Aalto University
School of Science
Degree Programme in Industrial Engineering and Management

Miikka Holkeri

Strategies of closed online advertising platforms — cases Google and Facebook

Master's Thesis
Espoo, May 30, 2018

Supervisor: Professor Robin Gustafsson
Instructor: Arto Tolonen, M.Sc. (Tech.)

Aalto University
School of Science

Abstract of master's thesis

Author	Miikka Holkeri
Title of thesis	Strategies of closed online advertising platforms — cases Google and Facebook
Degree programme	Industrial Engineering and Management
Major/minor	Strategy and Venturing **Code** SCI3050
Thesis supervisor	Professor Robin Gustafsson
Thesis advisor(s)	Arto Tolonen, M.Sc. (Tech.)
Date 30.5.2018	**Number of pages** 64 **Language** English

Abstract

This thesis studies closed ad platforms in the modern online advertising industry. The research in the field is still nascent and the concept of a closed ad platform doesn't exist. The objective of the research was to discover the main factors determining the revenue of online advertising platforms and to understand why some publishers choose to establish their own closed ad platforms instead of selling their inventory for third-party ad platforms.

The concept of a closed ad platform is defined leveraging the existing online advertising literature and the platform governance structure theory. Using the case study method, Google and Facebook were chosen as the cases as they have driven most of the innovation in the field and quickly gained significant market share. In total, 47 people were interviewed for this study, most of them working for advanced online advertisers. Based on the interviews, a microeconomic mathematic formula is created for modeling an ad platform's net advertising revenue. The formula is used to identify the five main drivers of an ad platform's revenue an each of them are studied in depth.

The results suggest that the most important revenue drivers the ad platforms can affect are access to an active user base, the efficiency of ad serving and the comprehensiveness of measurement. Setting up a closed ad platform requires significant investments from a publisher and should be only done if it can improve the advertisers' results. After it's been established, a closed platform can leverage its position to collect user data and structured business data to optimize its performance further. The results provide a structured understanding of the main dynamics in the industry that can be used in decision-making and a basis for future research on closed ad platforms.

Keywords	Online advertising, closed ad platform, Google, Facebook

Aalto-yliopisto
Perustieteiden
korkeakoulu

Diplomityön tiivistelmä

Tekijä	Miikka Holkeri
Työn nimi	Suljettujen online-mainosalustojen strategiat — tapaukset Google ja Facebook
Koulutusohjelma	Tuotantotalous
Pääaine	Strategy and Venturing **Koodi** SCI3050
Työn valvoja	Professori Robin Gustafsson
Työn ohjaaja	Arto Tolonen, DI
Päivämäärä 30.5.2018	**Sivumäärä** 64 **Kieli** Englanti

Tiivistelmä

Tämä diplomityö tutkii suljettuja mainosalustoja nykyaikaisella online-mainonta-alalla. Alan tutkimus on vielä aluillaan ja suljetun mainosalustan konseptia ei ole olemassa. Tämän tutkimuksen tavoitteena oli löytää online-mainosalustojen liikevaihdon määrittävät tekijät ja ymmärtää miksi jotkut julkaisijat valitsevat omien suljettujen mainosalustojen perustamisen mainospaikkojen kolmansien osapuolien mainosalustoille myymisen sijaan.

Suljetun mainosalustan konsepti määritellään olemassaolevaa online-mainontakirjallisuutta ja alustojen hallintarakenneteoriaa hyödyntäen. Tapaustutkimusmenetelmää käyttäen, Google ja Facebook valittiin tapauksiksi, sillä ne ovat ajaneet eniten innovaatioita alalla ja nopeasti saavuttaneet merkittävän markkinaosuuden. Yhteensä 47 henkilöä haastateltiin tätä tutkimusta varten, useimmat heistä edistyneiden online-mainostajien työntekijöitä. Haastattelujen perusteella luodaan mikrotaloudellinen matemaattinen kaava mainosalustan nettoliikevaihdon mallintamiseksi. Kaavaa käytetään tunnistamaan mainosalustan liikevaihdon viisi pääkomponenttia, ja kuhunkin niistä perehdytään syvällisemmin.

Tulokset viittaavat, että tärkeimmät liikevaihdon ajurit, joihin mainosalustat voivat vaikuttaa ovat pääsy aktiiviseen käyttäjäkantaan, mainosten näyttämisen tehokkuus ja mittaamisen kattavuus. Suljetun mainosalustan perustaminen vaatii merkittäviä investointeja julkaisijalta ja tulisi tehdä ainoastaan, jos sillä voidaan parantaa mainostajien tuloksia. Suljetun alustan perustamisen jälkeen sen positiota voidaan hyödyntää käyttäjädatan ja strukturoidun liiketoimintadatan keräämiseksi suorituskyvyn edelleen optimoimiseksi. Tulokset tarjoavat toimialan päädynamiikkojen ymmärryksen, jota voidaan käyttää päätöksenteossa sekä pohjana suljettujen mainosalustojen edelleen tutkimiseksi tulevaisuudessa.

Avainsanat	Online-mainonta, suljettu mainosalusta, Google, Facebook

Acknowledgments

"Prediction is very difficult, especially about the future."

— Niels Bohr

Online advertising is developing at warp speed, and the industry has gone through many revolutions during its life of 23 years. This thesis attempts to provide perspectives on the future developments, but I'm afraid many elaborate predictions are bound to fail more or less miserably. Thus, the lifespan of this work is going to be short, but at least by writing this, I have helped myself to make some sense of it all for a fleeting moment.

Thank you, Robin, for your guidance on the work.

Thank you, Arto, Karl, Lauri, Otto and Tuomo, for actually reading this thesis and giving your feedback. (Thank you, Tuomo, also for holding my laptop charger on the plane while I'm writing this.)

Thank you, my fellow students, for the memorable years and especially, Anni, Janne and Wolf, for the many kick-ass projects together; and Heikki, Lauri and Mikael for the good TIMES we had.

Thank you, family, for making me what I am today.

Thank you, Anna, for your continuous support.

Miikka Holkeri

Espoo, May 30, 2018

Contents

List of acronyms....................7
1 Introduction....................8
1.1 A brief history of online advertising....................8
1.1.1 The emergence of performance-based advertising....................8
1.1.2 The dawn of the programmatic value chain....................10
1.1.3 Closed ad platforms integrate vertically....................12
1.1.4 Search engines introduce a new way to advertise....................13
1.1.5 Ads move with users from desktop to mobile....................15
1.2 A glance at Google and Facebook....................16
1.2.1 Google....................16
1.2.2 Facebook....................17
1.3 Research questions....................18
2 Theory....................19
2.1 Online advertising....................19
2.1.1 Types of online advertising....................19
2.1.2 Targeting....................22
2.1.3 Auctions....................23
2.1.4 Measurement....................26
2.1.5 Performance-based pricing....................27
2.1.6 Ad platforms....................27
2.2 Open and closed platforms....................28
3 Methods....................31
3.1 Case study research....................31
3.2 Case selection....................31
3.3 Data collection....................32
3.4 Data analysis....................33
4 Results....................35
4.1 Price dynamics....................35
4.1.1 Pricing from an advertiser's perspective....................36
4.1.2 Pricing from an ad platform's perspective....................38
4.2 The drivers of ad platform revenue....................39

4.2.1 Access to an active user base 41
4.2.2 The effectiveness of ad serving 42
4.2.3 The comprehensiveness of measurement 43
4.2.4 Ability to price discriminate 46
4.2.5 Competition for off-premise impressions 47
4.3 The case for a closed ad platform 47
4.3.1 Sources of competitiveness 48
4.3.2 Collecting user data from advertisers 49
4.3.3 Collecting business data from advertisers 50
4.3.4 Risks to advertisers 51
4.4 A comparison of Google and Facebook 52
5 Discussion 53
5.1 Strategic implications 53
5.1.1 For publishers 53
5.1.2 For open ad platforms 53
5.1.3 For closed ad platforms 54
5.1.4 For advertisers 55
5.2 Further research 56
5.2.1 The effects of data privacy and regulation on online advertising 56
5.2.2 Measurement 57
5.2.3 Branding 57
References 58
Appendices 62

List of acronyms

COGS	Cost of goods sold
CPA	Cost per action
CPC	Cost per click
CPM	Cost per mille (cost per thousand impressions)
CVR	Conversion rate
DMP	Data management platform
DSP	Demand-side platform
EU	European Union
FBX	Facebook Exchange
GDPR	General Data Protection Regulation
GFP	Generalized first-price (auction)
GSP	Generalized second-rice (auction)
GPS	Global Positioning System
IAB	Internet Advertising Bureau
IO	Insertion order
IPO	Initial public offering
LTV	Lifetime value
MAU	Monthly active users
PII	Personally identifiable information
ROAS	Return on ad spend
ROI	Return on investment
RTB	Real-time bidding
SaaS	Software-as-a-service
SSP	Supply-side platform
TAC	Traffic acquisition cost
TIMES	Tournament in Management and Engineering Skills
VCG	Vickrey-Clarke-Groves (auction)

1 Introduction

1.1 A brief history of online advertising

1.1.1 The emergence of performance-based advertising

"Half the money I spend on advertising is wasted; the trouble is I don't know which half."

—John Wanamaker (apocryphal)

The biggest question advertisers face is whether a marketing investment is justified or not. Who are the people reached? What kind of effect does the campaign have on the target audience? How to measure the impact?

Over time, marketers have invented various ways to measure the impact indirectly: e.g., measuring sales lift in a certain timeframe or geography following a campaign or surveying a sample to determine the increase in brand awareness. These types of measurements can yield rough estimates, but it's not possible to get a conclusive answer due to the interplay of outside factors, including other marketing channels and the varying timeframe of the effects. Moreover, the methods are expensive, require large amounts of data and can't be used in the middle of a campaign.

The prices in traditional advertising—also known as *offline advertising*—are typically determined by the number of people reached with the advertisements (referred to as "ad" from now on): newspaper or magazine subscribers, television viewers, radio listeners, traffic passing a billboard and so on. To make a decision, the advertiser considers the reach and the type of audience associated with that channel.

As internet penetration has grown and time spent online accounts for an increasingly significant share of total time spent with media, ad inventories have also moved online. Online advertising spending constitutes an ever-larger part of the total advertising spend globally (Figure 1). The growth has fueled innovation in online advertising technology, providing continually better results for advertisers, again increasing online ad spending.

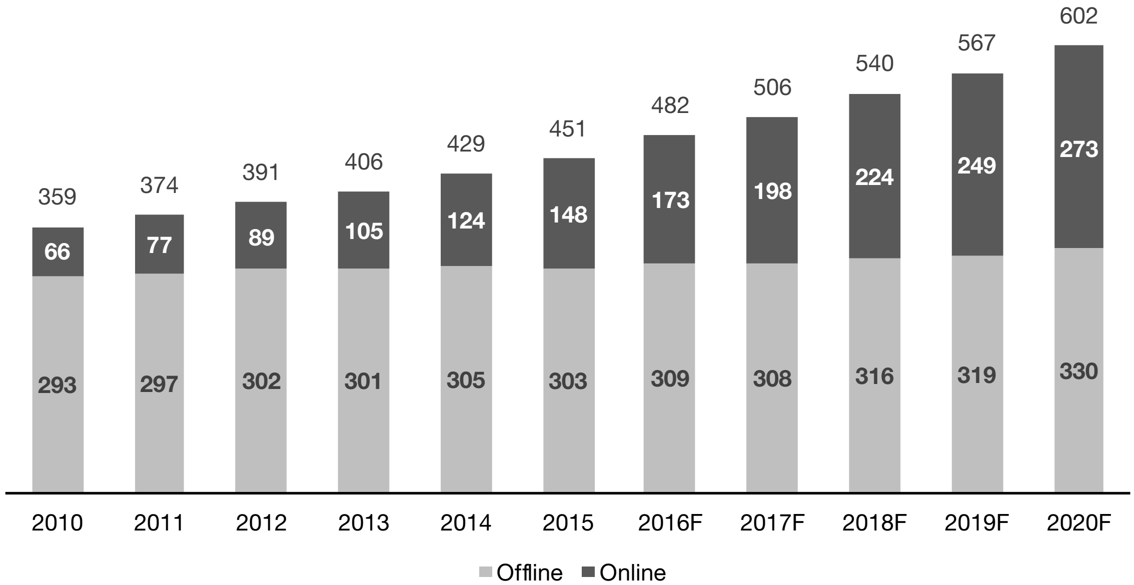

Figure 1. Global offline and online advertising spending (US $ billions at 2015 average exchange rates). Years 2016–2020 forecast. (McKinsey & Company, 2016)

Part of the success of online advertising comes from the fundamental difference to traditional advertising: the improved ability to serve customized ads individually and track the actions taken as a result of being exposed to them.

Being better at tracking user actions has far-reaching implications. First, the results are used to justify marketing expenditures. This applies especially to digital businesses in which the user actions are easier to track. For example, if an e-commerce advertiser knows for sure that spending $10 000 in a marketing campaign yields $12 000 in incremental profits, the decision becomes obvious. Advertisers start to think of ad spend as part of the cost of goods sold (COGS) instead of a line expense. Second, the advertisers don't have to care where precisely an ad is shown, as long as it provides results—except for placements compromising brand safety such as alongside disturbing or adult content. This type of advertising in which the advertiser pays based on the measurable results is called *performance-based advertising*.

Many digital services have massive amounts of data of their users that can be used to segment them in various ways. Also, many parties involved in ad serving can track user actions across web domains using browser cookies and across mobile applications using device identifiers. This data can be used to inform targeting. For example, an advertiser might want to reach 25–34-year-old women interested in swimming to deliver a specific message tailored for them.

Gathering user data and tracking of user actions after an ad *impression*—a single ad shown once to a single user—can be further used with optimization based statistical data analysis. The value of an ad impression to a particular user can be estimated based on similar users' observed probability to complete the desired action.

1.1.2 The dawn of the programmatic value chain

The first online ads were launched in 1994 (Figure 2). They were banners on websites, nowadays classified as *display* advertising. The term encompasses banners, rich media, sponsorships and videos shown on third-party websites or in applications.

Figure 2. AT&T's "You Will" banner ad, known as the first online ad in the world, launched on hotwired.com among ads from 14 companies on 27 October 1994. (Singel, 2010)

All the first online advertising deals happened through direct sales between the advertisers or their agencies and the *publishers* owning the websites where the ads were served. While this is a common practice for some large publishers and advertisers still today, typically part of the inventory is left over. Also, as this type of operation is very cumbersome with a large amount of supply and demand sources, *ad networks* were born to aggregate the supply and demand by grouping impressions into segments and reselling them to advertisers. However, the number of ad networks started also proliferating rapidly, and the resulting system was complicated, inefficient and lacked transparency both for advertisers and publishers. *Ad exchanges* emerged to allow transparently facilitating ad buying and selling between various parties.

Ad exchanges operate through *programmatic buying*: instead of placing an order for a fixed amount of impressions, each impression is auctioned between the advertisers in real time when the page is loaded—also known as *real-time-bidding* (RTB). Moreover, before entering the auction, the buyers get information about the user's device and have the opportunity to see if they have previous data about the user, e.g. based on website cookies or device identifiers. The buyers use all this information to estimate the *conversion rate* (CVR)—the probability of a user to complete a particular desired action—and value of that conversion to bid accordingly for the impression.

Supporting all the operations in RTB requires advanced infrastructure, and there are many steps that can be optimized with better tools, analysis or data. Thus, a value chain between publishers and advertisers, consisting of various kinds of specialized operators (Figure 3), started to form organically.

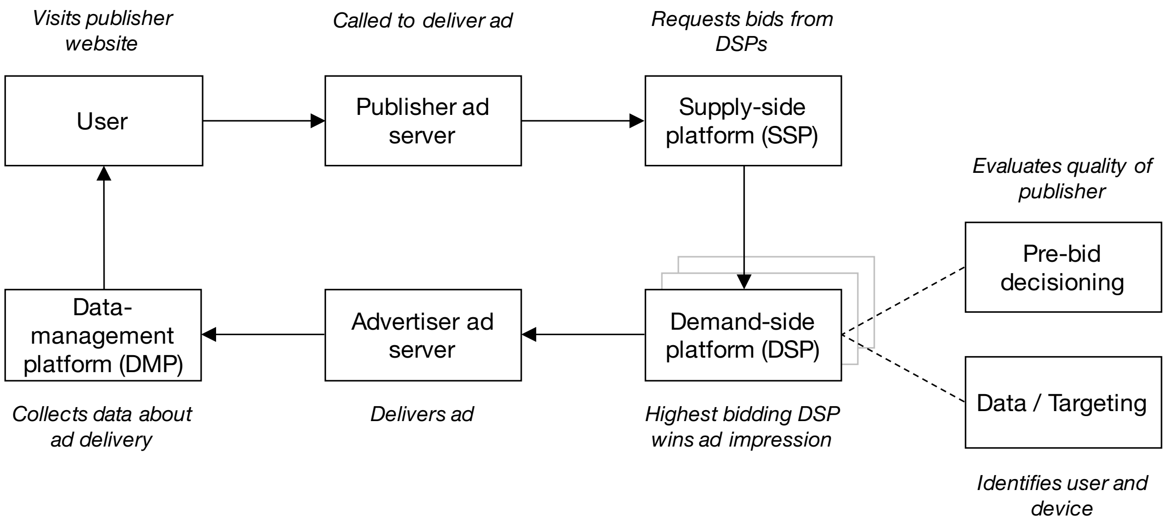

Figure 3. A simplified diagram of the most typical value layers involved in programmatic ad serving.

Typically, the advertisers access the ad exchanges through specialized software called *demand-side platforms* (DSP). These are paid by the advertiser and usually include bidding algorithms, data integrations, attribution and reporting. Respectively, publishers use *supply-side platforms* (SSP) to manage available demand sources.

As the publishers only provide the screen estate and the advertisements are served from an external server, various *advertiser ad serving* services, paid by the advertiser, provide centralized storage, tracking and delivery of the assets. *Publisher ad servers* help publishers manage their ad inventory and provide reports on the ads shown. Some advanced publishers try to maximize their revenue by using *header-bidding* (not visualized) to offer their inventory simultaneously to multiple ad exchanges and choosing the highest bid before making calls to their ad servers.

The quality of ad impressions varies from publisher to publisher due to viewability, brand safety and possible fraud. *Pre-bid decisioning tools* allow advertisers to evaluate the quality to influence decision-making before bidding. The advertiser typically pays for these. *Verification tools*, paid either by the advertiser or the publisher, measure the quality of delivery.

Advertisers have the option of optimizing their bidding and delivery on user-by-user basis, but any single advertiser seldom has enough data about the users they want to reach. Various *data and targeting services* collect user data from diverse sources and allow advertisers to target specific types of users and devices.

Data management platforms (DMP) allow both advertisers and publishers collect data from multiple sources in real time, enrich it with third-party data, aggregate and segment it to be used in multiple services. It is the “plumbing” advertisers need to access all of the other services.

Although there has been some consolidation and many providers include multiple aforementioned services in their offering, the number of companies operating in programmatic ad buying is still very high. The trend seems to be to integrate multiple services under yet another layer.

The extensiveness of the programmatic value chain has adverse side effects. Each service takes a cut of the revenue, and the billing models are typically based on the number of impressions served or a percentage of the advertising spend. Online advertising interest group IAB estimated that in 2014, ad technology services cumulatively captured 55% of the programmatic revenue and the publishers only got the remaining 45%. (Interactive Advertising Bureau [IAB], 2015).

1.1.3 Closed ad platforms integrate vertically

As programmatic buying allows each ad impression to be evaluated and individually targeted, *first-party* advertiser data—e.g., the past online behavior of the user—started to become more valuable than publisher data—e.g., what's on the page where the user currently is. Furthermore, as a side-effect of letting third parties to serve targeted advertisements on their websites, the publishers had to allow the third parties to collect data of their users constantly. This had the effect of shifting power from publishers to the advertisers and technology providers.

However, some of the biggest publishers—such as Google and Facebook (Figure 4)—are protective of their vast amounts of user data and not willing to let third parties collect and monetize it. Instead, they opted for creating their own infrastructure for buying, targeting, serving and measuring advertisements—essentially, everything done by the various value layers of the programmatic value chain—on their platform. The payoffs can be high: these *closed ad platforms* (also known as "walled gardens") don't have to let the programmatic value chain capture their share of the advertising revenue, they don't have to hand over their valuable user data and they can better control the user ad experience through standards and reviews. This solution, however, is viable only for the biggest publishers as it takes a lot of resources and imposes additional overhead to advertisers who desire to operate with them.

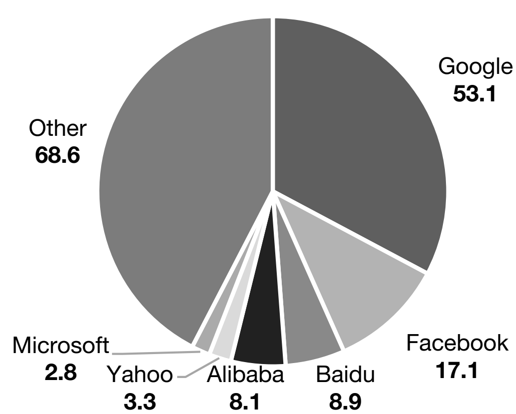

Figure 4. Net online advertising revenues worldwide in 2015, by company (US $ billions). After traffic acquisition costs (TAC) to partner sites. (Liu, 2016)

As explained in section 1.1.1, the ad revenue of a performance advertising channel is mostly determined by the measurable results its advertisers are getting. To provide the best possible results, the closed platforms offer a variety of targeting options—e.g., user demographics or certain types of behavior on the platform—and in some cases, automatic optimization based on user-level data only accessible by the platform itself. Many of the options are similar to the ones provided by the data and targeting services in programmatic buying.

However, the advertisers can often further improve their results by using first-party data—typically to *retarget* their existing customer base or known prospects such as website visitors. Thus, many closed platforms allow advertisers to upload their data to the platform to be matched to its users. This way, instead of giving out user data, the platforms can gather more data while providing targeted advertising.

1.1.4 Search engines introduce a new way to advertise

In the early days of online advertising, search engines were facing an issue: display advertising was their primary revenue source, but ideally, people spend as little time on the search results pages as possible which makes them less likely to click the ads. In 1998, four years after the first display ads, GoTo.com (renamed Overture in 2001 and acquired by Yahoo! in 2003) introduced the first *search ads*: advertisers paying for web traffic based on users' search phrases—called *keywords* (Laffey, 2007).

Search ads are usually sponsored links displayed next to the *organic*—i.e., non-paid—search results. Their price is also typically settled in an auction: the order of the sponsored links is determined by how much the advertisers are willing to pay for a click from a specific keyword and a calculated estimate of the link's relevance to the user.

Search ads have been extremely successful for multiple reasons. First, search engines are a common tool for finding information about products and services online and indicate the type of potential purchase intent precisely. Consequently, the value of a single click from a well-defined keyword leading to a purchase can be significant to the advertiser. The auction-based pricing guarantees that the click prices reflect that value (Table 1).

Table 1. The most expensive Google Search keyword categories in 2017 (Gabbert, 2017).

Keyword category	Average cost per click (US $)
Business services	58.64
Bail bonds	58.48
Casino	55.48
Lawyer	54.86
Asset management	49.86
Insurance	48.41
Cash services & payday loans	48.18
Cleanup & restoration services	47.61
Degree	47.36
Medical coding services	46.84

Second, due to the limitations in tracking technologies, the farther a conversion is from the ad impression in the user's decision-making process, the harder it becomes to track and attribute (more on tracking in section 4.2.3). In search advertising, it's common that the conversion happens on the same device in the same session when the ad was clicked, making its effect easily measurable. In fact, many argue that most attribution models are, by ignoring various other online and offline touchpoints, showing inflated results for search advertising.

It's often profitable for businesses to also bid on their competitors' brands. However, advertisers have to also bid on their own brand to ensure a user doesn't see only competitors' ads when searching for it. Consequently, the own brand's keywords can constitute up to 50% of a search advertiser's budget.

Today, search advertising constitutes nearly half of total online ad spending (Figure 5).

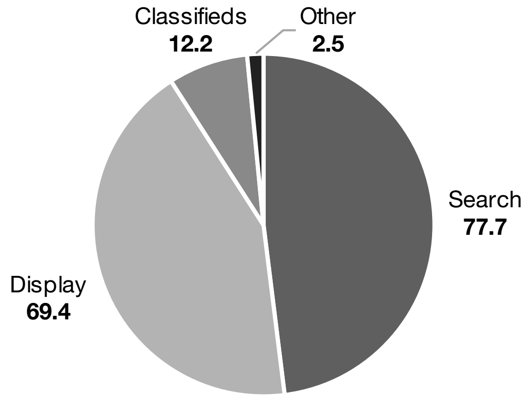

Figure 5. Worldwide online ad spending in 2015, by format (US $ billions). "Other" includes email, mobile messaging and lead generation. (Liu, 2016)

1.1.5 Ads move with users from desktop to mobile

Until 2010, nearly all online advertising took place on desktop computers. With the increase in smartphone usage, online advertising saw a quick shift to *mobile*—defined by IAB (2017a) as "advertising tailored to and delivered through wireless mobile devices such as smartphones, feature phones (e.g., lower-end mobile phones capable of accessing mobile content), and media tablets". Increased smartphone penetration and time spent on mobile enabled larger ad inventory, larger screens enabled more area to be dedicated for ads, and fast mobile networks allowed richer and more engaging ad formats to be used. In the United States, mobile advertising constituted just 2.3% of online ad spending in 2010, but it surpassed non-mobile spend already in 2016 (Figure 6).

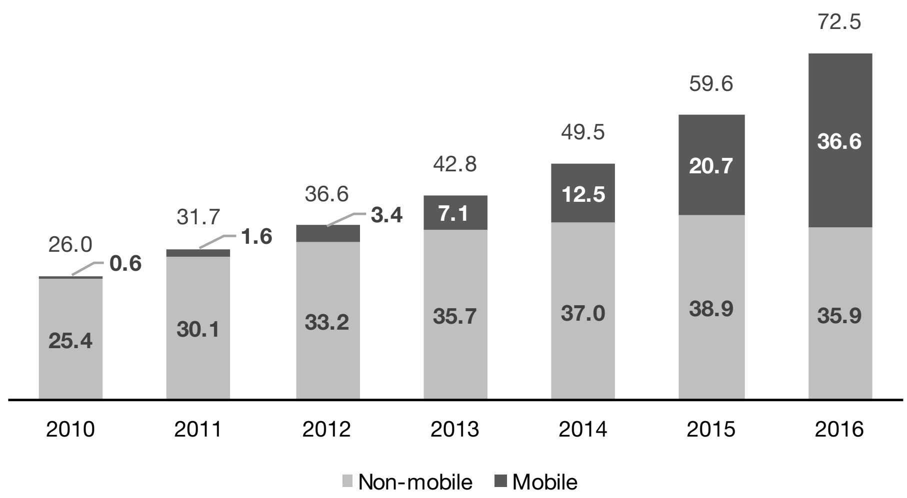

Figure 6. Online ad spending in the United States, by device type (US $ billions). (IAB, 2017)

Although not having seen as rapid a shift as ad spending, mobile accounted for 34% of online retail purchases in March 2016 (Google, 2016). The consumer decision-making journey is becoming more and more dispersed across multiple channels: 61% of internet users start shopping on one device but continue or finish on a different one, and 82% of smartphone users say they consult their phones on purchases they're about to make in a store (Google, 2016). The purchase journey is increasingly being recorded as digital touchpoints, but they form a complex network posing a difficult challenge for unified tracking.

1.2 A glance at Google and Facebook

In 2015, Google and Facebook together made 43% of the global net advertising revenue. Both of them operate popular online services, and advertising is their primary revenue source but the types of ads they serve differ. Google dominates all search advertising and runs some display advertising outside its properties while Facebook serves only display ads, mostly on its own properties (Figure 7).

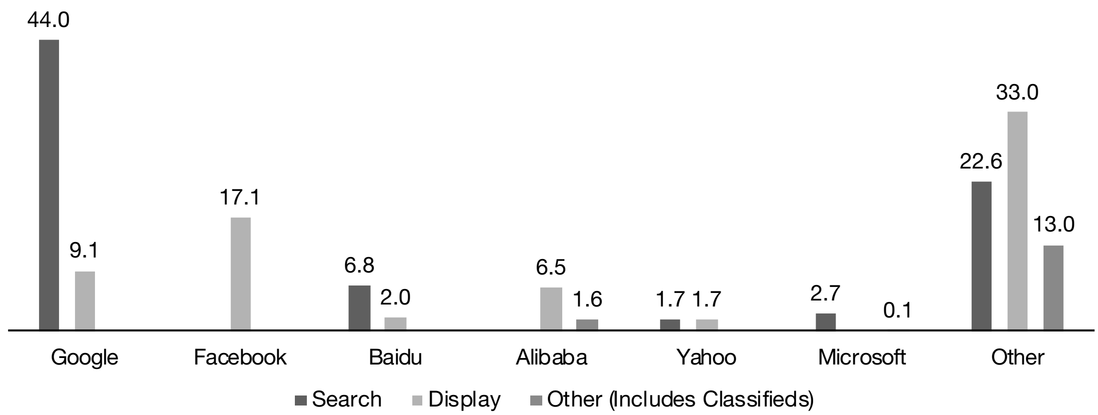

Figure 7. Net online ad revenues worldwide in 2015, by company and format (US $ billions). After traffic acquisition costs (TAC) to partner sites. (Liu, 2016)

1.2.1 Google

Google started in 1998 as a search engine but has rapidly grown to a series of products beyond that, including email service Gmail, office suite & cloud storage Drive, video sharing service YouTube, web browser Chrome, mobile operating system Android, smartphone Pixel and smart speaker Home—many of them acquisitions (Google, n.d.). Google made its initial public offering (IPO) in 2004 (Google, n.d.). In 2015, it was moved under a freshly established umbrella company Alphabet Inc that was founded to host the company's efforts not directly related to Google's business such as the self-driving car company Waymo (Alphabet Inc., 2017).

The majority of Google's products are free to use for consumers and are funded by ads: in 2016, advertising constituted 89% of Google's revenue (before subtracting traffic acquisition costs [TAC]; Alphabet Inc., 2017). The company launched its first ads in Google Search in 2000 (Google, 2000). It moved to display ads by launching AdSense—its ad network and partner program for publishers—in 2003 and buying DoubleClick—an ad exchange with software products for all sides of the platform—in 2007 (Google, 2003; Google, 2007). Search ads are still the bigger side of the business: out of Google's 2015 net ad revenue, approximately $44.0B was from search and $9.07B from display (Liu, 2016).

Table 2 lists Google's sources of ad inventory. Currently, all ads on Google's properties—92% of its net ad revenue (Alphabet Inc., 2017)—are sold through its closed AdWords platform. Third-party buying of display ads on YouTube.com was previously possible through DoubleClick Ad Exchange, but Google stopped supporting it in 2015 (Mohan, 2015). The ads Google sells outside its properties are from publishers selling their inventory directly to Google's ad network AdSense and from third-party ad networks. Advertisers can buy this inventory through the closed AdWords platform (as a part of Display Network or Search Network) or through Google's open DoubleClick Ad Exchange.

Table 2. Google's sources of ad inventory, by placement and type of buying.

	Closed buying	**Open buying**
Served on own properties	Google Search Play Store YouTube Gmail	(YouTube, – 2015)
Served on third-party properties	Display Network Search Network	DoubleClick Ad Exchange

1.2.2 Facebook

Facebook started in 2004 as a social networking platform and is nowadays also operating social image sharing service Instagram, mobile messaging application WhatsApp and virtual reality hardware maker Oculus—all of them acquisitions (Facebook, n.d. -a).

In 2016, 97% of Facebook's revenue came from advertising (Facebook, 2017). In the early days of the platform, it was monetized by letting Microsoft to exclusively serve its ads on the site through its exchange (Facebook, 2006; Schonfeld, 2010). Facebook launched its first "native" ads in 2007—these were based on businesses having a social presence on the platform, and they were made an integrated, unobtrusive, part of the user experience (Facebook, 2007). The company had part of its ad inventory on its properties sold and served by third parties through Facebook Exchange (FBX) from 2012 to 2016 (Constine, 2012; Ha, 2016).

Table 3 lists Facebook's sources of ad inventory. Currently, all ads are sold through the company's closed ad buying platform. Most of the ads sold are served on Facebook's properties. In addition to them, Facebook offers Audience Network—launched in 2014—allowing its advertisers to expand their campaigns to partnering third-party application and websites while still using Facebook's ad buying and targeting (Facebook, 2014).

Table 3. Facebook's sources of ad inventory, by placement and type of buying.

	Closed buying	Open buying
Served on own properties	Facebook Instagram Messenger	(Microsoft Ads, 2006 – 2010) (Facebook Exchange, 2012 – 2016)
Served on third-party properties	Audience Network	(LiveRail, 2014 – 2016) (Atlas DSP, 2013 – 2016)

Also, the company has briefly facilitated open ad buying outside its properties with video ad network LiveRail and demand-side platform (DSP) Atlas—both from acquisitions—but closed them purportedly to favor Audience Network (Peterson, 2016).

1.3 Research questions

In just 23 years, the online advertising industry has grown from zero to encompassing more than third of the world's total advertising spending and gone through significant changes in its dynamics. The two largest companies, Google and Facebook, are capturing more than 40% of the net online advertising revenue. This thesis explores what that revenue is made up of.

While there's a widely used system for selling and purchasing ads through ad exchanges, many of the largest publishers—including Google and Facebook—have chosen to build their own infrastructure for selling and serving ads. The extant literature on closed ad platforms and their implications is scarce. This thesis explores closed ad platforms in more detail.

The research questions are the following:

1. What are the main factors determining the revenue of online advertising platforms?
2. What drives publishers to establish their own closed ad platforms instead of selling their inventory for third-party ad platforms?

2 Theory

This section is divided into two parts. First, an overview of the online advertising literature is provided. Second, theory on multi-sided platforms is used to help to define the concept of *closed ad platform*, mostly absent from the online advertising literature.

2.1 Online advertising

Evans (2009) defines online advertising as "advertising delivered over the Internet". In some contexts, it's called *internet advertising* (Bergemann & Bonatti, 2011). It is also often used interchangeably with the term *digital advertising* which, technically, is an umbrella term also encompassing advertising delivered over digital media other than the Internet, e.g., SMS advertising but, in practice, there's no clear division between the terms and almost all digital advertising is also online advertising.

According to Evans (2009), the fundamental differences between online and offline advertising result from the internet technologies and the nature of the web which enable learning considerably more about online users. This allows advertisers to target relevant messages to consumers who are most likely to take action as a result of receiving them (Evans, 2009).

2.1.1 Types of online advertising

There are taxonomies of varying granularity for online advertising. Goldfarb (2013) divides it into three general categories: display advertising, search advertising and classified advertising. There are also some formats that don't fall into these categories, such as email and digital audio ads, but as can be seen from Figure 5 (p. 15), their share of total online ad spending is marginal.

2.1.1.1 Display advertising

According to Goldfarb (2013), Display advertising includes "simple banner ads, plain text ads (such as Google's AdSense), media-rich ads, video ads, and the typical ads that are shown on social media websites such as Facebook" (Figure 8).

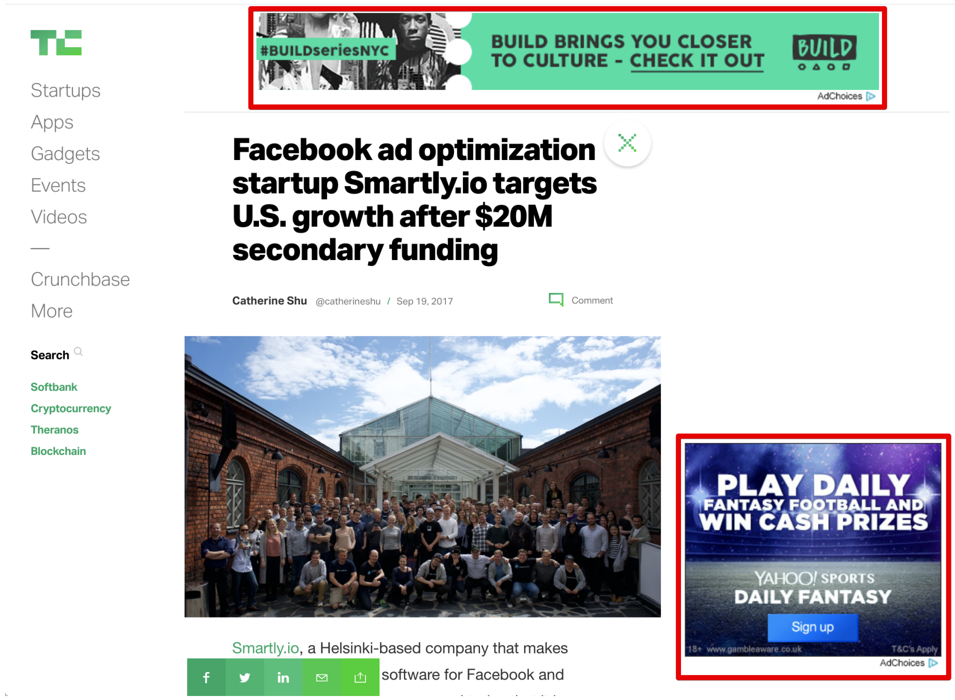

Figure 8. An example of display ads on techcrunch.com [emphasis added]. The publisher sells its ads through ad exchanges and insertion orders.

The pricing of display advertising varies by publisher, from fixed pricing and negotiated purchases to specialized auction mechanisms. Typically, advertisers pay per impression or click. (Goldfarb, 2013)

2.1.1.2 Search advertising

According to Goldfarb (2013), search advertising is "the advertising that appears along with the algorithmic (or 'organic') results on search engines such as Google or Bing" (Figure 9). Terms *paid search* (Laffey, 2007) and *sponsored search* (Jansen & Mullen, 2008) are also used to describe the same concept.

Search ads are targeted based on the users' search keyword strings and thus allow advertisers to show relevant ads at the exact moment when users are looking for something. Typically, the advertisers pay when the user clicks on an ad, and a special-purpose auction mechanism determines the price. (Goldfarb, 2013)

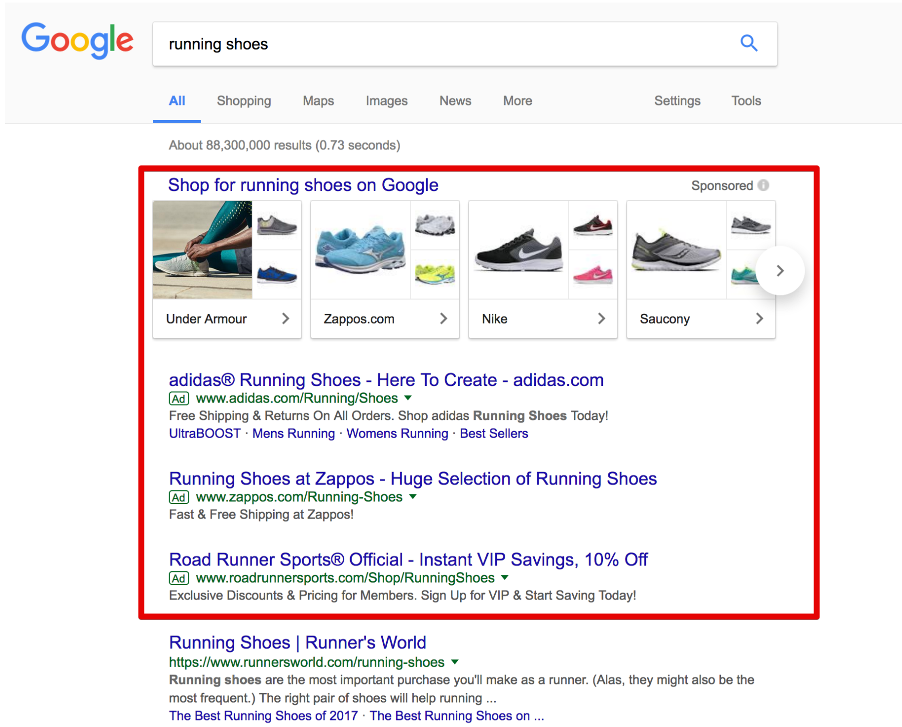

Figure 9. An example of search ads on google.com [emphasis added]. The ads are sold in Google's Generalized Second-Price (GSP) auction.

According to Sayedi et al. (2014), one of the main characteristics differentiating search from other forms of advertising is that, instead of building awareness, it uses technology to enable targeting customers in the later stages of the purchase process, usually with a higher conversion rate. The authors argue that this quality makes advertisers inclined to free-ride on their competitors' awareness-building efforts and poach potential customers from them. However, the authors continue to use game theory to prove that the search engines benefit from limiting competition in their auctions which is in line with Google, Yahoo! and Bing using "keyword relevance scores" to discourage bidding on competitors' keywords. (Sayedi et al., 2014)

2.1.1.3 Classifieds advertising

According to Goldfarb (2013), classified advertising consists of "advertising that appears on websites that do not provide other media content or algorithmic search" (Figure 10). Online classified ads are a substitute for their offline equivalents in local newspapers. Online job and dating sites also fit into this category. (Goldfarb, 2013)

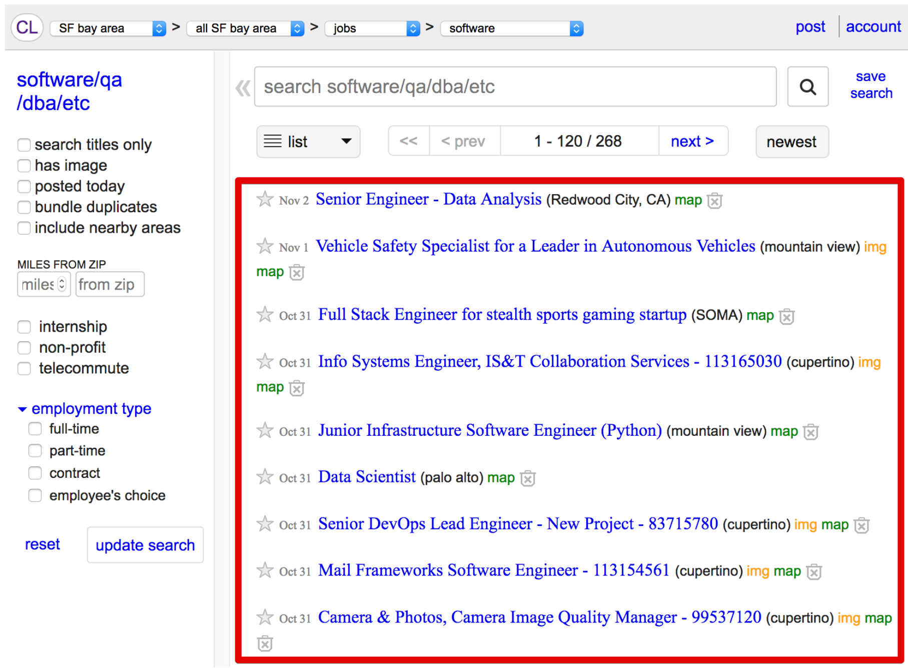

Figure 10. An example of classified ads on craigslist.com [emphasis added]. The service provider charges $75 for each job posting in San Francisco Bay Area.

2.1.2 Targeting

Goldfarb (2013) argues that the most fundamental economic difference of online advertising to offline advertising is its substantially lower cost of targeting. It is made possible by the Internet's one-to-one communication between identifiable computers (Goldfarb, 2013). Targeting enables advertisers to more effectively find suitable consumers for their advertisement messages, consequently helping smaller businesses to access advertising markets (Bergemann & Bonatti, 2011).

Goldfarb (2013) categorizes targeting into three forms: demographic, contextual and behavioral (Table 4). *Demographic targeting*, mostly used in display advertising, can be at its simplest just selecting the publishers with the appropriate audience demographics but nowadays advertisers can target specific demographic subgroups within the overall audience based on information users provide online. In *contextual targeting*, the content of the website is used to select the ads displayed on it. This is the way how search ads are mainly targeted: they match to the keywords of the search. Targeting options in classifieds ads are mostly limited in grouping the listings by category and geographical location which also falls under contextual targeting. *Behavioral targeting* involves using users' data based on their past online behavior to determine if they are a good fit for an ad. A special form of behavioral targeting, *retargeting*, involves showing users content similar to the one they've previously interacted with. (Goldfarb, 2013)

Table 4. Forms of targeting commonly used with types of online advertising.

	Display	Search	Classifieds
Demographic	Specific publisher's main audience Demographic subgroups	Demographic subgroups (such as geographic region)	
Contextual	Page content	Search keywords	Listing category & location
Behavioral	Browsing & search behavior Retargeting		

2.1.3 Auctions

Auctions have become the dominant method for selling online advertising (Goldfarb, 2013). Goldfarb (2013) argues this is the result of reduced targeting costs online, driven by both the need to price a large number of keywords efficiently and a desire to price discriminate between advertisers.

The first online ad auctions were implemented in search advertising and used Generalized First-Price (GFP) auction: the advertiser with the highest bid wins the first slot and pays the price equal to its bid. The advertiser who bids second highest wins the second slot, pays the price equal to its bid and so on. While the concept of GFP is simple, it quickly results into bidding wars as each bidder has the incentive to lower their bids as close as possible to the next advertiser's bid—until someone starts raising their bid again, causing an ever-continuing cycle. (Edelman & Ostrovsky, 2007)

Generalized Second-Price (GSP) auction—used, for example, by Google to sell its search ads—addresses that problem. In it, the slots are allocated in the same way, but each bidder only pays the next highest bid price plus some small delta. (Jansen & Mullen, 2008) Vickrey (1961) proves that second-price auctions can be *incentive compatible*—i.e., the optimal strategy for bidders is to bid their true valuation—under certain conditions such as single item auctioned once with sealed bids (not fulfilled by GSP). So, while GSP eliminates some wasteful strategic play compared to GFP, it's not completely incentive compatible for auctioning multiple items which often is the case in online advertising.

Vickrey-Clarke-Groves (VCG) auction—used, for example, by Facebook (Metz, 2015)—is an incentive compatible version of the second-price auction for multiple items. In it, the bidders pay the externalities imposed on the other bidders—i.e., a bidder pays the price equal to the difference to the total value the other bidders would have captured if that bidder wouldn't have participated in the auction. This maximizes the auctioneer's profit and ensures that the item is sold to the bidder who values it the most. (Jansen & Mullen, 2008) Before the emergence of online advertising, the VCG mechanism was generally thought to be of academic interest only due to fear of cheating and disincentives to follow truth-revealing strategies (Rothkopf et al., 1990).

Table 5 illustrates a very simple VCG auction. Bidder A uses a bid equal to its true value but ends up only paying the price equal to bidder B. Thus, there's no incentive to change the bid. Bidder C doesn't get the item but doesn't have an incentive to increase its bid—otherwise, it would have to pay more than its true value if it wins the item.

Table 5. An example of VCG auction with three participants bidding their true value for one item in an auction of two items.

	Bidder A	**Bidder B**	**Bidder C**
True value for an item	5	4	3
Bid	5	4	3
Outcome	Win	Win	Lose
Value of outcome	5	4	0
Value of outcome if bidder 1 didn't participate		4	3
Value of outcome if bidder 2 didn't participate	5		3
Value of outcome if bidder 3 didn't participate	5	4	
Total value of outcome if this bidder didn't participate	4 + 3 = 7	5 + 3 = 8	5 + 4 = 9
Total value of outcome for other bidders	4 + 0 = 4	5 + 0 = 5	5 + 4 = 9
Payment (externality imposed to others)	7 – 4 = 3	8 – 5 = 3	9 – 9 = 0
Net utility	5 – 3 = 2	4 – 3 = 1	0 – 0 = 0

Table 6 illustrates a similar setup for a GSP auction. Both bidder A and bidder B get the same item, but bidder B pays more for it, thus having an incentive to bid less than its true value and even less than bidder B—as long as it wins the item. If bidder A and bidder B are competitors, bidder B has an incentive to bid as high as possible while still bidding less than bidder A—this increases the amount bidder A has to pay while it doesn't affect how much bidder B pays. Thus, the bidders are likely to speculate what others are bidding to maximize their net utility, causing them to diverge from bidding their true value and causing instability in the auction.

Table 6. An example of GSP auction with three participants bidding their true value for one item in an auction of two items.

	Bidder 1	**Bidder 2**	**Bidder 3**
True value for an item	5	4	3
Bid	5	4	3
Outcome	Win	Win	Lose
Value of outcome	5	4	0
Payment (next highest bid)	4	3	0
Net utility	5 – 4 = 1	4 – 3 = 1	0 – 0 = 0

Szymanski and Lee (2006) find in their simulation based on a search advertising setting with dynamic bid strategies that unstable bidding patterns caused by lack of incentive compatibility also remain when changing from GFP to GSP auction (Figure 11). Because of the instability of GFP and GSP, from the platform's perspective, VCG yields the most revenue when advertisers' minimum return on investment (ROI) is zero, i.e., the costs equal the profits. However, if the advertisers demand an ROI higher than zero, VCG is the most affected auction mechanism as any decrease in the price they are willing to pay is directly reflected to all bids. (Symanski & Lee, 2006)

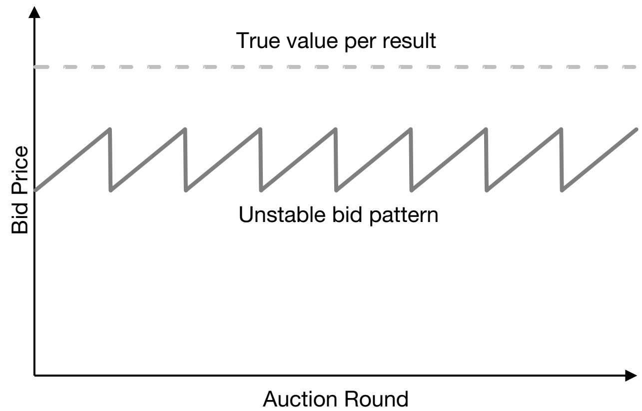

Figure 11. The "Sawtooth" bid pattern in GFP and GSP of the bidder with the highest true value with dynamically adjusting bid strategy (Symanski & Lee, 2006).

The bids are typically not entered in the auction as they are but are instead combined with various *quality scores* that try to estimate the ad's relevance to the user seeing it. Effectively, the ranking of advertisers in the auction is based on both the platform's expected revenue and the users' perceived interest. (Jansen & Mullen, 2008)

2.1.4 Measurement

Goldfarb (2013) notes that "the literature that measures online ad effectiveness is thriving" and attributes the effect mostly to the relative ease of measuring online advertising. Immediate responses such as clicks are easily logged and, in many cases, the advertisers can track if the persons who've seen ads complete the desired transaction. Furthermore, the one-to-one communications between the media source and the user enable easy experiments, also allowing randomization at the end-user level. (Goldfarb, 2013)

However, Goldfarb (2013) calls for recognizing that, despite those advantages, there remain significant challenges and refers to a study by Lewis et al. (2011) demonstrating how observational methods can overstate the effectiveness of advertising. Furthermore, Lewis and Rao (2013) argue that as the performance of a single campaign is difficult to evaluate with precision, some parties on the ad supply side are not incentivized to report ROI estimates truthfully and selectively filtered reports with noisy data might be hard to prove wrong.

Berman (2015) uses an analytical model to demonstrate that advertising performance can be compromised if the optimization is linked to an attribution model not aligned with the advertiser's goals—demonstrating that attribution is not only a measurement issue but can also affect the campaign efficiency. This can be caused by the baseline conversion rate of consumers (i.e., the share of users who would convert also without seeing ads) which often is the case with *last-touch attribution* which only credits the last ad shown before a conversion. (Berman, 2015)

Lewis et al. (2011) conclude that those biases can be avoided with fully randomized experiments—the gold-standard for measuring "treatment" effects. However, Lewis and Rao (2013) show that sometimes—as the advertiser is trying to notice a relatively subtle effect in an environment with a huge random variation—massive tests have to be conducted to determine in a statistically significant way if a campaign is profitable.

2.1.5 Performance-based pricing

Publishers can make various improvements to increase the effectiveness of the ad campaigns on their sites. While some of these—such as the ad's size, placement, and schedule—are contractible, many of the efforts are either impossible or too expensive for the advertiser to observe and monitor. An example of these non-contractible efforts is the platform's ability to use contextual, demographic and behavioral targeting to serve the ads to the users who're most likely interested in them. (Hu et al., 2016)

If publishers are only paid based on the number of impressions they serve, they're incentivized to only focus on attracting bigger audiences with better content. Using performance-based pricing—online i.e. linking advertising payments directly to campaign measurement data—gives incentives for both the publisher and the advertiser to make non-contractual efforts to improve the effectiveness of advertising. (Hu et al., 2016)

Hu et al. (2016) further compare two performance-based pricing models: cost per click (CPC) and cost per action (CPA). CPA model—being closer to the advertiser's desired end result than CPC model—is considered to be preferred by advertisers as it gives a greater incentive for the publishers to exert incremental efforts. However, some publishers fear that CPA shifts most of the advertising campaign risk to them and doesn't incentivize advertisers to improve their efforts. (Hu et al., 2016)

In ad auctions, typically, instead of choosing the winning advertisers purely based on their CPA bid, publishers rank advertisers based on the expected revenue using historical data from them (Hu et al., 2016). Based on a mathematical model, Hu et al. (2016) show that in general, the CPA model achieves greater social welfare than CPC as long as the estimates match the reality.

2.1.6 Ad platforms

Online advertising is a two-sided business in which consumers consent to receive advertising messages in exchange for content and services and advertisers pay to send these messages. Between them are various intermediaries, most of them also operating multi-sided platforms. The fully integrated intermediaries touch directly both advertisers and consumers. For example, most search engines operate like this. Intermediaries can be also partly integrated, for example, publishers combining direct sales and ad networks. (Evans, 2009)

The various agents involved are presented in Table 7. In this thesis, the businesses incorporating at least the intermediation function, responsible of managing and selling ad inventory, are called *ad platforms*. The term *closed ad platform* is used for publishers running their own intermediation—often referred to as "walled gardens".

Table 7. The relationship between online advertising businesses. Ordered by relative position: uppermost closest to advertisers; bottommost closest to consumers. (Evans, 2009)

Business	Function
Advertising agencies and creative tools	Producing ads
Advertiser tools	Managing ad campaigns, sending ads to publishers
Intermediation: ad networks, ad exchanges, direct sales	Matching advertisements to inventory and setting prices
Publisher tools	Managing publisher inventory, serving ads into ad space
Publishers	Attracting consumers with content

2.2 Open and closed platforms

Multi-sided platforms are entities enabling direct interactions between two or more distinct customer groups—such as buyers and sellers or consumers and advertisers—so that each side is affiliated with the platform by continually making platform-specific investments necessary for the interaction (Hagiu & Wright, 2015). They are typically characterized by the presence of network effects or non-neutral price structure between the groups—features often used to distinguish multi-sided platforms but shown by Hagiu & Wright (2015) not to be sufficient for defining them.

Publishers are a particular type of multi-sided platform Casadesus-Masanell & Zhu (2013) call a *sponsor-based* business model: the platform monetizes its product (content) through sponsors (advertisers) instead of charging its customer base directly. To persuade the sponsors to pay, the platform needs its consumers to provide something to them in return (look at ads). As a result, the utility the consumers derive from the product or service can be decreased, often in the form of impoverished consumption experience.

According to Eisenmann et al. (2009), multi-sided platforms have two distinct roles: sponsors and providers. *Platform sponsors* control the platform's technology and determine who may participate as a provider or user but don't deal directly with the users. *Platform providers* adhere to the platform's rules and supply its components, being the users' primary point of contact. Each role may be fulfilled by one or multiple companies, resulting in four possible models for organizing platforms (Table 8).

Table 8. Platform governance structures (Eisenmann et al., 2009)

	One provider	**Multiple providers**
One sponsor	Proprietary	Licensing
Multiple sponsors	Joint Venture	Shared

A platform can have a varying degree of openness—i.e., uniformness or lack of restrictions on participation to development, commercialization or use—in several dimensions (Eisenmann et al., 2009). Of the four structures mentioned above, the *proprietary* model is the most closed. In this thesis, the term *closed ad platform* refers to publishers operating with the proprietary governance structure—such as Google and Facebook. Correspondingly, the *shared* model is the most open. The programmatic ad buying ecosystem falls into this category as it's operated by a plethora of providers based on standards evolved without a centralized sponsor.

Strategies employed by platform sponsors can be categorized as horizontal or vertical (Table 9). Absorbing complements is a vertical strategy especially important to proprietary providers and makes it harder for the standalone third-party suppliers of those complements to compete. It can add efficiency gains through economies of scope in customer acquisition and quality advantages through simplification of interfaces in addition to helping to avoid double marginalization from separate monopolists. A *platform envelopment* occurs when the absorbed complement is itself a platform. (Eisenmann et al., 2009)

Table 9. Platform sponsors' horizontal and vertical strategies (Eisenmann et al., 2009).

	Horizontal strategies	**Vertical strategies**
Description	Target a company's current and potential competitors	Open or close the platform's supply-side
Examples	Interoperating with established rival platforms	Managing backward compatibility with prior platform generations
	Licensing additional platform providers	Securing exclusive rights to certain complements
	Broadening a platform's sponsorship	Absorbing complements into the core platform

Successful proprietary platform providers can often exploit their market power to extract a significant share of the economic value generated through platform transactions. However, they have to leverage their dominance without provoking end users, complementors, regulators and antitrust authorities too much. Aggressive value extraction can lead to users perceiving their platform provider to abuse its power and, for example, rally around new market entrants. On the other hand, too loose control can lead to decreased competitiveness and the platform being enveloped by another platform. (Eisenmann et al., 2009)

3 Methods

It's worth mentioning that I've worked for a technology partner operating in the Facebook's ad ecosystem for close to three years. While that has accumulated me a lot of knowledge, it also involves inevitable biases that—despite my efforts to overcome them—have affected how the data was collected and interpreted. On the other hand, I believe having worked directly with dozens of online advertisers prior to this study and knowing the technology applied by the ad platforms allows me to form a deep understanding required for a thorough synthesis of the subject.

3.1 Case study research

This thesis researches the phenomenon of closed online advertising platforms through the inductive case study method. Building theory with case studies involves creating theoretical constructs and propositions from case-based, empirical evidence (Eisenhardt, 1989). Yin (2009) defines a case study as "an empirical inquiry that investigates a contemporary phenomenon in depth and within its real-life context, especially when the boundaries between phenomenon and context are not clearly evident".

According to Yin (2009), case studies are the preferred method for studies asking "how" or "why" questions. Moreover, Eisenhardt (1989) argues that the method is especially suitable for new research areas with yet insufficient theory. This indeed is the case with closed online ad platforms: while the existing literature can explain some of the basic online advertising concepts, it's not up-to-date with the most recent developments of the rapidly-changing industry. Neither does it provide the satisfactory theory on what are the factors contributing to the competitiveness of closed ad platforms. One sign of this is that there doesn't even seem to be an agreed upon term for "closed ad platform".

3.2 Case selection

Eisenhardt & Graebner (2007) note that the sampling in case study research should be theoretical instead of representing some population as the goal is to develop theory instead of testing it. Revelatory and exemplary cases particularly suitable for finding logic between constructs should be selected.

Google (Alphabet, Inc.) and Facebook (Facebook, Inc.) were chosen as the cases because they have been leading the change in online advertising innovation, can be considered extraordinarily competitive and constituted 43% of the whole industry in terms of net ad revenue after traffic acquisition costs in 2015 (Figure 4, p. 12). As this thesis strives to understand better the strategic reasons why publishers opt to establish their closed ad platforms, it is worth taking a closer look at the strategies the case companies have used to reach their market positions.

In addition to having quite a different portfolio of consumer-facing products, they represent well the two dominant types of advertising: Google has mostly concentrated on search ads, and Facebook is only serving display ads (Figure 7, p. 16). The customer base of the company I work for also ensured superior access to the appropriate people for studying these two cases.

Using multiple cases is considered to create more robust theory because the propositions are more deeply grounded in varied empirical evidence (Eisenhardt & Graebner 2007). However, the small number of cases in this study can be justified by their uniqueness—an argument Yin (2009) also uses as a rationale for single-case studies. The cases in a study should be regarded analogous to multiple experiments (not multiple subjects within an experiment), standing as their own analytical units and serving as replications, contrasts, or extensions to the emerging theory (Yin, 2009).

3.3 Data collection

According to Eisenhardt & Graebner (2007), interviews are an efficient way to gather rich, empirical data about intermittent and strategic phenomena. The authors stress the importance of using many knowledgeable interviewees who view the case from diverse perspectives to make it less likely that they engage in convergent retrospective sense-making or impression management.

41 interviews with 33 advertisers were conducted between February and May 2017 (full list in Appendix 1). The companies were selected on the basis of the estimated scale and technological sophistication of their digital marketing activities on Google and Facebook in addition to access to the relevant people working at them. Most of the advertisers interviewed were customers of the company I represented. The most common industries they operated in were e-commerce and travel. In addition to direct advertisers, some of them were marketing agencies, running campaigns for their client companies; and some were group or venture capital companies, overseeing the marketing activities of their portfolio companies (Figure 12). The aim was to get a diverse cross-section of advanced advertisers from the industries most present in online advertising.

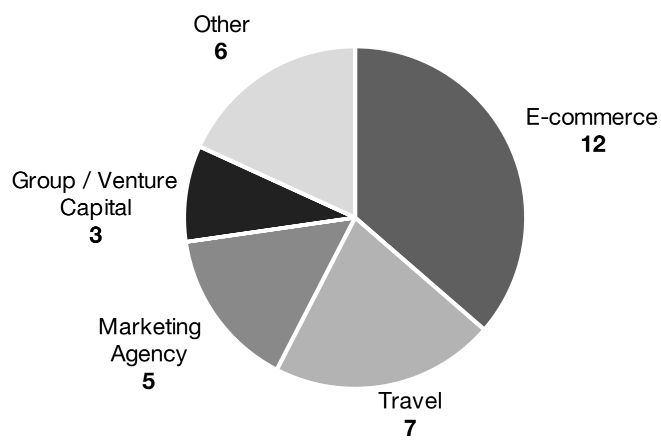

Figure 12. The advertisers interviewed, by industry

The people interviewed were mostly directors or heads of department, responsible for the strategic direction of a subset of digital marketing activities; or marketing managers, carrying out the day-to-day marketing operations. The rest of them were marketing team leads, overseeing a team of marketing managers; marketing technology managers, responsible of selecting the appropriate marketing technologies and partners across advertising channels; and executives, i.e., C-level management (Figure 13). As the literature is lacking detailed and up-to-date descriptions of today's online advertising, it was judged that this set of expert roles ranging from the people executing campaigns to the people making the strategic decisions provides the most accurate and insightful collection of data.

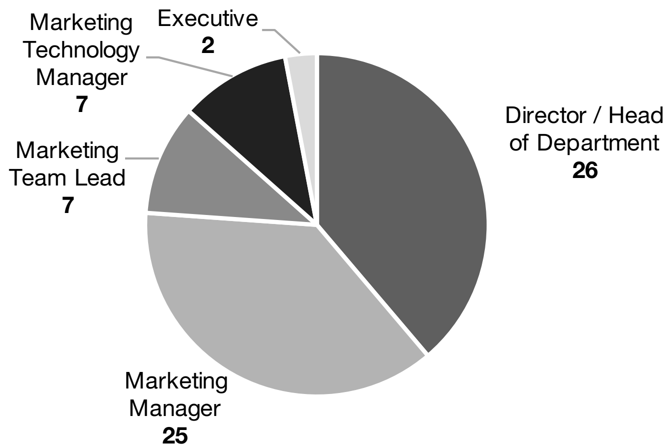

Figure 13. The people interviewed, by title

Also, six interviews with people representing advertising platforms or technology partners were conducted during the same timeframe (full list in Appendix 2).

The interviews were semi-structured with mostly open-ended questions to allow us to flexibly get immersed in the topics the interviewees were the most knowledgeable about. As I was more familiar with Facebook to begin with, the questions had a bigger emphasis on Google. The focus was placed on the challenges the advertisers were facing as those manifest some of the most advanced aspects of online advertising, highlight the differences between platforms and indicate what are the issues the ad platforms might potentially address next.

The interviews were conducted by me and my colleague and out of the total of 47 interviews, I was present in 40. The interviews lasted from 30 to 60 minutes and were carried out in person, through a video call or a regular phone call. The interviewees gave recording permission in 19 interviews; the rest weren't recorded. Thorough notes were written during the interviews and transcribed within 24 hours from them.

3.4 Data analysis

According to Eisenhardt & Graebner (2007), in case study research, the theory is developed by "recognizing patterns of relationships among constructs within and across cases and their underlying logical arguments". The theory-building process is iterating between the case data and the emerging theory—later accompanied by the existing literature (Eisenhardt & Graebner, 2007). Even though the data analysis step is the least codified part of the process in case study research, there are tactics to introduce structure and diverse views in the analysis to avoid human information-processing biases and go beyond the initial impressions (Eisenhardt, 1989)

As suggested by Eisenhardt (1989), the analysis started with becoming familiar with each case individually before starting the cross-case analysis to allow unique patterns to arise before starting to generalize them. As there was also business interest in the findings emerging from the interviews, they were extensively discussed with several colleagues, including the management of the company I work for.

Already after the first interviews, common patterns started to emerge. Whenever there was a feeling of saturation within a topic, it was left out from the interviews to accommodate new questions arisen from the improved understanding. It was also found out that some of the questions were too broad and we weren't able to ask the appropriate clarifications due to our initial lack of understanding. That was later on addressed by more explicitly asking about specific ad products which seemed to catalyze the interviewees' thoughts. It also surprised us how fragmented Google's advertising ecosystem was (at least compared to Facebook where we were coming from) which made us split the questions more based on the different ad products.

The cross-case analysis utilized tactics recommended by Eisenhardt (1989): listing similarities and dissimilarities between the cases and analyzing them through a number of dimensions. The latter supported the former: the primary framework for analysis (see section 4.2) was a mathematical model built on the generalized cross-case learnings. The idea for the revenue equation indeed originated from the need to introduce structure to the analysis but later proved to be a valuable standalone contribution.

Saloner (1991) argues that this kind of microeconomic modeling can be valuable in strategic management theory building. Especially the models that assume complex rationality—such as game-theoretic models—should not be used literally, but rather metaphorically. In contrary to most models in management science trying to algorithmically produce the answer to a problem based on some inputs, the primary interest in metaphorical microeconomic modeling is to understand *how* the model works. Another benefit of mathematical modeling—compared to e.g. the boxes-and-arrows modeling widely used in theory development in strategic management—is that it's easier for the reader to review the underlying assumptions critically. (Saloner, 1991)

The foundation of the price dynamics analysis was largely based on my prior understanding of the subject but was supported by the collected data as it was decided to act as a bridge from the auction literature to the revenue equation.

Lastly, the emergent theory was compared with the existing literature—for finding both similarities and conflicts. Ignoring conflicts with literature would decrease the confidence in the findings and potentially cause missing the opportunity to deepen both the existing and the emergent theory and better define the limits of generalizability (Eisenhardt, 1989). Most of the time, the findings were in line with the literature. Literature especially helped to form a consistent terminology with unambiguous definitions and boundaries.

4 Results

4.1 Price dynamics

Online ad auctions enable finding a market price for each ad impression, i.e., when a specific individual sees an ad in a particular place on a particular publisher's site or application. Some of the typical mechanisms used are GSP and VCG auctions (see section 2.1.3). In general, each impression is sold to the advertiser valuing it the most with a price determined by what others are willing to pay for it.

The value of an impression to an advertiser equals the conversion rate (CVR)—i.e., the estimated probability of the user to complete the desired action as a result of seeing the ad—multiplied by the value of that action to the advertiser. The estimation is based on historical tracking data, and its accuracy can also be checked post hoc.

As explained in section 2.1.5, sometimes publishers auction clicks or other actions instead of impressions. While the values advertisers define in this type of auction are called "bids", they often don't participate in the auction per se but are converted to the actual bids instead. This is based on the publishers' estimates of the probability of users to click the ad or complete the defined action. Sometimes the publishers also incorporate a relevance factor in the auction to weigh-in the ads' estimated effect on user experience.

The publisher can either bear the risk instead of the advertiser—and typically take a price premium for that—or leave the risk for the advertiser while still optimizing delivery for the desired actions. For example, Facebook's bidding system nominally charges for impressions, leaving the advertiser to pay a small amount for the delivery in case there are no conversions (Facebook, n.d. -b). This properly incentivizes the advertisers to see the effort to improve their campaign performance. However, Facebook still has the incentive to exert non-contractual efforts to get the most conversions for the advertiser as they know that's what they're in the end measured against when determining the advertising budgets. This seems like the optimal solution to the issues with CPA pricing model Hu et al. (2016) present in their paper (see section 2.1.5).

A more traditional way to sell ads is through insertion orders (IO) in which the publisher agrees to serve a certain amount of impressions to a certain target audience in a certain timeframe for a certain price. In many cases, the advertiser has a clear idea of the audience so that it can estimate the implications the campaign will have to its business. While typically this is not as effective as impression-level bidding, in the end, the value of the ads to the advertiser is determined by the proven or estimated results achieved from them and the price other advertisers are willing to pay. One publisher can sell ads using multiple different ways simultaneously.

In conclusion, the ad prices are determined by supply and demand—each advertiser valuing ad impressions based on their estimated average impact on its business. Different purchasing types allow different levels of granularity and affect the effectiveness of ad buying.

4.1.1 Pricing from an advertiser's perspective

As the price of ads is determined by what others are willing to pay, the profitability of an advertiser's efforts is determined by how much more efficiently it can reach its target audience than others. If others can get better results from the same impressions, they're willing to pay more for them. Increased impression prices require more efficiency from an advertiser to maintain the same level of profitability.

Profitability varies by scale. The smaller and more well-known the audience, the better the performance usually is. Correspondingly, the larger the audience the advertiser wants to reach, the more expensive conversions get. For example, a golf equipment manufacturer is likely to get good returns targeting 50-year old men with high household income and interest in golf, but the more scale it wants, the more expensive each incremental result gets (Figure 14). This can result from either decreasing conversion rate (targeting audience segments with less purchase intention) or increasing costs to reach the audience (targeting audience segments more valuable to other advertisers).

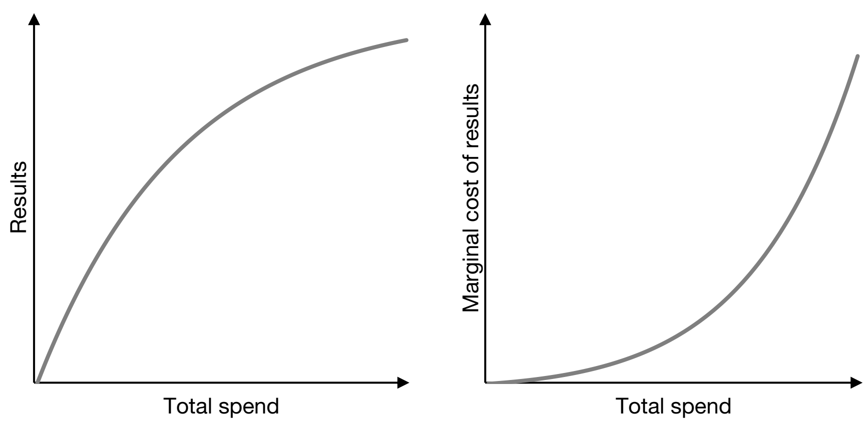

Figure 14. An advertiser's results as a function of advertising spend

The shape of the curve can vary between advertisers and channels. For a niche product, the marginal cost rises steeper whereas a mass-market product can get good performance also at a significant scale. The position of the curve can be shifted by making optimizations in ad serving—either by the advertiser or the ad platform.

Typically, advertisers' budgets are determined by the profitability of advertising. I.e., when an advertiser determines its budgets for an ad channel, they analyze their performance data measured in, for example, (marginal) cost per action (CPA) or (marginal) return on ad spend (ROAS). In theory, an advertiser maximizes its profits by setting its budget at the point in which the marginal cost reaches the marginal benefit (Figure 15).

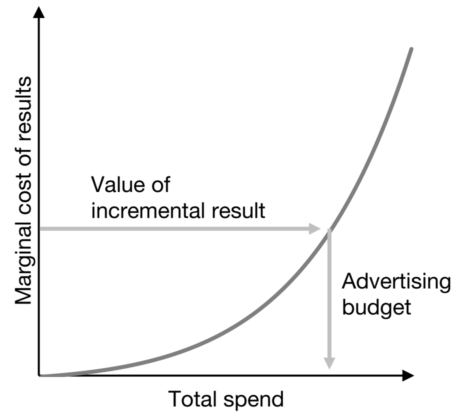

Figure 15. Determining advertising budget based on marginal cost of results and value of an incremental result

In practice, there are various ways for accomplishing this: some of the advertisers interviewed are flexible with the maximum budget as long as the marginal cost of results stay within the target range while others set the total marketing budget, e.g., quarterly based on the last quarter's results.

Setting the budget to the optimal point maximizes what we call here *advertiser surplus*—the difference between the value and cost of results, and essentially the total value an advertiser derives from its advertising efforts (Figure 16). Spending more would have a higher price than the value resulting from it and decrease advertiser surplus. Spending less would leave profitable opportunities unused and not maximize advertiser surplus.

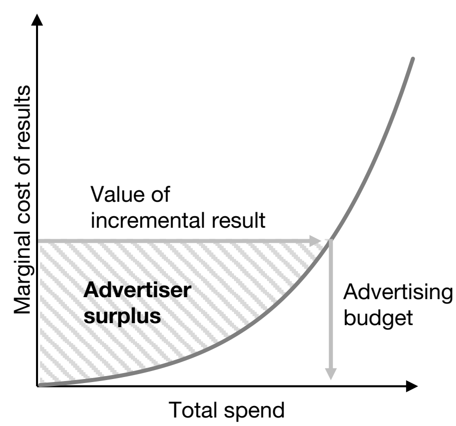

Figure 16. Calculating advertiser surplus from the marginal cost of results and value of an incremental result

Other things equal, improvements in the effectiveness of ad serving—whether they originate from the advertiser's or the ad platform's efforts—are reflected as increases in advertising budgets: the advertisers adjust their budgets until a new equilibrium is reached (Figure 17).

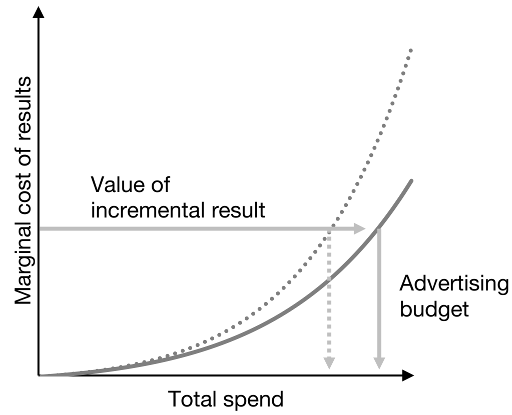

Figure 17. An advertiser adjusting to its new budget when advertising efficiency changes

In practice, measuring value is non-trivial. Moreover, determining the distribution of value and cost—i.e., determining the marginal cost—might not be possible at a very granular level. Some of the advertisers interviewed often revert to use average cost (measured, e.g., in CPA or ROAS)—which is always lower than the marginal cost. Still, they aim to find a scale that maximizes their profitability. (If the advertisers paid the price equal to the value, their entire advertising efforts would yield zero profits.)

The value is not necessarily determined in directly attributable profit. In customer acquisition, estimated lifetime value (LTV) might be used, and sometimes growing businesses are willing to acquire users unprofitably to reach a critical scale faster than their competitors. Sometimes a proxy metric is measured to estimate the actual goal it correlates with. Some of the advertisers interviewed allocate a separate budget for branding campaigns which are measured with clicks, video views or more advanced brand recall metrics. Nevertheless, they define a monetary value for each conversion.

4.1.2 Pricing from an ad platform's perspective

Ad platform revenue is made up of advertisers' budgets. Because these budgets depend on measured performance, the publisher also has an incentive to improve advertisers' performance.

In other words, if an ad platform can deliver more results to its advertisers with the same amount of ad impressions, it's reflected in the impression prices which comprise its revenue. Another way to think about this is that the platforms are selling measurable results instead of ad impressions.

Figure 18 gives some indication of the rapid historical growth of impression prices on Facebook, although it should be kept in mind that the sample it uses is not representative of the whole platform—there are, e.g., significant differences in impression prices between countries. The increase of impression prices can be mostly explained by improvements in the efficiency of ad serving and increased value of measured conversions—as argued in the next section.

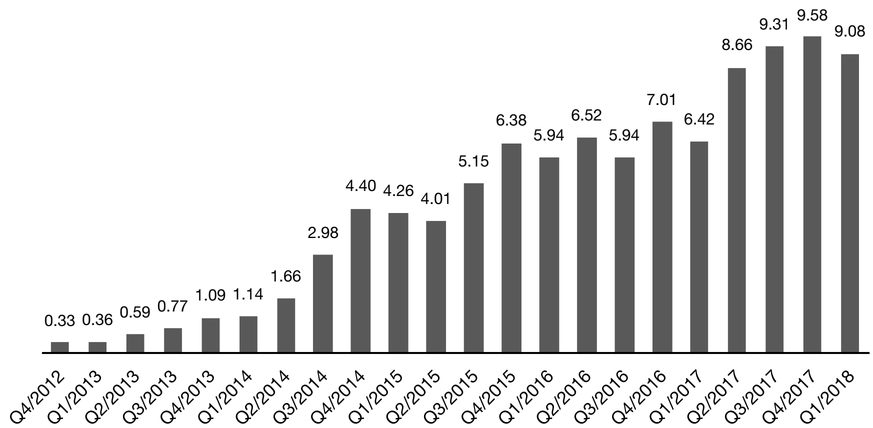

Figure 18. The average cost per thousand impressions (CPM, US $) of ads on Facebook delivered by advertisers using Nanigans software. Includes Audience Network; excludes Facebook Exchange and Instagram. The numbers reflect the company's customer portfolio of mostly e-commerce, gaming, and other internet and mobile companies with $700 million annualized ad spend in 2018. (Nanigans, 2013 – 2018)

4.2 The drivers of ad platform revenue

Typically, ad platforms' costs of delivering their service don't scale proportionally with the number of users. Consequently, they can mostly ignore marginal costs other than the traffic acquisition cost and focus on maximizing their net advertising revenue. In this section, ad platforms' net revenue is divided into its main components to help understand how ad platforms can affect it with their efforts.

To begin with, the ad platforms are selling impressions, i.e., single views of an ad. Total advertising revenue in a certain timeframe can be expressed as

$$advertising\ revenue = \sum_{i=1}^{ad\ impressions} price\ of\ ad\ impression_i \tag{1}$$

Many ad platforms—such as demand-side platforms (DSP)—are buying impressions from partner sites, ad networks or ad exchanges and immediately reselling them to the end advertisers. The price the advertising platform pays for offsite impressions is called *traffic acquisition cost* (TAC). For impressions sold on the ad platform's own properties, TAC is essentially zero. To compare revenues between the platforms, it's more illustrative to use net advertising revenue after TAC.

$$net\ advertising\ revenue = \sum_{i=1}^{ad\ impressions} \begin{matrix} price\ of\ ad\ impression_i \\ -traffic\ acquisition\ cost_i \end{matrix} \tag{2}$$

The prices of ad impressions are determined in auctions or one-to-one contracts between the buyer and the seller (see section 4.1). For many of the impressions, the price the advertiser ends up paying is lower than how much the advertiser values it:

$$advertiser\ surplus\ rate = \frac{value\ of\ ad\ impression - price\ of\ ad\ impression}{value\ of\ ad\ impression} \tag{3}$$ [1]

which can be formulated as

$$price\ of\ ad\ impression = (1 - advertiser\ surplus\ rate) \times value\ of\ ad\ impression \tag{4}$$

The impressions themselves don't have inherent value for the advertisers. Instead, their value is determined by the probability of a user to convert after seeing an ad—known as conversion rate (CVR)—and the value of that conversion to the advertiser:

$$\text{value of ad impression} = \text{conversion rate} \times \text{measured value of conversion} \tag{5}$$

Therefore, we can express the total advertising revenue of a platform in the following form:

$$net\ advertising\ revenue = \sum_{i=1}^{ad\ impressions} \begin{matrix} (1 - advertiser\ surplus\ rate_i) \\ \times\ conversion\ rate_i \\ \times\ measured\ value\ of\ conversion_i \\ -traffic\ acquisition\ cost_i \end{matrix} \tag{6}$$

The components of (6) are listed in Table 10 along with their further subcomponents and main drivers which will be discussed in the following sections.

---

[1] Using (5) and $\text{price of ad impression} = \text{conversion rate} \times \text{price of conversion}$, we can formulate (3) into $\text{advertiser surplus rate} = \frac{\text{value of conversion} - \text{price of conversion}}{\text{value of conversion}}$ which is in line with the definition of advertiser surplus in section 4.1.1.

Table 10. The drivers and components of advertising platform's net revenue.

Driver	Component	Subcomponents
Access to an active user base	Ad impressions	Users Visits per user Impressions per visit
The effectiveness of ad serving	Conversion rate	
The comprehensiveness of measurement	The measured value of conversions	The accuracy of measurement The value of conversions
Ability to price discriminate	Advertiser surplus rate	
Competition for off-premise impressions	Traffic acquisition costs	Distribution of on/off-premise impressions

4.2.1 Access to an active user base

The number of total impressions shown on a platform is typically determined by the number of its users and how actively they use the platform. The number can be further broken into subcomponents to illustrate this:

$$ad\ impressions = users\ \times\ visits\ per\ user\ \times\ impressions\ per\ visit$$

The number of impressions per visit is highly related to the characteristics of publisher platforms. In practice, all publishers tend to show as many ads as possible without making the user experience suffer too much. In search advertising, as the goal is to direct the users to what they were looking for, they typically see only one set of impressions per visit. In display advertising, the rate at which ads are shown is usually constant while the publishers try to maximize the amount of time spent on their premises in each visit.

The number of visits per user also reflects the characteristics of publishers, mainly how engaging they are and how broad their offerings to their users are. For example, Facebook shows ads on its social media platform, messaging application Messenger and social image sharing platform Instagram. Google displays ads in its search engine, email client Gmail, video streaming service YouTube and mobile application database Play Store.

The straightforward way to serve more ad impressions is to grow the user base. In May 2017, Google had seven unique products with over one billion monthly active users (MAU) each (Matney, 2017). In June 2017, Facebook had two billion monthly active users (Constine, 2017a). For reference, there were 3.4 billion internet users globally in 2016 (International Telecommunications Union, n.d.).

They've reached such a scale in terms of money and user data that they can either acquire competitors or push them out of the market. For example, Google has acquired YouTube (1.5 billion MAU in June 2017). Facebook has bought Instagram (700 million MAU in

April 2017) and WhatsApp (1.2 billion MAU in June 2017). In August 2016, Facebook heavily took influences from Snapchat's "Stories", built a similar feature to Instagram, and its usage surpassed Snapchat's in monthly active users in less than a year (Constine, 2017b). Both Google and Facebook even have programs for distributing internet access to developing countries—Project Loon and Internet.org respectively—as they have nearly reached saturation in developed countries. The profitability of these new users is, however, only a fraction of that in developed countries.

However, the active user base doesn't have to be on the ad platform's own premises. Many ad platforms such as demand-side platforms (DSP) buy ad impressions from exchanges and resell them to the end advertisers. Closed platforms can also expand their advertising outside their premises. This allows them to show more impressions to their users while still utilizing the data they have on their users. The net revenue from off-premise impressions is significantly lower as explained in section 4.2.4.

4.2.2 The effectiveness of ad serving

Conversion rate (CVR) is defined as the probability of a user to convert after seeing an ad—or simply, the number of conversions divided by the number of impressions in a sample. It is determined by the platform's capability to enable advertisers to show the right kind of advertisement to the right person.

The quality of the ad *creative*—the media shown in the ad unit—has a significant effect on the conversion rate. While designing creatives is mostly done on the advertiser side, the platform can affect their quality via the supported creative formats: text, static images, video, interactive ads and so on. Closed platforms have more freedom with the ad formats than open platforms which have to adhere to a set of commonly defined standards (Internet Advertising Bureau [IAB], 2017b). Some examples of emerging creative formats are augmented and virtual reality ads that allow the user to, e.g., virtually travel to a destination or see how an apparel would look like when worn. Increasing immersiveness of ads, however, also increases their obtrusiveness and thus can't be increased beyond a certain point without harming the user experience.

To help the advertisers pick the optimal users to see a particular creative, platforms offer a variety of *targeting* options. The available options vary and typically reflect the amount of information the platform has about its users. Typical options include user demographics, location, interests and behaviors as well as the option to use first-party audiences collected by the advertiser.

Both creative and targeting can be significantly improved by the platforms' *optimization*. Optimization usually consists of automated techniques based on data analytics with the goal of directly improving advertiser results. In display advertising, a successful ad might be automatically shown to people similar to those who have already converted as a result of seeing it. In search advertising, investments might be shifted to the best-performing keywords. Alternatively, multiple permutations of a creative can be automatically generated and tested to choose the best performing one.

As with targeting, most of the optimization techniques rely on detailed user or contextual data. Besides, optimization depends on high-quality measurement data about the variable it's trying to improve. While the sophistication of optimization varies from platform to platform, merely the amount of data available is already a big differentiator between them.

The most advanced optimization methods are based on modeling the advertiser's business and mapping the semantics of various user signals to it. For example, if a user has purchased flights to a destination, the optimized creative can feature hotels in that destination. This is discussed more in section 4.3.3.

Targeting options and targeting optimization are somewhat overlapping solutions for maximizing campaign performance. While targeting options provide the advertisers with means to micro-manage the user segments seeing each ad, too strict targeting specifications don't leave enough options for optimization to manage the ad delivery. Ideally, the advertiser only uses the amount of targeting proven to improve results, and lets optimization take care of the rest.

However, optimization algorithms are typically opaque to the advertisers—especially when run by closed ad platforms or third parties—and while they improve the performance, the advertiser doesn't get information of what kind of message resonates with each customer segment. The information can be valuable to the advertisers as it not only allows them to fine-tune their marketing messaging and long-term strategy across channels but signals how users perceive the advertisers' offerings and allows them to use that information to develop their product or service further and improve interactions in their purchase path. Thus, the advertisers balance optimization and targeting to get the optimal ratio of performance and learnings out of their campaigns. Some of the advertisers interviewed mostly trust the platforms' optimization while others take more control themselves with a more granular structure and micro-management.

There are also other ways of improving the effectiveness of ad serving. For example, some platforms provide *split testing* tools to allow the advertisers to run controlled experiments to learn what kind of advertising setups perform best. Overall, both the platform and the end advertiser share the mutual goal of improving the ad serving with various techniques.

4.2.3 The comprehensiveness of measurement

Measuring the value of conversions relies on two complementary techniques: tracking and attribution. *Tracking* involves detecting and storing the desired actions users take. *Attribution* is about modeling which of those actions can be determined to have originated from a specific ad.

Tracking relies on a multitude of methods. Online actions are typically tracked by matching the user's device to a profile—either anonymous or containing personally identifiable information (PII). The devices are identified, for example, by their digital fingerprints (software and hardware configuration), their mobile advertising IDs or browser cookies stored on them. The matching can be deterministic (based on unique identifiers) or probabilistic (based on the probability that multiple matching values refer to the same entity). If a closed ad platform can get a user to log in to the service consistently, it can further match multiple devices to that single profile.

Offline actions can be tracked, for example, by using unique offer coupon codes, matching PII collected from purchase orders or loyalty programs to an online profile, seeing which

Wi-Fi and Bluetooth beacons users' devices connect to and monitoring the GPS-location of the user's device.

The level of invasiveness of data collection varies in both online and offline tracking methods. The more invasive methods usually involve users installing an application on their device. It's possible for consumers to take measures to prevent many ways of tracking, ranging from disabling it from the service's settings to installing tracking prevention software or not using the service at all. Doing that, however, is relatively uncommon—either because people are not concerned about it or they don't know how.

Although attribution is a powerful tool required for almost any decision in performance marketing, it is based on observational methods and can never tell the full truth (as mentioned in section 2.1.4). For example, if a person sees an ad for a product and purchases it on the same day, it could be reasonably determined that the ad will get the credit for the conversion. But how to be sure that the person wouldn't have made the purchase regardless of the ad? And if that person saw another ad after the first one before converting, which ad should get the credit?

The decision is based on an *attribution model*. It determines which touchpoints—e.g., views and clicks—are counted and what are their relative priorities, how long are the timeframes for including each type of touchpoint and if multiple touchpoints are involved, how is the credit distributed for each ad. Some examples of typical attribution models are

- *last-touch*: always attribute the conversion to the ad that received the last interaction before conversion,
- *time decay*: distribute credit to multiple touchpoints so that the one closest to the conversion gets the most and
- *position-based*: assign, e.g., 40% of the credit to the first and last touchpoints each and distribute the remaining 20% to the rest of the touchpoints.

A part of an attribution model is the *lookback window*, i.e., how long after the ad interaction can the conversion happen while still being attributed to the ad. Typical examples of lookback windows are 28 days after a click on an ad and one day after an ad impression without click but, ideally, each advertiser chooses the one most suitable for their business.

Choosing the right attribution model is crucial for advertising performance. The wrong model can cause both humans and computers to direct ads to be shown to people who would have converted even without seeing them and consequently inflated performance numbers might falsely advise to invest more in the wrong campaigns. Correspondingly, failure to give credit to effective advertising will cause investments to it to disappear. Some of the interviewees even mentioned internal disputes in their companies when the choice of attribution model, for example, makes the social advertising team look bad compared to the search advertising team, consequently affecting their compensations.

Not all types of conversions or advertising channels have the same basis to be appraised. The measured value of a conversion can be further broken down into two factors:

$$measured\ value\ of\ conversion = accuracy\ of\ measurement\ \times\ value\ of\ conversion$$

These two are strongly related to each other. Digital performance advertising can be widely adopted in industries with conversions relatively easy to track and attribute to the ad touchpoint—for example, installations and usage of mobile applications or purchases in an e-commerce store.

In other industries, the advertising budgets can be constrained when accurate tracking and attribution is not available. For example, conversion tracking is significantly harder when the conversions happen offline or the buying process is long and includes many brand touch points from multiple channels and devices—which increasingly is the case as mobile advertising has rapidly grown alongside desktop in the recent years (see section 1.1.5). As an anecdotal rule, the more valuable the conversion, the harder it is to track and attribute—mostly because the buying decisions are less impulsive and require more time and inputs for consideration.

Also, some channels are better positioned to receive attributed conversions. For example, search ads are typically closer to purchase in the buyer decision-making process and thus have the tendency to be valued relatively more. This factor is partly out of the hands of the platforms, but they can affect it shaping their offering in a way that allows showing easier-to-attribute ads.

Another way for platforms to increase their accuracy and value of measured conversions is to build their own tracking and attribution systems. While some platforms make their advertisers rely on third-party measurement tools, a proprietary measurement system has many benefits. First, it allows the platforms to gather more granular data that can be better used for optimization as explained in section 4.2.2—without measurement, there's no optimization. Second, it allows the platforms to gather user data from the advertisers' websites and applications as explained in section 4.3.2.

Third, it can be more accurate than third-party tracking and attribution as it can match all data across multiple browsers and devices to one user profile—although this applies only if the platform can enforce the users to log in while using the service. Practically all Facebook users are logged in whenever they're using the platform and even most of the time when they're not. Google requires login, e.g., for Gmail, and many of its products provide a better experience for logged-in users, but it's not a requirement for access. Publishers merely providing static content for users to consume have a harder time trying to incentivize users to log in and have to resort to less reliable tracking methods such as browser cookies.

Although they have a lot of benefits, the proprietary measurement systems are typically not capable of attributing the events to other platforms. As most conversions are a result of multiple ad touchpoints from various advertising channels, this results in multiple different platforms claiming the same conversion. Besides, they have different definitions for some metrics such as video views—e.g.. how many seconds does the video have to play and how big share of it has to be visible on the user's screen—making them not comparable with each other. For those reasons, most advertisers base parts of their decision-making on a third-party measurement tool while using the platforms' own systems for day-to-day optimization.

As measurement has such a big impact on the advertising budgets, the platforms are inclined to influence it. The results reported based on platforms' own tracking systems typically ignore any touchpoints from other advertising channels and are favorable for the platform. Google is offering Google Analytics, the most used website traffic analytics tool

(Empson, 2012), for free. Due to limitations in its tracking capabilities, ad touchpoints closer to the conversion—such as search ads—seem to perform disproportionally better. As those constitute the bulk of Google's net advertising revenue (Liu, 2016), the platform is biased to preserve the status quo. Facebook, on the other hand, is rolling out their own free-to-use measurement suite Atlas, aiming to solve many of the current limitations in cross-channel tracking by using Facebook's two billion user profiles for data matching. Atlas is likely to make Facebook look more attractive performance-wise for most advertisers compared to Google Analytics.

There's also one way to measure the real impact of a marketing campaign without attribution. A *conversion lift test* is a setup in which an ad is shown to a group of people and not shown to another group at all after which the lift in the chosen metric is calculated. A similar technique is used in many traditional advertising media such as television, print and billboards. The test groups are often selected based on e.g. geography which introduces a bias, although, with the help of digital tracking technologies, some ad platforms offer a way to set up a proper randomized controlled trial in which the subject groups are randomly generated from the same population just for the test so that they share the equal distribution of demographics and other properties.

The upside of this approach is that no attribution modeling is required, but instead the real conversion lift can be measured. This is why the most sophisticated advertisers use data gathered from their conversion lift tests to improve their attribution models to be closer to the truth. But attribution modeling still stays very relevant. To get statistically significant results, conversion lift tests require large amounts of data and thus substantial budgets. They can't be used as a tool in day-to-day decision-making and optimization.

4.2.4 Ability to price discriminate

As explained in section 4.1.1, we can't expect the advertisers to pay their full value for each impression. The ad platforms can lower the advertiser surplus to some extent by being effective at price discrimination. However, most of them are already equally efficient at price discrimination, and thus, this is not a measure they can use to increase their competitiveness significantly.

According to Samuelson & Marks (2012, p. 100), to price discriminate profitably, a firm must:

1. identify market segments that differ with respect to price elasticity of demand and
2. be able to enforce the different prices paid by different segments.

In online advertising, the heterogeneousness of ad inventory—countless keywords and user segments—creates the foundation for price discrimination. The aim is to split the inventory into as granular pieces as possible and find the advertisers willing to pay the most for each.

In the auction setting, this is very efficient as, at least in principle, each impression is auctioned individually. Furthermore, the types of auctions used are typically good for setting the prices. For example, as explained in section 2.1.3, the dominant strategy in VCG auctions for the advertisers is to simply bid their true value—although the auction dynamics prevent the platforms from charging that full value. While GFP and GSP auctions are not incentive compatible, revenue-wise they are quite close to VCG from the platform's perspective.

In a direct sales setting, the platforms sell impressions in larger sets, and thus, the inventory is more uniform. Instead of offering a fixed price for everyone, the platforms typically negotiate deals one-to-one, i.e., advertisers won't know how much others have paid. While this allows some price discrimination, it's not as effective as in an auction.

4.2.5 Competition for off-premise impressions

Many ad platforms are buying impressions—either as an addition to their on-premise impressions or as their only source of inventory—from ad exchanges, ad networks or directly from publishers and reselling them. To keep this activity profitable, they have to add value somehow so that they can charge more than they pay for the impressions. Some of the added value can originate from aggregating multiple sources of supply—i.e., what demand-side platforms (DSP) do—or various services in the programmatic value chain (see section 1.1.2).

The most effective way of adding value is making the impression itself more valuable. The value of showing an ad to an unknown person on a not-so-widely-known publisher's website in negligible but an ad platform with data about the user can add value significantly by helping to identify individuals with purchase intent and showing them relevant ads. That said, other ad platforms can have their data about the user, and the price of an impression is determined by how much the competition is willing to pay for it (as explained in section 4.1). Consequently, the profit margin a platform makes from reselling an impression results from the differences in the effectiveness of ad serving, tracking and attribution it has over others.

For example, in 2016, for the impressions served outside its properties, Google paid on average a traffic acquisition cost (TAC) of 69.9% (Alphabet, 2017). That means that it was able to add on average 43% value on impressions with its ad serving, targeting and buying solutions.

For the impressions served on the ad platforms' own properties—i.e., when the publisher runs its own ad platform—there's no traffic acquisition cost. This kind of vertical integration can be profitable in certain circumstances, as explained next in section 4.3.

4.3 The case for a closed ad platform

Table 11 summarizes the main differences between closed and open ad platforms. If a publisher reaches the critical scale required to build its own ad serving infrastructure and get advertisers directly on board, it may opt for becoming a closed ad platform.

Table 11. *The differences of closed and open ad platforms.*

	Closed ad platform	Open ad platform
The publisher's role	The publisher sells the ad inventory on its site directly to advertisers.	The publisher lets a third party sell the ad inventory.
User tracking	Only the publisher tracks users on its properties.	The publisher lets third parties track the users on its property.
Ownership of targeting data	The publisher owns all data used for targeting. Advertisers don't have direct access to it. Advertisers can provide their business and user data to the publisher.	The platform and advertisers use their data without giving it to the publisher.
User identification methods	Login, browser cookies, device identifiers	Browser cookies, device identifiers
Ad formats	Publisher defines	Standardized across exchanges

4.3.1 Sources of competitiveness

Becoming a closed ad platform can be a good strategic move for a publisher: instead of allowing third parties to collect data from its users—a side effect from programmatic ad buying—and monetize it, closed platforms retain exclusive control to the ad infrastructure from selling to serving themselves.

However, looking at the components of ad platform's revenue (section 4.2), a publisher benefits from the move only if its conversion rates and the measured value of conversions are high enough to warrant a higher impression price than what the third-party ad platforms would be willing to pay for advertising to the user base. In other words, letting third parties serve ads on its site, a publisher can still get the market rate reflecting the value of its users to advertisers.

For example, Facebook ran its ad exchange, Facebook Exchange (FBX), on the side of its closed advertising platform from 2012 to 2016 (Constine, 2012; Ha, 2016)—purportedly to address their post-IPO short-term revenue pressures. FBX allowed third parties use their data instead of the limited targeting options Facebook had back then, resulting in superior performance and increased ad investment in specific cases.

Still, closed platforms have multiple advantages over that. First, they can leverage rich user data collected from their service for improved efficiency in ad serving. The platforms with a significant proportion of logged-in users have an advantage over this. For example, Facebook has a massive database of detailed demographic data—mostly self-reported by its users—whereas many targeting data providers in programmatic ad buying sometimes struggle knowing even the gender of the user. The more information an ad platform has per user, the better it can target ads and the higher the price per impression it can charge.

Second, as explained in section 4.2.3, closed ad platforms with logged-in users are sometimes in a better position to track them for measuring the effectiveness of ads. For example, instead of relying on short-lived and device-specific browser cookies, Facebook can track touchpoints from the same user across multiple devices and thus more effectively prove the value of advertising on the platform.

Third, closed ad platforms are vertically integrated, capturing the whole value chain (see Figure 3, p. 11; Table 7, p. 28) instead of only the publisher's slice of revenue—on average, 45% (Interactive Advertising Bureau [IAB], 2015)—while avoiding the externalities imposed by double marginalization. Owning the whole value chain also enables increased efficiency from the significantly smaller number of intermediaries, providing opportunities for cost savings and drastically decreasing site loading times, considerably improving the user experience.

Fourth, closed ad platforms can better control the user experience of people seeing the ads compared to publishers selling their ad inventory through an exchange. For example, Facebook and Google have their custom policies for eligible ads and weight bids in ad auction based on the estimated impact on user experience. Publishers using open ad platforms have a limited say over what gets served on their properties. Controlling user experience can improve user engagement and retention, consequently having a positive long-term impact on revenue.

Fifth, the closed ad platforms can collect extremely valuable data from the advertisers themselves in an unparalleled way and use it to power their ad delivery. More on this in the next sections.

4.3.2 Collecting user data from advertisers

The data a closed platform can collect from its users is not limited to behavior within its properties: many of them provide advertisers various ways to supply their data which is then matched to the users of the platform. The advertisers benefit from using their first-party data in the form of better returns on their ad spend through improved ad serving efficiency. The improved advertiser performance consequently benefits also the platforms through increased overall prices of ad impressions.

But more importantly, the platforms use all of this data to enrich their user profiles. In practice, advertisers often have to allow the platforms to record all the relevant user interactions on their site or in their app. This is in sharp contrast to buying ads through an open ad exchange in which the advertisers can choose what data to use from their data management platform (DMP).

This can be used to build more detailed and reliable targeting options and improve the platform's automatic optimization algorithms—both increasing the overall effectiveness of ad serving on the platform. Effectively, this means that the platforms are collecting data from advertisers and profiting from allowing other advertisers—sometimes competitors—tap into its power.

The effect of gathering off-site data can be significant. For example, knowing that someone browsed a certain product category on multiple websites is a very strong commercial signal. In contrast, within many publisher platforms, the on-site user behavior either has very little commercial intent or is in a form that makes it very hard to collect and analyze it automatically. E.g., in the case of social platforms such as Facebook, having a detailed view of a social network has only limited commercial value and analyzing commercial cues from messages with electronic natural language processing is difficult due to informality, irony and sarcasm.

On the other hand, inherently commercial platforms—such as the visual discovery platform Pinterest—or platforms at the end of a consumer purchase process—such as search engines—can gather a larger share of their user data within their platform and the effect of data collection from advertisers is subtler.

4.3.3 Collecting business data from advertisers

The primary ad delivery optimization is relatively simple: finding common patterns between users and delivering ads to people similar to the ones the message resonates with. This doesn't necessarily require the algorithms to be aware of what's advertised to the user.

That's not an issue for advertisers with only one or few messages they want to convey. For example, mobile game studios have been widely successful in digital advertising as they can find out in a data-driven way what kind of users are the most profitable and what kind of message is the most effective for them.

But retailers, e-commerce, travel agencies and other businesses with thousands or millions of products or other offerings face the difficulty of finding the right products that draw each user's attention and lead to a purchase. When retargeting people who have already visited the advertiser's website or application, the browsing behavior can be used to infer what should be advertised to that person. This just has to be operationalized with the platform. But when acquiring new customers, it's more difficult: the advertiser's business data has to be merged with the platform's user data.

To address both of these needs, some platforms such as Google and Facebook offer the possibility for advertisers to upload their product and other business information in a machine-readable format to the platforms. This allows the platforms to understand not just what websites users visit but what types of products, services and content they interact with. This is used to determine what's the product that should be shown to a user in an ad.

The platforms typically have separate solutions for each industry and thus can compare the business data and match products across advertisers. This allows them to interpret commercial interactions better to be used across advertisers. For example, Facebook's Dynamic Ads product has separate solutions for e-commerce, retail, travel, automotive and real estate that can be used to build comprehensive buyer profiles which are, in turn, used to generate product recommendations across advertisers.

Again, this can be controversial from the advertisers' perspective. For example, a closed ad platform can learn from a travel agency's website that a user is considering a trip to a certain destination. This can be used to show another travel agency's ad of the same destination to the same user.

4.3.4 Risks to advertisers

Why are advertisers willing to share data with closed platforms if they know it's being used to benefit other advertisers? First of all, it's rather hard for an advertiser to quantify the impact data sharing has on its business and thus it can be underestimated.

But it can also be argued that the benefits are higher than the costs. Especially small businesses contribute a relatively small amount of the total data in the user profiles but can leverage it all in the form of more extensive targeting options and better optimization of its ad delivery. Engaging in this kind of controlled mutual data sharing might make all the parties better off. This is the case especially with complementary businesses not directly competing with each other: airlines and hotel chains; diapers and strollers; bicycles and helmets.

Not all businesses might be equally well off from this arrangement, though. Large enterprises are concerned about the disproportionally large amount of data they contribute that their competitors might effectively use to capture traffic to their site by advertising the same products at a lower price.

The ad platforms can also use the business data to make an increasingly large share of the customer decision process happen in their service, making it harder for resellers, aggregators and agencies to compete with qualities other than price. For example, Google Shopping allows advertisers to feature their products in Google's search results—however, multiple advertisers and their respective prices are displayed next to a generic product image. The comparison happens on Google's platform, and the user is directed to the advertiser's site only for the transaction. Similarly, online travel agencies pay to get their hotels and flights featured in Google's search results while having to give up a large part of the customer experience and ways of differentiating.

The consumers see this as increased efficiency, and it's putting pressure on aggregators between the suppliers and the advertising channels. As mentioned by Eisenman et al. (2008), absorbing complements helps reducing the double marginalization caused by multiple layers of businesses. It remains to be seen if this is enough to drive some of the aggregators out of the market and if, consequently, the ad platforms can start charging disproportionate margins.

In addition to having to share data with the ad platforms, advertisers have limited options for pulling data from the closed platforms. They don't directly have access to the user data which makes it harder to orchestrate campaigns among multiple channels. Advertisers call these platforms often "black boxes" as there's no way to see what's happening inside them while it's still possible to verify that the ads are effective.

For the above reasons, there has been some pushback from advertisers against closed ad platforms, but it could be argued that Google and Facebook have simply just reached such a large scale that they can continue to exploit the position they're in. Some of the advertisers interviewed for this study described closed ad platforms even as a threat to their businesses in the long term but they "can't afford not advertising on them" as large shares of their traffic or user growth depend on them. Some other advertisers interviewed refuse to give Google and Facebook access to all of their data for the same reason, even if it would make their campaigns perform better in the short-term.

4.4 A comparison of Google and Facebook

The most significant difference between Google and Facebook as ad platforms is their primary source of revenue. Google sells mostly search ads, helping people to find what they're already looking for. Facebook sells display ads, targeting people with content they didn't know they should be looking for. While the same revenue drivers (section 4.2) apply for both, this difference has an impact on the way each platform approaches improving their effectiveness of ad serving—one of the five drivers.

Facebook has been able to improve its advertisers' results first with detailed targeting options and later on with automatic optimization of ad delivery to users similar to those who have already converted. Both of these rely on building comprehensive profiles of the platform's users.

Google, on the other hand, hasn't been so user-centric. In search advertising, it's more important to support advertisers finding the right keywords bringing them the desired results. This also applies to its display and YouTube video ads: both are contextually targeted based on keywords and searches on those sites.

Google also collects and leverages user data to some extent, but the nature of many of its services is not so good at enforcing users to log in and provide data about themselves. In comparison, Facebook requires all of its users to log in and encourages them to share information about themselves.

Both of the platforms are moving to more closed ad products that—while being simple to use and provide good results—are mostly opaque to advertisers, letting them extract fewer insights from their advertising campaigns. Both platforms have also started to allow advertisers to provide their business data to improve results: on Google, to optimize the right content to be shown with the right keywords; and on Facebook, to optimize the right content to be shown to the right user.

Many of the advertisers interviewed perceived Google's rate of innovation in ad products slower than Facebook's. Part of that might be attributed to the different types of advertising they support, part of that might be related to how they run their businesses.

While on Facebook, most advertisers are using automatic bidding to allow the platform to optimize the bid for each user, many Google advertisers optimize their keyword-level bids manually and still get better performance that way. An advertiser might manage millions of keywords while on Facebook, the same advertiser might use only a few hundred audiences.

Nevertheless, both the platforms have been able to provide results for advertisers and to improve them over time steadily. Both of them have also built hugely successful products for consumers and stayed competitive on that front—arguably their main business despite their revenues coming from the other side of the platform.

5 Discussion

5.1 Strategic implications

5.1.1 For publishers

A publisher growing its active user base faces the question of whether to sell its ad inventory for a third party or to set up its own closed ad platform. This thesis provides them with a framework for splitting the decision into its five main drivers (section 4.2) and assessing the effect on each of them individually. And if they end up embarking on such an endeavor, the five drivers help them to concentrate on the activities yielding them the most incremental revenue.

Some of the publishers might set up their closed ad platforms to better protect the users' data and privacy or provide them a better experience using the service—both helping to grow the active user base. But for most publishers, the decision depends on the quality of data they can collect from their users and the resulting performance they can provide for their advertisers—as that's a direct component of the ad platform revenue.

Establishing the required infrastructure to leverage the collected data and serve the ads requires significant investments and can't be done by any small-scale publisher. However, once a publisher has established the closed ad platform, it can find various ways to leverage its position to collect even more data it previously didn't have access to. Google and Facebook are good examples of this.

But would Google and Facebook have been as successful if they would have chosen to open their ad inventory for third-party ad platforms insyead? They both have had tremendous success with their consumer-facing products which can be argued to be a prerequisite for their revenue growth. The platforms could have been able to monetize their service through open ad platforms, but the impression prices might not have been as high as they're now. Furthermore, building the infrastructure for collecting user information and optimizing the ads might have had positive side effects on improving the service based on data-driven insights.

However, being able to charge higher impression prices from the advertisers than these now well-established mega ad platforms can pay is becoming increasingly difficult due to their dominance. Thus, publishers should focus on where their sustainable competitive advantage comes from. If their uniqueness lies in simply producing high-quality content, they should probably concentrate on that. If their strength is in optimizing user experience in a data-driven way, they might have a chance at building an ad platform.

Even if a publisher decides to sell its ad inventory for third parties, the ruthless competition between the ad platforms ensures the publishers' impression prices increase as well. Technologies such as header-bidding help them to pick the ad platforms yielding them the most revenue.

5.1.2 For open ad platforms

Open ad platforms' primary source of competitiveness is typically the effectiveness of their ad serving. While this can be improved with better statistical modeling to some extent, what matters in the end, is the sheer amount of data. The more publisher sites they operate on, the more comprehensive profile they can build from each user, and the better they can optimize the ads. Consequently, scaling up as an ad platform improves simultaneously two of the five drivers of ad platform revenue (section 4.2): active user base and effectiveness of ad serving. This is a sign that the currently still relatively fragmented industry needs to consolidate to remain competitive.

Collecting data from users and measuring the results of advertising is becoming increasingly difficult for open ad platforms due to people using more devices, tracking-prevention software and tightening data regulation. Also, it's rather restricted to the online world. To stay competitive against closed ad platforms, they have to innovate on ways to collect data—potentially through partnerships or mergers with possessors of that data. The more detailed answers for how to do that in practice are out of the scope of this thesis, though.

5.1.3 For closed ad platforms

While it's vital for a closed ad platform to ensure its user-facing service stays competitive, maximizing net ad revenue can help providing some of the necessary capital to do that. This thesis provides them with a framework divided into five drivers (section 4.2) that helps them to understand which of their activities are contributing to generating incremental ad revenue and how those can be improved.

The three drivers identified in this thesis as the ones where the platforms can gain the most edge against their competitors are access to an active user base, the effectiveness of ad serving, and the comprehensiveness of measurement.

The smaller closed ad platforms with limited user penetration should concentrate on scaling up their user base as that, while linearly growing the platform's ad revenue, also increases their competitiveness against other similar services. This is true especially for ad platforms operating in industries with winner-take-all dynamics or the risk of being enveloped by another platform. That's also how Google and Facebook grew their businesses before their dominance.

For the mega ad platforms Google and Facebook to maintain their growth, product innovations are in a significant role. The giants are starting to reach the limits of expanding their user base due to the lack of potential new users. While more and more people have online access, the vast majority of new internet users are from the least developed countries (LDC) and developing countries, consequently being less profitable for them (International Telecommunications Union, n.d.).

The remaining growth avenues for the mega ad platforms are

1. increasing user exposure to the platform (more impressions per user) and
2. improving the efficiency of ad serving and measurement (more valuable impressions).

Serving more impressions per user can be achieved with products that provide more utility and are increasingly engaging, consequently occupying a larger share of the user's day. But that has its limits as well. In 2016, Facebook users globally already spent on average more than 50 minutes per day using the platform's applications (Constine, 2016).

In contrast, there are still many ways to increase the impression prices. The vast majority of online ads users see are irrelevant. By improving the efficiency of ad serving, platforms can reduce that waste. By enhancing tracking and attribution technology, ad platforms can prove the value of their ads and get new verticals adopt them, consequently increasing the demand and prices.

Both ad delivery optimization and measurement can be improved by ensuring all the necessary systems are in place for collecting user data—not just from the service itself but also from the advertisers. Besides, the platforms can build industry-specific ad products to collect structured business data from the advertisers and provide superior results. The closed platforms should have a strategy for tracking users across multiple devices and in the offline world.

There also remain significant opportunities to innovate in new creative formats. The way consumers shop and discover new products is actively shifting from physical locations to the digital storefront. For example, the efficiency of ad serving can be improved by enabling brands to use augmented and virtual reality to build engaging and emotionally appealing experiences to make it easier for users to visualize the benefits of the advertised product or service. And as an increasing share of people's social activities takes place digitally, social platforms such as Facebook are in an excellent position to leverage it to build more social ad experiences.

5.1.4 For advertisers

This thesis provides a simple model for advertisers to guide their budgeting decisions (section 4.1.1) and explains why in online advertising the focus should be on measuring and optimizing the results instead of concentrating too much on the reach or ad impressions served.

When setting their budgets, advertisers should consider the method outlined in section 4.1.1: finding the point where the marginal cost of conversions reaches the value of conversions—ideally measured as lifetime value. It's common for advertisers to measure average (instead of marginal) cost of results and they might not acknowledge that some of the results are much more expensive than the average.

Advertisers should be aware of the long-ranging effects their choice of attribution model can have. If the model in use doesn't reflect how the ads yield incremental conversions, it most likely leads to wrong budgets being allocated to the wrong advertising channels and showing wrong creatives to the wrong users. It can even lead to suboptimal organizational dynamics as the performance of individuals and teams is often assessed based on the attribution model. Ideally, advertisers should test incrementality with randomized controlled trials and adjust the attribution models based on the results.

Also, as online advertising provides superior measurement data on how people react to ads, advertisers should leverage that when developing their creatives: partly by utilizing various creative optimization tools the platforms offer and partly by incorporating a data feedback loop from their campaigns to their creative process.

Advertisers should also pay attention to the data the ad platforms collect and how they're using it. Sometimes—especially for larger companies—sacrificing campaign performance to prevent their data from being used to benefit the competition might be justified. It's often possible to refrain from sharing some parts of the data or even obfuscate it in a format that can't be used to benefit others.

Online advertising has become a significant source for user acquisition, especially for many online businesses. Some companies have been even built around online advertising with most of their sales originating from ads. This is a risky strategy for companies not investing in building their brand or owning the experiences that keep the users coming back—they have to win the user again for each new sale. This might not be profitable anymore as the competition for ad impressions increases and the more traditional industries with high customer lifetime values participate in it.

5.2 Further research

5.2.1 The effects of data privacy and regulation on online advertising

One interesting and relevant consideration is assessing the potential effects various regulatory changes can have on the industry. The current legislation applied to ad platforms mostly predates the era of online advertising and they have been allowed to operate with relatively few restrictions.

European Union's (EU) General Data Protection Regulation (GDPR) became enforceable on May 25th, 2018, and while it applies only to individuals within the EU, most globally operating companies have made changes to all their operations to be compliant with it. The regulation sets rules on the processing of personally identifiable information (PII), expands data subjects' rights and introduces substantial penalties for non-compliant companies (European Commission, n.d.).

As a result of GDPR, companies are allowed to collect only the appropriate user data specific to the service they're providing—and only with the user's consent. This can potentially hit publishers hard as it can prevent them from letting third-party ad platforms to collect data from the service's users. In particular, publishers are prohibited from collecting any personal data from first-time visitors who haven't registered and given their consent to data collection.

While many publishers and ad platforms have been lagging behind in making their services GDPR-compliant, the regulation can impact their business models. Publishers might have to shift from their current model heavily relying on third-party data to a more first-party focused model or contextual targeting instead of personal profiling. On the other hand, closed ad platforms such as Google and Facebook will remain relatively untouched as they're using first-party data to target ads on their premises. Especially search ads are mostly well off as the search queries are not regarded as personal data.

But the data privacy trend is not limited to GDPR and regulations. People are becoming more aware of their privacy, and this is reflected, e.g., in interest towards more closed services and efforts on circumventing various tracking technologies. While the public and the media have directed part of their dissatisfaction directly towards the ad platforms, the most viable solution would be through regulation.

The consequences of regulatory changes and predicting how they start to unfold are out of the scope of this thesis. However, understanding them would be extremely important for both businesses and legislators. It's clear that many publishers and ad platforms have to change their business models and lawmakers have to assess the impact on companies and users.

5.2.2 Measurement

Goldfarb (2013) identifies measurability as a major difference to offline advertising and explains its effect on online advertising literature at length. However, the paper doesn't recognize good measurability as a fundamental economic factor of online advertising in the same way as targeting. I think it is. Online advertising is more performance-focused: advertisers are buying measured results instead of impressions. And as shown in section 4.2, tracking and attribution play a significant role in an ad platform's net ad revenue.

Goldfarb (2013) notes that "the literature that measures online ad effectiveness is thriving". The examples he points out, however, are mostly studies showing that advertisers get results from their campaigns—which shouldn't be a surprise. There exist, however, little literature on *how* advertisers should measure the effectiveness of ads. As selecting the right attribution model has such an impact on how the advertising budgets are spent, more research should be done on how to define and refine it based on tests.

5.2.3 Branding

This thesis takes mostly a performance-based view to online advertising and puts a lot of weight on measuring the results relevant to the advertisers' business. While the effects of brand building activities are not as easily quantifiable, they can't be denied. Some of the challenges are the long conversion times, moderately low impact of each individual ad and the low number of user interactions—such as clicks—with the ads. Nevertheless, many online advertisers allocate budgets also for branding campaigns.

Those campaigns are typically measured and optimized based on proxy metrics such as clicks, video views or other engagement. Some of the more advanced measurement types, e.g., Facebook uses are questionnaires and measuring the time spent looking the ad to estimate the lift in ad recall.

More research should be done on the effects of such campaigns on brand awareness and determining what the right metrics advertisers should use to measure and optimize these campaigns are.

References

Alphabet. (2017). *Alphabet 2016: Form 10-K.* Retrieved from https://abc.xyz/investor/pdf/2016_google_annual_report.pdf

Bergemann, D., & Bonatti, A. (2011). Targeting in advertising markets: implications for offline versus online media. *The RAND Journal of Economics, 42*(3), 417-443.

Berman, R. (2015). *Beyond the last touch: Attribution in online advertising* (Working paper). Retrieved from http://ron-berman.com/papers/attribution.pdf

Casadesus-Masanell, R., & Zhu, F. (2013). Business model innovation and competitive imitation: The case of sponsor-based business models. *Strategic management journal, 34*(4), 464-482.

Constine, J. (2012, June 13). Facebook Exchange: A New Way for Advertisers to Target Specific Users with Real-Time Bid Ads. *TechCrunch*. Retrieved from https://techcrunch.com/2012/06/13/facebook-exchange/

Constine, J. (2016, April 28). Users average 50 minutes per day on Facebook, Messenger and Instagram. *TechCrunch*. Retrieved from https://techcrunch.com/2016/04/27/facediction/

Constine, J. (2017a, June 27). Facebook now has 2 billion monthly users… and responsibility. *TechCrunch*. Retrieved from https://techcrunch.com/2017/06/27/facebook-2-billion-users/

Constine, J. (2017b, August 2). Instagram Stories turns 1 as daily use surpasses Snapchat. *TechCrunch*. Retrieved from https://techcrunch.com/2017/08/02/instagram-stories-anniversary/

Edelman, B., & Ostrovsky, M. (2007). Strategic bidder behavior in sponsored search auctions. *Decision support systems, 43*(1), 192-198.

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of management review, 14*(4), 532-550.

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. *Academy of management journal, 50*(1), 25-32.

Eisenmann, T. R., Parker, G., & Van Alstyne, M. (2009). Opening platforms: how, when and why?. *Platforms, markets and innovation*, 131-162.

Empson, R. (2012, April 12). Google Biz Chief: Over 10M Websites Now Using Google Analytics. *TechCrunch*. Retrieved from https://techcrunch.com/2012/04/12/google-analytics-officially-at-10m/

European Commission. (n.d.). *Data Protection in the EU.* Retrieved from https://ec.europa.eu/info/law/law-topic/data-protection/data-protection-eu_en

Evans, D. S. (2009). The online advertising industry: Economics, evolution, and privacy. *The journal of economic perspectives, 23*(3), 37-60.

Facebook. (2006, August 22). Microsoft and Facebook Team Up for Advertising Syndication. *Facebook Newsroom*. Retrieved from https://newsroom.fb.com/news/2006/08/microsoft-and-facebook-team-up-for-advertising-syndication/

Facebook. (2007, November 6). Facebook Unveils Facebook Ads. *Facebook Newsroom*. Retrieved from https://newsroom.fb.com/news/2007/11/facebook-unveils-facebook-ads/

Facebook. (2014, April, 30). Introducing Facebook's Audience Network. *Facebook Business*. Retrieved from https://www.facebook.com/business/news/audience-network

Facebook. (2017). Facebook Annual Report 2016: Form 10-K. Retrieved from https://s21.q4cdn.com/399680738/files/doc_financials/annual_reports/FB_AR_2016_FINAL.pdf

Facebook. (n.d. -a). Company Info. *Facebook Newsroom*. Retrieved from https://newsroom.fb.com/company-info/

Facebook. (n.d. -b) Ads Buying and Optimization. *Facebook for Developers*. Retrieved from https://developers.facebook.com/docs/marketing-api/bidding-and-optimization

Gabbert, E. (2017, December 18). The 25 Most Expensive Keywords in AdWords – 2017 Edition!. *WordStream Blog*. Retrieved from https://www.wordstream.com/blog/ws/2017/06/27/most-expensive-keywords

Google. (2000, October 28). Google Launches Self-Service Advertising Program. *News from Google*. Retrieved from http://googlepress.blogspot.com/2000/10/google-launches-self-service.html

Google. (2003, June 18). Google Expands Advertising Monetization Program for Websites. *News from Google*. Retrieved from https://googlepress.blogspot.com/2003/06/google-expands-advertising-monetization.html

Google. (2007, April 13). Google to Acquire DoubleClick. *News from Google*. Retrieved from http://googlepress.blogspot.com/2007/04/google-to-acquire-doubleclick_13.html

Google. (2016, July). How Mobile Has Redefined the Consumer Decision Journey for Shoppers. *Think with Google*. Retrieved from https://www.thinkwithgoogle.com/marketing-resources/micro-moments/mobile-shoppers-consumer-decision-journey/

Google. (n.d.). *From the garage to the Googleplex*. Retrieved from https://www.google.com/about/our-story/

Ha, A. (2016, May 25). Facebook will shut down FBX, its desktop ad exchange. *TechCrunch*. Retrieved from https://techcrunch.com/2016/05/25/facebook-will-shut-down-fbx/

Hagiu, A., & Wright, J. (2015). Multi-sided platforms. *International Journal of Industrial Organization, 43*, 162-174.

Hu, Y., Shin, J., & Tang, Z. (2013). Performance-based pricing models in online advertising: Cost per click versus cost per action. *Georgia Institute*.

Hu, Y., Shin, J., & Tang, Z. (2016). Incentive Problems in Performance-Based Online Advertising Pricing: Cost per Click vs. Cost per Action. *Management Science. 62*(7): 2022–2038.

Interactive Advertising Bureau. (2015, July). *IAB Programmatic Revenue Report 2014 Results*. Retrieved from http://www.iab.net/media/file/PwC_IAB_Programmatic_Study.pdf

Interactive Advertising Bureau. (2017a, April). *IAB Internet Advertising Revenue Report: 2016 Full Year Results*. Retrieved from https://www.iab.com/wp-content/uploads/2016/04/IAB_Internet_Advertising_Revenue_Report_FY_2016.pdf

Interactive Advertising Bureau. (2017b, July). *IAB New Standard Ad Unit Portfolio*. Retrieved from https://www.iab.com/wp-content/uploads/2017/08/IABNewAdPortfolio_FINAL_2017.pdf

International Telecommunications Union. (n.d.). *Global ICT Developments*. Retrieved from https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx

Jansen, B. J., & Mullen, T. (2008). Sponsored search: an overview of the concept, history, and technology. *International Journal of Electronic Business, 6*(2), 114-131.

Laffey, D. (2007). Paid search: The innovation that changed the Web. *Business Horizons, 50*(3), 211-218.

Lewis, R. A., Rao, J. M., & Reiley, D. H. (2011, March). Here, there, and everywhere: correlated online behaviors can lead to overestimates of the effects of advertising. In *Proceedings of the 20th international conference on World wide web* (pp. 157-166). ACM.

Lewis, R. A., & Rao, J. M. (2013). On the near impossibility of measuring the returns to advertising. Unpublished paper, *Google, Inc. and Microsoft Research*. Retrieved from http://justinmrao. com/lewis_rao_nearimpossibility. pdf.

Liu, C. (2016). *Worldwide Ad Spending: eMarketer's Updated Estimates and Forecast for 2015–2020*. Retrieved from http://www.strathcom.com/wp-content/uploads/2016/11/eMarketer_Worldwide_Ad_Spending-eMarketers_Updated_Estimates_and_Forecast_for_20152020.pdf

Matney, L. (2017, May 17). Google has 2 billion users on Android, 500M on Google Photos. *TechCrunch*. Retrieved from https://techcrunch.com/2017/05/17/google-has-2-billion-users-on-android-500m-on-google-photos/

McKinsey & Company. (2016, December) *Global Media Report 2016*. Retrieved from https://www.mckinsey.com/industries/media-and-entertainment/our-insights/global-media-report-2016

Metz, C. (2015, September 21). Facebook Doesn't Make as Much Money as It Could—On Purpose. *Wired*. Retrieved from https://www.wired.com/2015/09/facebook-doesnt-make-much-money-couldon-purpose/

Mohan, N. (2015, August 6). Focusing investments to improve buying on YouTube. DoubleClick Advertiser Blog. Retrieved from https://doubleclick-advertisers.googleblog.com/2015/08/focusing-investments-to-improve-youtube-buying.html

Nanigans. (2013 – 2018). *Facebook Advertising Trends Reports Q4 2013 – Q1 2018*. Retrieved from http://www.nanigans.com/marketing-resources/reports/

Peterson, T. (2016, June 17). How Facebook turned an end-to-end ad tech strategy on its head. *Marketing Land*. Retrieved from https://marketingland.com/facebook-turned-end-end-ad-tech-strategy-head-181395

Rothkopf, M. H., Teisberg, T. J., & Kahn, E. P. (1990). Why are Vickrey auctions rare?. *Journal of Political Economy, 98*(1), 94-109.

Saloner, G. (1991). Modeling, game theory, and strategic management. *Strategic management journal*, *12*(S2), 119-136.

Samuelson, W. F. & Marks, S. G. (2012). *Managerial Economics* (7th ed.). Wiley.

Sayedi, A., Jerath, K., & Srinivasan, K. (2014). Competitive poaching in sponsored search advertising and its strategic impact on traditional advertising. *Marketing Science, 33*(4), 586-608.

Schonfeld, E. (2010, February 5). Facebook Takes Over Its Own Display Advertising From Microsoft, Keeps Bing For Web Search. *TechCrunch*. Retrieved from https://techcrunch.com/2010/02/05/facebook-display-advertising-microsoft-bing/

Singel, R. (2010, October 27). Oct. 27, 1994: Web Gives Birth to Banner Ads. *Wired*. Retrieved from https://www.wired.com/2010/10/1027hotwired-banner-ads/

Szymanski, B. K., & Lee, J. S. (2006, June). Impact of ROI on Bidding and Revenue in Sponsored Search Advertisement Auctions. In *Second Workshop on Sponsored Search Auctions*.

Yin, R. K. (2009). *Case Study Research, Design & Methods* (4th ed.). Sage publications.

Appendices

Appendix 1: List of interviews with advertisers

Advertiser	Titles	Duration	Author present	Recording
E-commerce 1	Marketing Manager	30 min	Yes	No
E-commerce 2	Director / Head of Department, Marketing Technology Manager	30 min	Yes	No
E-commerce 2	Director / Head of Department	45 min	Yes	No
E-commerce 3	Director / Head of Department	30 min	Yes	No
E-commerce 3	Director / Head of Department, Marketing Technology Manager, Marketing Team Lead	60 min	Yes	Yes
E-commerce 4	Director / Head of Department	45 min	Yes	Yes
E-commerce 5	2x Director / Head of Department, Marketing Team Lead, Marketing Manager	60 min	Yes	Yes
E-commerce 6	Marketing Manager	30 min	Yes	No
E-commerce 7	2x Director / Head of Department	45 min	Yes	Yes
E-commerce 8	Director / Head of Department	30 min	Yes	Yes
E-commerce 9	2x Director / Head of Department	30 min	No	No
E-commerce 10	Director / Head of Department	60 min	Yes	No
E-commerce 11	3x Marketing Manager	45 min	No	No
E-commerce 12	2x Marketing Manager	60 min	Yes	Yes
E-commerce 12	Director / Head of Department	60 min	Yes	Yes

Financial services 1	Marketing Team Lead, Marketing Manager	45 min	Yes	Yes
Financial services 1	Marketing Team Lead, Marketing Manager	45 min	Yes	No
Gaming 1	Director / Head of Department	30 min	No	No
Gaming 1	Director / Head of Department	30 min	Yes	No
Gaming 2	Director / Head of Department	45 min	Yes	Yes
Group / Venture capital 1	Marketing Manager	60 min	Yes	Yes
Group / Venture capital 2	2x Executive, Director / Head of Department, Marketing Technology Manager	60 min	Yes	No
Group / Venture capital 3	Director / Head of Department, Marketing Manager	30 min	Yes	Yes
Marketing agency 1	3x Marketing Manager	45 min	Yes	No
Marketing agency 2	2x Director / Head of Department	30 min	Yes	Yes
Marketing agency 3	Director / Head of Department	30 min	Yes	No
Marketing agency 3	Director / Head of Department	30 min	Yes	No
Marketing agency 4	Marketing Manager	30 min	Yes	No
Marketing agency 5	2x Marketing Manager	30 min	Yes	No
Real estate 1	Marketing Technology Manager	30 min	Yes	Yes
Real estate 1	Marketing Manager	30 min	Yes	No
Real estate 2	Marketing Team Lead	45 min	Yes	No
Transportation 1	Marketing Technology Manager	30 min	Yes	Yes
Travel 1	Marketing Team Lead, 2x Marketing Manager	45 min	Yes	No

Travel 2	Marketing Technology Manager	60 min	No	No
Travel 2	Marketing Technology Manager, Marketing Manager	60 min	Yes	No
Travel 3	Marketing Manager	60 min	Yes	Yes
Travel 4	Director / Head of Department	45 min	Yes	Yes
Travel 5	Marketing Team Lead, Marketing Manager	30 min	Yes	Yes
Travel 6	Director / Head of Department, Marketing Team Lead	45 min	Yes	No
Travel 7	Director / Head of Department, Marketing Manager	30 min	No	No

Appendix 2: List of other interviews

Company	Titles	Duration	Author present	Recording
Ad platform 1	Director / Head of department	60 min	Yes	Yes
Ad platform 1	Senior Consultant	30 min	Yes	Yes
Ad platform 1	Director / Head of department	30 min	No	No
Ad platform 1	Director / Head of department	60 min	Yes	No
Technology partner 1	Account Manager	30 min	No	No
Technology partner 2	Senior Consultant	45 min	Yes	No