate, market share diff.	Yes	No
Chu and Manchanda (2013)	User base on other group's growth	T	Max. likelihood	C2C retail platform	Growth of other user group	Yes	No
Clements and Ohashi (2005)	Indirect NEs, hardw. diffusion	M	Two-stage least squares	Video game systems	Hardware and software adoption	Yes	No
Gandal et al. (2000)	Hardw. prices and softw. on diffusion	M	OLS	CD players and titles	Change in variety and sales	Yes	No
Mantrala et al. (2007)	Marketing invest on profits	M	Two-segment SURE	Newspapers	Subscriptions, ad revenue, sales	Yes	No
Nair et al. (2004)	Indirect NEs in competition	M	Monte Carlo, OLS	PDAs and software	Hardw. demand, softw. provision	Yes	No
Rysman (2004)	Importance of CNEs	M	Nested Logit	Yellow Pages	Consumer and advertiser demand	Yes	No
Rysman (2007)	Card usage and acceptance	M, T	Logit	Payment card transactions	Choice of favorite network	Yes	No
Shankar and Bayus (2003)	Network strength in competition	M	SEM	Video game consoles	Network strength	Yes	No
Wilbur (2008)	Ads on audience size and vice versa	M	Logit	TV ads	Viewer and advertiser demand	Yes	No
Asvanund et al. (2004)	Incremental value of new users	T	Logit, OLS	Peer-to-peer networks	Network value	Yes	Yes
Sridhar et al. (2011)	Optimal marketing invests with CNEs	M	DMR	Local newspaper	Demand from both sides	Yes	(Yes)
Tucker and Zhang (2010)	Installed base on listing behavior	F	Probit	Classifieds platform	Number of listings	Yes	Yes
This Paper	Network effects on revenue; revenue-optimal user split	T	SURE, Logit, OLS	Online dating platform	Revenue, user net gain, number of subscribers	Yes	Yes

Table 20: Empirical Studies Assessing the Economic Results of Network Effects across User Groups

Data generation: F = Field experiment, M = Market level data, T = Transactional company data

Our paper is related to the studies shown in Table 20, but with some notable differences. Chu and Manchanda (2013) state that previous work often focused on the benefits (or costs) a user obtains from additional users from either the same or the opposite user group, but not simultaneously from both sides. As a consequence, many studies thoroughly quantify CNEs, yet do not consider SNEs (e.g., Brynjolfsson and Kemerer 1996) or use lagged sales as a proxy for SNEs (Sridhar et al. 2011). The few existing studies that investigate both direct CNEs and SNEs use their results to model individual behavior (Tucker and Zhang 2010) or network value (Asvanund et al. 2004), while our study examines the direct impact of network effects on the intermediary's revenue, number of users and subscribers. We also notice that most studies employ data on a market level, while our study – as few others – uses a unique transactional data provided by a company. In addition, our work is the first empirical paper that studies network effects in the online dating industry.

2.2 Expected Network Effects on an Online Dating Platform

Online dating. Three parties are involved in such a market, namely the intermediary that provides the platform and the two user groups, women and men, looking for potential partners. For reasons of simplicity (see likewise Armstrong 2006), we focus our analysis on participants looking for users of the opposite gender. Men searching for men and women searching for women are both homogeneous user groups without interaction with other user groups, and thus form a one-sided market, which is not part of our study.

Users of a dating platform clearly belong to one market side. When registering, a new user provides information on his/her gender and whether he/she is interested in meeting men or women. After this, the user typically does not change his/her role. In contrast, an eBay user can both sell and buy items at the same time, which makes it more difficult to identify the occurring network effects.

Most online dating platforms possess a 'freemium' pricing model. On platforms with this model, new users can create a profile for free, browse through the profiles of other users, see who visited their own profile, and send preset short messages known as 'winks' (such as 'your picture looks nice') to other users.

However, only paying users, purchasing a subscription, can start full-text conversations with others and reply to winks. This means that at least one person (man or woman) needs to be a paying user to initiate the contact and possibly a 'first date' later on. A look at (each) the 100 top-grossing dating and social networking apps for iPhone (AppAnnie 2015) in the US, Japan and Germany shows that 30 out of 34 of such apps (i.e., 88%) follow such a freemium strategy.

Kinsey et al. (1948) describe that the traditional gender role expects men to initiate contacts and women to respond. In real-life dating, women usually receive more offers from men than vice versa (Gutek et al. 1990). In addition, Fisman et al. (2006) report from a speed dating experiment that men respond more strongly to their counterparts' physical attractiveness. If this holds true for online dating, one can expect men's willingness to subscribe to the paid service to be stronger than those of women.

CNEs. The main purpose of using an online dating platform is to look for, find, and contact potential partners of the opposite gender. Hence, users of one user group (e.g., men) care especially about the number of users on the other side (in this case: women) (Armstrong 2006; McIntyre and Subramaniam 2009; Tucker and Zhang 2010). Two-sided markets yield effects in which users in one group choose a good that affects another group's choice of a different good (Parker and Van Alstyne 2005). For example, a woman joining the dating platform may motivate men to contact her. Thus, the utility of the platform to a paying male (female) user increases when he (she) can communicate with more women (men) (Yoo et al. 2002), which means that paying users on both market sides enjoy positive network effects from the installed user base on the opposite market side. This network effect can reflect the increased probability of finding a satisfactory match among the other side's users (Bakos and Katsamakas 2008). Keeping the number of men constant, more women offer men a wider variety of matches (Ellison and Ellison 2005; Gehrig 1998), a greater chance of finding a unique fitting match (Caillaud and Jullien 2003), and reduce the competition between men for a specific woman (Dai and Kauffman 2006; Wang and Seidmann 1995; Yoo et al. 2002).

Previous research has shown that positive network effects leading to increased user enjoyment of the underlying service also have a positive impact on customers' willingness to pay (e.g., Borgatti et al. 2009; Brynjolfsson and Kemerer 1996; Farrell and Saloner 1985; Katz and Shapiro 1985). Eisenmann et al. (2006) as well as Ellison and Ellison (2005) show that both user groups in two-sided markets are willing to pay more for access to a bigger network.

CNEs can also positively influence user acquisition (Villanueva et al. 2008) and retention (Chen and Xie 2007; Nitzan and Libai 2011). Single men or women are more likely to join a platform that possesses a large number of relevant users than one that does not (Li et al. 2010). The impact of CNEs on retention or churn however are not trivial in the given freemium context: On the one hand, a smaller number of users of the opposite gender makes a dating service less attractive because the chances of finding a partner are lower. Thus, many users would be frustrated and may sign off earlier. On the other hand, a smaller number of users of the opposite gender may hinder people from signing up to the service (if they know in advance) or aggravate existing users' search for a fitting match, which may then lead to a longer usage lifetime for both sides.

SNEs. While CNEs are usually positive (but not always, as Sridhar et al. 2011 show), SNEs can be commonly found both ways in two-sided markets. For example, positive effects on each user's network utility can be found if game console owners appreciate co-playing and trading games with friends who possess the same console (Eisenmann et al. 2006), or if the platform users create a community that can provide support, collaborate, and share information with other users (Bakos and Katsamakas 2008). However, in most cases, SNEs have a negative effect on users' utility, especially in markets where users prefer fewer rivals (e.g., sellers on eBay competing for the same buyers) (Dai and Kauffman 2006; Li et al. 2010; Tucker and Zhang 2010; Wang and Seidmann 1995). Following the aforementioned idea that the utility of the online dating platform to a specific user increases when he/she can contact more users of the opposite gender, the utility of the service should decrease when there are more users of the same gender (i.e., rivals) competing for the users of the other group.

At any point in time, men and women on the platform can use the search function to check the number of users of each gender. Here, the number of users of the opposite gender is more relevant as users are looking for a partner, not a rival. Still, men/women have to option to search the platform for users of their own gender. In practice however, they often estimate the number of rivals and the chance to find a match based on 'weak signals' such as the number of profile visits they receive from interested users of the opposite gender (Borgatti et al. 2012) or the share of received messages or winks. Having too many rivals may eventually lead to fewer registrations from that user group, faster churn, and/or fewer subscriptions to the charged service. It will be interesting to see if we find substantive negative SNEs at all in our empirical study and how they differ between men and women.

3. Theoretical Validation: Identifying Direction and Magnitude of Network Effects

3.1 Platform and Data Description

In this section we aim to empirically examine the existence and measure the magnitude of various network effects. To do so, we use customer and payment data from a leading European online dating platform that has been operational for approximately ten years. Users can register and create a profile for free. Every user must provide a nickname, his/her gender, place of residence and whether he or she would like to meet men or women. Additionally, users can share profile pictures, age, hobbies and other personal details. All users can actively search and browse through the profiles of other (male or female) users in their vicinity. As mentioned above, we focus on the cases of men searching for women and vice versa.

The online dating platform applies the industry-typical freemium model described in section 2.2: signing up and searching for other users is free of charge; however, users have to subscribe to one of the two available premium packages to be able to initiate conversations with other users. The premium packages, which we refer to as 'Silver' and 'Gold', can be purchased through a monthly subscription and can be renewed at any time. The monthly prices lie between €20 and €60 per month, depending on the length of the subscription (1 to 12 months; longer-term packages incur a lower monthly price) and the chosen package (Gold is more expensive than Silver). The subscription prices were not changed during the entire investigated timeframe and are the same for both women and men. The Silver package allows subscribers to send messages, initiate chats and see which members are interested in their profile. The Gold package additionally highlights its subscribers in the search results and recommends users of the opposite gender in the same city with similar interests and hobbies.

Our data set covers two and a half years, from July 1, 2010 to December 31, 2012 (i.e., 915 consecutive days). We examine the data from one sample city of approximately 100,000 inhabitants. A total of 8,923 users registered within our sample period, of which 40.8% were women.

The analyzed payment data covers all transactions (i.e., subscriptions to a premium package) including the start and end date of the subscription, the product type (Silver or Gold), and the price. All incomplete transactions, such as fraud, chargebacks, and free upgrades ('Try our Gold membership for free for one month') are excluded from the sample. The dating platform generated a total revenue of approximately €90,000 from paying users. The majority (89.3%) of the revenue is produced by male users. Not only do men spend more money on the platform, they are also more loyal to it. The median lifetime (i.e., interval between registration and sign-off) is 102 days for a male user and 75 days for a female user. Table 21 provides a data summary and Table 22 shows the key figures on a daily basis. Additionally, we show in Table 29 of the Appendix that Gold customers have significantly higher daily and total revenue compared to Silver users.

Number of registrations			Median user lifetime in days			Revenue share	
Women	Men	Total	Women	Men	Total	Women	Men
3,640	5,283	8,923	75	102	86	10.7%	89.3%

Table 21: Descriptive Data

	Min.	Max.	Mean	Median	SD
Installed user base	1,365	1,924	1,536.7	1,505	133.0
Number of new registrations	1	22	7.38	7	3.61
Share of paying users in %	3.74	7.71	6.21	6.37	0.92
Share of women in %	35.5	41.1	38.4	38.3	1.1
User age (upon registration) in years	18	99	37.1	35	11.3
Lifetime (of the platform) in days	3,835	4,749	4,292	4,292	264.3

Table 22: Descriptive Data on a Daily Basis, N = 915 Days

3.2 Model and Variables

Kraemer et al. (2012) summarize that network effects in two-sided markets can be measured in several ways. Among them are choice models (e.g., Pavlou 2002; Rysman 2009; Stock and Yogo 2005), diffusion models (e.g., Gandal et al. 2000; Gupta et al. 2009; Chu and Manchanda 2013), vector autoregressions (e.g., Chen et al. 2001) and linear regressions (e.g., Hendel et al. 2007; Seamans and Zhu 2013). To account for the specifications of both user groups, we estimate simultaneous equation models (SURE; seemingly unrelated regression equations), as used by Mantrala et al. (2007) and Sridhar et al. (2011). To address the challenges that outliers pose for some statistical models, we use the Huber-White sandwich estimators (Huber 1967; White 1980) in all our models, thereby obviating minor concerns about the potential failure to meet assumptions, such as normality, heteroskedasticity, or observations that exhibit large residuals, leverage, or influence.

Dependent variables. For the purposes of our study, we consider revenue maximization on a per-user level and in total to be the primary economic variable, and aim to assess to what extent network effects (both CNEs and SNEs) describe the investigated platform's total revenue within a given timeframe. We break down the activity and revenue data on a daily basis. When a user subscribes to a premium package, we split the relevant revenue evenly over the entire subscription period. An example: a free user subscribes to a premium package from January 1, 2012 to March 31, 2012 (i.e., 90 days) for a total of €180, and returns to using the service for free afterwards. In our data set, he/she shows daily revenue of €2 in these three months, and daily revenue of zero before and after. Using this approach, revenue can be stated (for any day) as the product of the average revenue per user and the installed base (per user group). In our regression models, we will consecutively check for network effects, first describing the daily revenue per user (*DailyRevenuePerWoman/Man*), second the net user gains (*NetGainWomen/Men*, i.e., variation of the installed base compared to the previous day), and finally the total revenue (*DailyRevenueAllWomen/AllMen/AllUsers*).

Independent variables. Most research models (e.g., Armstrong 2006; Bakos and Katsamakas 2008; Fudenberg and Tirole 2000; Katz and Shapiro 1985; Pang and Etzion 2012; Yoo et al. 2002) consider network effects to be linear in the size of the relevant user base. For our models in section 3.3, we also employ a linear specification of network effects, counting the number of active *Men* and *Women* as the relevant user bases. Later, in section 4, we use a modified model to ascertain the optimal user split between men and women.

According to the intermediary, most dating customers register in the evening and need some time setting up their profile and uploading appropriate profile pictures. We therefore assume that they start affecting other users with a time lag of one day (see likewise Chu and Manchanda 2013); *Men* and *Women* are therefore the number of users at the end of the previous day. In addition, we consider several control variables such as the platform lifetime in days as well as dummy variables for extraordinary TV events, seasonality, and major updates to the game. These dummy variables are set at 1 if applicable to a certain case, and 0 if not. For example, *Update2* went live on day 4,088; all cases prior to the update have been labeled with 0 and with 1 as of that day. During the sample period of two and a half years, the platform underwent ten permanent game updates such as design changes and the introduction of new features. Table 23 describes the independent variables used in our model.

Covariate	Description	Min	Max	Median	SD
Women	Installed base of female users on the previous day	506	782	572	63.3
Men	Installed base of male users on the previous day	832	1,144	931	73.1
PlatformLifetime	Lifetime of the platform since launch (in days)	3,835	4,749	4,292	264.3
Update1	Bug fixes, selected inactive users deleted	0	1	1	0.34
Update2	Payment website update	0	1	1	0.45
Update3	New payment website	0	1	1	0.49
Update4	Introduction of new flirt game (1)	0	1	1	0.50
Update5	New registration process	0	1	0	0.48
Update6	Introduction of monthly billing (step 1)	0	1	0	0.46
Update7	Introduction of monthly billing (step 2)	0	1	0	0.43
Update8	New Internet law implemented for payment website	0	1	0	0.37
Update9	Monthly billing complete	0	1	0	0.37
Update10	Introduction of new flirt game (2)	0	1	0	0.11
TVevent1	UEFA EURO 2010	0	1	0	0.11
TVevent2	FIFA World Cup 2012	0	1	0	0.16
Winter	Season	0	1	0	0.41
Spring	Season	0	1	0	0.40
Summer	Season	0	1	0	0.46
Fall	Season	(omitted because of collinearity)			

Table 23: Description of the Independent Variables

3.3 Identification of CNEs and SNEs

Our first analysis investigates how network effects describe the average daily revenue per user. The employed SURE model treats the average *DailyRevenuePerWoman* and *DailyRevenuePerMan* (both in eurocent) as dependent variables. We estimate several models to ensure the robustness of our results. We begin considering only the number of users of the same gender as independent variables (SNEs; model 1) and successively include additional parameters: the number of users of the opposite gender (CNEs; model 2), platform parameters (model 3), and eventually seasonal parameters (complete model 4). Table 24 summarizes the results. We detect no change of algebraic signs for the significant variables from one model to another and thus conclude that our findings are robust. We emphasize that these results are only of descriptive nature and we can only assume causality due to the strong theoretical background available in the domain of network effects.

		Dependent variable: *DailyRevenuePerWoman*				Dependent variable: *DailyRevenuePerMan*			
Independent variables		Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Installed base	*Women*	-.00233***	-.00327***	-.00324***	-.00495***		.01414***	.00798***	.00664***
	Men		.00099***	.00203***	.00274***	-.00819***	-.01917***	-.00772***	-.00831***
Platform parameters	*PlatformLifetime*			-.00161***	-.00172***			-.00158***	-.00177***
	Update1			.24203***	.13408			1.92923***	1.177824***
	Update2			.62657***	.6469***			.03142	-.09009
	Update3			.2999***	.24713***			.41002***	.12682
	Update4			-.20911***	-.16894***			.21692**	.56356***
	Update5			.18542***	.18566***			-.87221***	-.85609***
	Update6			-.55129***	-.58451***			-.32383***	-.3563***
	Update7			.57989***	.55077***			.95582***	.83301***
	Update8			.08138***	.10276***			.36529***	.24856***
	Update9			.60853***	.62466***			-.83949***	-.54311***
	Update10			.27583***	.32232***			.5254***	.58091***
Seasonal parameters	*TVevent1*				-.5141***				-1.17277***
	TVevent2				.11135**				.02654
	Winter				-.08727**				.05107
	Spring				-.07847*				.07906
	Summer				-.02351*				.41086***
Constant		2.77099***	2.23918***	7.3951***	8.34538***	14.97672***	16.99564***	14.79339***	17.02908***
Number of observations (days)		914	914	914	914	914	914	914	914
R^2		.1199	.1259	.5316	.5485	.3664	.5229	.7018	.7444

Table 24: Results from SURE Model (Dependent Variables: *DailyRevenuePerWoman* and *DailyRevenuePerMan* in Eurocent)

*p<.1; **p<.05; ***p<.01

As we expected, we see that male users generate a much higher basic daily revenue (Constant is 17.03, p<.01) compared to female users (8.35, p<.01). Without considering any network effects, adding more men to the platform would therefore be much more remunerative than adding additional women. However, our model also finds support for negative SNEs on both sides: we can see that the installed base of female users *Women* is negatively correlated (p<.01) with *DailyRevenuePerWoman*, as *Men* is with *DailyRevenuePerMan*. We can also find positive correlations between *Men* and *DailyRevenuePerWoman* as well as between *Women* and *DailyRevenuePerMan*. Both are highly significant (p<.01) and support positive CNEs. Looking at the magnitude of the network effects, we see that the positive CNEs that women exert on men are stronger than vice versa (.00664 vs. .00274). Moreover, the negative SNEs effected by women are weaker than those by men (-.00495 vs. -.00831). While such positive CNEs could be expected, it is interesting to see that we find significant negative SNEs in both cases. Users – and primarily men – are indeed affected by stronger competition, which leads to reduced user expenditures on the focal service.

Next, we estimate a SURE model with *NetGainWomen* and *NetGainMen* as dependent variables. For each day, *NetGainWomen/Men* describes the change of the installed user base (per user group) compared to the previous day (i.e., new registrations minus churners). Table 25 shows the results.

		Dependent variable: *NetGainWomen*				Dependent variable: *NetGainMen*			
Independent variables		Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Installed base	*Women*	-.0052943*	-.0187988**	-.0647049**	-.063719**		-.0106566	-.0410637	-.022364
	Men		.0130922**	-.0237064	-.0366864	-.0074022*	.0030014	-.0538267**	-.0760516**
Platform parameters	*PlatformLifetime*			-.0016744	-.0137804**			.0055423	-.0073152
	Update1			-14.54164*	-16.75659*			-16.51846***	-17.78324*
	Update2			.2594894	3.189207			-1.454399	2.120249
	Update3			-2.506983	-1.784541			-3.559547*	-2.754921*
	Update4			-.4020995	-.5808471			-1.340044	-1.788673
	Update5			.2353828	1.926006			1.081561	3.278738**
	Update6			-1.83712**	.2069084			-.9842817	2.111515*
	Update7			4.191521***	4.927273***			3.126861*	3.290054
	Update8			1.401801	2.04894			-1.848275	-1.146902
	Update9			-1.101929	-.6813836			.7950864	1.252844
	Update10			-1.498372	-2.560496			-.5833106	-2.264057
Seasonal parameters	*TVevent1*				-5.24849				-.0268828
	TVevent2				.5644956				1.164045
	Winter				1.771118*				2.985986***
	Spring				-.6904099				-.5966981
	Summer				-.3859537				-.001084
Constant		3.017029*	-1.380181	81.15897**	142.6788*	6.891396*		68.70649*	129.7221*
Number of observations		914	914	914	914	914	914	914	914
R^2		.0003	.0070	.0932	.1046	.0001	.0050	.0898	.1037

Table 25: Results from SURE Model (Dependent Variables: *NetGainWomen* and *NetGainMen* in Number of Users)

**p*<.1; ***p*<.05; ****p*<.01

While we cannot find any significant CNEs (in the final model), we observe significant negative SNEs on both user sides. The more women (men) on the platform, the higher the number of churning women

(men). We interpret this result as a competition effect that strengthens the negative SNEs we have seen regarding *DailyRevenuePerUser*: in case of strong competition, users do not only tend to stay free users, but they are also more likely to leave the platform. We do not observe positive reputation or popularity effects (i.e., the site growing faster as prospective customers learn that more people are using it; see Table 201 in the Appendix for a respective analysis).

These results are especially interesting as they indicate that each user group has a reasonable maximum size. With additional users, it becomes increasingly hard (and probably expensive) for the intermediary to acquire and keep users of a certain gender. At such a point, it may become more effective to acquire new users of the opposite user group (which brings us to the determination of the optimal split between men and women in section 4.2).

We will now examine the impact on total daily revenue that additional *Women* and *Men* have. Table 26 displays the results of this analysis. Consistent to our previous analyses, we employ a SURE model to estimate *DailyRevenueAllWomen* and *DailyRevenueAllMen*, while we apply a separate OLS regression model to estimate *DailyRevenueAllUsers*.

		Dependent variable: *DailyRevenueAllWomen*			Dependent variable: *DailyRevenueAllMen*			Dependent variable: *DailyRevenueAllUsers*		
Independent variables		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Installed base	*Women*	-.0094565***	-.0121272***	-.0207466***	.1214191***	.0768262***	.0687561***	.1119683***	.0647126***	.0480195**
	Men	.006163***	.0132575***	.0160938***	-.1057493***	-.002672	-.0128498	-.099591***	.0105712	.003222
Platform para-meters	*PlatformLifetime*		-.0118641***	-.0123831***		-.011132**	-.0136595**		-.0229988***	-.0260558***
	Update1		1.561665**	.96887		19.52734***	18.02646***		21.08901***	18.99346***
	Update2		3.971721***	3.924199***		-.2991901	-1.652735		3.672342***	2.274371*
	Update3		1.774566***	1.370269***		3.258874***	.6961245		5.033364***	2.066448***
	Update4		-.8161869***	-.3984026		1.27061	4.795525***		.4548655	4.39736***
	Update5		1.086508***	1.056412***		-7.615938***	-7.457788***		-6.527697***	-6.397927***
	Update6		-2.937902***	-3.147122***		-3.04403***	-3.270945***		-5.981674***	-6.415782***
	Update7		3.465234***	3.204152***		8.563072***	7.528386***		12.02826***	10.73254**
	Update8		.6102715***	.7128671***		3.106759***	2.044481***		3.715196***	2.756013***
	Update9		3.714678***	3.994181***		-8.110425***	-4.956301***		-4.394706***	-.9608749
	Update10		1.422225***	1.652886***		4.824756***	5.087945***		6.24615***	6.739328***
Seasonal para-meters	*TVevent1*			-3.454805***			-17.28362***			-20.74243***
	TVevent2			.7322851***			.1460649			.8795812
	Winter			-.3442243			1.083799*			.740641
	Spring			-.2320078			1.421362*			1.187716
	Summer			.1909255			4.473041***			4.663272***
Constant		7.894175***	47.7862***	53.14111***	96.13324***	55.66326**	81.10901**	104.0282***	103.4657***	134.3192***
F		n/a	n/a	n/a	n/a	n/a	n/a	94.58	134.42	148.57
Number of observations		914	914	914	914	914	914	914	914	914
R^2		.0135	.4211	.4429	.2051	.4786	.5530	.1506	.4363	.5215

Table 26: Results from SURE Model (Dependent Variables: *DailyRevenueAllWomen*, *DailyRevenueAllMen* in €) and OLS Regression (Dependent Variable: *DailyRevenueAllUsers* in €)

*p<.1; **p<.05; ***p<.01

We can see that additional women always generate additional revenue. Despite the negative SNEs leading to lower daily revenue per woman (Table 24), higher churn of female users (Table 25) and lower total revenue from women (Table 26), more women still have a positive revenue effect because of the positive CNEs they exert. While one additional female user reduces the daily *DailyRevenueAllWomen* by €0.21, it has a positive effect on the daily *DailyRevenueAllMen* of €0.69, which eventually increases *DailyRevenueAllUsers* by €0.48 per day. We see that a user's basic willingness to pay including positive CNEs overcompensates here the negative SNEs.

On the other side, despite being the main payers (independent of network effects), increasing the number of men does not always mean additional revenue. While we can find significant positive CNEs on *DailyRevenueAllWomen*, the effect of purely adding male users to *DailyRevenueAllMen* and *DailyRevenueAllUsers* is insignificant, mostly because of the aforementioned negative SNEs. Knowing of the existence of these effects, we aim to find to revenue-optimal split of men and women in the next section.

4. Practical Application: Determining the Revenue-Optimal Share of Men and Women

4.1 Motivation and Numeric Example

Most two-sided markets are managed with the objective of maximizing profit generation via the paying installed user base (Yoo et al. 2002, 2007). Due to budgetary constraints, intermediaries are only able to acquire and serve a finite number of users. Such intermediaries may fail to maximize their revenue if they do not consider the network effects present on their platform. To demonstrate how such circumstances can lead to mismanagement of the platform, we will now examine a numerical example using the results from our previous analyses.

In section 3.3, we found that male users spend more money on average than female users, but female users carry an additional indirect revenue potential because the positive CNEs they exert on revenue generated per male user are stronger than vice versa. Additionally, the existing negative SNEs are stronger for men than for women. We apply these results to the simplified numerical example in Table 27.

Variable name	Description	Group 1: Men (*m*)	Group 2: Women (*w*)
$prob_m$ / $prob_w$	Basic probability to become a paying user	6%	2%
fee_m / fee_w	Avg. fee per paying user	€100	€100
CNE_m / CNE_w	Positive CNEs on other user group's revenue per user	€0.02	€0.06
SNE_m / SNE_w	Negative SNEs on same user group's revenue per user	-€0.015	-€0.01

Table 27: User Characteristics in a Fictitious Two-Sided Dating Market

For our example we assume the network provider possesses a budget to acquire 100 users of any gender and is looking for the split between men m and women w yielding the highest overall revenue. Total revenue equals the sum of the revenue generated by both men and women:

(1) $Rev_{m,w} = m\ prob_m fee_m + \ w\ prob_w fee_w$ with $m + w = 100$

In this stylized two-sided market men are more likely to become paying users than women ($prob_m$ = 6% vs. $prob_w$ = 2%). In both groups, paying users pay the same average fee ($fee_m = fee_w$ = €100). This means an average man generates revenue of 6% · €100 = €6, while a woman generates on average only 2% · €100 = €2. An intermediary who does not consider network effects would thus conclude that they should only acquire men as users and not a single woman.

This strategy, however, seems clearly questionable as a dating platform without women offers men no reason to become paying users on. We will now consider the impact of CNEs and SNEs upon the basic purchase likelihood. As shown in the following quadratic equation, each user's expected revenue is influenced by positive CNEs from all users of the opposite gender and negative SNEs from all other users of the same gender.

(2) $Rev_{m,w} = m \cdot (prob_m fee_m + CNE_w w + SNE_m \cdot (m-1)) + \ w \cdot (prob_w fee_w + CNE_m m + SNE_w \cdot (w-1))$
with $m + w = 100$

Differentiating the revenue formula (2) with respect to m and setting the derivate to zero allows to determine the revenue-optimal split of male and female users (we expand this process in section 4.2). Figure 9 shows the total revenue in our example of all male and female users combined when considering user-split dependent network effects. Changing the share of women (i.e., the horizontal axis in Figure 9) shows two effects: First, as men generally have a higher probability for becoming paying users, the revenue stemming from this basic likelihood is highest with more men, even in light of the negative revenue impact of SNEs. Second, an elevated proportion of female users exerts CNEs, which have the highest positive revenue impact at 50% of the user base. The CNE-induced revenue curve follows an inverted U-shaped form, and the revenue surplus is incrementally reduced with a lower/higher share of women. Taken together, these effects lead to a revenue optimum at circa 67% men and 33% women. Given the same total number of users, the intermediary's revenue is 5.4% higher than in a 50/50 user split (€567.99 vs. €538.75).

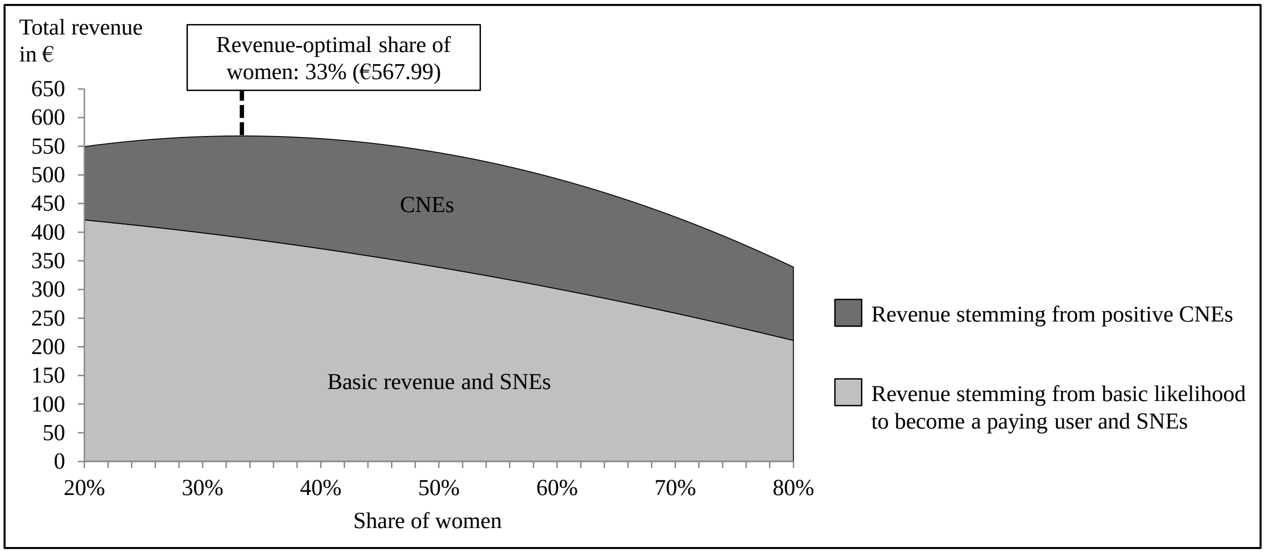

Figure 9: Revenue-Optimal Share of Women in the Numerical Example

This simple example demonstrates that intermediaries with knowledge of network effects can make better business decisions, for example by identifying and profitably acquiring those customers who promise the highest revenue contribution to the network; such an identification enables the intermediary to optimize the user split on their platform.

4.2 User Split Optimization for the Investigated Platform

We will now use authentic data to empirically determine the optimal ratio of male to female users with regard to the highest possible revenue generation. Our approach is usable for platform intermediaries in two-sided markets that aim at an effective use of their limited user acquisition budgets.

In this section, we use the same data set as in section 3 with slightly adjusted variables in the OLS model. First, we now use *DailyRevenuePerUser* as the dependent variable (i.e., *DailyRevenueAllUsers* / *Users*) to ascertain the proportion of women that yields the best results. We also replace the previously used absolute user numbers *Men* and *Women* with a dependent variable which represents the proportion of female users, both in linear and quadratic form (*ShareOfWomen* and *ShareOfWomenSquared*, each as a percentage of total users). All other variables remain the same as those in Table 24. Table 28 shows the results of the employed regression model.

		Dependent variable: *DailyRevenuePerUser*		
Independent variables		Model 1	Model 2	Final model 3
User split	*ShareOfWomen*	334.2746***	312.4332***	346.8351***
	ShareOfWomenSquared	-468.437***	-428.2298***	-479.6163***
Platform parameters	*PlatformLifetime*		.00136***	.00159***
	Update1		.06716	.29307***
	Update2		.13269*	-.27801***
	Update3		-.25703***	-.17709**
	Update4		-.36184***	-.14882
	Update5		-.5221***	-.70081***
	Update6		.29947***	-.05956
	Update7		-.68634***	-.53678***
	Update8		.33535**	.40668**
	Update9		.53921***	.69158***
	Update10		.21367	.36379*
Seasonal parameters	*TVevent1*			.38896*
	TVevent2			-.07567
	Winter			-.08448
	Spring			.49053***
	Summer			.24884***
Constant		-56.39442***	-58.46802***	-65.29321***
F		162.70	347.90	258.91
Number of observations		1,005,275	1,005,275	1,005,275
R^2		0.0002	0.0034	0.0035
Optimum (highest revenue dep. on share of women)		35.7%	36.5%	36.2%

Table 28: Results from OLS Regression (Dependent Variable: *DailyRevenuePerUser* in Eurocent)

*p<.1; **p<.05; ***p<.01

Table 28 shows positive linear and negative quadratic influence of the proportion of female users on total revenue per user, which yields a single point of female-dependent maximized revenue. The regression formula (3) slightly differs from the equation used in the numeric example (2) as we are not restricted to a total of 100 users and have different variables compared to the previously used, simplified model. Differentiating the abridged regression formula (3) shown below with respect to *ShareOfWomen* and setting the derivate to zero (4) yields a critical point at a proportion of female users of 36.2% (5). As we can easily see from (4), the function's second derivative is negative and the identified point is therefore a local maximum in terms of revenue: the desired revenue-optimal proportion of female users.

$$(3)\ DailyRevenuePerUser = \beta_0 + \beta_1\ ShareOfWomen + \beta_2\ ShareOfWomenSquared + \ldots + \varepsilon$$

$$(4)\ \frac{d\ DailyRevenuePerUser}{d\ ShareOfWomen} = 346.8351 + 2 \cdot (-479.6163) \cdot ShareOfWomen = 0$$

$$(5)\ (Optimal)ShareOfWomen = \frac{-346.8351}{-2 \cdot 479.6163} = 36.2\%$$

Similar to the previous approach, the Logit regression model in Table 202 (in the Appendix) aims to assess the proportion of women yielding the highest share of paying users. In both analyses, we find similar results: a share of women of 34.6% leads to the highest share of premium subscribers, while 36.2% maximizes the intermediary's revenue. Below this optimum, additional female users contribute higher utility to the overall network (through positive network effects) than men, leading to either more subscribers or additional revenue. When the optimum is surpassed, adding more men to the platform will be more valuable than adding more women.

Figure 10 illustrates the relationship between the share of female users and its correlation to the expected total revenue. Like in our numerical example, the curve has an inverted U-shape. As shown previously in Table 22, the proportion of women fluctuated between 35.5% and 41.1% over the course of our 915-day observation period. However, our results show that, given a constant number of users, the intermediary's total daily revenue will be approximately 2% higher with a women's share of 36.2% compared to the historical maximum of 41.1%, and a full 17.2% higher compared to a 50/50 split. Our results display that the intermediary in our study should abandon its previous goal of reaching a 50/50 user split.

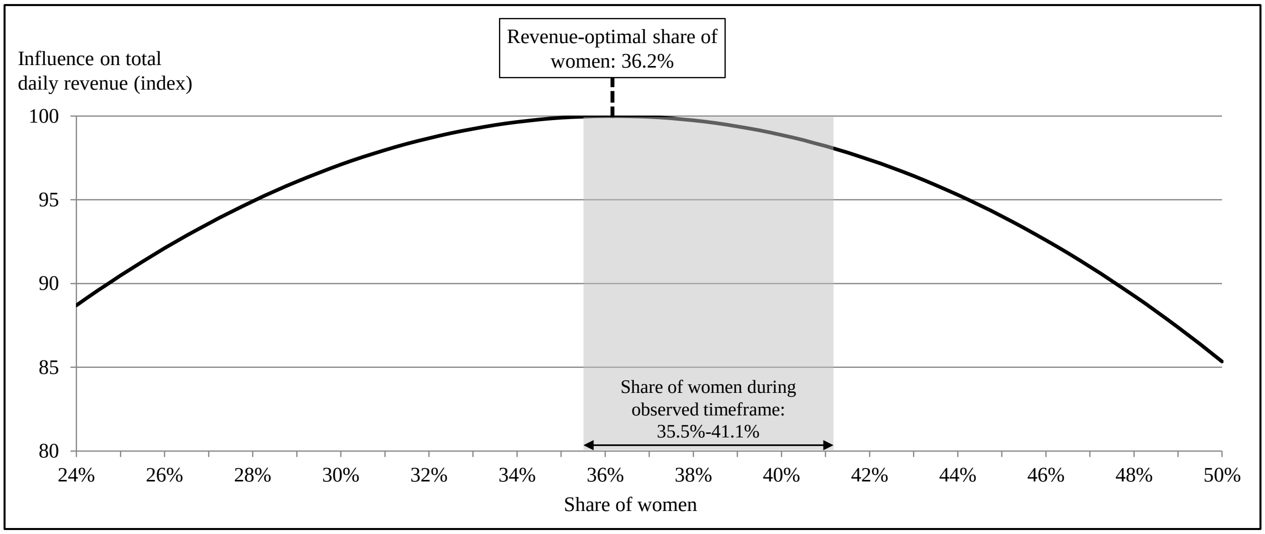

Figure 10: Revenue-Optimal Share of Women

5. Discussion

5.1 Research Contributions

Our study investigates users' spending behavior on an online dating platform. Despite progress in gender equality, findings from more than 60 years ago (Kinsey et al. 1948) still seem to apply. Asymmetric societal norms still exist in people's mate searching behavior that prevent women from making the first move (Bapna et al. 2012; Fisman et al. 2006; Piskorski 2012). This aspect certainly accounts for the results of our study, where we could see men are more likely willing to pay for online dating services assuming a sufficient installed user base of women than vice versa.

Our study identifies the existence and the magnitude of the various network effects in this market. Estimating a SURE model reveals positive CNEs in both directions: having more female users increases the average revenue per male user and the total revenue generated by men, and vice versa. A larger choice set of potential partners increases the chance of a free user finding someone he/she is interested in and eventually subscribing to a premium package that allows him/her to send messages to other platform users.

Furthermore, we find negative SNEs for both men and women. Increasing the number of women reduces the revenue per woman, leads to a higher churn of female users, and reduces the total revenue generated from the installed base of women. Increasing the number of men reduces the revenue per man and leads to a higher churn of male users while there is no significant negative impact on total revenue. In the given freemium model, free users might be deterred from purchasing the premium package if there are too many people competing for a given number of users of the opposite gender. Existing premium users who send messages to potential partners may receive fewer answers if there is too much competition, and become frustrated. As a consequence, the share of customers who renew their subscription may decrease and the number of users leaving the platform may increase.

In addition, we observe that the positive CNEs that women exert are stronger than the SNEs on the women's side. As long as the number of male users clearly exceeds female ones, more women always mean extra revenue. For men, we could not find statistical support in this case. As a combination of positive CNEs and substantial negative SNEs, the total revenue impact of solely increasing the number of male users is not significant.

5.2 Practical Contributions

We have shown that operators of two-sided markets who aim to optimize their revenue can use information on network effects to acquire, manage and monetize their user base more effectively. We present an approach that determines the optimal split between the two user groups in terms of revenue and the number of premium subscribers. We find a positive linear and a negative quadratic influence of the proportion of women on revenue and number of subscribers. Thus, the utility of incremental women (who are the user group that exert the strongest CNEs) for the entire network follows an inverted U-shape. This is in line with the work by Bapna and Umyarov (2012) who discovered in an online social music network that the strength of influence decreases with a user's number of friends. Our model can be easily extended, for example to other regional markets, or to any other two-sided platform with network effects.

We find that a female proportion of the user base of 34.6% leads to the highest share of premium subscribers, while the revenue-optimal proportion of women was 36.2%. As the platform's share of female users was at circa 40% and therefore above the revenue optimum at the end of our observation timeframe, acquiring more male users promised higher future revenue at that time. Our findings are in conflict with the intermediary's initial strategy to achieve a 50/50 user split between women and men. Our results indicate that the optimal user split generates 17.2% more revenue with the same number of users than the targeted, intuitive 50/50 split.

The company that provided us with the data used the results from our analysis to develop a decision support system that assesses the expected customer lifetime value of an additional male or female user. The system is continuously collecting information to provide an updated assessment of the revenue-optimal share of women at any time. This allows the company to identify those users who promise the highest incremental value for the platform and to adapt its customer acquisition strategy accordingly. Based on our static results from the end of our observation timeframe, the network intermediary relocated its marketing budgets to acquire more male users; it adapted the costs per install (CPI) for new users according to the CLV projection for new users and launched a marketing campaign that primarily targeted male singles.

5.3 Limitations

The limitations of our study offer several avenues for interesting future research. First, there are other possible ways to measure the influence of network effects on revenue. Besides the employed SURE, OLS and Logit regression models, a random-effects or fixed-effects panel data model would also be appropriate. Alternatively, a hazard model could be used to better understand the dynamics of the development. In our work, we employed a linear – and for the optimization problem additionally a quadratic – specification of network effects. Apart from these forms, logarithmic and polynomial relationships (or combined functions; Asvanund et al. 2004) between the installed user base and dependent economic variables are also possible.

Second, unobserved causes may exist that could bias the estimates of network effects (Liu et al. 2007). It is hard to imagine that omitted variables could easily reverse the assessed direction of the network effects. However, the estimated coefficients may still be biased in terms of their magnitude (Kraemer et al. 2012).

We tried to employ instrumental variables but failed to identify valid orthogonal variables. This would have certainly helped us to build additional confidence in our results.

Third, the observed network effects are likely to strongly depend on the underlying price model. In our study, we observe that additional female users increase male users' willingness to pay more strongly than vice versa. Depending on the magnitude of the (asymmetric) CNEs, several researchers suggest increasing the price difference between the two user groups on a two-sided market (e.g., Strauss 1999) or to charge only one user group and give away the service to the other under certain conditions (e.g., Armstrong 2006; Bakos and Katsamakas 2008; Caillaud and Jullien 2003) – a possible (but in practice hardly used) strategy for dating platforms that might yield a different revenue-optimal user split. Jullien (2005) provides a list of possible price models for intermediaries in two-sided markets. Empirical testing of the impacts of a price model change (e.g., moving from a subscription-based to a transaction-based pricing model) upon the revenue-optimal user split would be a worthwhile supplement to the examination carried out in our study.

Lastly, not only price model changes but also price level changes may alter the network effects and thereby the revenue-optimal proportion of women in the user base of such a platform. In our case, the intermediary kept prices fixed during the entire observation period; however, a price change may result in a new optimal user split, depending on each user group's respective price sensitivity.

6. Summary and Conclusion

This study's objectives were to empirically assess the influence of CNEs and SNEs on revenue in a two-sided online network and to derive the revenue-optimal split between the two user groups, men and women. Therefore, we investigated a leading online dating platform's user activity and payment data over a period of two and a half years. Our sample covered 8,923 users in one city who spent approximately €90,000 by subscribing to one of the premium packages offered by the platform provider.

In general, men are more willing to pay for dating services than women (if the installed base of women is sufficiently large). Additionally, we observed that both user groups (i.e., male and female users) exert positive CNEs with regard to revenue and user enrollment of the other group; however, the positive CNEs women exert on revenue generation per man are stronger than vice versa. Moreover, we identified negative SNEs which lead to lower revenue per user and an increased churn rate on a market side, when that side exclusively grows.

Operators of two-sided markets can use information regarding asymmetric network effects such as these in order to acquire, manage, and monetize their user base more effectively. For the online dating platform in our study, we calculated the revenue-optimal user split and found that a female proportion of the user base of 36.2% yielded 17.2% more revenue than a 50/50 split for the same total number of users. Our model is transferrable not only to other online dating platforms, but to all kinds of two-sided markets with network effects. Platform intermediaries can use the results from this optimization problem to develop more efficient user acquisition and monetization strategies.

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Appendix

Additional Information on Silver and Gold Packages

The dating platform offers two different subscriptions (Silver and Gold). Following our argumentation in section 2.2, a growing number of users of the opposite gender should increase a user's utility of the subscription packages and his/her willingness to subscribe to the Gold product. At first glance, this should more beneficial to the intermediary, as the subscription's price (per day) is higher for Gold than for Silver. However, if Gold customers unsubscribe faster than Silver customers, their revenue per day would be higher, but their total revenue contribution might be lower. For example, a Silver customer generating €1 per day for 90 days creates a total revenue of €90, while a Gold customer generating €1.50 for 30 days has a higher revenue per day, but a lower total revenue of only €45. We checked our data for this potential conflict and conducted an independent t-test on a sample of all 636 subscribers. Table 29 shows that Gold customers have statistically significantly higher daily and total revenue compared to Silver users, while we cannot find significant differences in terms of the length of a subscription. Overall, we can consider that customers subscribing to the Gold package generate higher revenue than Silver customers.

		Silver customers	Gold customers	*p*-value (t-test)
# of subscriptions		595	41	-
Revenue per day	Average	€1.07	€2.06	0.003
	Median	€0.98	€1.31	
	SD	€0.98	€4.01	
Subscription length in days	Average	165	160	0.886
	Median	93	152	
	SD	214.9	132.8	
Total revenue per subscription	Average	€133.95	€204.26	0.000
	Median	€89.70	€199.26	
	SD	€147.34	€156.57	

Table 29: Silver vs. Gold Subscriptions: Comparison of Duration and Revenue

Additional Analytical Results

		Dependent variable: *NetGainWomen*			Dependent variable: *NetGainMen*		
Independent variables		Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Installed base (total)	*Users*	-.0016396	-.0443007***	-.0497915*	-.0033078	-.0474156***	-.0500245*
Platform parameters	*PlatformLifetime*		-.0020917	-.0148538**		.0056722	-.0051835
	Update1		-15.03112***	-16.96543*		-16.36608***	-17.36849*
	Update2		.2033772	3.326949*		-1.436931***	1.846689
	Update3		-2.532174**	-1.657824		-3.551705***	-3.006583*
	Update4		-1.004848	-.894958		-1.152406	-1.164841
	Update5		1.528642	2.69635*		.6789633	1.748814
	Update6		-1.40788	.6638192		-1.117906	1.204078
	Update7		4.228326***	5.070342***		3.115403**	3.005915
	Update8		1.447247	2.048838		-1.862423	-1.146699
	Update9		-1.505206	-.7951453		.9206287	1.478778
	Update10		-1.061267	-2.555395		-.7193835	-2.274187
Seasonal parameters	*TVevent1*			-4.914585			-.6900263
	TVevent2			.3246244			1.640435
	Winter			2.176263**			2.181358**
	Spring			-.5037326			-.9674439
	Summer			-.2441007			-.2828075
Constant		2.406945	90.62937***	151.0396**	4.975004	65.75831**	113.1174
Number of observations		914	914	914	914	914	914
R^2		.0012	.0899	.1035	.0041	.0896	.1002

Table 30: Results from SURE Model (Dependent Variables: *NetGainWomen* and *NetGainMen*)

$^*p<.1$; $^{**}p<.05$; $^{***}p<.01$
Note: *Users* is the total installed base (i.e., *Men* + *Women*) at the end of the previous day.

		Dependent variable: *IsPayer*		
Independent variables		Model 1	Model 2	Model 3
User split	*ShareOfWomen*	168.1591***	198.7777***	219.8497***
	ShareOfWomenSquared	-232.8991***	-285.3661***	-317.5482***
Time parameters	*PlatformLifetime*		.0007249***	.0008232***
	UserLifetime		-.000601***	-.0006021***
	Update1		.0038217	.0220544
	Update2		.0106529	-.0783018**
	Update3		-.0309305	.0075203
	Update4		-.1802073***	-.1577811***
	Update5		-.0754961**	-.1610922***
	Update6		.1274491***	.0378605
	Update7		-.1883186***	-.1205443***
	Update8		.1423438**	.1926842***
	Update9		.1261103**	.1554679***
	Update10		.0661558	.0442279
Seasonal parameters	*TVevent1*			.2236641***
	TVevent2			-6.59e-06
	Winter			.0374548*
	Spring			.1818007***
	Summer			.0576748***
Constant		-33.53169***	-40.6881***	-44.57342***
Number of observations		1,005,275	1,005,275	1,005,275
Pseudo R^2		.0021	.0172	.0175
Optimum (highest share of payers dep. on share of women)		36.1%	34.8%	34.6%

Table 31: Results from Logit Regression Analysis (Dependent Variable: *IsPayer*)

*p<.1; **p<.05; ***p<.01

To determine the share of women (and men) that results in the highest number of premium subscribers, we build a Logit regression model with a random sample of our data set consisting of approximately one million data points (i.e., user-day-combinations). It comprises 5,643 users with an average lifetime of approximately 178.1 days. We use *IsPayer* (i.e., 1 for paying customers, 0 for free users) as the dependent variable and the share of female users, both in a linear and a quadratic form (*ShareOfWomen* and *ShareOfWomenSquared*, each in percentage of all users) as additional independent variables. To account for user dynamics, we also add *UserLifetime*, which is (starting with 1) the number of days since a user's registration. All other variables remain the same as those in Table 5. The regression results show a positive linear and a negative quadratic influence of the share of women on the number of premium subscribers.

Article IV: ASSESSING THE ECONOMIC EFFECTS OF SERVER LAUNCHES IN FREE-TO-PLAY MMO GAMES

Abstract

In MMO (massively multi-player online) games, the interaction among thousands of players can produce both positive and negative network effects. It is therefore crucial for a company managing MMO games to establish how the entire user base should be distributed across different game instances (‘servers’) in order to optimize the players’ game experience and, ultimately, the company’s revenues. While splitting the user base onto different game servers is a common measure in the industry, there is a conspicuous lack of clear guidelines as to when launching new game servers would be advisable. Our work notably fills this gap: for a popular MMO real-time strategy game, our counterfactual simulation shows that a division of the user base across different game servers can lead to additional revenues if implemented at the right time. For the game in focus, our results indicate that launching multiple new game servers would be beneficial in terms of revenue when the game was new, and additional servers every 90 to 120 days when it was in decline.

Key words: Free-to-play MMO gaming; Network effects; Server launch strategy; Counterfactual simulation; Revenue forecasting

1. Introduction

With an estimated annual turnover of $99.3bn world-wide in 2016 (Newzoo 2016), video gaming revenues exceed those of the global film box industry (i.e., approx. $38bn in 2015; The Hollywood Reporter 2015). MMO (massively multi-player online) gaming has become a $29.1bn market (Newzoo 2016) that is expected to grow furthermore within the next years. In this kind of games, players are simultaneously interconnected, taking part in the same game world. Social interaction with others plays a key role. Depending on the game type, players battle each other, trade goods, chat or team up against opponents.

Many researchers (e.g., Bonardi and Durand 2003; Lin and Kulatilaka 2006; Venkatraman and Lee 2004) name video gaming as a typical industry where network effects occur. However, the studies often focus on investigating indirect network effects that occur from complementary products (e.g., a game console plus a range of games that run on it; Clements and Ohashi 2005; Shankar and Bayus 2003).

In MMO games, the user base may exert strong direct network effects that can be both positive and/or negative. It is realistic to assume that many players join these games because they wish to interact with other users (Siitonen 2007, p. 22; Yee 2006). Then, additional co-players add benefit to the gaming community (Gupta and Mela 2008). A growing user base can improve the game experience, and eventually the players' willingness to pay increases (Farrell and Saloner 1985; Katz and Shapiro 1985). On the other hand, one might also expect negative effects with a larger user base, especially in games where competition between players is central to the game experience: if players consider beating a disproportionate number of users as unrealistic, they might cease playing the game or might not be willing to pay for it (Lin and Sun 2011; Locke and Latham 1994).

To utilize the positive effects stemming from the user base and to mitigate negative ones, gaming companies often distribute their users on different game servers. In our paper, we use the term 'game server' synonymous to 'game instance', and not to hardware performing computational tasks. Launching new game servers in MMO games is a common measure in practice. Gaming companies create new servers on a regular basis to produce new impulses for the user base and to distribute players more effectively on the game servers. If different game servers exist, a new player signing up can choose on which server he wants to play. Based on his decision, he co-plays only with the other users on this game server and usually has no interaction with players on any other game server. With fewer users on a server, a player's chance of reaching a satisfying ranking in the score table (1st, 2nd, 3rd place etc.) increases. On the other hand, players may realize in such a case that their good ranking is only due to a reduced competition and is not that valuable anymore.

The MMO gaming market has become a highly contested market in the past few years. Although the number of empirical studies has been rapidly increasing in recent years, it is still an under-researched area given its business size and expected future growth. Optimally distributing the user base has become an increasingly important monetization challenge, however companies lack sophisticated models how to forecast the revenue impact of such server launches. In practice, determining the timing when to launch a new server is typically not purely data-driven, but mainly based on gut feeling and previous experience, and the outcomes may thus not be optimal.

Our study investigates in an MMO gaming context if and how server launches can be used to generate extra revenues. We theoretically and empirically assess to what extent the user base, a server's lifetime, and other parameters impact players' spending behavior in the game. Due to their large size and the complexity of their interactions, the topology of these kinds of networks is largely unknown (Barabási and Albert 1999). To gain a better understanding on the dynamics of the investigated player network, we use a high-quality and unique data set provided by a major European gaming company, comprising more than four years of data on user activity and payment information for a leading free-to-play MMO real-time strategy game. For 20 real server starts, we conduct a counterfactual simulation to validate whether or not the strategy chosen by the company yielded the highest possible revenue. For the parametrization of the simulation, we use the results from a regression model built upon the same data set. Simulation studies in connection with empirical parameterization are considered a promising research tool in social sciences and economics (Reiss 2011); however, they also bear risks which we discuss later in more depth.

Business problems of this kind are very common in networked industries such as online dating, peer-to-peer networks, and classified marketplaces. Several studies (e.g., Asvanund et al. 2004; Butler 2001; Henderson and Bhatti 2001) show that the network value of incremental users differs and can even be negative under certain circumstances. If new users do not add value to an existing network, it may make sense to allocate them to a different network, or (in MMO gaming) to a different game server.

To the best of our knowledge, our study is the first of its kind. Our findings will help researchers to get a better understanding of server launch effects, and gaming companies to better monetize their user base. The presented model can also be applied to other online services splitting their user base, such as the aforementioned classifieds marketplaces, peer-to-peer networks or social networks.

2. Industry and Theoretical Background

2.1 Free-to-Play MMO Games

The gaming database MobyGames (2016) now lists around 105,000 commercially released video games since 1979, and especially the number of MMO games of all kind is rapidly growing. Over the past years, *free to play* became the dominant pricing strategy for this game genre. Players can join such games for free and usually play them as long as they like without being forced to pay. The free-to-play model allows gaming companies to suppress entry barriers and thus to attract a much larger audience than subscription-based *pay-to-play* games in which all players have to pay a one-off or recurring fee. The larger user base results in extensive social interaction possibilities among free-to-play users.

In May 2013, 62% of the top 200 grossing games in the US AppStore were free to download; by April 2016, this share increased to 96% (Think Gaming 2016). Almost all of these games (paid or free) contain an in-game shop where players can buy virtual items and premium services, either directly or through a virtual currency (Hamari and Lehdonvirta 2010; Hinz and Spann 2008; Lehdonvirta 2009). The purchasable items or premium services mainly allow users to get in-game advantages vs. non-paying users (e.g., to progress faster or to experience a more convenient game play) or are vanity items to provide the own in-game appearance with a unique look (mostly without giving an in-game advantage).

For providers of free-to-play games, the efficient conversion from players to payers is a key monetization aspect (Clemons 2009). Our data from a dozen of MMO games shows that the payer conversion rates (i.e., share of new users becoming payers) are usually only between one and 15 percent. Once players become paying users, they spend on average much more money in free-to-play games than in subscription-based games. For example, we got data from nine MMO role-playing games that report monthly average revenues per paying user (ARPPU) of $54, compared to the usual monthly subscription fees of $5-15 for comparable pay-to-play games. Especially the money spent by dedicated gamers makes free to play so remunerative: in our data, we found numerous players who spent hundreds of euros per month in the game.

2.2 MMO Games as Social Networks

In the past years, several researchers conceptually proposed reasons why people play online games of all kinds, however empirical evidences are hard to find. Most of them find that social interaction positively influences the degree of enjoyment players experience during a game, and the gaming intensity. The analysis by Yee (2006) reveals that three overarching motivation components (sociability, achievement, and immersion) account for 60 percent of the overall variation in players' motivations to play online games. Di Loreto and Gouaich (2011) assume that the success of Facebook games is mainly linked to the blending of personal and social aspects. Cole and Griffiths (2007) come to a similar conclusion. They find that social interactions in online games form a considerable element in the enjoyment of playing. Players may be involved more strongly into certain games with competitive (i.e., playing against a friend) or collaborative activities (i.e., teaming up with a friend against others) and thus spend more time and money in it. Ducheneaut et al. (2007) show that players who join a guild (i.e., an alliance of players, are likely to spend more game time (playing together) than average players without guild affiliation. Putzke et al. (2010) hypothesize that the frequency of social interactions positively impacts a player’s game performance, however without providing empirical support.

Game developers have realized that social elements are relevant for a game’s success, and design their MMO games more and more as social networks. Boyd and Ellison (2007) define social networks as web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system. These characteristics can easily be transferred to online games, taking the action-role-playing game *Diablo III* as an example: in this game people create a profile of their own plus one or several in-game avatars (barbarians, sorcerers, monks etc.), they can play together with real-life friends or strangers (met in the game), add them to their contact list to join them more quickly in future games, chat with others and finally browse through others players' profiles to check their items, achievements and progress.

Many researchers (among them Gupta and Mela 2008; Katz and Shapiro 1985; Kim et al. 2008; Lin and Bhattacherjee 2008; Yang and Mai 2010) have claimed or empirically shown that the utility a user perceives depends on the size of the service's user base – a phenomenon called 'network effect' or 'network externality'. Katz and Shapiro (1985) state that for many technologies, consumers benefit from a growing user base. Services such as the telephone, e-mail or social networks exhibit such (direct) positive network effects. These occur if individuals are able to interact within this network, increasing their utility of the network, and eventually the willingness to pay for their usage. Considering MMO games as social networks with significant social interaction between players, we can expect that the number of co-players also affects a player's degree of enjoyment. Yang and Mai (2010), for example, empirically verify the existence of direct network effects for online games; in their study, the game's value to the players increases when more of them join the game.

2.3 Network Effects as Important Input for a Server Launch Strategy

If only positive (and no negative) network effects existed, any larger network would provide more value to users than a smaller network (Shapiro and Varian 1999). Thus, in a free-to-play MMO gaming context, more users would always mean higher revenues. Nevertheless, launching additional game servers to split the user base is a common practice in MMO gaming, as the next three examples of real-time strategy games show. *Dark Orbit* by Bigpoint has launched more than 60 servers in six years, *Tribal Wars* by Innogames 79 servers in ten years, and *OGame* by Gameforge more than 700 servers in nine years. When a gaming company starts a new server, it usually informs its players (e.g., via an in-game message), so not only (entirely) new players can access it, but also existing players may leave their current game server and restart on the new server. In most cases, the different game servers host the same game version, while some can have slight deviations (in terms of language, rules, speed, limitations etc.) to target specific user groups.

Thanks to flexible hardware scaling, MMO games can typically accommodate a large number of players at the same time without suffering a performance loss. In interviews, game managers told us that launching additional game servers for real-time strategy games has no technical reasons and is exclusively driven by economic considerations. For the management of MMO games, it is therefore an important question how the entire user base should be distributed on different game servers to maximize the players' game experience and ultimately the company's profits.

Similar optimization problems can be found in related online industries. In a peer-to-peer network, new users sharing files increase the utility of other users. However, Bapna and Umyarov (2012) discovered that the strength of peer influence decreases with a user's number of peers. Asvanund et al. (2003, 2004) add that such networks are bound to an optimal size since additional users hardly add new content to the network, but consume scarce network resources. This leads to congestion and finally to a lower network utility. The authors investigate different means to incentivize users to share content and to thereby increase network utility. Henderson and Bhatti (2001) study network effects in MMO shooter games and examine why players join certain game sessions. While more co-players in a session can mean more fun for all participants, too many players can lead to performance issues and perceived unfairness, if the winning chances become too low.

Our paper is closely related to the aforementioned studies, but with some notable differences. Our data set is unique because it allows us to assess the results from numerous user base splits conducted by the MMO gaming company in question. We will use this data to determine the revenue impact of starting new game servers in a real-time strategy MMO game and evaluate the company's timing in doing so for each of the 20 examined cases.

3. Development of Hypotheses

3.1 Impact of the User Base on Free-to-Play MMO Revenues

If a network is of some positive minimal size (Bental and Spiegel 1995), networked services can have some degree of network value, which is the value stemming from other people already using the service. Lin and Kulatilaka (2006) assume that such effects are likely to be stronger in online gaming than in most other networked industries. For an MMO game, a larger number of co-players would make the game more fun, more interactive and more challenging. Previous research has shown that a larger user base leading to increased user enjoyment of the underlying service can also have a positive impact on customers' willingness to pay (e.g., Borgatti et al. 2009; Brynjolfsson and Kemerer 1996; Eisenmann 2006; Ellison and Ellison 2005; Farrell and Saloner 1985; Hinz et al. 2015; Katz and Shapiro 1985).

Reaching a high status or a good rank in the high score table is a desirable goal for many players. They may enjoy the competition with a certain number of opponents, however may consider beating a disproportionate number of users as unrealistic. An unrealistic goal (e.g., to become #1 in a very big game) may discourage a weaker player so that he quits playing the game or lowers his willingness to pay for the game (Locke and Latham 1994). The same logic is applicable to the stronger player: once a player has got a strong position in the game, and beating new players is no longer a challenge, the strong player may lose his motivation to play (and to pay).

Thus, the presumed impact of the user base on users' utility and ultimately the MMO game's revenue may not necessarily stay positive for an indefinite number of users. Different studies in comparable network industries have shown that the size of the user base can have a negative impact on the service's value. An extended number of players can also overstress a game's capacity, leads to waiting times, and thus dampens the enjoyment of all players on this server (Henderson and Bhatti 2001).

Barabási and Albert (1999) mention that the probability with which a new vertex (in our case: a new player joining the game) connects to the existing vertices is not uniform. Butler (2001) confirms that for growing online communities new users have increasingly fewer opportunities to participate and therefore form fewer personal relationships with other members. In MMO strategy games, new users are often placed at the fringe of the game's world map and should therefore have less interaction with more seasoned players. Following the 'small world' concept (Milgram 1967; Watts and Strogatz 1998), new players will most likely connect with their neighbors, but do not build 'long-range' relationships with older players. Backes-Gellner et al. (2014) assume the same decreasing level of network contribution in an entrepreneurial context: they hypothesize that the incremental efforts of team founders reduce with a growing team size and should thus follow an inverted U-shaped pattern. Based on this related research, we assume that additional users generate a decreasing incremental value to the overall network in MMO games.

While most of the papers assume homogeneous users, a differentiation might make sense: Taylor (1977) states that 'innovators' (i.e., the first individuals who adopt an innovation; Rogers 2003) also tend to be heavy users of the purchased product or service. Goldsmith and Newell (1997) show that early product adopters tend to be less price-sensitive than late buyers. Players joining an MMO game before others are likely to be more 'goal-oriented' than late followers (i.e., mostly casual gamers). These goal-oriented players may invest more time and money in the game to achieve certain in-game goals (such as a good position in the ranking table).

We see that two different factors influence a player's utility and money spent into a free-to-play MMO game: direct network effects, which can be positive (e.g., if more players mean more fun) or negative (e.g., if more players lead to an unbalanced game play), and the players' characteristics (i.e., if they are more goal-oriented or casual gamers). From now on, we use the term 'user base effects' to describe the combination of these two kinds of effects which both suggest that additional users add a linearly decreasing incremental value to the network. When the game reaches a certain size with 'too many' users (as illustrated in Figure 11), the incremental network value and revenue of a new user can even become negative. Utility and revenue follow an inverted U-shape, and the game reaches a revenue maximum with a certain number of users. This is in line with previous studies that indicate that the relationship between the user base and the economic dependent variable is not linear, but follows an inverted U-shape (e.g., Asvanund et al. 2004; Chacko and Mitchell 1998; Shankar and Bayus 2003).

Hypothesis 1: The incremental revenue an additional user generates decreases with the size of the user base. Therefore, the impact of the user base on revenue follows an inverted U-shape and has thus an absolute revenue maximum.

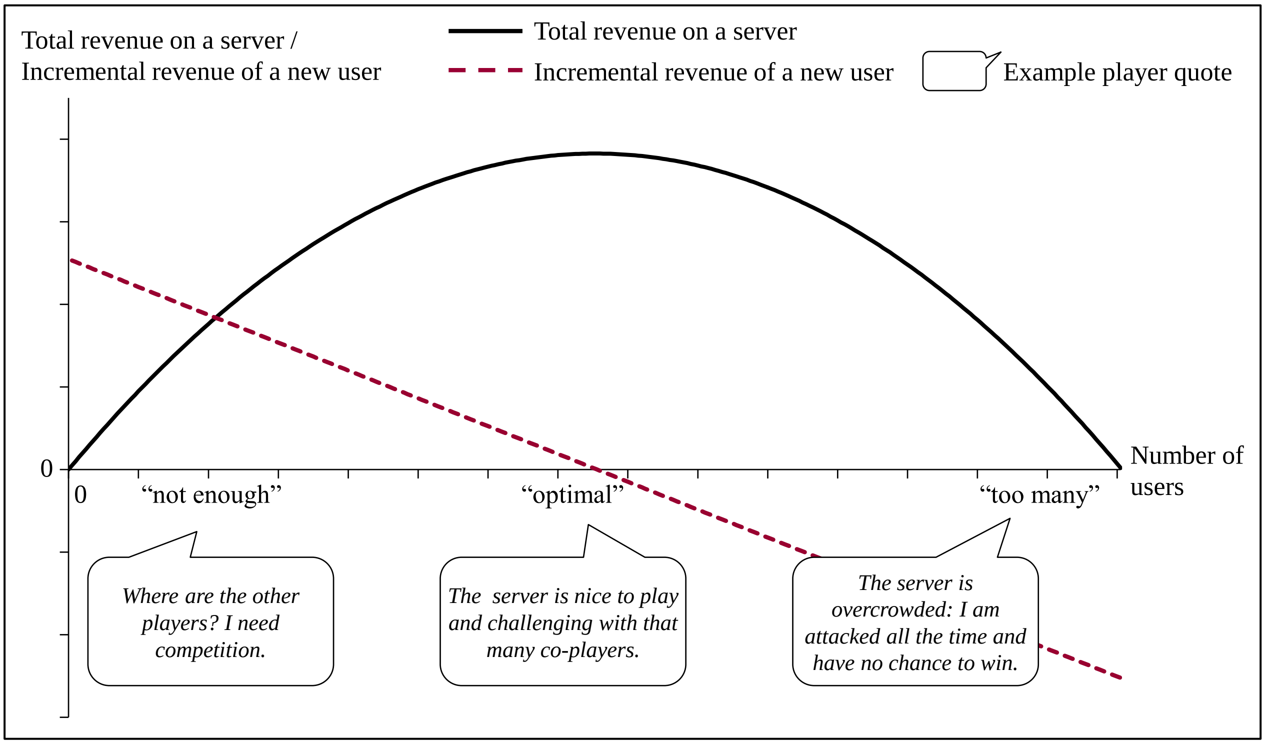

Figure 11: Expected User Base Effects on Total and Incremental Revenue

3.2 Server Lifetime Effects

When a game is newly launched, all players start with the same (or at least similar) preconditions. In this balanced and fair game environment, we suppose that every player has the same chance to reach his personal in-game objectives.

In the first days of a game server, goal-oriented players who spend a decent amount of time and money in the game may already be able to generate a strong position for the remaining game time. Thus, investing resources in a free-to-play MMO game early after its start may be more attractive to users than later on, because these players can generate first-mover advantages (Lieberman and Montgomery 1988) through (1) a technological leadership (i.e., superior knowledge regarding rules and tactics of the game) and (2) a preemption of assets (i.e., superior buildings, armies and resources) which allow them to easily beat new players who do not (yet) have access to these advantages. Eisenmann (2006) shows that such first movers spend significantly more money than non-pioneers to get an early advantage. Once players achieved this advantage by spending money very early after the server start, they are likely to keep it even without being forced to spend the same amount of resources again at a later stage.

Hypothesis 2: Game servers yield the highest revenue right after their launch.

If a game server has already been running for a certain amount of time, it is unrealistic for a new player to catch up with the existing players' achievements or scores. Thus, new players are less likely to achieve a high in-game score or rank because other players who joined the server earlier are already much more advanced in terms of achievements or resources. Thereby, a game server becomes more and more unbalanced in terms of fairness over time. Lin and Sun (2011) argue that competing against superior opponents in online games creates a feeling of unfairness. Related research has shown that people usually punish unfairness: price unfairness leads to lower shopping intentions (Campbell 1999; Xia et al. 2004), unfair offers by people playing ultimatum games are associated with frustration and decline (Sanfey et al. 2003), and – in an online gaming context – (technical) unfairness reduces the players' game enjoyment (Brun et al. 2006). According to equity theory (Adams 1965), players perceiving unfairness may refrain from spending money in the game. Thus we conclude that a game server's lifetime negatively influences its revenue.

Hypothesis 3: The lifetime of a game server negatively affects its revenue.

3.3 Starting New Servers to Better Monetize the User Base

Efficiently monetizing new players is a crucial challenge for gaming companies to ensure their profitability. Against this background, a user base strategy that leverages the hypothesized user base and lifetime effects is vital for free-to-play MMO gaming companies to increase the share of paying users and eventually total revenues.

The question at hand is whether or not starting a new server can increase the total revenue (i.e., the sum of all servers' revenue) for a given time frame, as such a measure would change the allocation of users on all servers. Over time, the number of users for any other server is likely to decline because a) new users are more likely to sign up on the newest server and b) existing users may close their accounts to migrate to the new server. Overall, we expect lower total revenues from existing servers; however a new server can potentially more than compensate for the lost revenue. If total revenue increases with an additional server, then the server should be launched.

Launching a new game server while maintaining the existing ones, can have a positive revenue effect for several reasons. First, new servers can capitalize from positive user base effects and reduce the negative effects by avoiding 'too busy / too competitive' servers (see hypothesis 1). A new server allows existing users to leave overcrowded servers and have a better playing experience on the new one. Second, we expect especially goal-oriented players to switch from other servers. These players who are already experienced with the game might consider that participating on the new server is more enjoyable (e.g., because of the better game balance between strong and weak players) or increases their chances to reach their personal in-game objectives (e.g., becoming #1 in the new server's high score ranking). After all, these users might spend additional money early after the server launch to get an in-game advantage on others (hypothesis 2). Third, (entirely) new players may not choose an existing, unbalanced server, but the new one which provides a fairer and better game experience for all players (hypothesis 3). If we find support for our hypotheses, server launches should be able to increase total revenues (across all servers).

Hypothesis 4: Server launches can boost total revenues.

Even if our hypotheses find support, server launches might not always be profitable if executed at the wrong time. As summarized in Table 32, a server launch can invoke various effects that may influence total revenues in a positive or a negative way. We will use a regression model in section 4 to validate our hypotheses 1 to 3, and then will set up a counterfactual simulation model in section 5 to test hypothesis 4 as well as to determine the appropriate timing for the company in question to launch new game servers.

Expected positive server launch effects	Expected negative server launch effects
▪ User base of existing servers shrinks which may reduce negative user base effects ▪ Existing players may switch to the new server and amplify their activity / spending (e.g., to increase their chance to become #1 in the ranking) ▪ All players start with the same, fair preconditions on the new server, thus the balance between players improves ▪ The existing game servers' (technical) performance may improve with a smaller user base (only applicable to high-performance games)	▪ Positive user base effects might reduce on certain existing servers if the optimal user base has not yet been reached ▪ New servers cannibalize activity and revenues on existing servers; existing players might switch to new servers and possibly reduce their activity / spending

Table 32: Expected Positive and Negative Server Launch Effects

4. Empirical Assessment of Server Launch Effects in MMO Gaming

4.1 Data and Game Description

To assess the effects of server launches in MMO gaming, we use customer data provided by an international market leader for free-to-play MMO games. We assume that the gaming company focuses on optimizing its total revenues which equal the sum of every single server's revenue. The examined game is a competitive real-time strategy game. In such games, players construct a base, harvest different types of resources, explore new technologies, and build an army in order to battle and conquer opposite cities. Players can access the game with an Internet browser, or a Tablet or Smartphone app. The free-to-play game has an in-game store where users can buy a virtual currency they can trade for different game advantages (like producing extra resources, constructing buildings more efficiently or getting additional information on managed cities). The game offers a large selection of payment options, including Internet wallets, credit or prepaid cards. Most of the players are casual users who slowly build up their base. However, it requires intensive investments from goal-oriented users to reach the top of the high score table.

The data at hand contains all activity and payment data for one language version of the game from its start in January 2008 until November 2012. Since day 1, more than two million users have signed up for the game. Approx. 3.2 percent of them became paying users and spent on average €67 in the in-game shop during their customer lifetime. The in-game shop was launched 79 days after the initial game and was used approx. 350,000 times in our sample period, resulting in total revenue of approx. €5,000,000. The company deletes inactive accounts if a user did not log in for 30 days. However in most cases, a player's home base is conquered already after a few days of inactivity, which ends his game. Over time, the gaming company successively launched 22 servers; all servers are still up and running as of the time of this study. Table 38 in the Appendix presents additional information on the different servers and their launches.

4.2 Regression Model on Revenue

To validate our first three hypotheses, we build a linear Prais-Winsten regression (Prais and Winsten 1954) with the *Daily revenue per server* as the dependent variable. In all models, we use the Huber-White sandwich estimators (Huber 1967; White 1980) to assess robust standard errors and thereby deal with minor concerns about the potential failure to meet assumptions, such as normality, heteroskedasticity, or observations that exhibit large residuals, leverage, or influence.

The independent variables group into five categories:

1. Users: *Users3Days* describes the number of users that have been online at least once over the last three days. This is a common metric in online gaming, as players who are inactive for more than three days are often already considered as churners.
2. Servers: *NumberOfServers* equals the number of game servers on a given day. *LifetimeServer*, *LifetimeGame* and *LifetimeNewestServer* depict a server's, the game's and the newest server's lifetime in days, respectively. *IsNewestServer* and *IsServer#1* tag the newest and the oldest server. Additionally, a new server is labeled *IsBrandNew* on its launch day.

3. Updates: During the sample period of more than four years, the game underwent eight major game updates (*Update1*, …, *Update8*). These updates were permanent, and all cases have been labeled with 0 prior to the update and with 1 after the update.
4. Promotions: The gaming company ran several *HappyHour* promotions. When active, players could purchase the in-game currency at a lower price for a limited time. We additionally labeled the consecutive seven days with *WeekAfterHappyHour* to account for the typical post-promotional revenue decline. *InGameEvent* depicts a time-limited tournament with a prize for the winner(s).
5. Covariates: *BigTvEvent* describes days where a single TV event reached an especially high audience rating. The weekdays as dummy variables complete our model.

We apply both linear and quadratic functions for all ratio-scaled variables of the first two categories to check for the supposed inverted U-shape of the function. Table 39 in the Appendix includes basic descriptive statistics of the used variables.

We build several models to ensure the robustness of our results. We begin considering only the number of users (model 1) and successively include additional parameters: server information (model 2), game updates (model 3), promotions (model 4), and finally covariates (complete model 5). Especially considering promotions increases the R^2 of our model (from .193 to .587). Table 2 summarizes the regression results. We detect no change of algebraic signs at the significant variables from one model to another and thus assume that our final model 5 (R^2 = .589) is robust. To build additional confidence in the results, we ran an alternative model that excludes promotions (as proxy for outliers) which can be found in Tables 40 and 41 of the Appendix.

The applied Prais-Winsten regression takes care of serial correlation of type AR(1) in a linear model. Additionally, we set up the same model with Newey-West standard errors (Newey and West 1987) which allow a heteroskedastic error structure and possible autocorrelation up to some lag. We tested AR(1)-AR(3) and report the results and the minor differences between the two models in Table 42 in the Appendix.

Independent variables		Model 1: Users	Model 2: + Servers	Model 3: + Updates	Model 4: + Promotions	Model 5: + Covar.
Constant		94.0637***	57.3163	384.7192***	171.5761**	169.6154**
Users	*Users3Days*	.3612***	.07146***	.0688***	.0701***	.0702***
	Users3DaysSquared	-1.60e-06***	-3.39e-06***	-3.31e-06***	-3.37e-06***	-3.37e-06***
Servers	*NumberOfServers*		-64.8548***	-119.1012***	-75.1923***	-75.4659***
	NumberOfServersSquared		2.0389***	3.212***	1.4070***	1.4299***
	LifetimeServer		-.1404***	-.1515***	-.1463***	-.1460***
	LifetimeServerSquared		.0001***	.0001***	.0001***	.0001***
	LifetimeGame		.8775***	1.3565***	1.1395***	1.1383***
	LifetimeGameSquared		-.0003***	-.0005***	-.0004***	-.0003***
	LifetimeNewestServer		-.0975	-.4116***	-.4174***	-.4144***
	LifetimeNewestServerSquared		.0005*	.0012**	.0012***	.0012***
	IsNewestServer		108.4272***	109.8007***	109.5230***	109.4162***
	IsServer#1		130.9948***	138.5231***	136.4505***	136.0210***
	IsBrandNew		918.9627***	910.0590***	922.5910***	920.6780***
Updates	*Update1*			-6.6088	4.1837	4.0551
	Update2			7.6882	12.1830**	12.3361**
	Update3			-39.6038***	-44.8103***	-44.3386***
	Update4			-2.2966	-1.6166	-1.5376
	Update5			-21.2839***	-9.440382*	-9.2528*
	Update6			15.3270	-9.0408	-8.8136
	Update7			19.1498*	12.3781	12.4426
	Update8			71.3484***	37.4911***	37.7090***
Promotions	*HappyHour*				921.8200***	921.2654***
	WeekAfterHappyHour				-37.3145***	-37.4028***
	InGameEvent				23.6711*	24.0750*
Covariates	*BigTvEvent*					-2.0107
	WeekdaySun					-9.0178***
	WeekdayMon					5.0757*
	WeekdayTue					9.2105***
	WeekdayWed					6.7039**
	WeekdayThu					-.5427
	WeekdayFri					3.0050
	WeekdaySat					omitted
Dependent variable		Daily revenue per server in €				
R^2		.030	.188	.193	.587	.589
Adjusted R^2		.030	.187	.192	.587	.588
Durbin-Watson (transformed)		2.082	2.003	2.001	2.005	2.005
Number of observations (= server days)		25,404				

Table 33: Results from Prais-Winsten Regression (Dependent Variable: *Daily revenue per server*)

$*p<.1$; $**p<.05$; $***p<.01$

Before describing the results of our final model, we check how well it represents the observed daily revenues. Figure 12 shows all servers' observed revenue compared to the revenue predicted by our model, aggregated on a daily basis. In addition, it visualizes the strong revenue effect of the *HappyHour* promotions in the second half of the game's lifetime. The model explains a high fraction of explained variance and shows a low mean absolute error.

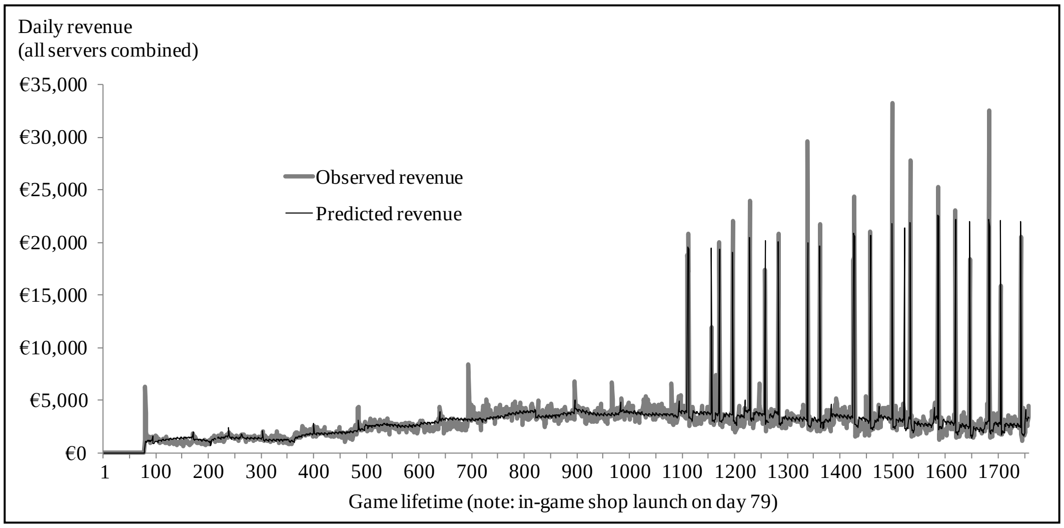

Figure 12: Daily Observed vs. Predicted Revenues across all Servers

According to common data mining practices, we additionally split our 1,759-day data set into training and test data sets, and use these to identify possible signs for overfitting. The Tables 43 and 44 in the Appendix delineate the different data models. All parameters (the full list can be found in the Appendix), including the minimal difference of .001 or below between R^2 and Adjusted R^2 in any model (Harrell 2015, pp. 110-111), do not indicate overfitting problems.

4.3 Observed Server Launch Effects

Figure 13 illustrates the user base in our sample period, aggregated on a daily basis across all servers. It also indicates at which point in time new servers were launched. We can see that new servers have often led to an overall larger user base soon after their launch, however hardly for a long time. Instead, we observe a negative trend in the user base development that even server launches could not break. While the number of users constantly decreases over time, we see in Figure 12 that total revenue tends to increase. This is typical for successful free-to-play games. Soon after the game launch, the company primarily aims to acquire as many players as possible to reach a critical mass. Over time, the company increasingly shifts focus to retaining and monetizing the players. Additional monetization features (in our case, the eight updates and the increasingly frequent promotions) are implemented to raise the daily average revenue per user.

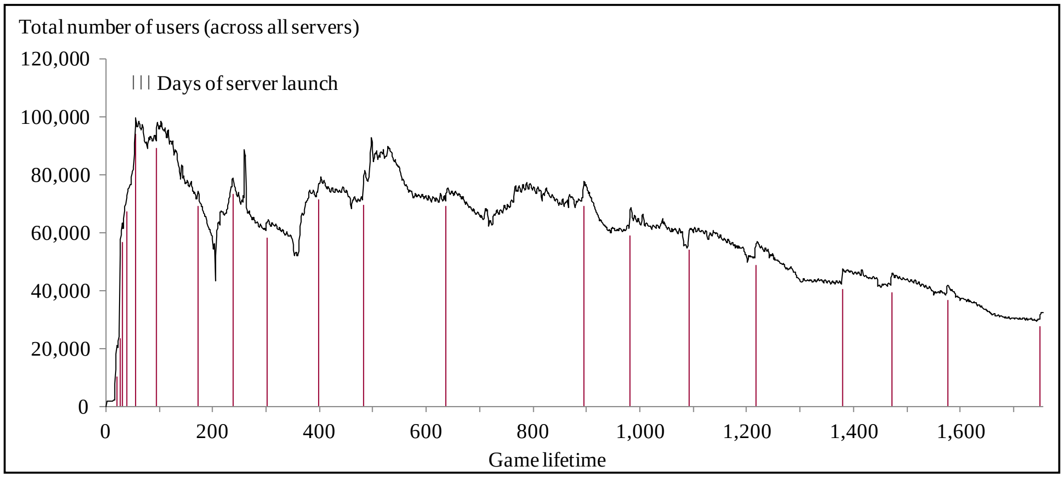

Figure 13: Development of User Count

The regression results in Table 33 show a positive linear (*Users3Days*) and a negative quadratic (*Users3DaysSquared*) influence of the number of active users on the daily revenue per server. In our final model, the results are significant for both *Users3Days* and *Users3DaysSquared* (p<.01).

Figure 14 illustrates the incremental revenue generated per user (i.e., the first derivative of the user variables' regression coefficients; other effects kept constant). We can see the incremental daily revenue is constantly declining: for user #100 it is €0.07, for user #1,000 it is €0.04, and for user #10,000 close to zero.

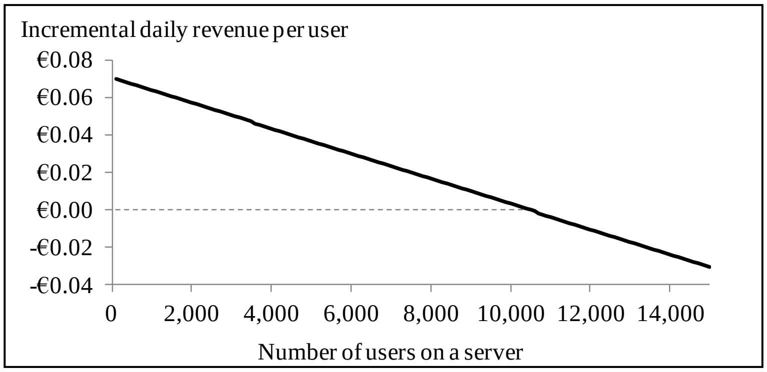

Figure 14: Incremental Daily Server Revenue per Joining User

In Figure 14, we also see that the incremental revenue per user becomes negative with a certain user base. At this point, the game world becomes 'too busy' and 'too unbalanced' in terms of players' strength so that new players negatively influence the overall game experience and thereby also reduce total revenues on that server. In our case, this means that a server reaches its absolute revenue maximum with 10,409 users, and revenues decline with a higher user base. Figure 15 illustrates the relation between the number of users and its impact on a server's daily revenue. Our findings provide evidence for our first hypothesis that the incremental revenue an additional user generates decreases with the size of the user base, resulting in a revenue curve that follows an inverted U-shape.

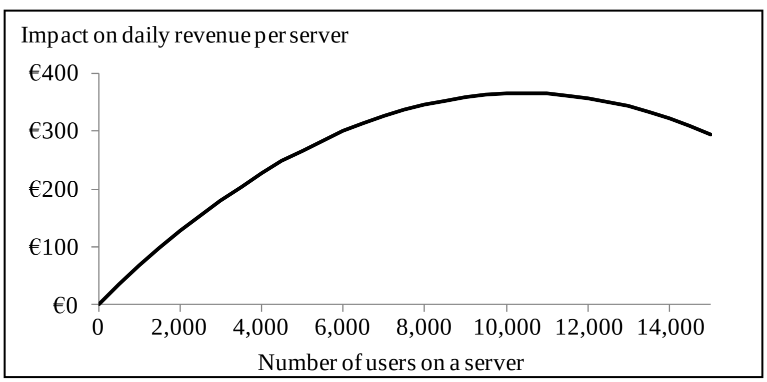

Figure 15: Number of Users and their Impact on Daily Revenue per Server

The game has performed 22 server launches which allow us to investigate their impact on revenue. We can find that the number of active servers has a negative influence on daily revenue per server for the linear term (*NumberOfServers*), but positive for the quadratic term (*NumberOfServersSquared*).

Therefore, as it could be expected, the negative effect flattens with an increasing number of servers. In addition, we find that the oldest server, tagged with *IsServer#1*, generates higher daily revenues (+ €136.02) compared to all other servers.

As we assumed in our second hypothesis, newly launched servers (marked by the tag *IsBrandNew*) generate high extra revenues. We can see that these servers make an additional €920.68 on day 1 of their lifetime. Players invest extra money in the game right after a server launch to gain an early advantage versus other players. In Figure 13, we can clearly see these spikes in revenue immediately after a server launch.

After a server's launch date, its lifetime effect on revenue is mostly negative: the linear term (*LifetimeServer* in days) on daily server revenue is negative, and the positive quadratic term (*LifetimeServerSquared*) has only a weak effect (for both terms, $p<.01$ applies). Figure 16 illustrates the server lifetime and its impact on the server's daily revenues (without the *IsBrandNew* effect on day 1). Thus, we can also find support for our third hypothesis that a game server's lifetime negatively impacts its daily revenues. All results on basis of the different training data sets also show support for hypotheses 1, 2 and 3 (see Table 44 in the Appendix).

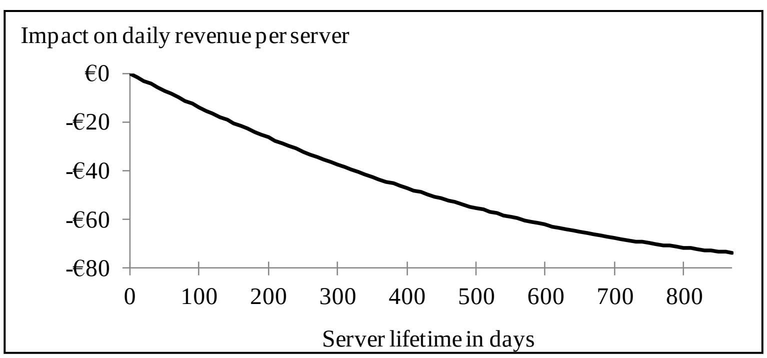

Figure 16: Server Lifetime and its Impact on Daily Revenue per Server

Game updates can be considered as indirect network effects. As long as the user base is *sufficient* from the gaming company's perspective, it will develop new content for the game – which then again influences the users' game experience. Clements and Ohashi (2005) describe the same causality for video game consoles: users derive basic utility from owning the console (in our case: playing the basic game) and get additional value from newly released games (in our case: content update) enriching the player experience. For two of the updates (*Update2* and *Update8*, see Table 39 in the Appendix for a brief description), we find a significant positive impact on daily revenue per server, while three others (*Update3*, *Update4*, *Update5*) have a negative impact. Game developers can use these results to prioritize similar functionalities versus others.

5. Counterfactual Simulation: Launching New Game Servers? If so, When?

5.1 Methodology

In this section, we investigate for different states of the game whether or not launching an additional server – and if so: when – is recommendable in terms of revenue generation. Our results from the previous section support our first three hypotheses, which suggest that the network utility is concave with regard to the number of users and that there is a specific user base that generates the highest possible revenue on a given server. With this user base in place, the incremental costs an additional user imposes on the network will be larger than the benefit he or she provides. New servers have a significant positive revenue impact on their starting day, while server revenues decrease constantly over the server's lifetime. Overall, we find that there are conditions under which server launches could be beneficial in terms of their positive impact on total revenue (i.e., our fourth hypothesis).

In order to improve the game's server start strategy, we will set up a counterfactual simulation model. *Counterfactuals* are mental representations of alternatives to the past ('what might have been'; Narayanan 2010; Roese 1997). The term *simulation* is often used in discussions of counterfactual thinking (Kahneman and Tversky 1982; Roese 1997). Reiss (2011) defines simulations as *"computer-implemented models [that] are aimed at drawing inferences about properties of a socio-economic system or socioeconomic systems of interest"*. Narayanan (2010) asserts that counterfactual simulations play a significant role in decision-making and performance improvement, for example: *"If only we had left earlier, we would have avoided the storm […] Henceforth, we will leave earlier [next time]"*.

In our case, the ‘what if’ questions are: How would revenue have developed if the server had been launched on a different day? What if the server had not been launched at all (‘do-nothing’ scenario)? Is the optimal timing for a server start depending on the current state of the game, or is there a universally recommendable interval between two server starts? In our simulation, we will compare the game’s real server start sequence to alternative scenarios (i.e., earlier, later and no server starts) to check which one would have been most beneficial in terms of revenue.

5.2 Simulation Model and Assumptions

For the empirical parametrization of our simulation, we use the results from our regression model, as shown in Table 33 (‘Model 5’). If set up properly, a classic approach with a regression study for the parameterization of an analytical model is usually a better approach with respect to the clearness of the interpretation of the results. However, the plethora of possible behavioral rules (e.g., network effects, playing behavior, user characteristics, sales approaches etc., just to name a few) significantly aggravates the creation of such a model in our case (Epstein 2007, p.30). Instead, the used mixed regression-simulation model retrospectively compares the company’s server start strategies with alternate scenarios in order to assess if and how the chosen timing could have been improved. We believe that the direct usage of the empirical data for the simulation reduces the level of noise stemming from the parametrization of a possible analytical model (Reiss 2011), and is thus more suitable to finding actionable suggestions how to improve the focal company’s server launch strategy.

Almost all independent variables from the model (e.g., lifetime, updates, promotions) can be used in their existing forms for the revenue simulation in the counterfactual cases (i.e., earlier, later or no server starts). There is one exception; the size of a server’s user base cannot be used, as it varies over time with the number of servers. When the operator launches a new server, existing servers will lose a certain number of users who switch to the new one. For example, server #8 was started 38 days after server #7. One of our counterfactual cases could be to start server #8 only one day after server #7. As a result, the entire user base from all seven existing servers would be affected much earlier by the server start; we consider this aspect with an auxiliary model that predicts the daily number of users per server. For this purpose, we use the existing independent variables, the number of users on the previous day (*Users3DaysYesterday*) as a server's real user base on day 1 of the simulation, and the day-by-day forecasted number thereafter. Table 45 in the Appendix shows the results, which feature an R^2 of .994. We can see that 95.5 percent of the previous day's users stay with the game for another day, which equals a daily churn rate of 4.5 percent. Not surprisingly, we observe similar server launch effects: +152 additional sign-ups per day on the newest server (*IsNewestServer*) and +2,664 on day 1 (*IsBrandNew*). Promotions (*HappyHour*) and in-game events targeted at existing players to spend more money in the game do not significantly influence the number of users. This seems plausible as only existing players can experience these features.

Out of the 22 servers launched in our observation time frame, we use 20 for our revenue simulation. We only exclude server start #1 (because not starting the first server would mean no game and no revenue) and server start #4 (because it was launched on the same day as server #3, which is a special case). For the remaining 20 server launches, our simulation time frame starts one day after the launch of the previous server and ends after 180 days. As a server start is possible on any of these 180 days, we simulate the revenue impact for all these 180 scenarios (i.e., a server start on day 1, day 2, …, day 180) plus for the do-nothing scenario of not starting a new server in this time frame. We consider all game updates, promotions and covariates in our simulation model and thus treat them as exogenously timed. As a result, we compare the 180-day revenue of all 181 scenarios to check if (and when) starting a new server generates extra revenue. Table 34 summarizes the simulation parameters.

Sample size	20 server starts (i.e., servers #2-3, 5-22)
Simulation time frame per server start	180 days as of day after the previous server start
Simulation scenarios	181 scenarios per server start: ▪ Do not start a new server ▪ Start a server after [1, 2, …, 180] days (one of them being the real case)
Results	▪ Retrospective determination whether or not a server start was profitable or not (vs. do-nothing case) ▪ Retrospective, atomic assessment of the optimal timing for each server start

Table 34: Description of Counterfactual Simulation Parameters

Before we come to the results of our simulation, it is worth mentioning that our simulation (like any other) is based on certain assumptions. First of all, we establish our simulation on the results from the regression analysis. We thus assume that they also hold for the counterfactual scenarios ('ceteris paribus' assumption; Boumans and Morgan 2001) to allow us to forecast the future based on information collected about the past. We kept all variables in the model to reduce the risk of having structural breaks which make our assumptions obsolete. Our model employs linear and quadratic specifications of the most relevant variables and is scrutinized in several alternative scenarios in order to build confidence in its validity (see for example Tables 40 to 43 in the Appendix). Still, logarithmic, polynomial, or combined functions between the user base and dependent economic variables remain to be examined (Asvanund et al. 2004). Whether the results of a counterfactual simulation are truly optimal can never be 100% validated, especially in light of the magnitude of the various input variables.

Second, the nature of the counterfactual simulation necessitates a time limit. In reality, the gaming company started 22 servers during the 1,759-day observation time frame, which translates to an average of approximately every 80 days. We chose a simulation time frame of 180 days per simulation in order to establish the optimal timing for server starts. Even if a certain scenario yields higher revenues than another one within these 180 days, it may be that the long-term effects beyond this limit diverge from our findings. For example, starting a new server every single day may be beneficial in the very short run (due to the revenue peak on day 1); in the long run, it may lead to the extreme (and probably not very enjoyable) case that each player plays on his own server. We will comment on this point furthermore in the next section and explain why we believe that the simulation time frame is appropriate.

Third, while we simulated each server start atomically (i.e., no additional server launches were considered within each 180-day simulation time frame), in reality we have the option of starting or declining to start a new server on any given day. For our time frame of 1,759 days (with the start of server #1 on day 1), a simulation would need to consider 2^{1758} different scenarios to determine the optimal sequence. Even by applying optimization algorithms, such a simulation is likely to be too computationally expensive with currently available technology.

5.3 Simulation Results: Can Additional Servers Boost Revenue?

Table 35 shows the results of our counterfactual simulations for all 20 servers. For each case, we compare the company's real server start decision against all 181 possible scenarios. For example, the gaming company launched server #13 on *GameLifetime* day 485 (see Table 38 in the Appendix for a list of all server launches). For server #14, we simulate the effects of a server start between *GameLifetime* day 486 (i.e., 485 + 1) and day 665 (i.e., 485 + 180). Within the chosen 180-day simulation time frame, the company could have started server #14 on any given day, or even decide against a server start (i.e., the do-nothing scenario).

Table 35 displays the results for three chosen simulation cases: first, the 'real case' (i.e., the strategy chosen by the gaming company), second, the 'best case' (i.e., the revenue-maximizing strategy), and finally the 'worst case' (i.e., the revenue-minimizing strategy). In our example for server #14, the company decided to start the server 154 days after server #13. The revenue-optimal strategy would have been to wait for only 107 days, while starting the server just one day after the previous one would have been the worst possible option. The best case yielded +0.1% revenues across all servers over 180 days compared to the real case and +7.3% compared to the worst case. Thus, the company timed this server launch quite well. As the best case outperforms the do-nothing scenario in terms of revenue in this example, we find support for our fourth and final hypothesis that server starts can be used to generate additional revenues.

Launch of server	Real case		Best case		Worst case		Revenue upside Best vs. Real	Revenue upside Best vs. Worst
	Days expired since last server launch	Simulated 180-day revenue across all servers	Days expired since last server launch	Simulated 180-day revenue across all servers	Days expired since last server launch	Simulated 180-day revenue across all servers		
#2	18	€717,450	1	€746,246	No launch	€449,984	4.0%	65.8%
#3	7	€948,939	1	€957,688	No launch	€711,120	0.9%	34.7%
#5	3	€1,135,544	1	€1,137,188	No launch	€990,762	0.1%	14.8%
#6	8	€1,107,073	1	€1,109,185	No launch	€1,008,762	0.2%	10.0%
#7	18	€1,008,859	9	€1,009,112	177	€951,543	<0.1%	6.1%
#8	39	€935,714	55	€936,376	No launch	€906,142	0.1%	3.3%
#9	77	€823,819	85	€823,921	1	€804,047	<0.1%	2.5%
#10	68	€755,871	99	€758,627	1	€729,434	0.4%	4.0%
#11	64	€699,202	109	€706,185	1	€665,800	1.0%	6.1%
#12	97	€585,606	121	€587,383	1	€536,416	0.3%	9.5%
#13	85	€734,629	102	€735,694	1	€685,924	0.1%	7.3%
#14	154	€801,654	107	€808,667	1	€765,385	0.9%	5.7%
#15	257	€854,904	102	€873,776	1	€831,314	2.2%	5.1%
#16	87	€936,198	96	€936,590	1	€896,558	<0.1%	4.5%
#17	111	€908,406	100	€909,009	1	€865,927	0.1%	5.0%
#18	125	€903,395	100	€907,396	1	€867,346	0.4%	4.6%
#19	164	€798,141	99	€819,358	1	€777,309	2.7%	5.4%
#20	91	€796,363	98	€796,464	1	€755,293	<0.1%	5.5%
#21	105	€690,234	98	€690,743	1	€647,041	0.1%	6.8%
#22	174	€643,713	92	€682,703	No launch	€638,056	6.1%	7.0%

Table 35: Results from Counterfactual Revenue Simulation[1]

For the gaming company in question, it is of particular interest to understand how to improve their server launch strategy. The best cases in Table 35 show that the revenue-optimal server start strategy differs over time. In the game's early stages, it has many players but few servers. In our simulation for the servers #2 to #7, fast server starts are the most profitable strategy. For servers #2, 3, 5 and 6, the highest revenues can be

[1] Note: We excluded server launch #4 from the simulation, as servers #3 and #4 were launched on the same day. Server #15 has been launched 257 days after server #14. As our simulation time frame was only 180 days, we used a launch after 180 days as a proxy for the real case.

realized if the new servers are started immediately (that is, one day after the previous one). Not launching these new servers at all is the worst of all possible options.

Once the user base is distributed across multiple servers, starting new ones every approx. 90 to 120 days is revenue-optimal. In all cases, launching an additional server at the right time is superior to a do-nothing scenario. However, this does not mean that the do-nothing scenario is always the worst of all options: for server #7, a very late server launch after 177 days equates to the worst possible strategy; for servers #9 to #21, starting one new server immediately after the previous one is the worst option. Therefore, server launches do not always outperform do-nothing scenarios if such launches are implemented randomly, but they always do if the right timing is applied.

In most cases, the gaming company timed their server launches near the respective optimum, which indicates on the one hand that their experience is quite valuable and on the other hand provides some face validity for our recommended timing. Still, our retrospective analysis shows that the company could have realized on average +0.9% higher revenues by using optimal timing for the respective server starts, and on average +9.4% by having avoided the identified worst case.

Figures 7 to 10 illustrate at what point in time the revenue differences between the best, real and worst cases kick in for the example launches of servers #2 and #22. Server start #2 is the first case in our simulation, while #22 is the last. Thus, the initial position differs substantially between these two simulations.

For the launch of server #2, we can see in Figures 17 and 18 that the best case benefits from a server start one day after the launch of server #1. In reality, the server launched 19 days after server #1, and the real case's daily revenues take some time to catch up with the best case. Keeping all users on one single server is clearly the worst possible option. The resulting total revenue of the best case is 65.9% higher than in the worst case (see Figure 18). This is the highest difference we found in any case.

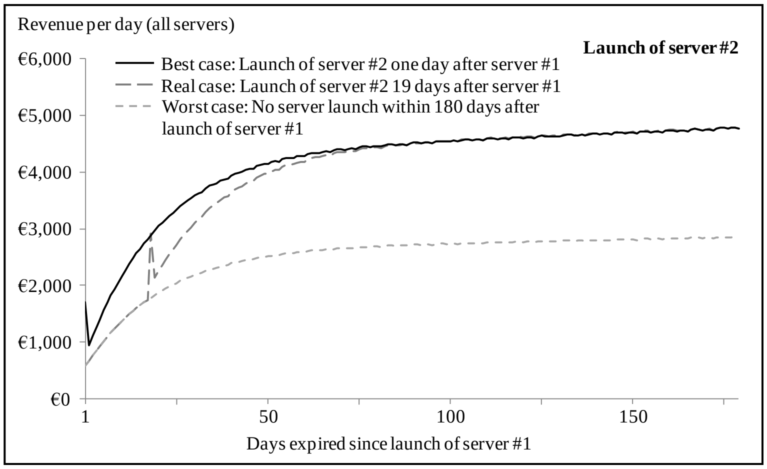

Figure 17: Simulated Revenue per Day for Server Launch #2

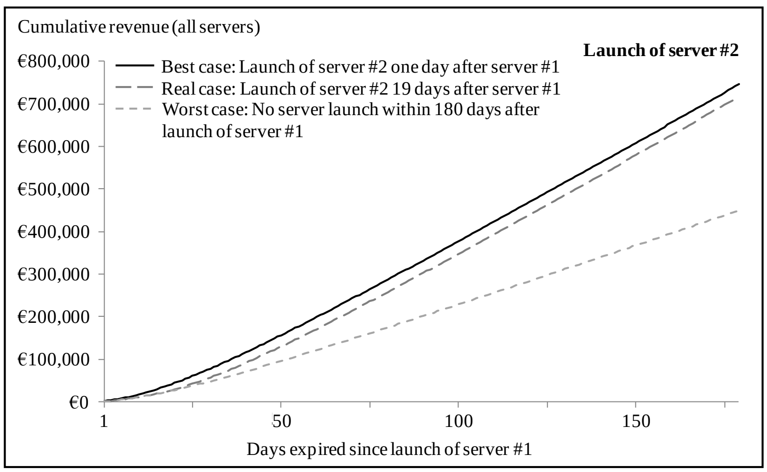

Figure 18: Simulated Cumulative Revenue for Server Launch #2

In all three cases for server start #22, we see no server start before day 92, thus the revenues in all cases are the same until that point. An early server start, as in the previous example, shows only a short-term upside and revenue losses over time. The suggested timing for a server start is on day 92. Compared to the worst case (= do-nothing scenario), this strategy generates ‘only’ 7.0% more revenue over the regarded time frame. We find that the importance of the targeted server start timing is highest at game launch and the relative benefit declines over time. Figures 8 and 10 also indicate that the results are reasonably consistent over time and tend to diverge rather than converge.

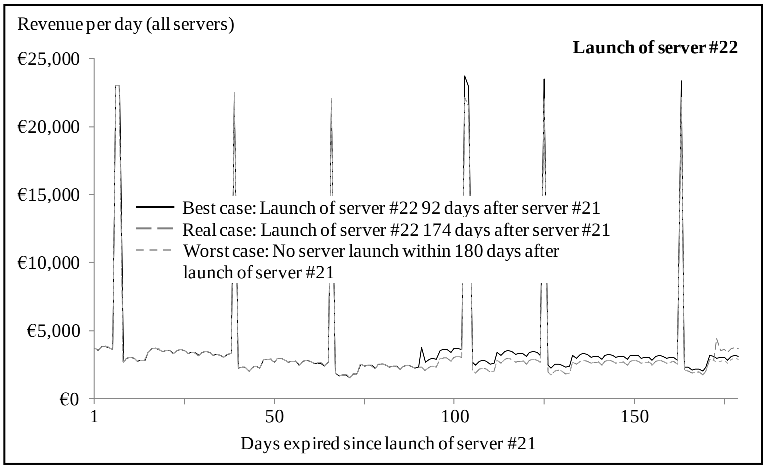

Figure 19: Simulated Revenue per Day for Server Launch #22

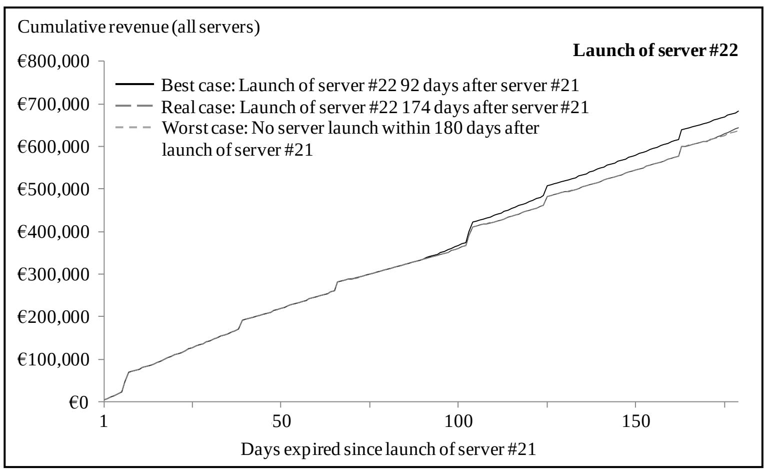

Figure 20: Simulated Cumulative Revenue for Server Launch #22

5.4 Additional 'Ceteris Paribus' Scenarios

Our simulation thus far has been based on real data for a specific game. We manipulated one variable in the data (the launch date of new servers and, resultantly, the total number of live servers) for the purposes of counterfactual analysis while keeping all other variables fixed. Our results are therefore applicable primarily to the game in question. To generalize our findings and offer recommendations to operators of other multi-instance games and platforms when to start new servers, we will now examine four additional scenarios, as described in Table 36. In each of these scenarios, we again apply the 'ceteris paribus' assumption and manipulate only one variable compared to the initial situation. While a nearly unlimited number of potential scenarios exist, we focus on modifying key variables, such as the lifetime of the game (scenario 1), the effect of server starts on new users and revenue (2), the magnitude of network effects (3), and the company's promotion strategy (4). We then assess the optimal timing for the 20 examined server starts – as we did before – and check whether the alternative scenarios lead to different results compared to the initial analysis. The results displayed in Table 37 show the server start days that maximize 180-day revenues. They are based on a total of 17,195 different simulations (= 5 scenarios × 16 to 20 examined server starts per scenario × 181 possible server start options). Overall, we find that our initial results largely hold true even if we manipulate key variables.

#	Scenario	Changed variable(s)
1	The game is one year older when server #2 is started.	Launch date (*LifetimeGame*) of Server #2 changed from day 19 to 384.
2	On any given server's launch day, user acquisition and revenue are doubled.	Impact of *IsBrandNew* on daily revenue and number of users doubled.
3	The size of the user base and revenue are linearly correlated.	Impact of *Users3DaysSquared* on daily revenue set to 0.
4	The game company does not run any promotions.	Impact of *HappyHour* and *WeekAfterHappyHour* on daily revenue and number of users set to 0.

Table 36: Description of Additional Scenarios

Launch of server	Best case: Days expired since last server launch (in brackets: difference in days vs Best case)				
	Best case (result from Table 35)	Scenario 1: Game is one year older	Scenario 2: Doubled server start effect	Scenario 3: Linear correlation: Users to revenue	Scenario 4: No promotions
#2	1	n/a	1	1	1
#3	1	1	1	1	1
#5	1	1	1	1	1
#6	1	1	1	1	1
#7	9	1 (-8)	9	1 (-8)	9
#8	55	1 (-54)	53 (-2)	37 (-18)	55
#9	85	1 (-84)	82 (-3)	70 (-15)	85
#10	99	1 (-98)	96 (-3)	84 (-15)	99
#11	109	14 (-95)	106 (-3)	91 (-18)	109
#12	121	36 (-85)	116 (-5)	107 (-14)	121
#13	102	45 (-57)	98 (-4)	88 (-14)	102
#14	107	72 (-35)	103 (-4)	92 (-15)	107
#15	102	72 (-30)	99 (-3)	90 (-12)	101 (-1)
#16	96	66 (-30)	93 (-3)	85 (-11)	96
#17	100	77 (-23)	96 (-4)	89 (-11)	100
#18	100	74 (-26)	97 (-3)	98 (-2)	100
#19	99	n/a	95 (-4)	90 (-9)	99
#20	98	n/a	94 (-4)	91 (-7)	98
#21	98	n/a	95 (-3)	94 (-4)	98
#22	92	n/a	89 (-3)	97 (-5)	92

Table 37: Results from Counterfactual Revenue Simulation with Different Scenarios[2]

In the analysis of the different scenarios, we see the following:

- Scenario 1: The results imply that an older, single-server game highly benefits from launching additional servers. Compared to the initial case, accelerating the interval between consecutive server launches is beneficial in this scenario.

[2] Note: Server #2 is excluded from scenario 1, as the scenario fixes server #2's start to 365 days after the launch of server #1. Servers #19 to #22 are also excluded, as they go beyond the simulation time frame.

- Scenario 2: Having a stronger *IsBrandNew* effect on day 1 affects the optimal server start timing to a negligible degree. The strong effect on day 1 dilutes over the course of our 180-day simulation time frame, mainly because the new server has a large number of users with decreasing incremental revenue per user.
- Scenario 3: On games or platforms that show no negative user base effects (i.e., *Users3Days* is only linearly correlated with *Daily revenue per server*), more frequent server starts can be remunerative as players tend to spend more money on (brand-)new, balanced servers than on older ones.
- Scenario 4: A company's promotion strategy seems to have little to no impact on the optimal server start timing. In our case, the revenue impact of a *HappyHour* is quite substantial in Table 33, however in determining the optimal time for a server launch, it is of only minor importance.

6. Discussion and Conclusion

6.1 Theoretical Contributions

This work's objective was to assess server launch effects in a free-to-play MMO game. We investigated a leading real-time strategy game's activity and payment data over a period of more than four years. We found a positive linear and a negative quadratic influence of the number of users on a game server's daily revenue, thus utility and revenue follow an inverted U-shape. The positive effects come from the players' extended possibilities to interact with other users, resulting in a better game experience. However, if a server grows beyond a certain number of users, the game becomes excessively unbalanced and new players have little chance to build powerful cities or to defeat players who joined earlier. A deterioration of the game experience eventually leads to lower absolute revenues. In our case, the absolute revenue maximum per server is reached at 10,409 users, decreasing afterwards with additional users. The results indicate that a sophisticated server strategy can help to enhance the players' enjoyment and ultimately the amount of money they spend in the game. We furthermore find that a server's lifetime negatively impacts its daily revenues. While revenues are highest right after the server start, we could observe that from then, daily revenues are in constant decline. We see that players joining the new server early after its launch are highly valuable to the gaming company. These players are likely to spend significantly higher amounts than players who join later.

6.2 Practical Contributions

In a counterfactual simulation that forecasts the user base and the revenue per server on a daily basis, we examined for 20 cases whether or not starting a new server can lead to higher revenues during the subsequent 180 days. In all 20 cases, we found that starting an additional server within 180 days could be more beneficial than not doing so. The right timing for the respective server start is vital to generating extra revenue with this measure.

The investigated game started with one server and quickly reached a large user base of up to 100,000 players within two months. Our simulation showed that the optimal strategy in the game's infancy is to start new servers in very quick succession. For example, our simulation showed that starting server #2 only one day after server #1 generated 65.9% higher revenues over 180 days compared to running only a single server the entire time. Here, managing the user base correctly showed the biggest positive revenue impact when compared to subsequent points in time.

As the game progressed in lifetime and experienced the according decrease in user base, the simulation showed that new servers should be launched only every 90 to 120 days to yield optimal results. Server starts outside of this window can still have a positive impact on revenue, but the magnitude of such impact decreases. In many cases, the revenue gap between best and worst case was only approx. 5%. Likewise, the risk of failure increases: in 13 of our 20 simulated server launches, we observed that a very early server start (i.e., only one day after the previous one) is the worst of all options if the company aims to maximize its revenues over the subsequent 180 days. Overall, applying the best point in time to start a new server yielded an average of 9.4% higher revenues than the respective worst case.

In practice, the rule of thumb ‘at the beginning, start new servers very quickly, later on every 90 to 120 days’ may already be sufficient. Still, to determine the optimal timing for a specific case, one also needs to consider other game-specific factors like the number of existing servers, the size of the user base, and the lifetime of the game. Promotions, such as the happy hour in our game, may amplify the revenue peak on the first day(s) of a new server and are worth testing soon after a server launch.

In our attempt to derive generalized, actionable rules about when to start new game servers, we manipulated single variables in the model and assessed whether the revenue-optimal interval between server starts changed. Among other things, we found that more frequent server launches are beneficial for older platforms or those with no network effects, and to a lesser extent for platforms with stronger positive ‘day-1’ effects. Conversely, changing the promotional strategy had no substantial impact on optimal server start timing.

The challenge of assessing the optimal size and configuration of the user base is not only interesting in the MMO real-time strategy gaming context, but also for different game types (Henderson and Bhatti 2001) or other online services such as peer-to-peer networks, online communities, online dating, and classifieds marketplaces (Asvanund et al. 2003, 2004; Bapna and Umyarov 2012; Butler 2001). Our model can be applied to these similar markets, which possess the ability to create a new instance of their platform. For example, a classifieds marketplace that reaches a sensible user limit could split into more regional offerings, or a peer-to-peer network could divide into multiple, more efficient ones (e.g., servers with special content such as movies, music, or software).

6.3 Limitations and Avenues for Future Research

Empirical studies examining the impact of the user base on economic variables are still scarce. To our knowledge, our study was the first that investigated how to leverage user base effects in MMO gaming through server launches. Though, the limitations of our study create several avenues for future research.

First, the computational power at hand merely allowed us to simulate each server start atomically. An interesting expansion of our work would be to retrospectively determine the revenue-optimal sequence of all server starts among the 2^{1758} different possibilities.

Second, our analysis aimed at finding alternate server launch timings that yielded higher revenues within 180 days than those chosen by the company in scope. However, comparing scenarios purely on the revenue they generate within these 180 days is risky as this disregards the residual value of each server start scenario's end state. Possibly, a certain scenario is revenue-optimal within 180 days, but not for a different period. The timing we chose for the analysis was aligned with the gaming company we worked with. The gaming industry is moving fast, and most metrics such as average revenue per user (ARPU), retention and conversion rates are optimized rather against a daily or monthly than against a longer-term benchmark (see e.g., GameAnalytics 2015). To check if the revenue optimum changes over time, we conducted additional simulations with an extended time frame of 360 and 720 days – which means factoring in residual values for 180 and 540 days after the initial simulation, respectively. We found that the best strategies for each individual server start case showed mostly marginal differences only, if compared to the original 180-day simulation (see Table 46 in the Appendix). Our extended analysis strengthens our confidence that the 180-day time frame is also a suitable indicator for longer-term revenue optima. In industries or cases with a longer scope or high long-term residual values, an infinite time frame could be applied.

Third, new players who just joined the focal game could freely choose on which server they wanted to play (although the gaming company set the newest server as default option for new players). A more rigid guidance of new players towards specific servers could be beneficial to capitalize from user base effects (Dinner et al. 2011; Park and MacInnis 2000). If, like in our case, the incremental utility of additional users is constantly decreasing, new players should possibly be directed to the server with the smallest user base. An experiment that proves the applicability of this approach could improve user base strategies in the gaming industry.

Moreover, it would be interesting to further assess the dynamics of MMO gaming, such as how players act if the game experience on a certain server changes (e.g., because the user base has shrunk after the start of a new server). A Hazard model with daily usage data from all players (instead of the aggregated usage and payment data per server that we applied) or a Logit model investigating under which conditions players tend to spend money, churn, or switch servers could be possible methods to approach this question.

Lastly, despite having had a very comprehensive data set at hand, it remains only *one* data set. As such, our conclusions may not be applicable to every gaming and non-gaming platform that exhibits similar effects to those described here. Overall, the workings of the MMO gaming industry present many interesting questions to which the research community has not yet provided answers. This area of study promises to be a rich source for future investigation.

7. References

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Appendix

Descriptive Information on Server Starts

	Launch day (*LifetimeGame)*	Days expired since last server launch	Number of users seven days after start	Min. users	Max. users
Server 1	1	n/a	1,869	1,764	20,569
Server 2	19	18	12,524	1,358	17,318
Server 3	26	7	11,372	1,217	17,579
Server 4	26	0	10,690	1,418	16,704
Server 5	29	3	13,478	1,220	17,097
Server 6	37	8	5,933	1,156	15,135
Server 7	55	18	10,019	1,218	14,749
Server 8	94	39	7,861	544	11,506
Server 9	171	77	4,914	541	9,052
Server 10	239	68	6,268	1,171	7,132
Server 11	303	64	4,826	1,110	9,457
Server 12	400	97	5,925	945	7,974
Server 13	485	85	6,574	954	9,079
Server 14	639	154	5,696	160	9,084
Server 15	896	257	9,657	1,058	9,807
Server 16	983	87	6,530	926	11,038
Server 17	1,094	111	5,536	918	7,065
Server 18	1,219	125	5,654	1,104	6,500
Server 19	1,383	164	5,093	1,296	6,480
Server 20	1,474	91	3,530	1,371	5,280
Server 21	1,579	105	3,025	2,099	3,947
Server 22	1,753	174	2,715	1,616	2,715

Table 38: Descriptive Information on Server Starts

Description and Descriptive Statistics of the Regression Variables

Variable	Description	Min	Max	Median	SD
Users3Days and *Users3DaysSquared*	Number of users on a server on a given day. Users must have been online at least once in the last 3 days	160	14,914	3,342.5	2,589.2
NumberOfServers and *NumberOfServersSquared*	Number of active servers on a given day	7	22	16	3.63
LifetimeServer and *LifetimeServerSquared*	Lifetime of the server in days. Is 1 on server launch day	1	1,759	691	474.4
LifetimeGame and *LifetimeGameSquared*	Lifetime of the game in days. Observation time frame starts on day 79 with the launch of the in-game shop	79	1,759	1,093	467.0
LifetimeNewestServer and *LifetimeNewestServerSquared*	Lifetime of the most recently started server in days. Is 1 on the day of a new server start	1	257	62	53.1
IsNewestServer	Dummy variable for a server. Is 1, if newest server, else 0	0	1	0	.25
IsServer#1	Dummy variable. Is 1 for server #1, 0 for all other servers	0	1	0	.25
IsBrandNew	Dummy variable for a server. Is 1, if server has been launched today	0	1	0	.02
Update1	New premium feature: Longer construction queue. Is 1 after update, else 0	0	1	1	.36
Update2	New premium feature: Investments in group advantages. Is 1 after update, else 0	0	1	1	.41
Update3	New premium feature: Inventory protection. Is 1 after update, else 0	0	1	1	.47
Update4	New feature: Larger storage rooms. Is 1 after update, else 0	0	1	1	.49
Update5	New feature: Introduction of a buddy list. Is 1 after update, else 0	0	1	1	.50
Update6	New feature: Daily login bonus. Is 1 after update, else 0	0	1	0	.47
Update7	New layout and GUI. Is 1 after update, else 0	0	1	0	.36
Update8	New premium feature: Research bonus. Is 1 after update, else 0	0	1	0	.25
HappyHour	Dummy variable. Is 1 if a happy hour promotion has been run that day, else 0	0	1	0	.14
WeekAfterHappyHour	Dummy variable. Is 1 on the seven days following a happy hour promotion, else 0	0	1	0	.31
InGameEvent	Dummy variable. Is 1 if an in-game event is active that day, else 0	0	1	0	.11
BigTvEvent	33 TV (all sports) events with an audience >20% of the population	0	1	0	.14
WeekdaySun	Dummy variable. Is 1 if Sunday, else 0	0	1	0	.35
WeekdayMon	Dummy variable. Is 1 if Monday, else 0	0	1	0	.35
WeekdayTue	Dummy variable. Is 1 if Tuesday, else 0	0	1	0	.35
WeekdayWed	Dummy variable. Is 1 if Wednesday, else 0	0	1	0	.35
WeekdayThu	Dummy variable. Is 1 if Thursday, else 0	0	1	0	.35
WeekdayFri	Dummy variable. Is 1 if Friday, else 0	0	1	0	.35
WeekdaySat	Dummy variable. Is 1 if Saturday, else 0. In our case, omitted because of collinearity	0	1	0	.35

Table 39: Description and Descriptive Statistics of the Regression Variables

Model Robustness Check: Excluding Outliers

The standard errors in the Prais-Winsten regressions used in the paper are robust to outliers, however the estimate itself may not necessarily be. We thus re-ran our regression analysis from Table 33 after excluding outliers. We used the 'ARPU' (Average Revenue Per User, i.e., Daily revenue on a server / active users on this server) to identify server-day-combinations with an especially high revenue (per user). This metric is commonly used in the online gaming industry.

We used the 2-sigma and 3-sigma cleaning approach to identify outliers for the 25,404 server-day-combinations. As the table below shows, most of them happened during the 496 *HappyHour* promotional server-day-combinations.

Applied heuristic	Definition of outliers	Number of outliers	… of them promotional days
2-sigma rule	ARPU values beyond two standard deviations of the mean ARPU	475	419 (88.2%)
3-sigma rule	ARPU values beyond three standard deviations of the mean ARPU	322	314 (97.5%)

Table 40: Identification of Outliers (i.e., Server-Day Combinations with Exceptionally High Revenue per User)

As *HappyHour* promotions and days with an ARPU beyond two standard deviations of the mean ARPU show a strong correlation of 0.86 (0.78 for 3-sigma), we decided to exclude all promotional days. This leaves our observation to 24,908 server-day-combinations.

To check whether a model without outliers yields the same results as the model reported in the paper, we exclude these outliers from our data set and re-run the same Prais-Winsten regression analysis as described in the section 'Regression model on revenue' on it. Table 41 below includes the 'Model 5 without promotions' (or outliers) and therefore compares the results of the two approaches.

Overall, we see only minor deviations between the complete model 5 used in the paper and the added model that excludes promotional days and therefore most outliers. All server-related variables *User3Days*, *NumberOfServers*, *LifetimeServer*, *LifetimeGame*, *LifetimeNewestServer* (each in linear and quadratic form), *IsNewestServer*, *IsServer#1*, and *IsBrandNew* show the same direction with similar magnitude and are all statistically significant in both models. The control variable *Update7* is statistically significant in the new model, while *InGameEvent* and *WeekdayMon* lost their significance compared to the original model. Overall, the outlier-free model also supports our hypotheses.

Independent variables		Model 1: Users	Model 2: + Servers	Model 3: + Updates	Model 4: + Promotions	Model 5: + Covar.	Model 5 without promotions
Constant		94.0637***	57.3163	384.7192***	171.5761**	169.6154**	141.9805**
Users	*Users3Days*	.3612***	.07146***	.0688***	.0701***	.0702***	.0574***
	Users3DaysSquared	-1.60e-06***	-3.39e-06***	-3.31e-06***	-3.37e-06***	-3.37e-06***	-2.46e-06***
Servers	*NumberOfServers*		-64.8548***	-119.1012***	-75.1923***	-75.4659***	-65.8774***
	NumberOfServersSquared		2.0389***	3.212***	1.4070***	1.4299***	1.3358***
	LifetimeServer		-.1404***	-.1515***	-.1463***	-.1460***	-.1371***
	LifetimeServerSquared		.0001***	.0001***	.0001***	.0001***	.0001***
	LifetimeGame		.8775***	1.3565***	1.1395***	1.1383***	1.0589***
	LifetimeGameSquared		-.0003***	-.0005***	-.0004***	-.0003***	-.0004***
	LifetimeNewestServer		-.0975	-.4116***	-.4174***	-.4144***	-.3085***
	LifetimeNewestServerSquared		.0005*	.0012**	.0012***	.0012***	.0008**
	IsNewestServer		108.4272***	109.8007***	109.5230***	109.4162***	110.4547***
	IsServer#1		130.9948***	138.5231***	136.4505***	136.0210***	112.8517***
	IsBrandNew		918.9627***	910.0590***	922.5910***	920.6780***	867.0429***
Updates	*Update1*			-6.6088	4.1837	4.0551	3.7961
	Update2			7.6882	12.1830**	12.3361**	16.4701***
	Update3			-39.6038***	-44.8103***	-44.3386***	-33.3007***
	Update4			-2.2966	-1.6166	-1.5376	-3.5168
	Update5			-21.2839***	-9.440382*	-9.2528*	-10.18445*
	Update6			15.3270	-9.0408	-8.8136	-.5359
	Update7			19.1498*	12.3781	12.4426	12.6112**
	Update8			71.3484***	37.4911***	37.7090***	45.2474***
Promo-tions	*HappyHour*				921.8200***	921.2654***	
	WeekAfterHappyHour				-37.3145***	-37.4028***	-29.4333***
	InGameEvent				23.6711*	24.0750*	5.2239
Co-variates	*BigTvEvent*					-2.0107	-.5843
	WeekdaySun					-9.0178***	-12.2865***
	WeekdayMon					5.0757*	3.0193
	WeekdayTue					9.2105***	5.3670**
	WeekdayWed					6.7039**	5.1167**
	WeekdayThu					-.5427	-.2518
	WeekdayFri					3.0050	6.8464***
	WeekdaySat					omitted	omitted
Dependent variable		Daily revenue per server in €					
R^2		.030	.188	.193	.587	.589	.378
Adjusted R^2		.030	.187	.192	.587	.588	.377
Durbin-Watson (transformed)		2.082	2.003	2.001	2.005	2.005	2.006
Number of observations (= server days)		25,404					24,908

Table 41: Prais-Winsten Regression Analysis (Dependent Variable: *Daily revenue per server*);

Comparison between Original Models and Model without Promotional Days

$*p<.1$; $**p<.05$; $***p<.01$

Model Robustness Check: Testing AR(1) to AR(3)

For all analyses shown in the main part of the paper, we use Prais-Winsten regressions with robust standard errors, corrected for autocorrelation of type AR(1). This model includes the somehow lagged, aggregated variable *Users3Days*; thus considering AR(1) may possibly not be sufficient. To check whether or not different time lags for the autoregressive process lead to different results, we re-ran our main model with Newey-West standard errors which allow a heteroskedastic error structure and possible autocorrelation up to some lag. We tested AR(1)-AR(3). In Table 42 below, we compare the results to the Prais-Winsten with AR(1) and the Newey-West regressions with AR(1), AR(2) and AR(3).

The first two columns show the differences of the coefficients and the levels of significance. We find that the coefficients slightly differ, however all still have the same direction. The significance levels for the coefficients in the Newey-West regressions are mostly the same for AR(1), AR(2) and AR(3), with only Constant (*/**) and *Update5* (*/**) surpassing the 5% threshold for AR(2) and AR(3). Overall, the Newey-West regression also provides support for all our hypotheses. Changing the maximum time lag in the Newey-West regression does not change the coefficients, but only the standard errors (and thus potentially the significance levels), which we document in the right columns of Table 42. Again, the differences to the Prais-Winsten regression are limited and support the validity of our main model.

Independent variables		Coefficients		Standard errors			
		Prais-Winsten	Newey-West Max. lag 1-3	Prais-Winsten	Newey-West AR(1)	Newey-West AR(2)	Newey-West AR(3)
Constant		169.615**	149.481*/**	78.86918	75.44575	81.8139	86.75049
Users	*Users3Days*	.0702***	.0718***	.004353	.0039113	.0041936	.0043981
	Users3DaySquared	-3.4e-06***	-3.4e-06***	2.61e-07	2.32e-07	2.46e-07	2.55e-07
Servers	*NumberOfServers*	-75.4659***	-73.6232***	12.57338	12.052	13.01484	13.78375
	NumberOfServersSquared	1.4299***	1.3950***	.476337	.450251	.4825999	.5099659
	LifetimeServer	-.1460***	-.1406***	.0171888	.0155559	.0166867	.0175927
	LifetimeServerSquared	.0001***	.0001***	9.21e-06	8.28e-06	8.82e-06	9.25e-06
	LifetimeGame	1.1383***	1.1274***	.0842077	.0805285	.0875431	.0931899
	LifetimeGameSquared	-.0003***	-.0004***	.0000358	.0000337	.000036	.0000379
	LifetimeNewestServer	-.4144***	-.4007***	.1034606	.0963078	.1032092	.1089098
	LifetimeNewestServerSquared	.0012***	.0011***	.0003759	.0003469	.0003695	.0003883
	IsNewestServer	109.416***	108.041***	6.58777	6.351236	6.994701	7.546834
	IsServer#1	136.021***	133.425***	12.94562	11.91363	12.6723	13.253
	IsBrandNew	920.678***	1008.95***	190.3164	193.3591	192.9179	192.6475
Updates	*Update1*	4.0551	2.4851	4.933026	4.740909	5.185027	5.559387
	Update2	12.3361**	12.9146**	5.355932	5.2067	5.705238	6.110337
	Update3	-44.3386***	-43.8713***	8.883854	8.101963	8.652519	9.143195
	Update4	-1.5376	-1.0478	6.685177	6.459476	7.120756	7.677547
	Update5	-9.2528*	-9.6071*/**	5.474899	4.850601	5.097159	5.310017
	Update6	-8.8136	-8.7352	6.964988	6.161585	6.426551	6.677018
	Update7	12.4426	12.9144*	7.684746	6.768821	7.035804	7.265038
	Update8	37.7090***	37.0339***	8.230046	7.243285	7.464583	7.713361
Promo-tions	*HappyHour*	921.265***	917.954***	27.26762	27.43015	27.89703	28.12417
	WeekAfterHappyHour	-37.4028***	-35.3153***	3.158225	2.5106	2.631434	2.739581
	InGameEvent	24.0750*	24.8440**	13.09588	11.65615	11.67523	11.73112
Covariates	*BigTvEvent*	-2.0107	-6.2204	6.492755	6.711838	6.674048	6.690257
	WeekdaySun	-9.0178***	-9.1216***	2.410669	2.538867	2.485101	2.457659
	WeekdayMon	5.0757*	4.8908*	2.762494	2.826131	2.756899	2.720584
	WeekdayTue	9.2105***	8.9849***	3.121893	3.169746	3.16701	3.125327
	WeekdayWed	6.7039**	6.3938**	2.809944	2.827878	2.820898	2.765016
	WeekdayThu	-.5427	-.7578	3.143792	3.210756	3.140312	3.099664
	WeekdayFri	3.0050	2.9019	2.622737	2.719299	2.638315	2.595049
Number of observations (= server days)		25,404					
F-Value				271.70	275.16	237.61	214.00

Table 42: Comparison of Results from Prais-Winsten and Newey-West Regressions (Dependent Variable: *Daily revenue per server* in €)

**p*<.1; ***p*<.05; ****p*<.01

Model Robustness Check: Split into Training and Test Data Sets

To identify possible signs for overfitting, we are applying three different training models (with corresponding test data sets) which use the first 75%, 67% and 50% of the available simulation days, respectively. All parameters we looked at show no indicators for overfitting:

- The R^2 for the full model is lower than if running the model solely on any of the three chosen test data sets.
- The full and all training models (see Table 44) show a very small difference of .001 or below between R^2 and Adjusted R^2. A large difference is a common indicator for overfitting (Harrell 2015, pp. 110-111).
- Overfitting is a problem that occurs when a model is very complex, has many explanatory variables, and a low number of observations. Our main model has over 25,000 observations and 31 variables – thus far more observations than the standard recommendation of having 15 for every explanatory variable.

All in all, our (full) model shows a good fit and no sign of overfitting. If we make the standard assumption that we can learn from the past to make better predictions for the future, we can rely on the full model that makes use of all observations.

<table>
<tr><th colspan="5">Training data set</th><th colspan="5">Test data set</th><th colspan="3">Application of training model on test data set</th></tr>
<tr><th>Days</th><th>N (server days)</th><th>Omitted variables</th><th>R^2</th><th>Root MSE</th><th>Days</th><th>N (server days)</th><th>Omitted variables</th><th>R^2</th><th>Root MSE</th><th># of vars</th><th>Corr. (real rev vs forecast)</th><th>MAPE</th></tr>
<tr><td>All
(days 1…1759)</td><td>25,404</td><td>None</td><td>.589</td><td>127.91</td><td>All
(days 1…1759)</td><td colspan="4">Same as left</td><td>31</td><td>.784</td><td>68.1</td></tr>
<tr><td>First 3/4
(days 1…1319)</td><td>16,633</td><td>Update6
Update7
Update8</td><td>.540</td><td>108.10</td><td>Last 1/4
(days 1320…1759)</td><td>8,771</td><td>Update1
Update2
Update3
Update4
Update5</td><td>.626</td><td>157.39</td><td>23</td><td>.783</td><td>94.8</td></tr>
<tr><td>First 2/3
(days 1…1172)</td><td>14,051</td><td>Update6
Update7
Update8
InGameEvent</td><td>.465</td><td>101.71</td><td>Last 1/3
(days 1173…1759)</td><td>11,353</td><td>Update1
Update2
Update3
Update4
Update5</td><td>.638</td><td>152.28</td><td>22</td><td>.741</td><td>123.8</td></tr>
<tr><td>First 1/2
(days 1…880)</td><td>9,417</td><td>Update4
Update5
Update6
Update7
Update8
HappyHour
WeekAfterHappyHour
InGameEvent</td><td>.342</td><td>84.33</td><td>Last 1/2
(days 881…1759)</td><td>15,987</td><td>Update1
Update2
Update3</td><td>.627</td><td>145.71</td><td>20</td><td>.285</td><td>174.7</td></tr>
</table>

Table 43: Split into Training and Test Data Sets

Independent variables		Full data set	Training set: First 3/4 (days 1…1319)	Training set: First 2/3 (days 1…1172)	Training set: First 1/2 (days 1…880)
Constant		169.6154**	148.4874	152.8847	-483.7047**
Users	*Users3Days*	.0702***	.0629***	.0571***	.02903***
	Users3DaysSquared	-3.37e-06***	-2.73e-06***	-2.32e-06***	-4.80e-07*
Servers	*NumberOfServers*	-75.4659***	-67.9883***	-63.1859**	104.1601**
	NumberOfServersSquared	1.4299***	.6489	.02964	-9.5744**
	LifetimeServer	-.1460***	-.1653***	-.2272***	-.24501***
	LifetimeServerSquared	.0001***	8.75e-05***	.0001***	.0002***
	LifetimeGame	1.1383***	1.3404***	1.5331***	1.5437***
	LifetimeGameSquared	-.0003***	-.0004***	-.0005***	-4.67e-05
	LifetimeNewestServer	-.4144***	-.5731***	-.6768***	-.9269***
	LifetimeNewestServerSquared	.0012***	.0015***	.0017***	-.0015*
	IsNewestServer	109.4162***	90.4121***	75.4375***	68.4306***
	IsServer#1	136.0210***	111.0555***	102.5429***	59.6826***
	IsBrandNew	920.6780***	938.1606***	888.7189***	571.6634***
Updates	*Update1*	4.0551	.7451	3.3626	31.9167***
	Update2	12.3361**	7.1203	7.0767	-18.3037***
	Update3	-44.3386***	-53.3784***	-53.8161***	-22.3193*
	Update4	-1.5376	.39219	6.4278	omitted
	Update5	-9.2528*	5.0756	20.2379**	omitted
	Update6	-8.8136	omitted	omitted	omitted
	Update7	12.4426	omitted	omitted	omitted
	Update8	37.7090***	omitted	omitted	omitted
Promotions	*HappyHour*	921.2654***	907.2558***	821.6421***	omitted
	WeekAfterHappyHour	-37.4028***	-36.5171***	-33.6683***	omitted
	InGameEvent	24.0750*	-2.8662	omitted	omitted
Covariates	*BigTvEvent*	-2.0107	-6.5919	-18.2270**	-4.1486
	WeekdaySun	-9.0178***	-9.9440***	-11.2578***	-5.9463**
	WeekdayMon	5.0757*	5.9661**	5.1467*	13.5035***
	WeekdayTue	9.2105***	8.0790**	8.8170***	19.5017***
	WeekdayWed	6.7039**	9.8766***	9.2284***	13.2572***
	WeekdayThu	-.5427	7.5408**	5.5238*	10.3484***
	WeekdayFri	3.0050	5.8813**	2.7055**	10.7104***
R^2		.589	.540	.465	.342
Adjusted R^2		.588	.539	.464	.341
Durbin-Watson (transformed)		2.005	2.007	2.009	2.021
Number of observations (= server days)		25,404	16,633	14,051	9,417

Table 44: Comparison between full data set and training sets; Prais-Winsten regression analysis, dependent variable: *Daily revenue per server* in €

**p*<.1; ***p*<.05; ****p*<.01

Auxiliary Regression Predicting the Number of Previous-Day Users

Independent variables		Coefficients
Constant		1344.3570***
Users	*Users3DaysYesterday*	.9546***
Servers	*NumberOfServers*	-132.9949**
	NumberOfServersSquared	1.9762
	LifetimeServer	-.0627**
	LifetimeServerSquared	.00003**
	LifetimeGame	.5424
	LifetimeGameSquared	-.0001
	LifetimeNewestServer	-.8716***
	LifetimeNewestServerSquared	.0032***
	IsNewestServer	151.7332***
	IsServer#1	212.0087***
	IsBrandNew	2663.8320***
Updates	*Update1*	89.7127***
	Update2	-38.2569*
	Update3	-55.6019**
	Update4	8.4929
	Update5	4.0149
	Update6	-9.5521
	Update7	4.9070
	Update8	-2.8886
Promotions	*HappyHour*	2.5930
	WeekAfterHappyHour	-.6555
	InGameEvent	2.9621
Covariates	*BigTvEvent*	-14.2085*
	WeekdaySun	-54.7046***
	WeekdayMon	-59.5732***
	WeekdayTue	-68.0853***
	WeekdayWed	-52.6245***
	WeekdayThu	-52.7735***
	WeekdayFri	-47.3738***
R^2 / Adjusted R^2		.994 / .994
Durbin-Watson (transformed)		1.671
Number of observations		25,770

Table 45: Results from Prais-Winsten Regression (Dependent Variable: *Users3Days* per server)

**p*<.1; ***p*<.05; ****p*<.01

Comparison of Results between Different Simulation Time Frames

Launch of server	Real case (from Table 35)	180-day simulation (from Table 35)		360-day simulation		720-day simulation	
		Best case	Diff. Best vs Real	Best case	Diff. Best vs Real	Best case	Diff. Best vs Real
#2	18	1	4.0%	1	3.8%	1	3.3%
#3	7	1	0.9%	1	0.7%	1	0.5%
#5	3	1	0.1%	1	<0.1%	1	0.1%
#6	8	1	0.2%	1	0.2%	1	0.2%
#7	18	9	<0.1%	1	0.3%	1	0.2%
#8	39	55	0.1%	15	0.4%	5	0.4%
#9	77	85	<0.1%	59	0.1%	55	0.3%
#10	68	99	0.4%	104	0.3%	98	0.3%
#11	64	109	1.0%	114	0.8%	107	0.7%
#12	97	121	0.3%	119	0.4%	115	0.3%
#13	85	102	0.1%	123	0.1%	127	0.1%
#14	154	107	0.9%	120	0.7%	132	0.6%
#15	257	102	2.2%	119	1.9%	130	1.8%
#16	87	96	<0.1%	115	0.1%	127	0.1%
#17	111	100	0.1%	112	0.1%	122	0.1%
#18	125	100	0.4%	107	0.3%	122	0.2%
#19	164	99	2.7%	100	1.7%	118	1.5%
#20	91	98	<0.1%	101	<0.1%	111	<0.1%
#21	105	98	0.1%	99	0.1%	112	0.1%
#22	174	92	6.1%	96	4.4%	107	3.7%

Table 46: Comparison between 180-Day, 360-Day and 720-Day Revenue Simulation

Article V: LAW ENFORCEMENT 2.0 – THE POTENTIAL AND THE (LEGAL) RESTRICTIONS OF FACEBOOK DATA FOR POLICE TRACING AND INVESTIGATION

Abstract

Innovative information technologies permit new approaches to fight crime. This study examines the police's state-of-the-art application of Facebook information and identifies two fields of usage: First, the police use Facebook to ask users for help, for example when they are looking for witnesses of a crime. Second, the police search the social network for information, pictures or social bonds of a specific person. As academic literature is amazingly quiet on this timely topic, this study compiles recent media reports and results from a German pilot project conducted by Hanover police. Although several success cases show the potential of this new approach, new areas of conflict such as how to protect the privacy of prospective offenders or witnesses, are created in this way. Our analysis reveals that the regulatory framework for the police work on Facebook is unclear. Thus we provide policy makers with a list of legal issues that remain to be clarified. Additionally, we compile hypotheses that provide avenues for future research.

Key words: Police; Facebook; Social network; Tracing; Investigation; Legislation; Data privacy

1. Introduction

Since the 2001 terrorist attacks in New York, security concerns have increased world-wide. Not only intelligence agencies intensified the collection and analysis of information to investigate terrorists' activities, but also local law enforcement agencies put more effort into modern information technologies (Chen et al. 2003; Custers 2012) which allow new approaches for public authorities to prevent crime and prosecute criminals, such as data mining (e.g., Abbasi and Chen 2005), Policeware (e.g., Nabbali and Perry 2004; Diffie and Landau 2009), intelligent camera tracking (e.g., Lee et al. 2012), mobile phone and computer surveillance (e.g., Nettleton and Watts 2006; COM 2010).

For a few years, police authorities use social networks such as Facebook for tracing and investigation purposes. In a simple case of an online tracing, the police may ask Facebook users for help, if searching for eye witnesses of a crime or the whereabouts of a missing person. In Germany, we find 14 local police authorities who regularly post requests for information on Facebook and more examples in the UK and the US. Besides, the police use the social network to collect information about a person. With more than one billion monthly active users (Facebook 2013a) sharing their pictures, social activities or interests, Facebook may be a useful source of information for the police.

Our work on the police's state-of-the-art usage of Facebook data provides an overview on technological, societal and legal issues and the new areas of conflict created hereby. While the police may wish to use information gathered via Facebook most effectively, they must consider existing laws and regulations that protect the privacy of prospective offenders or witnesses. However, the existing regulatory framework may not always be as precise as needed. Our review has three main objectives: First, as it is (to our knowledge) the first scientific paper exploring police work on Facebook, we review how police authorities use Facebook today for tracing and investigation, and assess the potential of this new approach. Second, we study if the legislation in Germany provides a clear regulatory framework for the police work on Facebook. We identify legal 'gray areas' and advise policy makers to focus on these existing legal issues. Third, we compile hypotheses that aim at stimulating researchers to conduct additional studies.

Interestingly, academic literature is rather quiet on this timely and important topic. To receive valuable information on the police's usage of Facebook and its restrictions, we compiled dozens of recent TV, radio and newspaper reports from different countries. Additionally, we looked into the results from a pilot project conducted by Hanover police, approaches from other public authorities, contributions from the European Union and the German federal government, existing laws and judiciary decisions. We selectively spoke with police staff specialized in the field of Internet crime to verify our findings.

The remainder of this paper is structured as follows: we start examining how police authorities already exploit Facebook information. As we describe in chapter 2, Facebook allows the police to publish requests for information, to find suspects or witnesses and thus to gain important hints for an ongoing tracing. In chapter 3, we explore how Facebook information, such as the one taken from a suspect's profile page, can be used to support an investigation. Both sections include a review on advantages and critical aspects of the authorities' work with the network, as well as several success cases, partly taken from the Hanover pilot project. Chapter 4 dares an outlook on the police's future application of Facebook. Chapter 5 concludes with advices for the policy makers and shows avenues for future research.

2. Police Tracings via Facebook

2.1 The Process of Tracings via Facebook Based on a Pilot Project

Germany's Polizeidienstvorschrift 384.1 (Official Police Instructions) defines a police tracing as the *"[...] search for individuals or properties in the context of a criminal prosecution, sentence execution or danger prevention [...]"*. The media used for tracings depend on the gravity of the crime and can include internal media such as police information systems as well as external media such as publishing requests for information in newspapers, TV shows or on the Internet. In case the police use external media, we refer to public tracings. In such, the requested person must be under strong suspicion of having committed a serious criminal offence (Spiegel 2012a; Bundestag 2007). Section 131a (3) StPO (Strafprozessordnung; Code of Criminal Procedure) determines the structure of a public tracing. It also applies to tracings on the Internet and via Facebook.

In Germany, the police in Hanover are considered a pioneer for public tracings in social networks. They carried out a pilot project between February and August 2011, publishing identikit pictures on Facebook to trace accused persons (Deutschlandradio 2012) and to support the investigation of a crime. If the police in Hanover decide to publish a request for information according to section 131a (3) StPO, a judicial decision has to be obtained first, according to section 131c (1) StPO. Only then a request for information, in many cases supported by an identikit picture with respect to section 131b StPO, is posted on the wall of the police's (public) Facebook page (Süddeutsche Zeitung 2011a). Facebook users can comment on tracing posts, however, the police always ask users to contact them via telephone. This way, the police want to avoid that personal details of accused persons or witnesses are published. Figure 21 shows the process of a tracing via Facebook and its legal basis in Germany.

Today, Hanover police are not the only police authority using Facebook for tracing purposes. In March 2013, we found 19 German police authorities who have a Facebook page, and 14 of them regularly publish tracings. Likewise, the FBI regularly post requests for information on Facebook. In the UK, Greater Manchester Police are a pioneer in Internet tracings by using Facebook and Twitter.

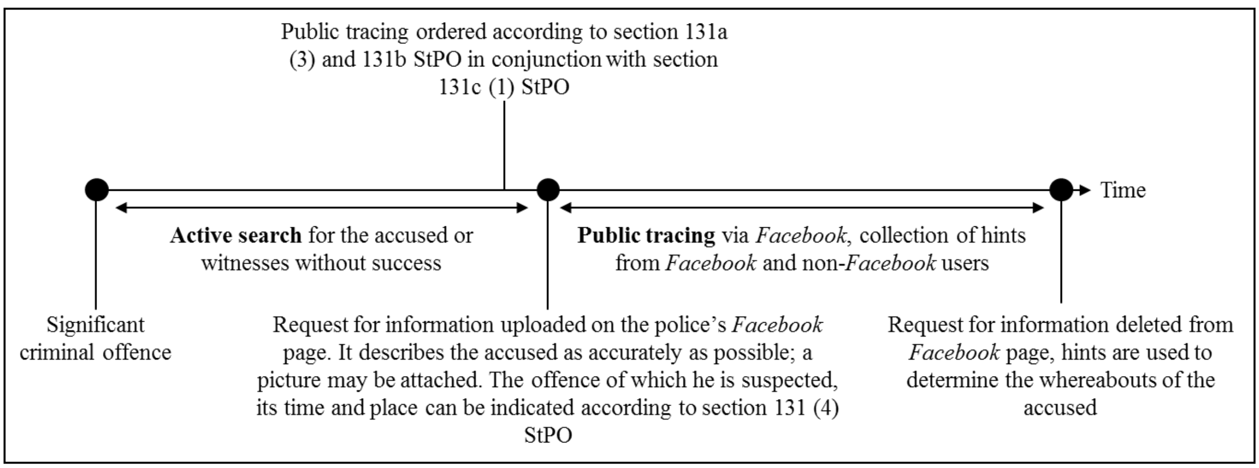

Figure 21: Tracing Process via Facebook

2.2 Advantages of Facebook Compared to Common Tracing Tools

Large and active audience. The number of active users is a major reason why the police refer to the social network as a tracing tool. In December 2012, Facebook had more than a billion monthly active users worldwide (Facebook 2013a) and about 25 million users in Germany (Statista 2013). Thus, Facebook offers an enormous coverage that can be used by the police to reach more potential witnesses than via any other communication channel. While requests for information in daily newspapers are usually read more often by elder people, a social network can reach younger people more easily (Deutschlandradio 2012). 27% of the

Facebook users are between 18 and 24 years old (Statista 2012), which is the most active age class of all Facebook users (Social Media Quickstarter 2011). In March 2013, Hanover police's Facebook page had more than 113,000 'Likes', Greater Manchester Police's had ca. 41,000. Both Facebook and non-Facebook users can access the pages and support the tracing. Facebook users can share posts with their friends. Thereby, the police are able to reach a large number of people within a short time. The requests for information published by Hanover police between September 2012 and March 2013 have on average been shared 1,232 times by its users (Facebook 2013b). Considering an average friend count of 190 (Facebook 2011a), a request for information can quickly reach hundreds of thousands of users. Requests for information published on Facebook are not restricted to certain regions, but are available throughout the entire (global) network.

Fast medium. Compared to other channels, Facebook is a very fast communication medium. Requests for information can immediately be commented. Posting a request can provide crucial information helping the police investigation already within a few minutes. A newspaper, however, must first be printed and published, so requests for information are read at a later time.

No publication costs. Publishing requests for information on Facebook incurs no media costs. This allows the police to publish offences independent of their gravity. In this way, the police can also collect hints regarding tracings that might not have been published in newspapers or other costly media. Even though the users' attention span for a post may be limited, the police are able to selectively repost the request for information at no cumulative costs. A tracing published on TV or in a newspaper incurs extra costs for every additional broadcast. So, it may only be perceived on its release date, and will not be available anymore for the remaining tracing period (NDR 2011a).

2.3 Successful Tracings via Facebook during the Pilot Project

During the pilot project in Hanover, 60 requests for information were published on Facebook to find criminals, witnesses and missing people (Hamburger Abendblatt 2011; RTL 2011). The posts were read about 150,000 times on average. Over six months, the police were able to solve eight cases with the help of Facebook users where previous tracings via other channels were unsuccessful (Spiegel 2011a). In the following, we present some of these success cases (for details see Presseportal 2011).

Theft. Hanover police were looking for three thieves. The investigations had been unsuccessful for four months. As a consequence, the police decided to publish pictures taken by a surveillance camera on Facebook. The offenders could be identified with the help of the network's users on the same day (Süddeutsche Zeitung 2011b). The case shows that Facebook is indeed a very fast medium. In another case, offenders stole a Volkswagen Polo in Wolfsburg and then committed a petrol theft near Hanover. The police in Wolfsburg asked their colleagues from Hanover for help. Common investigations were not successful, so the police decided to post a request for information on Facebook. A woman recognized the co-driver of the stolen car. With this information, the police were able to identify the driver.

Assault. A 17-year-old girl was attacked by two teenage girls. The accused girls were photographed by a surveillance camera. The police published the picture in regional newspapers (ARD 2012), but received no hints to identify the offenders. A judicial order was issued allowing the police to publish the picture on Facebook. One hour after the post on the social network, the first useful pieces of information were given so that Hanover police could identify the two accused girls.

Missing children. In one case a 14-year-old boy had been missing for two days and in another case a 12-year-old girl had disappeared for three days. In both cases the police in Hanover asked Facebook users for help. The missing boy contacted the police via telephone himself 45 minutes after the publication went online. In the case of the girl, her friends saw the request and convinced her to return back home. Both cases show that requests for information on Facebook can put a certain pressure on the missing persons or their social contacts (NDR 2011a).

Rape. A 16-year-old girl accused two men of rape after a night club visit. She recognized one of the potential offenders in a picture taken by a surveillance camera. The picture and a request for information were published on Facebook in order to identify the prime suspect. A few hours later the man in the picture contacted the police in order to prove that he was not the person they were looking for. Besides he could even give them valuable information concerning the real offenders who later confirmed that they had sexual contact with the girl, but denied having raped her.

2.4 Critical Aspects of Facebook Tracings

Public rush to judgement. As seen in the previous case, Facebook tracings bear the risk that users publish hints that may not target the offenders, but (accidentally) charge innocents. As the next example shows, this can lead to a public rush to judgement. A 17-year-old teenager was suspected of murder. A neighborhood girl saw the boy being arrested and spread the news directly on Facebook. As a consequence, the young man was condemned in public (NDR 2012a). By commenting posts, witnesses are able to publish the full name of a potential offender. Thus, in every request for information, the police ask witnesses to call them instead of commenting the post. The problem is that the comment function on Facebook cannot be switched off. Such comments can also contain wrong denunciations pillorying innocent people (ZDF 2012; Spiegel 2012a). Furthermore, giving hints by commenting on Facebook requests for information can also have consequences for the authors. Their names and comments are available for every Internet user. Thereby, users might even become a target. Insufficient data protection for witnesses and potential offenders in the social network is criticized.

Data storage/data deletion. Protecting sensitive information related to public tracings may conflict with the fact that Internet data is usually stored forever: search engine operators make backups of websites on a regular basis, and any Internet user has the possibility to copy and save online content (Lawblog 2012). Copies of requests for information and related comments could still be found on the Internet beyond the tracing period. This could have serious consequences for innocent people and for those who have been acquitted in a trial or have served their sentences (NDR 2012b). Those people might be associated with certain crimes or suspicions forever and be disadvantaged thereby.

Another issue is that Facebook data generated by users – including the police – cannot be completely deleted by these users. The data is only marked as deleted and cannot be seen by users any longer, but it is still saved in Facebook's databases (HR 2012; Heise online 2012a). Facebook states in its data policy that they *"cannot ensure that information you share on Facebook will not become public [...]"* (Facebook 2013c). This makes the exploitation of Facebook data for police purposes rather critical.

Legislation. Until now there are no laws that control tracings via Facebook. They are justified with the interpretation of section 131a (3) StPO. Appendix 2, Section 3.2 RiStBV (Richtlinien für das Strafverfahren und das Bußgeldverfahren; Guidelines for criminal and summary proceedings) says that public tracings on the Internet should be conducted on police websites. Private web sites should not be used. However, these are only guidelines for public authorities and no legal basis (Zeit 2012a).

The storage of Facebook's data on US servers is seen as a major problem (Hamburger Abendblatt 2011). All data belonging to Hanover police's Facebook page is stored in California. This includes profile data and IP addresses of users and visitors. Data protectionists criticize the transmission of personal data to the US since the police do not have any influence on what is happening to that data (ULD 2011). Data protection specialists and police unions demand an update of the German data protection laws (Hamburger Abendblatt 2011; Spiegel 2011b). The first version of the German BDSG (Bundesdatenschutzgesetz; Federal Data Protection Act) came into force in 1979, long before private Internet and Facebook usage, the last amendment was made in 2009. Thilo Weichert, data protection commissioner in Lower Saxony, emphasizes that tracings via Facebook are not compatible with German and European data protection laws (Spiegel 2011b). He refers to the following situation: Facebook's headquarters are in the US, but the central office in Dublin, Ireland, is in charge of data processing for European users (ULD 2011). Thus, European or Irish law should be applied. But the social network's conditions of use are based on American law which is less strict (ZDF 2011). According to European law, Facebook must inform its users how their data is used and analyzed. As this is not the case, the social network violates Article 10 of the 95/46/EG directive (European

Union, 1995) which states that *“data-processing systems [...] must, whatever the nationality or residence of natural persons, respect their fundamental rights and freedoms, notably the right to privacy [...]”*.

Personnel expenditure. When requests for information are published on Facebook, they must be supervised and maintained continuously. The police must follow all provided information, even if it does not seem useful (RTL 2011). In case the police want to prevent users from publishing hints or personal information through Facebook’s comment function, they permanently need to supervise the site and delete objectionable posts (Heise online 2011). On a platform like Facebook, a large number of comments can raise in a short time which can lead to increased personnel expenditure. Table 47 summarizes the main advantages and critical aspects of tracings via Facebook.

Police tracings via Facebook	
Advantages	Critical aspects
▪ Facebook tracings can reach a large (especially young) audience ▪ Facebook tracings are not limited to certain regions ▪ Medium is very fast, enables quick continuation of investigative work ▪ The police can (re)post a request for information without extra costs ▪ Requests for information can be published, independent of the offence’s gravity	▪ Wrong denunciations on Facebook risk to create a public rush to judgement ▪ Facebook data cannot be completely deleted, which may penalize innocent or acquitted people ▪ No clear legal basis, interpretation of section 131a (3) StPO for tracings via Facebook is disputed ▪ Facebook does not apply European data protection laws ▪ Higher personnel expenditures may be required to supervise Facebook tracings

Table 47: Advantages and Critical Aspects of Tracings via Facebook

2.5 Consequences for the Continuation of Tracings via Facebook

The pilot project in Hanover has been considered successful. The police continued to publish requests for information beyond the end of the pilot project in August 2011. From January to February 2012, tracings via Facebook were stopped because of legal concerns. The main reason was the transmission of personal data (i.e., detailed descriptions of suspects, incl. identikit pictures and requests to post hints on Facebook) to servers in the US. In February 2012, tracings via Facebook were resumed after having changed the information policy. First, Hanover police ceased posting the detailed description of suspects and identikit pictures on Facebook. Instead, this information is only available on the police's website which can be accessed through a link published on the social network. Other German police authorities (e.g., Cologne and Erfurt) did not adopt the Hanover approach and still post suspect descriptions and identikit pictures along with requests for information. A consistent national information policy remains to be passed. Second, Hanover police ask all users to only provide information via telephone, not via the comment function on Facebook. These two measures minimize the amount of sensitive data transferred to the US. Figure 22 points out which information has been published during the Hannover pilot project in 2011 and what has been published on Facebook (2013b, text translated and abbreviated). It rests upon a request for information published in January 2013.

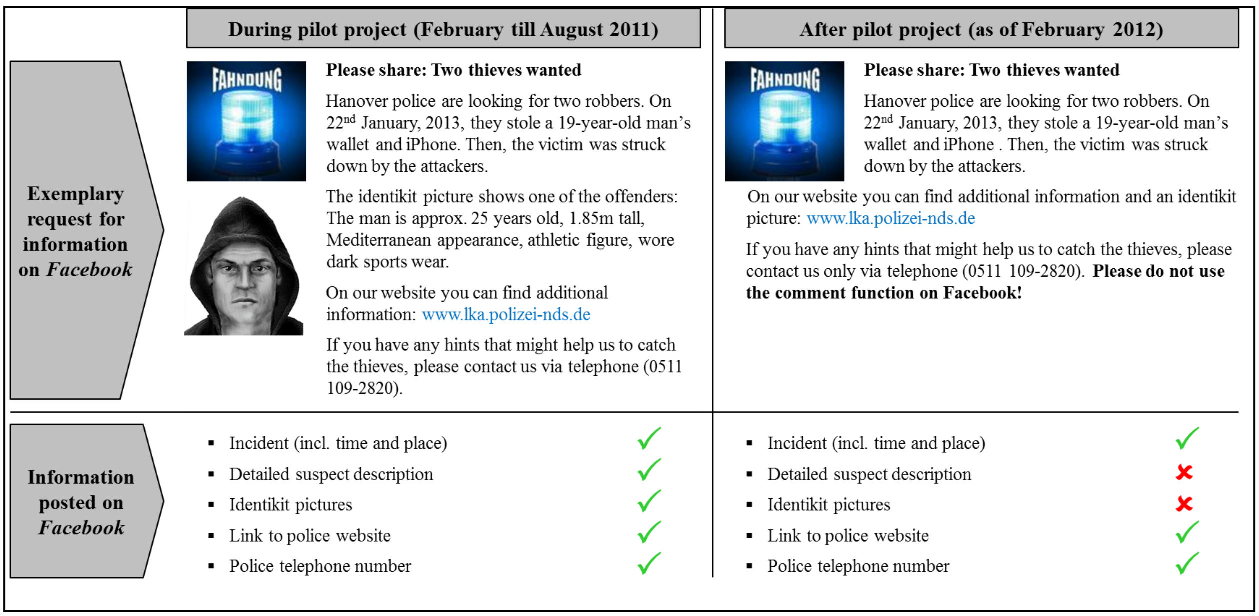

Figure 22: Exemplary Request for Information on Hanover Police's Facebook Page during the 2011 Pilot Project and afterwards

3. Police Investigations via Facebook

The police use Facebook not only to trace suspects and victims, but also to investigate actively in order to expose and prevent criminal acts. In this section, we present the advantages of the Facebook use in police investigations, show success cases, and close with (legal) limitations.

3.1 Advantages of Using Facebook for Police Investigations

Exposure of criminal acts. The information in social networks is often very valuable for the police. This includes a person's residence, occupation, friends, attitudes and hobbies (Spiegel 2011b; Gross and Acquisti 2005). Depending on the user's privacy settings, this information can be available to anyone. If a user's profile is public, the police can use the information without any restriction. If this is not the case, investigators may ask Facebook to hand out necessary information. Facebook is bound to give *"US security agency an insight into their membership data"* (Hamburger Abendblatt 2011). American police authorities can access it if a *"valid subpoena [...] in connection with an official criminal investigation"*, *"a court order [...] under 18 U.S.C. Section 2703(d)"* or *"a search warrant"* have been issued (Facebook 2013d). Non-US authorities need a letter rogatory to access the data.

Police staff can also work under false identity to access information, as six BKA (Bundeskriminalamt; Federal Criminal Police Office) investigators do. They send friend requests to suspects (Bundestag 2011) and then examine the social life of a person. The police can act if abnormalities occur, identify whereabouts of suspects or get personal information of friends who might support the investigation.

Using specialized Facebook search software is another way to extract information. Europol, European Union's criminal intelligence agency, already uses social network analysis tools (Heise online 2012b) that aim at identifying and analyzing relations between persons. Breadth and depth of such information are usually more extensive than those available in police databases. Such 'profile crawlers' can access a person's private information through his social network. Kosinski et al. (2013) show that Facebook 'Likes' can be used to accurately predict a range of sensitive personal attributes that might help a police investigation, including age, sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness or use of addictive substances. The crawler may also abuse common Facebook weaknesses: for example, even in case the searched person's profile is only accessible by friends, the list of friends is usually accessible and serves as a starting point for the progressive search (Balduzzi et al. 2010).

Likewise, it is even possible to make predictions regarding the acquaintance between two non-Facebook members with a high rate of success (Horvát et al. 2012).

Prevention of criminal acts. In Canada and the US, police and FBI use Facebook to recognize criminal behavior before a crime is committed. For example, authorities supervise prisoners' Facebook use (San Francisco Chronicle 2011) and scan public profiles from US high school students to prevent acts of violence at schools (Washington Post 2009). At the beginning of 2012, the FBI tendered the development of an early-warning system based on open-source information from different social networks (BBC News 2012). Beside Facebook, British police also target Bebo and MySpace to try to understand and to prevent teenage murders (Daily Mail 2008).

3.2 Successful Investigation on Facebook

Picture database. The police in Hamburg and Mecklenburg-Western Pomerania use public Facebook pictures to match them with pictures of prospective traffic offenders caught by a speed camera. This process is faster and more cost-efficient than identifying the driver personally. Two cases have been reported in which suspects could be freed from blame since their Facebook profile picture did not match the speed camera's photo.

Location identification. In the following two cases, US police used Facebook to locate suspects. They were able to find and arrest a fugitive who had fled to Mexico. Via his Facebook friends, they accessed the man's Facebook wall who regularly updated his profile with his current location (Stern 2010). In a similar case, a suspect posted on his wall: *"Catch me if you can, I'm in Brooklyn"* (San Francisco Chronicle 2011). The police located the computer the man had used and arrested him.

Alibi. A 19-year old man was accused of two robberies. He was on remand for 12 days and claimed to be at home during the time of the offence. After all, a Facebook message sent to his girlfriend one minute prior to the crime from his home computer could prove his innocence (Stern 2009).

3.3 Problems of Police Investigations via Facebook

Information on Facebook can be distinguished between public and private information. The collection and use of public data by the German police do not conflict with the right for informational self-determination ensured by the Articles 2 (1) and 1 (1) GG (Grundgesetz; Basic Law), which covers *"The right of the individual to decide what information about himself should be communicated to others and under what circumstances"* (Westin 1970). The German Federal Constitutional Court (Bundesverfassungsgericht 2008) confirmed that public authorities can use any public information on the Internet for their purposes. However, most of the information in online social networks cannot be accessed that easily. Most Facebook users disclose personal information and pictures only to friends (O'Brien and Torres 2012), making it difficult for the police to collect the required data.

One possibility for the police to access private data is to approach Facebook directly. However, non-US police authorities struggle accessing data directly from Facebook, as the following case shows: a German judge asked Facebook for access to an accused man's account. As the data is stored on US servers, his request was denied by both Facebook Germany and Europe who referred the judge to their headquarters. However, the US data protection laws forbid Facebook to provide data to non-US authorities if no official letter rogatory has been requested. As this request is a very time-consuming process (Spiegel 2012b, Heise online 2012c), it was not realized by the German judge.

The police can also use a covert or false identity to access private data, for instance pretending to be part of the suspect's network. It is judged critically to what extent communication in social networks is worthy of protection and thus not usable for undercover investigations. The German Federal Constitutional Court (Bundesverfassungsgericht 2008) decided that (undercover) police investigations on the Internet usually do not conflict basic rights. When communicating on the Internet, an individual cannot assess for sure if the communication partner is who he pretends to be, and thus he cannot be sure that he does not interact with a public authority. However, the police must not exploit data that it would not have received otherwise. This means that the police can use, among other things, information somebody freely shared in an online forum, but not private information the police specifically asked for under a false name.

Table 48 summarizes the main advantages and critical aspects of police investigations via Facebook.

Police investigations via Facebook	
Advantages	Critical aspects
▪ Information from public profiles (including a person's recent picture, place of residence, occupation or friends) can easily be accessed and used without a legal restriction ▪ US police can access private Facebook information, if an official decree is available ▪ Facebook search software can efficiently crawl profiles and extract additional information ▪ Data can be used to expose or to prevent criminal acts	▪ Most Facebook members disclose personal information and pictures only to friends ▪ US data protection laws forbid Facebook to provide data to non-US authorities without an official letter rogatory ▪ In Germany, information collected under covert or false identity can conflict with the right for informational self-determination (Articles 2 (1) and 1 (1) GG)

Table 48: Advantages and Critical Aspects of Investigations via Facebook

4. Outlook: Future Application of Facebook

In addition to publishing requests for information on the police's own Facebook page and to access user information for investigation purposes, Facebook offers more functions the police could use in the future. In this chapter, we present three possible evolutions.

Biometric facial recognition. On average, a Facebook user displays 282 pictures (Statista 2011). In June 2011, Facebook (2011b) started applying biometric facial recognition software. When a user uploads a new picture, it proposes which of his friends might be in the photo (ZDNet 2011a). If the proposal is wrong, the user can manually enter the name of the person. This way, the facial recognition software learns from the user. The police could apply Facebook as a picture database and use facial recognition to identify photographed people, for example in football stadiums or traffic controls.

European data protection authorities criticize Facebook for activating the face recognition function by default for all users without letting them know (ZDNet 2011b). In Germany, such kind of storage and usage of biometric facial data is legal only if supported by law or with the user's formal consent. Otherwise, it conflicts with the users' right for informational self-determination. Thus, an irreproachable legal application for biometric data use by the German police is not given today. In September 2012, Facebook deactivated the function by default for all users in Europe (Zeit 2012b) and finally deleted the data collected so far in February 2013 (Heute 2013).

Intelligent cameras. The idea of 'intelligent' cameras is to automatically recognize situations that require an intervention by policemen or guard staff, and to initiate the necessary next steps such as triggering an alarm. Ongoing research focuses on identifying violent-prone behavior before it comes to an act by analyzing a person's gesture, facial expression and body movements (Courtney 2011). In August 2012, New York police introduced an intelligent monitoring system for terror defense purposes which could also be used to fight common crime acts (Spiegel 2012c). It links pictures from surveillance cameras with police databases, maps and the emergency call system (Heise online 2012d). Some UK police cars have already been equipped with intelligent cameras linked to photo databases and facial recognition software. The information is used to identify 'crime hot spots', which are locations with a high likelihood for future crimes (Focus 2013). In addition to using police databases, a match with Facebook pictures may increase the success chance to identify criminal offenders. Besides, the police can collect additional profile data from the person's Facebook page. If a suspect is filmed by more than one camera, the police can create a movement profile and determine his last location. However, appropriate laws need to legitimate this approach, otherwise the right to informational self-determination may not be protected anymore. In July 2012, the FBI announced to deploy public photos from social networks, surveillance cameras and other sources for automatic face recognition purposes. The 'Next Generation Identification' program is scheduled to be fully operational in summer 2014, with approx. 12.8 million searchable front photos (FBI 2012).

Cookies / analyzing browsing habits. Since April 2010, Facebook's 'Like' button is not only applied within the social network, but can be placed on every other website. 19.2% of the top 1 million websites worldwide already use the 'Like' plug-in (Web Technology Surveys 2012). Using cookies, Facebook collects data on websites its users visited and whether or not they clicked the 'Like' button (ULD 2010). Roosendaal (2010) discovered that Facebook does not only track its own users, but also non-Facebook users through all websites that implemented Facebook Connect. The collected data includes the IP address, the browser used, and installed software and is stored for two years (ULD 2010). Facebook Connect's successor Open Graph (Facebook 2013e) expands Facebook's social graph (i.e., link to friends and groups) to third-party services and collects information from its members on popular websites such as Spotify, Netflix, IMDb and many others. Altogether, this large amount of information may permit police authorities to match a suspect's Facebook activity with his non-Facebook web activity, and thus to create an extensive profile of a suspect, including visited Internet pages, Facebook posts, messages and pictures very efficiently.

5. Discussion and Conclusion

Based on a comprehensive compilation of media reports, contributions from the European Union and the German federal government, as well as the study of existing laws and judiciary decisions, we examined the state-of-the-art police exploitation of the Facebook service. The main objective of the police's Facebook use is to collect information that helps them to trace criminals and to solve cases or prevent criminal offences. Facebook data can be used by the police for example to track the location of a suspect, get access to recent pictures or to interact with possible witnesses.

Recommendations for policy makers. The development of new information technologies, including social networks such as Facebook, is often much faster than the passage of appropriate laws. We found that the exploitation of Facebook information can interfere with (innocent) people's privacy and their right for informational self-determination. Creating a legal framework that protects personal rights, but enables the police to use Facebook information to prevent and solve crimes is a critical challenge that remains to be addressed by the respective working group of the ministry of justice. To achieve this, we have three concrete recommendations for policy makers which laws should be approached. First, there is no clear legislative in Germany that controls Facebook tracings. Appendix 2, Section 3.2 RiStBV is only a guideline for the police work, and is partly ignored (e.g., *"Private websites should not be used."*). A consistent national information policy to determine which information can be published on Facebook (e.g., identikit pictures) is still missing. Second, a solution to simplify the collaboration between Facebook and European authorities needs to be found. As of now, an alignment of US and European data policies, or the data storage on European servers may enable non-US authorities to access private Facebook data more effectively to support investigations. This may be addressed in the near future by the European Cybercrime Centre (EC3), effective since January 1, 2013. As part of Europol, it promotes the fight against cybercrime in Europe and *"pools expertise and information [and] supports criminal investigations"* (European Union 2012). Third, German data policies need to be updated to boost the efficiency of the police's Facebook usage. The EU passed the Data Retention Directive in 2006 (2006/24/EG) which obliges Internet service providers to store Internet traffic and transaction data (including IP address, e-mails sent and web sites visited) for up to 24 months on supply, so law enforcement agencies can access it after a committed crime or if a terroristic threat exists (Nettleton and Watts 2006). In Germany, the Directive has not been implemented yet as unsolved privacy issues still remain.

Avenues for future research. This paper shows several success cases of police work via Facebook, mainly taken from a six-month pilot project executed by Hanover police. There, Facebook information is already used successfully on a regular basis for tracing purposes. Nevertheless, academic literature on police tracings and investigations via social networks such as Facebook is still very scarce. Based on our findings, we will present hypotheses that provide avenues for future research.

Hypothesis 1: Tracings via Facebook are more effective than tracings via other media. Given the advantages of public tracings via Facebook (i.e., large audience, fast response rate, requests publishable at no costs), we assume that the social network is a very suitable channel to ask for the people's help in finding witnesses and prospective offenders. It remains to be proven empirically if the effectiveness of requests for information on Facebook are superior to those published through other channels such as TV, radio or newspaper. A large-scale comparison of Facebook vs. non-Facebook tracings which covers the number of received indications and the average time until the traced individual or property have been found, could uncover the effectiveness of the different channels.

Hypothesis 2: Tracings via Facebook are more efficient than tracings via other media. We have seen that tracings via Facebook may not only be very effective, but also more efficient (in terms of time and money) than via other media. First, Facebook is a very fast response medium enables quick input for the investigative work. Second, Facebook tracings can be published without additional costs, unlike TV spots or printed posters. However, a higher number of objectionable posts may occur. An efficiency study that identifies to what extent a larger personnel expenditure compared to traditional channels is justified, would be insightful.

Hypothesis 3: Many Internet users feel uncomfortable regarding police tracings and investigations via Facebook. Information as requested and shared during police tracings and investigations are pretty sensible and not necessarily something a user expects to see or wants to share within a social network. Users may oppose to cooperate for different reasons, for instance if they feel supervised by the police or mistrust Facebook's data management. Behavioral studies investigating how Facebook users feel about reading and possibly sharing sensitive information relevant to the police, could help to uncover findings that support the users' acceptance for this channel and thus eventually improve the police's communication policy and approaches.

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