Performance of Online Advertising: Search, Display and Social Media Ads

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Dissertation submitted in partial fulfillment of requirements for the degree of International Master in Management at Universidade Católica Portuguesa

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June 2016

ABSTRACT

Title of the dissertation: **“**Performance of Online Advertising: Search, Display and Social Media Ads”

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Digital advertising is becoming increasingly relevant. In particular, managers are gradually allocating the online budget to mobile and social media advertising. For that reason, it becomes essential to understand the performance of different ad types and the dynamics within each format and platform.

The present study aims to compare different ad types – search, display and social media – whilst assessing the impact of different devices – mobile devices and computers – on online campaign performance. Moreover, it seeks to understand the factors that explain the performance within each ad type. This dissertation focuses on a B2B company that advertises an invoicing software using Google and Facebook. To this end, the study is based on descriptive quantitative research, analyzing secondary data from sixteen campaigns.

The results show that search ads perform better on average than social media and display ads. However, the device of impression has also a significant impact on campaign performance. In fact, ads displayed on mobile devices yield more clicks and ads displayed on computer desktops generate more conversions. On Facebook, users often clicked on an ad in a mobile device and switched to a computer to convert. Besides, the targeting strategy adopted in display and social media ads has a significant influence on performance. On social media, ads retargeted to visitors of the company’s website originated significantly more conversions.

In conclusion, these findings are relevant for managers in allocating the online budget across ad types and in optimizing the ads for different devices and target audiences.

Keywords: Online Advertising, Search, Display, SNS, Social Media, Google, Facebook, Targeting.

SUMÁRIO

A publicidade digital tem um peso crescente na despesa em publicidade. Em particular, as empresas estão a alocar o orçamento digital a publicidade móvel e nas redes sociais. É essencial compreender o desempenho de diferentes tipos de anúncios e a dinâmica dentro de cada tipo de formato e de plataforma.

O presente estudo compara diferentes tipos de anúncios – anúncios de pesquisa, de *display* e de redes sociais – analisando o impacto dos dispositivos de exibição – dispositivos móveis e computadores – no desempenho de campanhas. Além disso, pretende identificar os factores explicativos do desempenho de cada tipo de anúncio. A dissertação foca-se numa empresa comercial que anuncia um software de facturação através do Google e do Facebook. Numa óptica de pesquisa quantitativa descritiva, este estudo analisa dados secundários de dezasseis campanhas.

Os resultados mostram que os anúncios de pesquisa têm em média um melhor desempenho. Contudo, o dispositivo de impressão tem uma influência significativa no mesmo. Os anúncios exibidos em dispositivos móveis geraram mais cliques e os anúncios exibidos em computadores mais conversões. No Facebook, alguns utilizadores clicaram no anúncio através de um dispositivo móvel e subscreveram ao software num computador. Adicionalmente, a estratégia de segmentação adoptada nos anúncios *display* e nas redes sociais influenciou o seu desempenho. No Facebook, os anúncios redireccionados aos visitantes do site da empresa originaram significativamente mais conversões.

Concluindo, estes resultados são relevantes na alocação do orçamento digital a vários tipos de anúncios e na optimização dos anúncios para diferentes dispositivos e tipos de público alvo.

Palavras-chave: Publicidade Digital, Pesquisa, *Display*, Redes Sociais, Google, Facebook, Segmentação.

ACKNOWLEDGEMENTS

I would like to express my gratitude to my thesis advisor, Professor Ana Isabel Costa, who was extremely helpful in all stages of the process. From the discussion of potential topics and statistical approaches to the thorough revisions and valuable feedback, her help was essential during the past four months.

Moreover, I would like to thank my mentor and former manager at Live Content, Sérgio Gonçalves, who helped me understand the dynamics of social media and contributed with important insights to my thesis. Besides, my internship at Live Content allowed me to access the data that is object of analysis in this study and that originated constructive results.

Finally, I want to show appreciation for my father, with whom I often discussed the practicality of my dissertation and who helped me define a relevant topic of analysis. In addition, his constant availability to debate on my work was a crucial input to this study.

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GLOSSARY

B2B – Business to business (B2B) companies focus on selling to other businesses, either to incorporate in other products or for final use.

B2C – Business to consumer (B2C) companies focus on selling to individuals as final consumers and market their products for personal use.

CPA – Cost per action (CPA) is the ratio between total cost and number of actions (subscription, purchase, etc.). As a pricing model, the advertiser pays to the publisher the CPA for the total number of actions.

CPC – Cost per click (CPC) is the ratio between total cost and number of clicks. As a pricing model, the advertiser pays to the publisher the CPC for the total number of clicks.

CPM – Cost per mille (CPM) or cost per thousand is the cost per thousand views/impressions. As a pricing model, the advertiser pays to the publisher the CPM for the total number of thousand impressions.

CR – Conversion rate (CR) is a performance metric that measures the number of clicks that resulted on conversions. It is given by the ratio between the number of conversions and clicks.

CTR – Click-through rate (CTR) is performance metric that measures the number of impressions that resulted on clicks. It is given by the ratio between the number of clicks and impressions.

SERP – Search Engine Results Page is the search engine's webpage that presents the results for a specific group of keywords.

SNA – Social Networking Advertising is the advertising on Social Networking Sites.

SNS – Social Networking Sites (SNS) are platforms to build social networks, often referred as social media. Examples of SNS are Facebook, Twitter and LinkedIn.

CHAPTER 1: INTRODUCTION

This chapter presents the topic and aim of the dissertation. It starts by analyzing the background of online advertising and the problem statement that led to the aim of the dissertation, presented afterwards together with the relevant research questions. Next, the research methods applied and the academic and managerial relevance of the topic are described, ending with the outline of the dissertation.

1.1. Background and problem statement

Online advertising is gaining relevance in the marketing budget of firms worldwide. It is estimated that, by the end of 2016, the amount allocated to digital advertising reaches $163 billion. This will represent 25% of the total expenditure on advertising (Kireyev, Pauwels and Gupta 2014). Another relevant trend is mobile advertising, which is expected to increase to $50.84 billion and come to represent 24.9% of the total media ad spending in the US market by 2017 (eMarketer, 2015). Online advertising also brought new targeting options to companies, such as remarketing, i.e., the ability to target customers who have been on the advertiser's website but did not complete a purchase on external websites (Lambrecht and Tucker, 2013).

Given the growing importance of online ad channels, managers are focusing on better understanding and using related metrics, such as cost-per-acquisition (CPA) and ad click-through rate (CTR), among others (Kireyev et al. 2014). However, unlike in traditional approaches, these metrics are highly dynamic and interconnected (Peters, Chen, Kaplan, Ognibeni and Pauwels 2013). Hence, the dynamic effects observed between different types of online advertising, such as paid search and display ads, have recently become subjects of study by academics (Xu, Duand and Whinston 2014; Lewis and Nguyen 2012). Kireyev, Pauwels and Gupta (2014), for instance, studied the impact of display ads on search behavior. Their results showed that display ads actually increased search conversion rates and boost search clicks and impressions, and that such cross-effects could actually be more important than the direct effects of this type of online ads. Therefore, other academic studies have suggested that combining different advertising formats may increase the conversion rates of online ad campaigns. Yet, the different digital ads a prospect consumer faces before becoming an actual buyer are often not taken into account when evaluating the performance of a campaign, since it is hard to trace the customer journey during the purchase funnel. Campaign

performance is thus typically based on last-click attribution models, that is, it assumes that sales conversions are essentially due to the one ad the consumers click on last and that leads them to make an actual sale on the advertisers' e-commerce website (Li and Kannan 2014).
Advertising in Social Network Sites (SNS) differs from online advertising in general (Zhang & Mao, 2016), as it has a specific ecosystem of users (Safko & Brake, 2009). However, there is still lack of research on the effectiveness of advertising on social media (Zhang & Mao, 2016). Michaelidou, Siamagka and Christodoulides (2011) assessed the use of SNS by a mail survey delivered to 1000 business-to-business (B2B) small and medium enterprises (SMEs) in the UK. The study showed that although almost half of the sample intended to increase their marketing spending on SNS, the majority did not adopt any metrics to assess SNS effectiveness (Michaelidou, Siamagka & Christodoulides, 2011).
It is important to notice that most academic studies regarding online advertising focus on the B2C market and the industries therein. There is still lack of research on how, for instance, companies make use Social Networking Sites (SNS), especially those operating in B2B markets (Michaelidou, Siamagka and Christodoulides, 2011). Mullarkey (2012) divided the current SNS literature based on the nature of the users, after reviewing 160 academic articles. According to his study, literature could be divided into two macro categories: SNS with Individuals as Users (IAU) and SNS with Organizations as Users (OAU). The author also divided the first category between users who act in a personal capacity and users who have a professional behavior - on SNS such as LinkedIn - (Mullarkey, 2012). According to Mullarkey (2012), a large number of studies discuss the use of B2C companies of SNS for the purpose of advertising and selling.
In line with this, there is still no clear measurement of performance of different ad formats, like display ads, paid search ads and social media ads. Moreover, there is still a great lack of research on the effect of device on online advertising performance.

1.2. Aims and scope

This dissertation aims to evaluate and compare the performance of different online ad types. The moderating effects of different targeting strategies and digital devices on ad performance will also be explored. In order to achieve the stated aims, the following research questions are addressed:
RQ1 – What is the relative performance of different ad types in online advertising?

RQ2 – What is the relative performance of different digital devices of impression in online advertising?
RQ3 – What factors influence the performance of display and social media ads?

This dissertation focuses on measuring the performance of different formats of digital advertising, specifically display ads (Google Display and Facebook ads) and paid search ads (Google Adwords). It focuses on the campaigns ran by a Portuguese digital agency, Live Content, for one of its clients operating in a B2B market, namely selling different types of management software (HR and CRM systems, invoicing software, among others) to other companies. It is important to note that, the product that is being advertised (an invoicing software) is targeted mainly to startups. Hence, the product is being advertised to individuals who represent their own startups and are able to take decisions on invoicing software adoption. In addition, given that these campaigns were ran both in mobile and desktop devices, it is also possible to investigate whether there are significant differences of type of digital device in ad performance.

Finally, this dissertation intends to detect if there are significant differences in performance for using different targeting options for each ad format, such as retargeting, contextual and placement targeting and targeting by interests, topics, industry, demographics and look-a-like users on Facebook.

The information used is limited to the metrics provided by the advertising platforms of Google and Facebook. The study focuses on sixteen campaigns for invoicing software targeted to startups, seven of which involved paid search ads and nine display ads. Most campaigns had overlaps and the general time scope considering all campaigns is from the 7th of September 2015 to the 2nd of February 2016.

Therefore, other advertising formats are not included in this study, neither advertising in other platforms besides Google and Facebook. Moreover, online campaigns outside Portugal and outside the defined time scope were not considered. Finally, campaigns for tangible products, for other industries are not object of analysis of this dissertation.

1.3. Research methods

Quantitative, secondary data about the features and performance of several ad campaigns, conducted for the above-mentioned B2B client advertiser by Live Content was compiled and statistically analyzed. All the campaigns were promoting the same product and offered a 50%

discount, which could be redeemed by subscribing the invoicing service for a 30-day free trial period.

The research approach of the dissertation is categorized as a descriptive quantitative research and all quantitative information was extracted from Google Adwords and Facebook Business Manager platforms. The dataset compiled the metrics for all sixteen campaigns, which in total comprised 729 groups of ads. The statistical analyses, ran on SPSS and STATA, included descriptive and inference statistics and multiple regression analysis using the Negative Binomial model. The dependent variables correspond to the performance metrics of ad campaigns, namely *clicks* and *conversions*.

1.4. Relevance

From an academic perspective, this dissertation contributes to the existing body of research about the performance of different types of online ads by including the influence of different devices. Of further value is the fact that it also investigates the potential moderating effects of ad targeting strategy on ad performance. Besides, there is still no existing theory developed specifically for understanding the effectiveness of advertising on social media (Zhang & Mao, 2016). Hence, this dissertation contributes with relevant insights on advertising performance in social media.

From a managerial perspective, this research should help marketers to understand better what are the key drivers of online ad performance and the potential effects of different formats, digital media devices and targeting strategies. Ultimately, this dissertation intends to help marketers to make more informed decisions when allocating the marketing budget in online advertising and to optimize ads to specific devices and target audiences.

1.5. Dissertation Outline

Chapter 2 presents a literature review about online advertising and the performance of different ad formats, along with the main conclusions and the research hypotheses. Chapter 3 describes thoroughly the research methods used, the data collected and the statistical analyses performed to test the hypotheses about the effectiveness of display, paid search and social media ads. Chapter 4 presents and discusses the main results obtained from data analysis. Lastly, Chapter 5 presents the main conclusions and implications of this dissertation, as well as the limitations and recommendations for future research addressing the effectiveness of online advertising campaigns.

CHAPTER 2: LITERATURE REVIEW AND CONCEPTUAL FRAMEWORK

2.1. Online Advertising

The Internet enables the extension of the traditional functions of offline advertising. For instance, it allows consumers to, through an ad format such as a banner, be immediately directed to an e-commerce website and complete a purchase online in a seamless manner (Li and Leckenby, 2004). Digital advertising spending worldwide in 2015 reached already 170.5 billion US dollars. This figure is estimated to increase nearly 48% until 2018. Moreover, global social network advertising was estimated to reach $25.14 billion in 2015, with Facebook driving its growth and capturing almost 65% of SNS ad revenues (*eMarketer*, 2016).

2.1.1. Online advertising industry in Portugal

In Portugal, the marketing agency service sector has changed considerably in the last 10 years, with the emergence of multiple digital agencies competing against the bigger traditional agencies that provide both offline and online services (Personal Communication, 2016). Most of these digital agencies have a clear focus, like lead generation or Search Engine Marketing (SEM). Live Content was founded in 2009 and focuses on social media marketing, having clients in both B2C and B2B industries. Generally speaking, client advertisers open a call for tenders by several marketing agencies, for a particular campaign. Each agency then develops an online strategy based on the briefing provided by the client. It is common for client advertisers in Portugal to work with more than one agency at the time, for the performance of online ad campaigns with different aims and scopes (e.g. paid search, lead generation, social media content and community management, website development, etc.) (Personal Communication, 2016).

2.1.2. Advertising Formats

The Internet brought along new channels and advertising formats such as search and display ads (Lewis and Nguyen, 2012). One of the most used terms in digital marketing is SEM, which entails the different means of marketing a website and comprises both organic, search engine optimization (SEO) and paid search strategies (Sen, 2005). SEO is based on optimizing website codes – such as title tags or links on the site – to make them more relevant and more search-engine compatible, resulting on higher positions in the search-results pages of search engines like Google (Sen, 2005). Paid search or paid placements differ from SEO since advertisers pay directly to the search engine for placement in the specific sponsored section of the search engine.

Buyers generally trust more the results in the editorial section rather than the sponsored section (Sen, 2005). Since this section has limited spots, search engines sell them through an auction, where advertisers make a bid to be placed on the 'recommended' list for a keyword search (Chen and He, 2011). Broadly speaking, paid search auctions are PPC (pay-per-click) continuous second-price auctions (Kitts and Leblanc, 2004). Each advertiser enters a bid, which represents the maximum amount they are willing to pay for a click in their advertisement. Then the auctioneer, such as Google, ranks the participants but these positions are re-calculated during the day and the advertisers may change their bids for that keyword. Finally, the auctioneer determines the price that each bidder will pay per click, which is usually the bid of the competitor immediately below – hence being a second-price auction (Kitts and Leblanc, 2004).

Display ads are graphical, sometimes interactive, advertisements displayed on regular web pages (Papadimitriou et al. 2011). According to eMarketer (2016), US spending on display ads will outweigh the spending in paid search ads in 2016 for the first time, being estimated to reach $32.16 billion (against $29.24 billion for paid search). Within display ads, the biggest player is Facebook, accounting for 25.2% of the total US digital display ad revenues in 2015, followed by Google with a 13% of revenue share (eMarketer, 2015). In fact, social media display ads are growing due to mobile advertising and according to eMarketer (2015), Facebook's US mobile ad revenues will grow more than 50% from 2014 to 2017.

The effect of display ads on search has been amply studied by academics. Lewis and Nguyen (2012), for instance, concluded that display ads increase search for the advertised brand by 30% to 45%. However, they also increase search for competitors' brands by 23% (Lewis & Nguyen, 2012). Although the online click rates are low in general, display ads were found to effectively lift retail sales both online and offline (Fulgoni & Lipsman, 2014). If search ads and display ads are used separately and exclusively, the former has a bigger impact on consumer behavior than the latter. This impact is superior both in online behavior and offline sales. However, the reach of display ads is generally higher than that of search ads (Fulgoni and Mörn, 2009). Moreover, there are clear synergies between the two formats in terms of performance, both in buying penetration and dollar sales per thousand customers exposed. In fact, when the two formats are combined, the overall performance is better than using two formats separately at different points in time (Fulgoni and Mörn, 2009).

2.1.3. Advertising Platforms

Within the paid search advertising market, **Google Adwords** is by far the ad platform most used by advertisers. It had a market share of nearly 76% in the second quarter of 2015, against 24% of its biggest competitor, Yahoo!'s Bing (*Search Engine Land*, 2015). When using Google Adwords, it is key to understand its ad bidding system, i.e., the system adopted by Google to rank ads to appear in its sponsored section of the SERP. The three main elements of a paid search campaign are the keywords, the ads and the landing page – a web page that serves as an entry point to a website or a particular section of the website. The ranking system that Google uses – Ad Rank – to select the ads that are displayed in the sponsored section of the SERP is based on the bid (money the advertiser is willing to pay for a click), the quality of the ad (relevance to the search query) and the landing page (how connected it is to the keywords selected), in order to provide a good user experience for the user (Google Adwords, 2014).

Regarding display advertising, advertisers can use the **Google Display Network** – group of websites, videos and apps – to display their ads. This network is created through Google AdSense, a Google product that allows web publishers to earn money by having ads on their websites (Google Support, 2014). When using the Google Display Network, advertisers can choose how the websites will be selected to display their ad. In one hand, it can be by relevant keywords or topics. On the other hand, they can select specific websites or even audiences (Google Support, 2014). All this can be managed using Google Adwords, the same platform where advertisers manage paid placements. One of the biggest advantages of AdSense is that it is contextual, i.e., it presents the ads within websites with the same context, providing a higher chance of users to click on them (Karch, 2016).

Facebook is the biggest SNS in the world, with 1.65 billion daily active users at the first quarter of 2016 (Statista, 2016). SNS ad revenues are growing worldwide, but Facebook dominates fiercely this industry. It had $16.29 billion in ad revenues worldwide in 2015 and is estimated to grow to $26.98 by 2017. Twitter ranks second in ad revenues with $2.03 billion in ad revenues worldwide in 2015 (*eMarketer*, 2016). Facebook Ads presents different options based on the main campaign objectives intended (e.g. page likes, click to website, website conversions, app installs, app engagement, event responses, etc.), the selected audience and the budget allocated. Ads can be presented as Link Ads, Carousel Ads or Page Post Engagement (boosting posts) (Facebook for Business, 2016). When, for instance, the main objective is conversions on the website (e.g. a registration, a sale, a lead, etc), the advertiser adds a conversion pixel (a code) to the HTML of the webpage it wants to track (Facebook for Business, 2016).

On Facebook, advertisers can select where they want their ads to be displayed, either on the newsfeed (both for mobile and desktop), on the right column, on third-party apps through audience network (network of mobile apps or mobile websites that have been approved by Facebook to show ads) or on Instagram, as it is represented on Figure 1 (Facebook for Business, 2016).

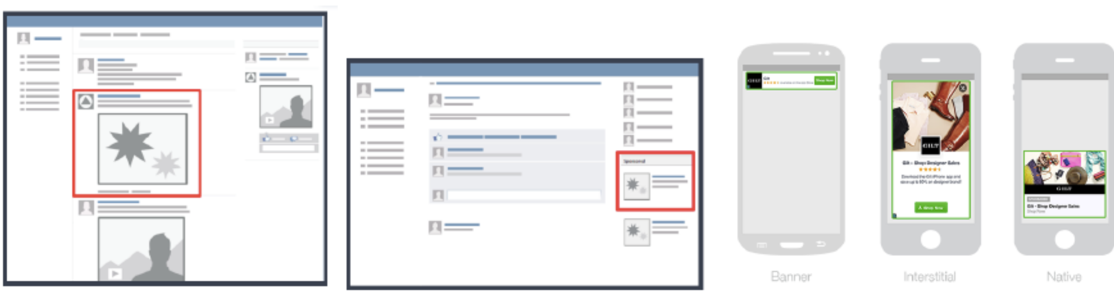

Figure 1 – Facebook ad placement: Desktop newsfeed, desktop right column and audience network (banner, interstitial and native).

One of the most recent functionalities of Facebook Ads is Canvas, a tool that enhances mobile ad experience. After clicking on an ad, users are directed to a full-screen interactive ad, which can include videos, text, still images and call-to-action buttons (Facebook for Business, 2016).

2.1.4. Targeting Strategies

Advertisers often tailor their ads to specific audiences and adopt targeting strategies in display advertising. Google provides several targeting tools for the ads displayed on its Google Display Network, presented in Table 1.

Table 1 – Targeting options at Google Display Network (Google, 2016).

Google Display - Targeting options	
Remarketing	Targets users who already visited the advertiser's website before.
Keyword Contextual targeting	Show ads on websites related to the specified keywords. Reaches users when they are reading about the advertiser's products, usually this type of targeting option is made at the keyword level.
Placement targeting	Show ads on websites specified by the advertiser.
Interest category targeting	Show ads based on user interests (e.g. sports or travel).
Topics category targeting	Similar to the interest category targeting, but in topics (e.g. fitness, entertainment).
Geographic and Language targeting	Show ads where the advertiser's customers are located: display ads by language and region.
Demographics targeting	Show ads based on age and gender. It can be combined with other targeting option.

Facebook also offers several targeting tools, based on location, demographics, interests and behaviours (*Facebook for Business*, 2016). One of the most used tools are Custom Audiences, a tool which allows advertisers to target their Facebook Ads to their current customers based on email and phone number provided in the user profile. The first step is to have a customer database in a CSV file – either with phone numbers or emails. Then, the CSV file can be uploaded to Facebook Power Editor, which is a Google Chrome plug in to manage Facebook Ads. Finally, Facebook will find the customers on Facebook and the ad will appear on their feed (Loomer, 2012). Moreover, Facebook included the possibility for advertisers to broaden their target audience with the Lookalike Audiences, i.e., audiences composed by users that are similar to the advertiser's established customers – with a minimum of 100 customers (*Facebook Developers*, 2016). Facebook creates Lookalike Audiences by finding a new segment based on similarity within the Custom Audiences. In that sense, advertisers are able to communicate not only to their established customers, but also to Facebook users that have similar interests. This is especially valuable to those advertisers that have limited customer bases (Loomer, 2014).

2.1.5. Pricing strategies

Pricing models in digital advertising have evolved over time. One of the most used pricing models in the early days of digital advertising is the cost-per-mille (**CPM**), which represents the cost per a thousand impressions. This model is similar to the one used in traditional media (print, outdoor and television) advertising (Hu, Shin and Tang, 2015). However, because this strategy incentivizes impressions and not clicks or conversions, performance-based pricing models started to gain relevance over a decade ago. The first performance-based pricing model to appear was the cost-per-click (**CPC**). This was adopted by Google and Yahoo in 2002 and was the most extensively used pricing model in paid search advertising for a long time (The Economist, 2006). It was subsequently defied by another performance-based pricing model – the cost-per-action (**CPA**), where the advertiser pays for a pre-specified action that could be a purchase, a lead, an email sign-up or a download (Hu, Shin and Tang, 2015).

There is some debate about which pricing strategy is more suited. On one side, many publishers claim that they prefer the CPM model because of the lack of control on some ad performance factors, such as design or attractiveness of the offer. On the other side, advertisers prefer a performance-based pricing, claiming that it does not make sense to pay for ads that do not generate value (Hu, 2004). Nonetheless, performance-based pricing models are gaining relevance. Based on a survey developed by PwC and IAB (Interactive Advertising Bureau) in the US market, approximately 65% of 2015 ad revenues were priced on a performance basis, against the 33% and 2% that were priced on a CPM and hybrid basis, respectively (IAB, 2016).

A potential explanation is that online publishers can improve the effectiveness of ad campaigns by making non-contractible efforts. Since these efforts are costly to publishers, they need the right incentives to do so (Hu, 2004). CPA models are usually more favorable for the advertisers, as they shift the risk to ad design and placement. In fact, the clicks on the ad that do not convert into sales do not represent a cost for advertisers. However, this type of model may lead to adverse selection problems, as the best advertiser also has higher costs and lower margins than in the CPC model (Hu, Shin and Tang, 2015). Besides, online publishers argue that the CPA model gives advertisers fewer incentives to convert clicks into purchases, causing a moral hazard problem. For instance, if advertisers' main goal is brand awareness, they can take advantage of such pricing model as they can display their ads without paying for the views or clicks (Hu, Shin and Tang, 2015).

2.1.6. Metrics

Online advertising entails several types of metrics to measure its effectiveness. One of the most common metrics is the Click-Through Rate (CTR) – the percentage of users who clicked on the ad from the total amount of users who saw the ad - since it reflects best the attractiveness of the ad and the offer. Nevertheless, advertisers are typically focused on ad conversions, i.e., the likelihood of a user to make a purchase, register or subscribe a service in its website after clicking on an online ad. This likelihood can be estimated from the measurement of conversion rates, the percentage of ad clicks that generate a purchase amongst all ad clicks (Xu, Duan and Whinston, 2014).

The return on advertising investment (ad ROI) is the ultimate metric to measure the performance of an advertising campaign. Different definitions and formulae of calculation are available for ad ROI. The most generic formula is the ratio between profit (sales revenue minus ad costs) and total ad cost. For a paid search campaign supported by a CPC pricing model, the ad ROI is thus influenced by ad design and placement costs, clicks, conversions and revenues, in case the relevant unit of action is a sale conversion (Karwal, 2014).

In order to perform well in paid search campaigns using a CPC pricing model, there are several key success factors. First, it is essential to get a high click-through-rate (CTR). Second, it is important to reduce the CPC, by improving the Google quality score of the ad. As explained before, the quality score influences the ad ranking and the amount paid per click, reducing wasted spend (paid clicks that do not convert to sales) (Karwal, 2014). Nonetheless, the pricing model adopted will influence the ROI, as the risk shifts between advertiser and publisher, as explained previously.

ROI in social media differs from the typical online advertising ROI, as it requires more qualitative measurements rather than qualitative and there is still controversy around its measurement (Fisher, 2009). The challenge arises by the need of not only measuring the effectiveness of online advertising within social media, but also the framework surrounding it. There is still an ongoing search to define the ROI in social media, since it moves beyond web analytics (Fisher, 2009).

2.1.7. Social Network Advertising

According to eMarketer (2016), total ad spending worldwide in SNS is expected to reach $41 billion by 2017, an estimated growth rate of more than 129%, compared to the $17.85 billion spent in 2014. Social media advertising differs from online advertising in general, as the perceived intrusiveness of advertising in social media is higher (Zhang & Mao, 2016) and also because social media has a unique ecosystem of users that differs from the regular Internet environment (Safko & Brake, 2009).

According to Taylor, Lewin and Strutton (2011), the key to integrate advertising successfully in SNS is consumer acceptance and excessive commercialization can lead to user abandonment. In their study, SNA (Social Network Advertising) included two forms of advertising: both explicit (banners and videos) and implicit (fan pages and firm-related posts) (Taylor, Lewin & Strutton, 2011). Results showed that, in the context of social media, the entertainment value of ads influences greatly consumers' attitudes towards online ads.

Meanwhile, consumer motivations play an important role in determining both the perceived entertainment value and the informativeness value of an ad (Zhang & Mao, 2016). Zhang and Mao (2016) studied how two types of motivations influenced ad clicks and behavioral intentions: consumption motivations (reading, watching or listening to social media content) and connection motivations (connect with friends, socialize and chat). The study conducted with 613 social media users in the US concluded that consumption motivations have a positive impact on both perceived entertainment value and informativeness value. On the other side, the effect of connection motivations on these two values is moderated by ad-media congruity (Zhang & Mao, 2016). Ad-media congruity is defined as the degree to which the ad material is thematically similar with the editorial content (Zanjani, Diamond & Chan, 2011), such as social media feeds. Both the mentioned perceived values and the attitudes towards SNS had an impact on ad clicks (Zhang & Mao, 2016).

2.1.8. Mobile Advertising

Mobile advertising investment is growing rapidly and it is estimated to surpass desktop ad spending for the first time in 2016, accounting for 51.9% of total digital spending in the US market (eMarketer, 2015). Within mobile ad spending, 51.1% of the budget was allocated to display ads and 44.7% to search campaigns in 2015. The display ads are estimated to continue having the highest share of digital ad spending until 2019, although its relative importance will decrease (eMarketer, 2015).

Mobile ads (ads displayed in mobile devices such as smartphones and tablets) differ from desktop ads in the sense that marketers can take advantage of targeting options, such as the ability to target based on location. In fact, not only location can have an impact on the effectiveness of an ad, but also other contexts such as physical crowdedness – for instance, commuters in crowded subways were shown to be more responsive to mobile ads than those in non-crowded trains (Andrews, Luo, Fang and Ghose, 2015). One possible explanation for these results is mobile immersion, i.e., as people in a crowded environment are susceptible to negative emotions such as anxiety, they turn their attention to their more mobile devices and hence become more likely to click on ads (Andrews et al., 2015). Moreover, according to Bart, Stephen and Sarvary (2014), mobile display ads are more effective for products with high involvement and with high on a utilitarian dimension, since they generate higher purchase intentions compared to low involvement products and products with hedonic dimensions.

2.1.9. Industry benchmarks for online advertising

Digital advertising in Portugal has risen from €20 million in 2008 to €40 million in 2013, and it is estimated to reach €55 million by 2015 (Statista, 2016). In order to assess the performance of advertising campaigns, it is key to compare metrics against industry benchmarks. Table 2 summarizes information from a Wordstream report with a sample of 2367 US-based firms in 2015. It describes the average click-through rate, cost-per-click, conversion rate and cost-per-action in the B2B industry and compares its average with the average of all the industries reported. These are legal services, auto, B2B, consumer services, dating and personals, e-commerce, education, employment services, finance and insurance, health and medical, home goods, industrial services, legal, real estate, technology, travel and hospitality (Wordstream, 2016).

Both B2B and B2C averages are relevant to this dissertation, since the advertiser is a B2B company but the invoicing software is advertised to individuals who represent startups. B2B industry metrics are higher for Google Adwords than for Google Display (Table 2). The B2B industry reported better results than the industries average in the CTR, CPC and CR of Google Adwords campaigns. On Google Display campaigns, it performed better at the CPC, CR and CPA levels. It is important to note that both CPA and the conversion rate depend on what the advertisers defines as a conversion in the Google Adwords platform (a sale, a lead, a registration, etc).

Table 2 – Metrics of Google Adwords and Google Display Network for the B2B industry, in the US market in Q2 2015 (Wordstream, 2016).

	CTR		CPC		CR		CPA	
	B2B	Industries average	B2B	Industries average	B2B	Industries average	B2B	Industries average
Google Adwords	2.55%	1.91%	$1.64	$2.32	2.58%	2.70%	$63.57	$59.18
Google Display	0.22%	0.35%	$0.37	$0.58	0.96%	0.89%	$38.54	$60.76

However, CTR for search might vary substantially depending on several factors, such as search ad position. For instance, a search ad ranked in the first position yields on average a 5.5% CTR, against an average of 4% in the second position (Kim, 2014). Regarding display ads, the Rich Media platform by Google provides benchmarks for display ads in the Google Display Network by country. According to the same platform, the average display ads CTR in Portugal is 0.23% ("Rich Media Gallery | Display Benchmarks", 2016), close to the benchmark in Table 2 for the B2B industry. On the other hand, according to a report from Salesforce Marketing Cloud about the performance of Facebook in Portugal (Salesforce, 2013), their average CTR is 0.375% and their average CPC is €0.06. However, the CTR varies greatly depending on the ad placement, with an average CTR of 2.03% for an ad placed on the newsfeed (Salesforce, 2013).

A report from Marin Global (2015) assesses information from Marin's business customers in 2014 that managed more than $6 billion in annualized search, social and display spend. These were located in Australia, Brazil, Canada, China, Eurozone, India, Japan, Mexico, New Zealand, Russia, Singapore, UK and USA and included large brands such as IBM, GAP, Lonely Planet, Symatec, Macy's and Bloomingdales. Hence, the report is biased towards large advertisers spending more than $100,000 on paid search, social and display and may not reflect trends for small and medium businesses (Marin Global, 2015). According to this study, CTRs are higher for ads appearing in mobile devices (both mobile phones and tablets) than in desktops, as represented in Figure 2. Search ads have notably higher CTRs than display and social medias ads, since search engines are still the main channel for users to find goods and services. This makes search campaign ads more likely to be clicked, given their relevance to the user (Marin Global, 2015).

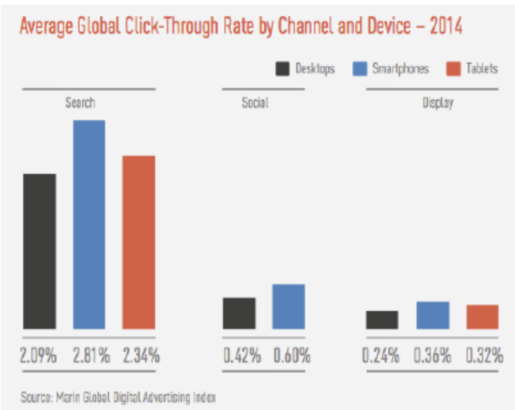

Figure 2 – Average CTR for search, social and display by device in 2014 of Marin's larger customers located in 12 countries and Eurozone (Marin Global, 2015).

Nonetheless, conversion rates are higher in desktop than mobile devices, independently of the channel or format used (Figure 3). It is interesting to note that some shoppers use mobile devices for browsing when they are at the start of the purchase funnel, later on moving to a desktop, as they get closer to the conversion stage. This cross-device interaction should be tracked, in order to achieve the highest advertising effectiveness by retargeting ads seen on mobile to the same consumers when they are using a desktop later on (Marin Global, 2015).

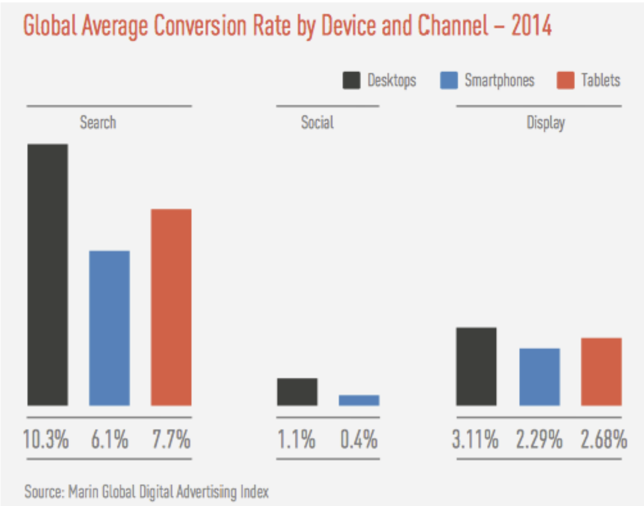

Figure 3 – Global average CR by device and channel in 2014 of Marin's larger customers located in 12 countries and Eurozone (Marin Global, 2015).

2.2. Conclusions

First of all, regarding the relative performance of different types of ads, paid search ads tend to perform better than display ads (Fulgoni and Mörn, 2009). In that sense, two hypotheses were formulated to address the first research question:

H1.a: Search ads generate more clicks per impressions than display and social media ads.
H1.b: Search ads generate more conversions per clicks than display and social media ads.

Nonetheless, display ads are gaining importance as the expenditure on display is expected to outweigh the expenditure on search by 2016 (eMarketer, 2016).
Secondly, mobile advertising is gaining relevance and according to a report from Marin Global (2015), users are more likely to click on mobile ads, but generally convert (e.g. complete a purchase, subscribe a service) on a desktop, which makes the cross-device

interaction critical for advertising effectiveness. Hence, to address the second research question two hypotheses were formulated:

H2.a: Ads displayed on mobile devices generate more clicks per impressions.
H2.b: Ads displayed on computers generate more conversions per clicks.

Finally, focusing on the factors that might influence the performance of display and social media ads, retargeting is a highly used targeting strategy due to its proven effectiveness in converting undecided users (Lambrecht and Tucker, 2013). In order to answer the third research question, two hypotheses was formulated:

H3.a: The targeting strategy influences the relative performance of display ads.
H3.b: The targeting strategy influences the relative performance of social media ads.

CHAPTER 3: METHODOLOGY

This chapter describes the research approach adopted to answer the research questions, depicting the methods used to collect the secondary data and the statistical analysis that it was subjected to test the research hypotheses presented in Chapter 2.

3.1. Research Approach

There are three main types of research approaches. Whilst exploratory research aims to clarify the research environment, and causal research to assess a cause-effect relationship between two variables, descriptive research intends to describe the characteristics of a population or phenomenon (Hyman and Sierra, 2010). In this dissertation, the research hypotheses will be addressed through descriptive research, making use of quantitative secondary data. Quantitative approach seeks to test objective theories, by examining the relationship between variables (Creswell, 2013). In addition, research can either be longitudinal, when data is collected over time, or cross-sectional, when the collected data is from one specific point in time (Hyman and Sierra, 2010). In this dissertation, although the campaigns analyzed were implemented for five months, the data is analyzed as cross-sectional and the time evolution is assessed separately.

3.2. Research Methods

3.2.1. Data Collection

Data referring to the characteristics and performance of past online advertising campaigns conducted by Live Content was collected and compiled in excel files. The time frame for campaign data collection was from September 2015 to February 2016. The sixteen campaigns selected always promoted exactly the same offer: a mobile invoicing software, offered at a 50% discount of the full yearly price, obtainable through a 30-day free trial subscription of the invoicing software. The campaigns were conducted using two platforms – Google and Facebook – and in two formats – search and display. For simplicity of analysis, they were divided into three types of ads – search, display and social media ads (Table 3).

In order to collect all the data from Google and Facebook, it was necessary to use the Google AdWords and Facebook Business Manager platforms. These platforms provide campaign information such as investment, number of impressions, clicks and conversions, and metrics such as CTR, average CPC and conversion rate.

Table 3 – Details of the 16 ad campaigns providing data for analysis, by platform and timeframe.

Platform	Format	"Type of Ad"	Date range of all campaigns	Number of campaigns
Google	Search	Search	7/09/2015 – 2/02/2016	7
Google	Display	Display	8/09/2015 – 30/09/2015	4
Facebook	Display	Social Media	9/09/2015 – 15/01/2016	5

3.2.2. Dataset preparation

After collecting all the data in excel files from Google Adwords and Facebook Manager platforms, these were combined into one single SPSS dataset. First of all, it was necessary to align some variables across platforms. Since the variable *device_impression* had different units for each platform, it was divided only between mobile and desktop for the purpose of simplicity of analysis. For instance, on Google both tablets and mobile devices were defined as mobile. For Facebook ads, all other devices were categorized as mobile (iPhone, iPad, android and others), except for computer. All categorical independent variables (with n categories) were subsequently recoded into n-1 dummy variables, to guarantee that the linearity assumption between variables is satisfied (Tabachnick &Fidell, 2007).

Finally, given that statistical inferences become less robust when variables do not follow a normal distribution, some variables were transformed through a logarithm transformation to improve their normality (Tabachnick &Fidell, 2007).

3.2.3. Performance variables

The B2B company that represents the advertiser of the invoicing software had one strategic goal: conversions, i.e., subscriptions to the 30-day free trial of the software. The customer lifetime value is considered reasonably high, so the focus was on maximizing customer acquisitions rather than minimizing the cost per acquisition. Hence, the primary goal was to increase the number of subscriptions and not the cost-effectiveness of the campaign.

The performance metrics assessed in this dissertation are the CTR, which are based on clicks and impressions, and the CR, based on conversions and clicks. The first metric is considered as the measure of *"attractiveness"*, as it represents the number of people who clicked on an ad after they were exposed to it. The latter is considered as the level of "*effectiveness*", as it represents the amount of people who converted after clicking on an ad.

Although it is key to understand cost levels of the campaigns, namely the CPC and CPA (cost per conversion in this case), these two last variables were not considered as dependent variables because the main goal of the campaigns was to maximize conversions.

3.2.4. Independent variables of the global regression model

This dissertation aims to compare different platforms and ad formats, but also to analyze the dynamics within each ad type. In order to do so, the research approach started with a broad comparison of all ads, followed by an in-depth study within each platform.

Table 4 lists the independent variables included in the global regression and their classes. The ad type corresponds to whether the campaign was search or display ads and the platform where it was delivered – either Google search (search), Google display (display) or a Facebook ad (social media ad). The device of impression corresponds to the type of device in which the potential customer searched for the keyword or saw the ad.

Table 4 – Independent variables and units of analysis included in the global regression model.

Independent variable	Unit of analysis
Ad type	Search Display Social Media
Device of impression	Computer Mobile device

The global regression model intends to assess whether the ad type and the device impression influences the dependent variables of performance. However, this model does not take into account specificities of each ad type. Since search ads are defined by keywords and not by a segmentation strategy, further research is focused on display and social media ads.

3.2.5. Independent variables of the display regression model

In order to understand what variables influence the ads performance within Google Display (named as display ads in the *ad_type* variable), a specific regression model for this platform was estimated. Its independent variables are presented in Table 5 and include both the device of impression and the targeting strategy adopted. The latter is classified according to the strategies defined by Live Content to advertise the invoicing software on this platform. Namely, the strategies adopted included contextual targeting, placement targeting, targeting by interests or topics and retargeting.

Table 5 – Independent variables and units of analysis included in the Google Display ads regression model.

Independent variables	Unit of analysis
Device impression	Computer Mobile device
Targeting strategy	Contextual – keywords Placement Interests Topics Retargeting

3.2.6. Independent variables of the social media regression model

In the same logic, a specific regression model was conducted to analyze other variables that may influence the performance of ads in social media, in particular on Facebook. Aside from the device of impression, the independent variables are presented in Table 6 and include also the targeting strategy, which differs from Google Display. On Facebook ads, Live Content targeted the invoicing software ads by demographics, interests and industry. Besides, it used a targeting tool described in chapter 2 – look-a-like users – and retargeting. The demographics of the target audience must always be defined (such as location, gender and age) before targeting by interests or industry. However, when Live Content did not add any type of segmentation besides demographics, the variable was classified as "demographics" only.

Moreover, the placement of ads on Facebook and the device through which users converted, i.e. subscribed to the free trial, were also considered as independent variables. Although the variable *device_impression* was defined for all campaigns, the variable *device_conversion* was only accessible for Facebook campaigns.

Table 6 – Independent variables and units of analysis included in the social media ads regression model.

Independent variable	Unit of analysis
Device of impression	Computer Mobile device
Targeting strategy	Demographics Interests Industry Look-a-like users Retargeting
Display Placement	Newsfeed Right column Third party apps – network audiences
Device of conversion	Computer Mobile device

3.2.7. Tests of Normality

Figure 4 presents the histograms of the performance variables considered (*CTR*, *CR*, *clicks* and *conversions*).

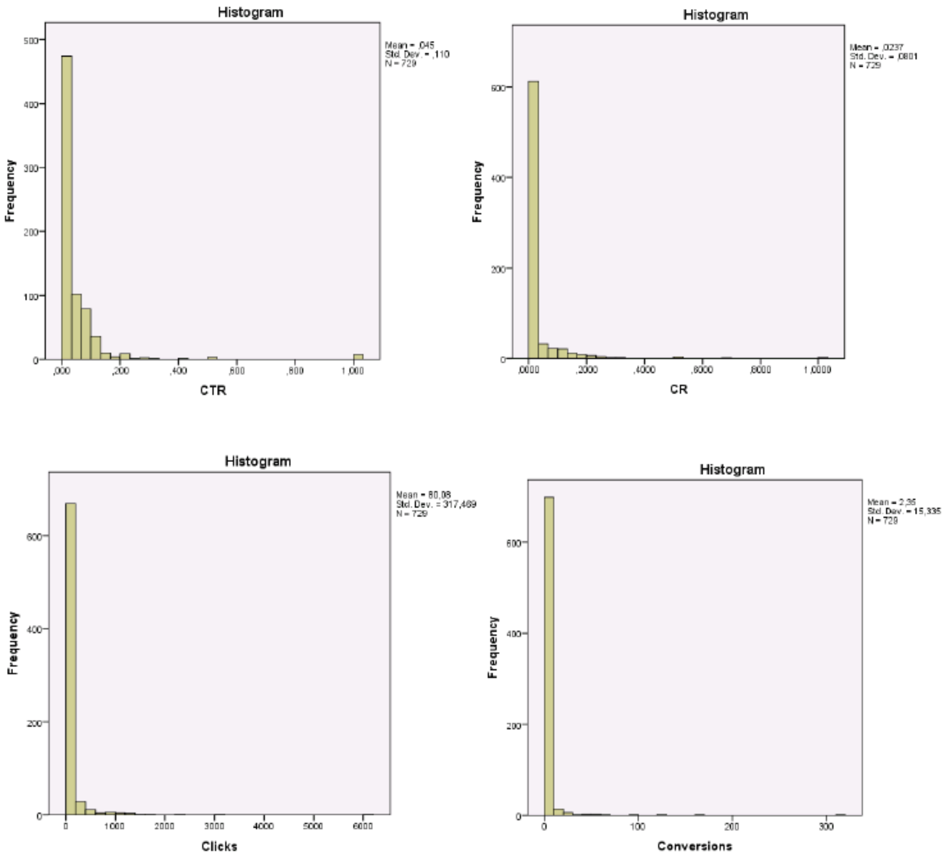

Figure 4 – Histograms of the distributions of *CTR*, *CR*, *clicks* and *conversions*.

After analyzing the histograms (Figure 4) and box plots (Annex 1) and observing that all performance variables tail off to the right, it was necessary to run the appropriate normality tests. Annex 2 presents the kurtosis and skewness levels for the two variables. First, all variables present positive kurtosis levels, confirming that the distribution is peaked in relation to the normal distribution. Second, all variables also present positive skewness values, which confirms that the variables have only a few large values and tail off to the right (Hair et al., 2010).

Finally, specific tests to assess normality, in particular the Shapiro-Wilk test and a modification of Kolmogorov-Smirnov test, which calculate the levels of significance for the differences from a normal distribution (Hair et al., 2010). The results from these tests are presented in Table 7 and given the low p-values for both tests for all the variables; the null hypotheses that these variables differ from a normal distribution are not rejected.

Table 7 – Results of Kolmogorov-Smirnov and Shapiro-Wilk tests of normality of *CTR, CR*, *CPC* and *CPA*.

Tests of Normality						
	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CTR	0.340	729	0.000	0.369	729	0.000
CR	0.386	729	0.000	0.319	729	0.000
Impressions	0.408	729	0.000	0.229	729	0.000
Clicks	0.400	729	0.000	0.236	729	0.000
Conversions	0.439	729	0.000	0.128	729	0.000

3.2.8. One-sample t-tests

In order to compare the average performance of the ad campaigns to benchmark performance values, a one-sample t-test was analyzed for each type of ad. The tested variable was *CTR*, as it includes both clicks and impressions. These are more easily compared than conversions. As earlier explained, a conversion may be defined by the advertiser as a sale, a subscription or other action. This limits the comparison between benchmarks. Moreover, since conversions only occur after a click, *CTR* also becomes an important variable in the performance analysis.

3.2.9. Zero-inflated negative binomial regression model

The metrics defined as appropriate to measure the performance of campaigns are ratios and, for that reason, they are concentrated close to zero and contain several zeros. This type of situations poses a problem in terms of multivariate analysis, since they cannot be altered simply trough a logarithm transformations without losing information.

The most appropriate regression model is a **zero-inflated negative binomial regression**. First of all, a zero-inflated model addresses the excess zeros in a distribution, without disregarding this information. Secondly, a negative binomial regression addresses the problem of over-dispersion, when compared against the Poisson regression (Yau, Wang, & Lee, 2003). Since this type of regressions requires count data, the ratios (CTR and CR) cannot be used, but rather the variables that generate these ratios, i.e., *clicks*, *impressions* and *conversions*.

Hence, in order to assess the level of "*attractiveness*" of the ad, given by the metric CTR, the variable *clicks* is defined as dependent variable, whilst controlling for the variable *impressions*, included in the regression as exogenous. Since *impressions* is not normally distributed, the variable included in the regression is its log transformation: *log_impressions*= $\log_{10}$ (*impressions*). The histogram of the latter is presented on Annex 3.

To assess the level of "*effectiveness*", given by the metric CR, the variable *conversions* is defined as the dependent variable, whilst the variable *clicks* is considered a control variable. The variable *clicks* is not normally distributed and some observations are zero. Hence, for all observations it was added one in this variable (the value that is usually set) before the log-transformation (O'Hara & Kotze, 2010). The variable included in the regression is: $log\_clicks1 = \log_{10}(clicks + 1)$.

For the sake of simplicity, the variables included in the inflate part of the model, i.e., the variables to predict excess zeros, are the same as the control and independent variables of the model. The inflate part is not object of analysis and hence this part will not be described further in detail.

3.2.10. The Cragg hurdle model

In order to increase the reliability of the results from the negative binomial model, a different model was tested for the global regression model. A hurdle model is also used in Economics to address excess zeros and is based on two "decisions" that are made in simultaneous: a participation decision (zero or one) and a consumption decision (level of variation within positive observations) (Humphreys, 2013). Moreover, a hurdle model assumes that zero observations are genuine zeros and not missing values. It is important to underline that the Cragg model, in particular, assumes that the unobservable factors affecting the first "decision" are uncorrelated with the unobservable factors affecting the second "decision" (Humphreys, 2013). Nonetheless, this model was tested merely to compare with the results from the zero-inflated negative binomial one.

CHAPTER 4: RESULTS AND DISCUSSION

4.1. Descriptive statistics

First of all, it is important to have an overall perspective of the dependent variable across different factors. The invoicing software that is being advertised aims to acquire new customers for the B2B company, especially startups and SMEs. However, the product's profitability is very low, since the main strategy is cross-selling other products and services after acquiring these new customers. Hence, the main goal of the company is customer acquisition, which in this case translates in the subscription of a 30-day free trial of the invoicing software. If customers are satisfied with the software, they can get the software for a year for half the price.

Table 8 describes the mean, standard deviation, minimum and maximum value of the *CTR*, *CR*, *CPC* and *CPA* across all ads and also the variables that help compute these ratios – number of *impressions*, *clicks*, *conversions* and *cost*.

The metrics compared included the number of *impressions* and *conversions* (service subscription), the *CTR*, *CR*, *CPC* and *CPA*. In a first look, it is easily detectable that all the variables are highly dispersed, since for all of them, the standard deviation is higher than its mean.

Table 8 – Descriptive statistics of *impressions*, *clicks*, *conversions*, *CTR, CR, CPC* and *CPA* (n=729).

Variable	Mean	Std. Dev.	Min. value	Max. value
CTR	4.52%	10.98%	0	100%
CR	2.37%	8.01%	0	100%
CPC	0.97€	1.33€	0.00€	8.75€
CPA	6.39€	19.10€	0.00€	265.84€
Impressions	12 532	54 067	1	821 586
Clicks	80	317	0	6 019
Conversions	2.35	15.33	0	316
Cost	30.43€	82.64€	0.00€	967.90€

Table 9 depicts the descriptive statistics by type of ad and provides more detail about variable distribution. Clear differences in performance are observable between search, display and social media ads. In fact, search ads have, on average, a much higher *CTR* and *CR* than display and social media ads. Social media ads perform better than display, on average. It is important to note that the number of observations in search ads was considerably higher than in the cases of display and social media ads.

Table 9 – Descriptive statistics of performance variables by type of ad.

Variable	Search (n=456)		Display (n=60)		Social media (n=213)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Clicks	50	337	160	257	121	279
CTR	6.46%	13.42%	0.54%	0.48%	1.48%	2.38%
Conversions	3.16	19	0.08	0.28	1.24	4.74
CR	3.34%	9.83%	0.26%	1.34%	0.88%	2.58%

In order to assess whether the difference in performance across ad types also varied when the ad was seen on a mobile device or on desktop, it was necessary to analyze in more detail the descriptive statistics for each performance variable. Table 10 presents the mean and standard deviation of *CTR* across ad types and device of impression. By analyzing it, the main conclusion is that the mean *CTR* is higher for ads seen on mobile, independently of the ad type. Nevertheless, the standard deviation is also always higher. Table 11 presents the mean and standard deviation of *CR* across ad types and device of impression. It can be seen that mean *CR* is always higher for ads seen on a computer rather than in a mobile device, although with higher dispersion.

Table 10 – Descriptive statistics of *CTR* per ad type and device of impression.

CTR				
Ad Type	**Device_impression**	**Mean**	**Std. Deviation**	**N**
Search	Computer	5.28%	4.95%	171
	Mobile device	7.16%	16.51%	285
	Total	6.46%	13.42%	456
Display	Computer	0.08%	0.04%	20
	Mobile device	0.77%	0.43%	40
	Total	0.54%	0.48%	60
Social Network Ad	Computer	0.31%	0.35%	47
	Mobile device	1.82%	2.59%	166
	Total	1.48%	2.38%	213
Total	Computer	3.86%	4.77%	238
	Mobile device	4.83%	12.96%	491
	Total	4.52%	10.98%	729

Table 11 – Descriptive statistics of *CR* per ad type and device of impression.

CR				
Ad Type	**Device_impression**	**Mean**	**Std. Deviation**	**N**
Search	Computer	5.41%	10.65%	171
	Mobile device	2.09%	9.11%	285
	Total	3.34%	9.83%	456
Display	Computer	0.29%	0.66%	20
	Mobile device	0.25%	1.58%	40
	Total	0.26%	1.34%	60
Social Network Ad	Computer	1.96%	3.41%	47
	Mobile device	0.57%	2.21%	166
	Total	0.88%	2.58%	213
Total	Computer	4.29%	9.32%	238
	Mobile device	1.43%	7.11%	491
	Total	2.37%	8.01%	729

4.1.1. Descriptive statistics of display ad performance

In order to have a thorough analysis of the dynamics within each type of ad, descriptive statistics for each type of ad were computed. Table 12 presents the mean, minimum and maximum of *clicks* and *CTR* of display ads, across different devices of impression and targeting strategies. Again, both *clicks* and *CTR* are substantially higher for display ads seen on a mobile rather than a computer. When comparing different targeting strategies, although *clicks* vary considerably for different strategy, the *CTR* variations are less pronounced. The only exception is retargeting, which has substantially more average *clicks* and *CTR*. The targeting option that seems to be less efficient when considering the *CTR* is "placement" or "managed placement". This is when the agency specified websites or mobile apps to display the ad.

Table 13 presents the mean, minimum and maximum of *conversions* and *CR* of display ads, across different devices of impression and targeting strategies the same information as there were only five conversions originated from display ads, which limits the comparison ability between devices or targeting options. In fact, there is no sizeable difference in *conversions* or *CR* between devices or between targeting strategies. The options that appear to be more effective are targeting by topics and retargeting. Still, the sample is limitedly small.

Table 12 – Descriptive statistics of *clicks* and *CTR* per device and targeting strategy of display ads.

		Clicks			CTR		
DEVICE	N	Mean	Min	Max	Mean	Min	Max
Computer	20	50	4	214	0.08%	0.03%	0.16%
Mobile	40	215	4	1196	0.77%	0.26%	1.68%
TARGETING							
Contextual	12	78	21	253	0.52%	0.05%	1.16%
Placement	12	132	5	374	0.37%	0.03%	0.98%
Interests	12	180	36	370	0.56%	0.11%	1.22%
Topics	12	22	4	57	0.55%	0.04%	1.50%
Retargeting	12	387	46	1196	0.69%	0.07%	1.68%

Table 13 – Descriptive statistics of *conversions* and *CR* per device and targeting strategy of display.

		Conversions			CR		
DEVICE	N	Mean	Min	Max	Mean	Min	Max
Computer	20	0.2	0	1	0.29%	0.00%	2.17%
Mobile	40	0.02	0	1	0.25%	0.00%	10%
TARGETING							
Contextual	12	0	0	0	0.00%	0.00%	0.00%
Placement	12	0	0	0	0.00%	0.00%	0.00%
Interests	12	0.08	0	1	0.06%	0.00%	0.74%
Topics	12	0.29	0	1	0.83%	0.00%	10%
Retargeting	12	0.25	0	1	0.43%	0.00%	2.17%

4.1.2. Descriptive statistics of social media ad performance

In order to have a first understanding on the dynamics of social media ads, descriptive statistics for the different performance variables were analyzed. Table 14 summarizes the information for different devices, targeting options and ad placement on Facebook. Similar to what was observed in all types of ads, *clicks* and *CTR* are substantially higher for social media ads seen on a mobile. On the other hand, when comparing different targeting strategies, the variable *industry* has the lowest average performance. The other options do not have accentuated differences, although *look-a-like* users have higher average *clicks*, followed by *retargeting*. In terms of ad placement, although *third-party apps* have more absolute clicks, the *ads on newsfeed* have higher average *CTR*.

Table 14 – Descriptive statistics of *clicks* and *CTR* per device, targeting strategy and display placement of social media ad.

		Clicks			CTR		
DEVICE	N	Mean	Min	Max	Mean	Min	Max
Computer	47	191	7	1010	0.31%	0.04%	1.34%
Mobile	166	102	0	2326	1.81%	0.00%	20%
TARGETING							
Demographics	150	119	0	1518	1.62%	0.00%	20%
Interests	18	108	0	552	1.35%	0.00%	8.70%
Industry	17	33	0	146	0.92%	0.00%	5.10%
Look-a-likes	16	212	0	2326	1.21%	0.00%	6.04%
Retargeting	12	170	0	559	1.15%	0.00%	4.09%
PLACEMENT							
Newsfeed	169	99	0	1355	1.71%	0.00%	20%
Right column	20	84	8	826	0.08%	0.04%	0.17%
3rd party apps	24	306	7	2326	1.09%	0.42%	1.75%

There were a total of 309 conversions originated from social media ads. Table 15 depicts the differences between variables in terms of *conversions* and *CTR*. Average *conversions* and *CR* are much higher for Facebook ads seen on a computer desktop than on mobile, which is opposite to what happens with *clicks* and *CTR*. Regarding targeting options, it is clear that retargeting is the most effective strategy in terms of average *conversions* and *CR*. Similarly, ads placed on the newsfeed appear to have a better performance than ads on the right column or third-party apps.

Table 16 shows cross-device conversions and is key to understand cross-device switch, i.e., whether users clicked on a social media ad in one device and switched to other device to convert, or the opposite. In fact, computers performed better in terms of absolute number of *conversions*. People who clicked on a Facebook ad on a computer always subscribed the invoicing software on the same device. However, from the users who clicked on the ad on a mobile device, 18 switched to a computer to subscribe the software trial. In terms of average cost performance, ads seen, clicked and converted through a mobile device had a lower average CPC and CPA. In this sense, it is relevant to envisage a cross-device approach to social media ads, for instance optimizing mobile ads for clicks and website in desktop for conversions.

Table 15 – Descriptive statistics of *conversions* and *CR* per device, targeting strategy and display placement of social media ad.

		Conversions			CR		
DEVICE	N	Mean	Min	Max	Mean	Min	Max
Computer	47	3.91	0	48	1.96%	0.00%	14.29%
Mobile	166	0.49	0	18	0.57%	0.00%	14.81%
TARGETING							
Demographics	150	0.55	0	12	0.48%	0.00%	14.29%
Interests	18	1.06	0	15	0.23%	0.00%	3.35%
Industry	17	0.82	0	9	1.35%	0.00%	8.91%
Look-a-likes	16	1.19	0	11	1.26%	0.00%	9.09%
Retargeting	12	10.92	0	48	5.64%	0.00%	14.81%
PLACEMENT							
Newsfeed	169	1.47	0	48	1.08%	0.00%	14.81%
Right column	20	0.4	0	4	0.21%	0.00%	2.86%
3rd party apps	24	0.38	0	4	0.06%	0.00%	0.72%

Table 16 – *Conversions*, *CR*, *CPC* and *CPA* of social media ads per device of impression and conversion.

Device of impression	Device of conversion	Number of conversions	Average CTR	Average CR	Average CPC	Average CPA
Computer	Computer	48	0.42%	3.84%	0.39€	26.53€
Computer	Mobile	0	NA	NA	NA	NA
Mobile	Mobile	8	2.18%	5.58%	0.14€	8.27€
Mobile	Computer	18	0.84%	3.44%	0.12€	15.61€

4.2. One-sample t-tests

In search ads, the campaigns average was compared against the CTR benchmark of 5%, based on the assumption that best performers in paid search advertising achieve CTRs close to this value (Kim, 2014). In display ads, the benchmark is specific for Portugal, which increases the validity of the results obtained for the campaigns under analysis ("Rich Media Gallery | Display Benchmarks", 2016). In social media ads, the benchmark is also specific for the Portuguese market, but it is an average of all types of Facebook ads (Salesforce, 2013). Nonetheless, it is important to notice that the CTR on Facebook ads varies greatly, yielding higher CTRs for ads placed on the newsfeed (Salesforce, 2013). Table 17 summarizes the information from the statistical t-tests ran in SPSS (Annex 4) to compare means. As observable, the p-values for all the tests fall below 0.05, rejecting the null hypothesis that campaigns average *CTR* are statistically equal to the tested benchmark value. In conclusion, all campaigns performed above average when compared to market benchmarks.

Table 17 – One-sample t-tests for each type of ads, comparing average *CTR* and benchmark for each ad type (Kim, 2014; Rich Media Gallery, 2016; Salesforce, 2013).

	Campaigns					
	N	**Mean**	**Std. Dev.**	**Benchmark – tested value**	**Mean difference**	**Sig. (2-tailed)**
Search	456	6.46%	13.42%	5%	**+1.46%**	**0.021**
Display	60	0.54%	0.48%	0.23%	**+0.31%**	**0.000**
Social Media	213	1.48%	2.38%	0.375%	**+1.11**	**0.000**

4.3. Global regression model

In order to assess the variation of *clicks*, controlling for *log_impressions*, a zero-inflated negative binomial (ZINB for abbreviation) regression model was estimated in STATA. The main purpose was to assess the components that explained the variance of the level of "*attractiveness*" of all the ads. The likelihood ratio chi-square of the model can be defined as the test that at least one of the predictors' coefficient is different from zero ("Annotated STATA Output: Zero-Inflated Negative Binomial Regression", 2016), having four degrees of freedom in this case.

Table 18 depicts the results of model estimation. The LR Chi-square is 1200.89 and the model is significant (p-value = 0.000). All variables included in the model are significant. The control variable's coefficient is approximately 0.91, which is smaller than 1. This means that although it is not exactly the variable *CTR*, it is still a useful proxy. The independent dummy variable *device_impression* has a positive coefficient (0.4443), which means that *clicks* are higher for ads seen on a mobile device than on a computer. The variable with higher impact on *clicks* is the dummy variable for search ads. This implies that this type of ads has much more *clicks* than display or social media ads. Hence, one can infer that *clicks* are higher for search, followed by social media and then display ads significantly.

All these results are consistent with those obtained by the estimation of a Cragg hurdle model, where the dependent variable is *log_CTR* and the independent variables are the same as in the ZINB model (Annexes 5 and 6). The estimated coefficients vary, but are consistent with those of the previous model. It is also relevant to point that the latter approach excludes all zero observation, given that it is applies a logarithm function.

Table 18 – Results of multiple regression models.

Results of the zero-inflated negative binomial, global regression model of *clicks* (n=729).			
Variable	**Units**	**Coefficient**	**p-value**
Log_impressions	Metric	0.9132	0.000
Device_impression	0 = computer | 1 = mobile	0.4443	0.000
Ad_type_d1	0 = other | 1 = search	1.4048	0.000
Ad_type_d2	0 = other | 1 = display	- 0.6978	0.000
Constant		- 4.0766	0.000
Nonzero observations = 555; zero observations = 174. LR Chi^2 (4) = 1200.89; Prob > Chi^2 = 0.000 (p-value)			
Results of the zero-inflated negative binomial, global regression model of *conversions* (n=729).			
Variable	**Units**	**Coefficient**	**p-value**
Log_clicks1	Metric	0.8926	0.000
Device_impression	0 = computer | 1 = mobile	- 0.6990	0.000
Ad_type_d1	0 = other | 1 = search	0.9055	0.000
Ad_type_d2	0 = other | 1 = display	- 3.2712	0.000
Constant		- 3.0008	0.000
Nonzero observations = 168 ; zero observations = 561 LR Chi^2 (4) = 275.01; Prob > Chi^2 = 0.000 (p-value)			
Results of the negative binomial, display regression model of *clicks* (n=60).			
Variable	**Units**	**Coefficient**	**p-value**
Log_impressions	Metric	1.6606	0.000
Device_impression	0 = computer | 1 = mobile	2.8446	0.000
Display_targ_d1	0 = other | 1 = placement	- 0.8199	0.000
Display_targ_d2	0 = other | 1 = interests	- 0.3193	0.027
Display_targ_d3	0 = other | 1 = topics	0.9136	0.000
Display_targ_d4	0 = other | 1 = retargeting	- 0.5291	0.001
Constant		- 13.9892	0.000
LR Chi^2 (6) = 179.10; Prob > Chi^2 = 0.000 (p-value)			
Results of the negative binomial, social media regression model of *clicks* (n=213).			
Variable	**Units**	**Coefficient**	**p-value**
Log_impressions	Metric	0.8351	0.000
Device_impression	0 = computer | 1 = mobile	0.9448	0.000
Facebook_display_d1	0 = other | 1 = right column	- 1.5615	0.000
Facebook_display_d2	0 = other | 1 = 3rd party apps	- 0.1365	0.394
Facebook_targ_d1	0 = other | 1 = interests	0.0268	0.882
Facebook_targ_d2	0 = other | 1 = industry	- 0.4712	0.016
Facebook_targ_d3	0 = other | 1 = look-a-likes	- 0.3223	0.096
Facebook_targ_d4	0 = other | 1 = retargeting	0.3079	0.136
Constant		- 3.7488	0.000
LR Chi^2 (8) = 460.46; Prob > Chi^2 = 0.000 (p-value)			
Results of the zero-inflated negative binomial, social media regression model of *conversions* (n=213).			
Variable	**Units**	**Coefficient**	**p-value**
Log_clicks1	Metric	0.8319	0.000
Device_impression	0 = computer | 1 = mobile	- 0.4766	0.062
Facebook_display_d1	0 = other | 1 = right column	- 0.9724	0.156
Facebook_display_d2	0 = other | 1 = 3rd party apps	- 2.2102	0.000
Facebook_targ_d1	0 = other | 1 = interests	0.6027	0.146
Facebook_targ_d2	0 = other | 1 = industry	1.2754	0.013
Facebook_targ_d3	0 = other | 1 = look-a-likes	0.4521	0.236
Facebook_targ_d4	0 = other | 1 = retargeting	2.0611	0.000
Constant		- 3.4869	0.002
Nonzero observations = 48; zero observations = 165 LR Chi^2 (8) = 76.95; Prob > Chi^2 = 0.000 (p-value)			

In order to understand the variance in the level of "effectiveness", a ZINB regression model for the dependent variable *conversions* was estimatied. This model is significant, with a LR Chi-Square of 275.01 (Table 18). The coefficient of the control variable, *log_clicks1*, is slightly below 1 (0.8926), which means that the regression is still a good proxy of the variable *CR*. If the defined control variable was *log_clicks,* which would exclude all the zero observations for *clicks*, the results would be similar (Annexes 7 and 8).

The independent variables are all significant. The *device_impression* has a negative coefficient (-0.699), hence *conversions* are generally lower for ads seen on a mobile device. The ad type also explains the variation in *conversions*, with search generating significantly more *conversions* (coefficient of dummy variable for search is 0.9055), followed by social media ads (null group) and display ads (coefficient is – 3.2712). The dummy variable that represents the display ads is the variable with the highest impact on the variance of *conversions*.

4.4. Display regression model

Within display ads, it is relevant to understand what influences the variance of the level of "*attractiveness*" of the ads. To enable this, a negative binomial regression model (there were no zero observation in *clicks* for display ads) was estimated; results are depicted in Table 18 (Annex 9).

The model is significant with a LR Chi-square of 179.10 and all variables included in the model are significant. In this case, the control variable *log_impressions* has a coefficient above one (1.6606), so the regression is not exactly representative of the ratio CTR. The independent variable with the highest impact on *clicks* is the display of impression, with a positive coefficient of 2.8446, meaning that display ads seen on mobile devices yield substantially higher number of *clicks*. Regarding targeting, the null group is contextual targeting and all other targeting options perform worse on *clicks*, except for targeting by topics (coefficient of 0.9136). Placement targeting is the option that influences more negatively the number of *clicks* (coefficient of -0.8199). Given that only five conversions originated from display ads and only 60 observations were collected for this ad format, a regression model for the variable *conversions* was not estimated.

4.5. Social media regression model

In order to understand the variation in the level of "attractiveness" and "effectiveness" of social media ads, two separate regressions models were estimated. To study the variance of *clicks*, a negative binomial model was first estimated, given that there were only 26 zero observations in a total of 213. The model estimated is significant and has LR Chi-square of 460.46 (Table 18). However, not all variables included in the model are significant.

The control variable is significant, but again its coefficient is slightly under 1. The *device_impression* is significant and is in line with previous results, which showed that mobile devices yield more *clicks* than other types of devices (coefficient of 0.9448). Regarding the placement of the ad on Facebook (and given that the null group is the newsfeed), the two other options – right column and third-party apps – generate relatively less *clicks*. However, only the difference of the former is statistically significant (the p-value of the dummy variable for third-party apps is 0.394). Regarding the targeting options, the null group is demographics targeting, i.e., when no other option was included in the ad description. In this case, the only significantly variable is the dummy for industry targeting. This implies that only the ads targeted by industry performed significantly worse than those targeted by demographics, in terms of *clicks*.

STATA results for both the negative binomial and the zero-inflated negative binomial models estimated are given in Annexes 10 and 11; model results were slightly different.

In terms of “effectiveness”, a zero-inflated negative binomial regression for the variable *conversions* was conducted; the results are depicted in Table 18. There were only 48 conversions from the 213 social media ads, which pose a limitation in the modeling of a regression. Still, the model is significant with a LR Chi-square of 76.95, which is substantially smaller than the previous models. As previously, the control variable is *log_clicks1*, so that all zero observations for *clicks* are not excluded. Although the results between the model that uses *log_clicks* and the model that uses *log_clicks1* as a control variable are extremely similar in terms of coefficients, there are more significant variables at a 95% confidence level in the former model. The STATA results for both models are in Annexes 12 and 13. The results from the latter model are presented in Table 18.

The coefficient of the control variable is close to one and is similar to the previous models (0.8319). The independent variable *device_impression* has a p-value of 0.062, but in the ZINB model with *log_clicks* it is significant (p-value of 0.047). The social media ads displayed in mobile devices yielded fewer *conversions* (coefficient of -0.4766). In terms of ad placement display, the ads displayed on third-party apps through audience networks originated significantly less *conversions* than those in the newsfeed (coefficient of -2.2102). Regarding the targeting options all options had positive coefficients. However, the only ads significantly different in terms of *conversions* were the ones targeted by industry (coefficient of 1.2754) and those with the retargeting option (coefficient of 2.0611). So, ads with the retargeting option yield significantly more *clicks* and more *conversions*. However, ads with the industry targeting option yield less *clicks*, but more *conversions* from the users who clicked on the ad.

4.6. Ad campaign optimization

Since the campaigns analyzed in this dissertation were implemented across a time span of almost five months, it is important to investigate whether the campaigns were optimized over time and how. However, it was only possible to collect data for the total of this period in regards to search and social media ads (Table 3). Hence, performance data for these two types of ads were aggregated (one campaign is composed my multiple groups of ads, which are the unit of analysis) and their evolution over time plotted, taking into account the start dates of the campaigns.

In search ads, both the *CTR* and *CR* sustainably increased during the five months (seven campaigns), except for the slight decrease in the *CTR* level of the last campaign (Figure 5). In social media ads, the *CR* increased but the *CTR* decreased over the five campaigns (Figure 6). Therefore, only search ads seem to have been optimized for both clicks and conversions during this period. One plausible explanation is that, the person responsible to optimize the search campaigns at Live Content is certificated by Google and has experience in search bidding optimization. Whereas in social media ads, optimization is less linear as it involves the Facebook newsfeed algorithm (Personal Communication, 2016).

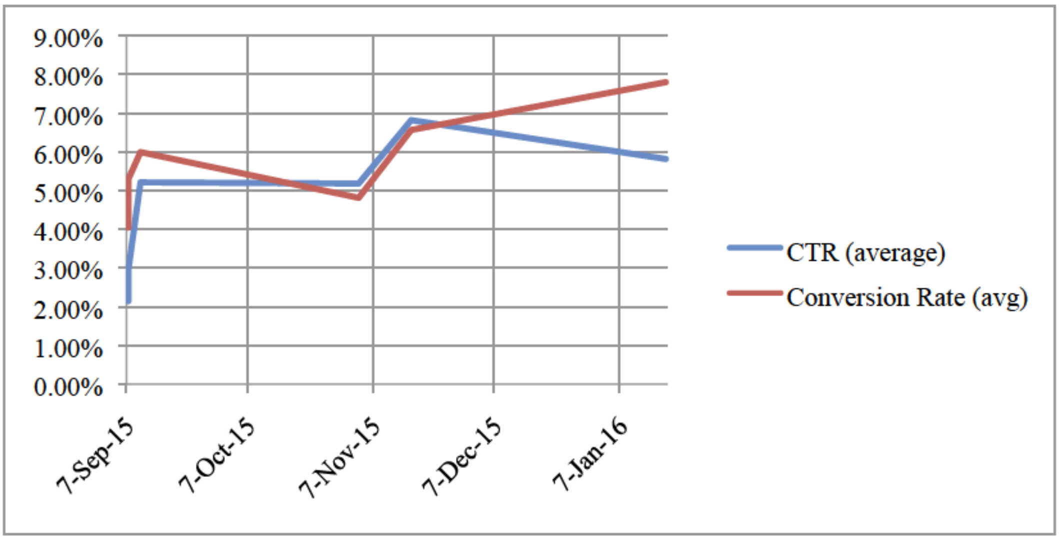

Figure 5 – Evolution of the *CTR* and *CR* of search ads over the campaign period.

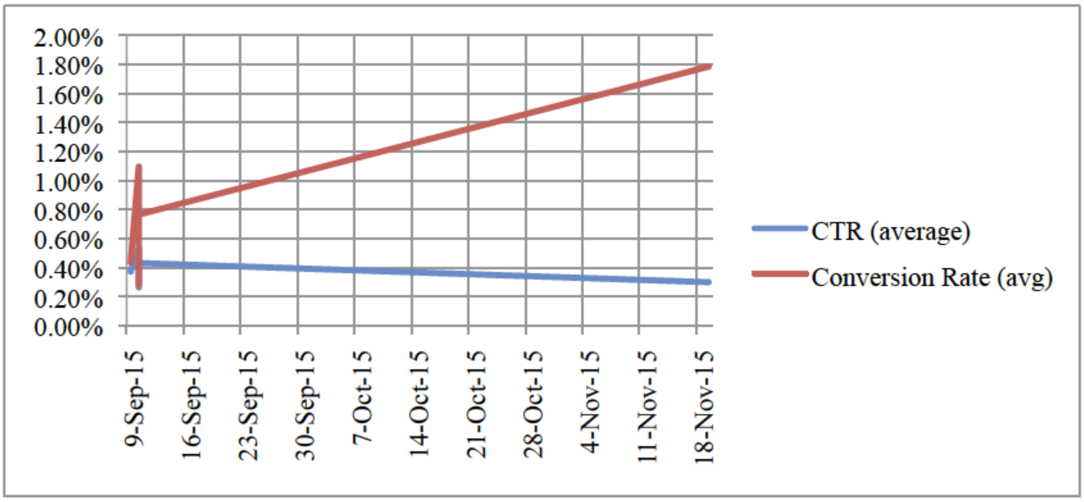

Figure 6 – Evolution of the *CTR* and *CR* of social media ads over the campaign period.

4.7. Summary of the results and discussion

The descriptive statistics and statistical regressions estimated aimed to answer the three research questions presented in Chapter 1, by testing the respective research hypotheses.

RQ1 – What is the relative performance of different ad types in online advertising?

H1.a: *Search ads generate more clicks per impressions than display and social media ads.*

The descriptive statistics that compare different ad types show that search ads have substantially more *clicks* and a higher *CTR*. Indeed, in the global regression model for *clicks*, the dummy variable for search ads is significant and the variable with the highest impact on the performance variable, with a coefficient of 1.4048. Search ads perform better in terms of *clicks* per *impressions*, followed by social media ads (null group) and display ads (coefficient of -0.6978). In conclusion, H1.a is not rejected.

H1.b: *Search ads generate more conversions per clicks than display and social media ads.*

Similarly, the descriptive statistics present clearly more *conversions* and *CR* for search ads, compared to display and social media ads. In the global regression model for *conversions*, the dummy variable for search is significant with a coefficient of 0.9055. Hence, search ads convert more users per *clicks*, followed by social media ads (null group) and display ads (coefficient of -3.2712). In conclusion, H1.b is not rejected.

RQ2 – What is the relative performance of different digital devices of impression in online advertising?

H2.a: *Ads displayed on mobile devices generate more clicks per impressions.*

For all types of ads, the average *CTR* is higher for ads displayed in mobile devices, as depicted in Table 10. In fact, in the global regression model, the variable *device_impression* is statistically significant with a coefficient of 0.4443 (Table 18), meaning that *clicks* are higher for ads seen on a mobile device, ceteris paribus. Furthermore, both in the display regression and the social media regression, the same variable is significant with a positive coefficient (2.8446 and 0.9448, respectively). Hence, the device of impression is even more critical in display ads in terms of *clicks* per *impressions*. In conclusion, H2.a is not rejected.

H2.b: *Ads displayed on computers generate more conversions per clicks.*

Likewise, the results are inverted in terms of *conversions*. Namely, the average *CR* is higher for ads displayed on computers (Table 11). In the global regression model, the variable *device_impression* is statistically significant with a coefficient of -0.699 (Table 18). In conclusion, H2.b is not rejected.

RQ3 – What factors influence the performance of display and social media ads?

H3.a: *The targeting strategy influences the relative performance of display ads.*

In the descriptive statistics of display ads, presented in Table 12, both *clicks* and *CTR* vary across different targeting options. In the display regression, all targeting options are statistically significant in explaining the variable *clicks*. Namely, the best performing targeting option is by topics (coefficient of 0.9136), followed by contextual targeting (null group), interests targeting (coefficient of -0.3193), retargeting (coefficient of -0.5291) and placement targeting (coefficient of -0.8199), as shown in Table 18. Therefore, H3.a is not rejected.

H3.b: *The targeting strategy influences the relative performance of social media ads.*

In the descriptive statistics of social media ads, both *CTR* (Table 14) and *CR* (Table 15) vary considerably across different targeting options. In the social media regression for *clicks* (Table 18), ads targeted by industry performed significantly worse in terms of *clicks* (with a coefficient of -0.4712). However, the same ads with this targeting option performed but significantly better in terms of *conversions* (with a coefficient of 1.2754). Moreover, social media ads designed with the retargeting option yielded significantly more *conversions* (coefficient of 2.0611), ceteris paribus. In conclusion, H3.b is not rejected as some targeting strategies influence the performance of social media ads in terms of *clicks* and *conversions*.

In summary, the results of this dissertation are in line with academic literature. In fact, search ads perform better than display ads (Fulgoni and Mörn, 2009) and both in terms of clicks and in terms of conversions. In addition, if comparing display and social media ads, the latter perform better on average at both levels. Moreover and in conformity with the results from Marin Global's report (2015), users click more on mobile ads, but generally convert on a desktop. The device-switching occurrence is traceable on the social media ads, where 18 users switched from a mobile device to a desktop to complete the software subscription. The opposite never occurred in the sample of social media ads. These significant differences between devices on performance must be taken into account when designing online ads.
Furthermore, these results support the findings by Lambrecht and Tucker (2013) regarding the effectiveness of retargeting in converting undecided users. In social media ads, retargeting was significantly more effective than other targeting options. However, in this type of ads the industry targeting option was also more effective in converting users, although it generated less clicks than other options. Hence, it is also relevant to distinguish between these two steps – clicking and converting – and optimize digital ads accordingly.

CHAPTER 5: CONCLUSIONS AND LIMITATIONS

This chapter presents the main limitations faced by this study and recommendations for future research. It ends with the conclusions of the dissertation based on the research questions that aims to answer.

5.1. Limitations and future research

The conclusions of this dissertation should be analyzed taking into consideration the limitations of the present study. First of all, the object of analysis is an invoicing software from a company that operates in the B2B Portuguese market, but that advertises as a B2C company to individuals who represent a startup. In this study, a conversion is defined as a subscription to the software free trial. In fact, when compared against market benchmarks, the campaigns performed above average. For that reason, the conclusions should be interpreted for this industry and country. Future research should compare different industries and countries and assess whether these results are consistent with other contexts, in order to assess the robustness of these findings. For instance, it would be interesting to compare different ad types for different companies within the B2C market and for different industries, such as the FMCG. Besides, it would be relevant to consider other European countries in the analysis to understand whether these results are sustained for the European market.

Furthermore, the variables considered as performance variables are based on clicks and conversions, disregarding costs. In this specific case, the company aimed to optimize conversions since the customer lifetime value is sufficiently high. In that sense, future research should include cost variables such as CPC and CPA in the comparison between ad types. In this case, a cost-benefit analysis would be the most appropriate approach, for instance by aiming to minimize the CPA. Besides, future studies could compare different statistical approaches to the performance metrics and measure the consistency of these results.

Finally, this research has a time span of five months and there is only a simple analysis on campaign optimization. For this reason, future research could include a wider time frame and analyze panel data, accounting also for differences across time. In this type of analysis, it would be interesting to analyze the campaign optimization evolution and understand if, for instance, it is linear or exponential.

5.2. Conclusions

Online advertising expenditure worldwide is estimated to represent 25% of total advertising expenditure on advertising (Kireyev, Pauwels and Gupta 2014) and in particular, mobile advertising is estimated to surpass desktop ad spending in the US (eMarketer, 2015). In addition, it is essential to understand the dynamics of Social Network Advertising, which has a specific ecosystem of users (Safko & Brake, 2009). However, there is still no clear in-depth analysis of different types of ads, nor extensive research on the effectiveness of advertising on social media (Zhang & Mao, 2016).

This dissertation compares different ad types in terms of campaign performance, assessing the not only the impact of different formats, but also on the influence of different devices of impression. Moreover, it analyzes the factors that influence performance within display and social media ads to have a deeper insight on these ad types.

Firstly, the results of this study show that search ads perform better on average, both in terms of clicks and conversions, followed by social media ads and display ads. A valuable insight is the impact of the device of impression on performance: ads displayed on mobile devices yielded more clicks, whilst ads displayed on computer desktops generated more conversions. In the display ads, this influence is even stronger, with ads displayed on mobile generating significantly more clicks. Besides, in the social media ads ran on Facebook, users often switched devices to convert (from a mobile to a desktop), i.e., to subscribe to the invoicing software free trial. Marketers should consider these findings, especially when managing the digital advertising budget, as they can allocate a higher share for mobile advertising. Besides, they can design specific ads for mobile devices and mobile applications if their primary goal is to generate interest and clicks. However, it is essential to understand that the potential customer faces two important steps: clicking and converting (whether that is a registration, a subscription, a sale or something else). Hence, the landing page to where users are directed once they click on the ad must also be optimized for desktop, as they generally convert more on a desktop computer.

Secondly, the targeting strategy adopted explains some of the variance in performance both in display and social media ads. In display ads, the targeting option that is associated with more clicks per impressions is targeting by topics. In social media ads, those retargeted to the visitors of the company’s website generated significantly more conversions than those targeted by other factors. Therefore, if the advertiser has for an e-commerce website, it is advantageous to retarget the ads on social media to prior visitors of its website. The social media ads targeted by industry generated less clicks, but more conversions per number of clicks, which means that if the advertiser is focused on conversions, it might consider this type of targeting option. In addition, it is important to understand that the display placement on Facebook is relevant as it has a significant impact on clicks and conversions. In that sense, advertisers should focus on displaying their ads on the newsfeed, since both the ads on the right column and on third-party apps perform worse in clicks and conversions.

In conclusion, these results contribute to the existing literature by adding the device of impression as an explaining variable of online campaign performance and by examining in-depth the factors that influence the performance of display and social media ads.

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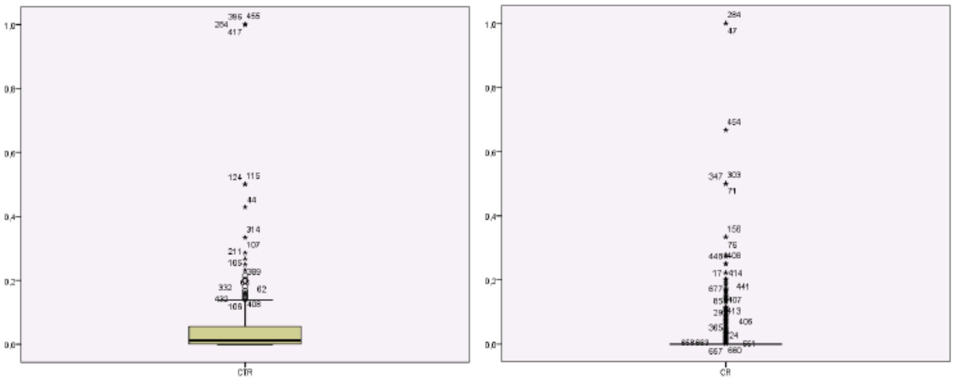
ANNEXES

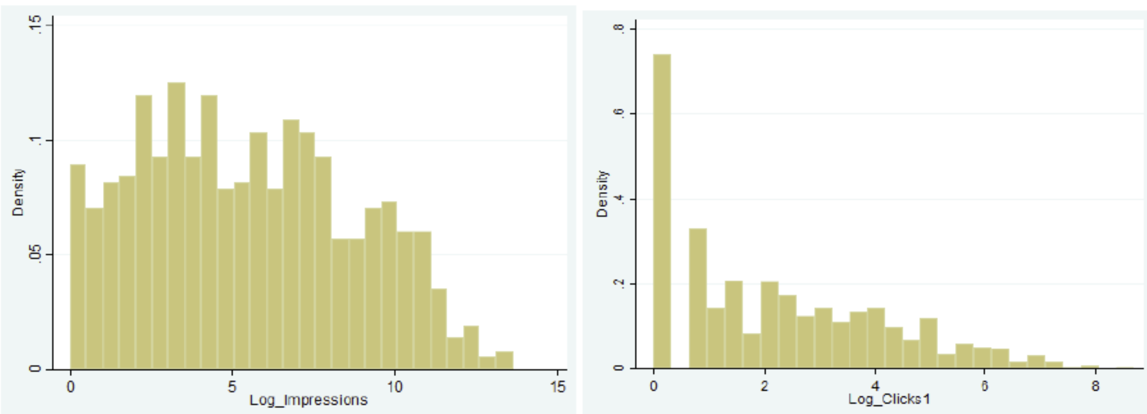
Annex 1 – Box plot of performance variables *CTR* and *CR*.



Annex 2 – Kurtosis and skewness levels of the variables *CTR* and *CR*.

Variable	Kurtosis	Skewness
CTR	54.018	6.789
CR	70.924	7.211
Impressions	101.33	8.97
Clicks	183.9	11.52
Conversions	266	14.78

Annex 3 – Histogram of variables *log_impressions* and *log_clicks1*.



Annex 4 – One-sample t-tests SPSS results.

One-Sample Test

	Test Value = 0.05					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
CTR	2,316	455	,021	,0145614	,002207	,026915

One-Sample Test

	Test Value = 0.0023					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
CTR	5,018	59	,000	,0030967	,001862	,004331

One-Sample Test

	Test Value = 0.00375					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
CTR	6,806	212	,000	,0110885	,007877	,014300

Annex 5 – STATA results of zero-inflated negative binomial, global regression model of the variable *clicks*.

```
Zero-inflated negative binomial regression      Number of obs     =        729
                                                Nonzero obs       =        555
                                                Zero obs          =        174

Inflation model = logit                         LR chi2(4)        =    1200.89
Log likelihood  = -2399.038                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
           Clicks |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------
Clicks            |
  Log_Impressions |   .9131865   .0197961    46.13   0.000     .8743869     .951986
Device_impression |   .4442626   .0985969     4.51   0.000     .2510163     .637509
       Ad_Type_d1 |   1.404776    .109768    12.80   0.000     1.189635    1.619917
       Ad_Type_d2 |  -.6977919   .1308747    -5.33   0.000    -.9543015   -.4412823
            _cons |  -4.076594   .2117731   -19.25   0.000    -4.491662   -3.661527
------------------+-----------------------------------------------------------
inflate           |
             limp |  -.4306728   1.094094    -0.39   0.694    -2.575057    1.713712
Device_impression |    11.2835   723.6105     0.02   0.988    -1406.967    1429.534
       Ad_Type_d1 |   10.64987   937.0816     0.01   0.991    -1825.996    1847.296
       Ad_Type_d2 |  -16.71962    6997677    -0.00   1.000    -1.37e+07    1.37e+07
            _cons |  -25.76396   1183.959    -0.02   0.983    -2346.282    2294.754
------------------+-----------------------------------------------------------
         /lnalpha |  -.4197998   .0682433    -6.15   0.000    -.5535542   -.2860453
------------------+-----------------------------------------------------------
            alpha |   .6571784    .044848                      .5749029    .7512285
------------------------------------------------------------------------------
```

Annex 6 – STATA results of Cragg hurdle, global regression model of the variable *log_CTR*.

```
Cragg hurdle regression                         Number of obs     =        555
                                                LR chi2(3)        =     503.46
                                                Prob > chi2       =     0.0000
Log likelihood = -326.56515                     Pseudo R2         =     0.4353
```

LOG_CTR	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
LOG_CTR						
Device_impression	.3919709	.038024	10.31	0.000	.3174452	.4664966
Ad_Type_d1	.8828712	.0399451	22.10	0.000	.8045802	.9611623
Ad_Type_d2	-.3921987	.0622713	-6.30	0.000	-.5142483	-.2701491
_cons	-2.367645	.0418327	-56.60	0.000	-2.449636	-2.285655
selection_ul						
Device_impression	3.995314	217.711	0.02	0.985	-422.7104	430.7011
Ad_Type_d1	4.049123	247.6094	0.02	0.987	-481.2563	489.3546
Ad_Type_d2	.042366	480.1605	0.00	1.000	-941.0549	941.1397
_cons	-9.792518	329.7097	-0.03	0.976	-656.0116	636.4265
lnsigma						
_cons	-.8694789	.0309529	-28.09	0.000	-.9301455	-.8088124
/sigma	.4191699	.0129745			.3944963	.4453867

Annex 7 - STATA results of zero-inflated negative binomial, global regression model of the variable *clicks* with control variable *log_clicks1*.

```
Zero-inflated negative binomial regression      Number of obs     =        729
                                                Nonzero obs       =        168
                                                Zero obs          =        561

Inflation model = logit                         LR chi2(4)        =     275.01
Log likelihood  = -576.6093                     Prob > chi2       =     0.0000
```

Conversions	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Conversions						
Log_Clicks1	.892576	.0713357	12.51	0.000	.7527606	1.032391
Device_impression	-.6990484	.1929254	-3.62	0.000	-1.077175	-.3209214
Ad_Type_d1	.9054815	.1970047	4.60	0.000	.5193593	1.291604
Ad_Type_d2	-3.271173	.5118102	-6.39	0.000	-4.274303	-2.268044
_cons	-3.000808	.4271864	-7.02	0.000	-3.838078	-2.163538
inflate						
Log_Clicks1	-.9118767	.2219401	-4.11	0.000	-1.346871	-.4768821
Device_impression	1.088245	.607466	1.79	0.073	-.1023668	2.278856
Ad_Type_d1	-2.700196	.61851	-4.37	0.000	-3.912454	-1.487939
Ad_Type_d2	-15.09285	758.7894	-0.02	0.984	-1502.293	1472.107
_cons	3.078752	1.177035	2.62	0.009	.7718055	5.385699
/lnalpha	-.3768604	.175447	-2.15	0.032	-.7207302	-.0329905
alpha	.6860119	.1203587			.4863969	.9675478

Annex 8 - STATA results of zero-inflated negative binomial global regression of variable *clicks* with control variable *log_clicks*.

```
Zero-inflated negative binomial regression      Number of obs     =        555
                                                Nonzero obs       =        168
                                                Zero obs          =        387

Inflation model = logit                         LR chi2(4)        =     284.85
Log likelihood  = -566.3016                     Prob > chi2       =     0.0000
```

Conversions	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Conversions						
Log_Clicks	.9814621	.0494811	19.84	0.000	.884481	1.078443
Device_impression	-.6320802	.1695889	-3.73	0.000	-.9644684	-.299692
Ad_Type_d1	1.144641	.183319	6.24	0.000	.7853418	1.503939
Ad_Type_d2	-1.595326	.589127	-2.71	0.007	-2.749994	-.4406585
_cons	-3.658376	.3072374	-11.91	0.000	-4.26055	-3.056201
inflate						
Log_Clicks	-.0482382	.2344733	-0.21	0.837	-.5077973	.4113209
Device_impression	15.33703	901.5376	0.02	0.986	-1751.644	1782.318
Ad_Type_d1	-14.87949	792.4243	-0.02	0.985	-1568.003	1538.244
Ad_Type_d2	2.448659	1.198438	2.04	0.041	.0997641	4.797553
_cons	-15.21824	901.5395	-0.02	0.987	-1782.203	1751.767
/lnalpha	-.256571	.1579711	-1.62	0.104	-.5661887	.0530467
alpha	.7737001	.1222223			.567685	1.054479

Annex 9 - STATA results of negative binomial, display model regression model of variable *clicks*.

```
Negative binomial regression                    Number of obs     =         60
                                                LR chi2(6)        =     179.10
Dispersion     = mean                           Prob > chi2       =     0.0000
Log likelihood = -270.10036                     Pseudo R2         =     0.2490
```

Clicks	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Log_Impressions	1.660578	.0842299	19.71	0.000	1.49549	1.825665
Device_impression	2.844598	.1259362	22.59	0.000	2.597768	3.091428
Display_targ_d1	-.8199721	.152447	-5.38	0.000	-1.118763	-.5211814
Display_targ_d2	-.319262	.144584	-2.21	0.027	-.6026413	-.0358826
Display_targ_d3	.9136342	.1792407	5.10	0.000	.5623289	1.26494
Display_targ_d4	-.5290696	.1579392	-3.35	0.001	-.8386248	-.2195144
_cons	-13.98918	.8803414	-15.89	0.000	-15.71462	-12.26375
/lnalpha	-2.497222	.2450269			-2.977466	-2.016978
alpha	.0823133	.020169			.0509217	.133057

```
LR test of alpha=0: chibar2(01) = 347.71                Prob >= chibar2 = 0.000
```

Annex 10 - STATA results of negative binomial, social media regression model of variable *clicks*.

```
Negative binomial regression                    Number of obs     =        213
                                                LR chi2(8)        =     460.46
Dispersion     = mean                           Prob > chi2       =     0.0000
Log likelihood = -884.34076                     Pseudo R2         =     0.2066
```

Clicks	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Log_Impressions	.835135	.0283722	29.44	0.000	.7795266	.8907434
Device_impression	.944767	.1695754	5.57	0.000	.6124053	1.277129
Facebook_display_d1	-1.561524	.2002394	-7.80	0.000	-1.953986	-1.169062
Facebook_display_d2	-.1365073	.1600331	-0.85	0.394	-.4501665	.1771519
Facebook_targ_d1	.0268348	.1812999	0.15	0.882	-.3285065	.382176
Facebook_targ_d2	-.4711786	.1951717	-2.41	0.016	-.8537081	-.0886492
Facebook_targ_d3	-.3222889	.1934441	-1.67	0.096	-.7014323	.0568546
Facebook_targ_d4	.3078828	.2064964	1.49	0.136	-.0968428	.7126083
_cons	-3.748844	.3250493	-11.53	0.000	-4.385929	-3.111759
/lnalpha	-.9115485	.1153589			-1.137648	-.6854493
alpha	.4019014	.0463629			.3205722	.5038638

```
LR test of alpha=0: chibar2(01) = 5762.19            Prob >= chibar2 = 0.000
```

Annex 11 - STATA results of zero-inflated negative binomial, social media regression model of variable *clicks*.

```
Zero-inflated negative binomial regression      Number of obs     =        213
                                                Nonzero obs       =        187
                                                Zero obs          =         26

Inflation model = logit                         LR chi2(8)        =     406.00
Log likelihood  = -879.5544                     Prob > chi2       =     0.0000
```

Clicks	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Clicks						
Log_Impressions	.8037025	.0293691	27.37	0.000	.74614	.861265
Device_impression	.9012223	.1638287	5.50	0.000	.5801239	1.222321
Facebook_display_d1	-1.532446	.1915862	-8.00	0.000	-1.907948	-1.156944
Facebook_display_d2	-.1201048	.1541009	-0.78	0.436	-.4221369	.1819274
Facebook_targ_d1	.0016642	.1746301	0.01	0.992	-.3406046	.3439329
Facebook_targ_d2	-.4890308	.1922294	-2.54	0.011	-.8657934	-.1122681
Facebook_targ_d3	-.2757039	.1937444	-1.42	0.155	-.655436	.1040282
Facebook_targ_d4	.3211786	.2025369	1.59	0.113	-.0757865	.7181437
_cons	-3.425263	.3341998	-10.25	0.000	-4.080283	-2.770244
inflate						
Log_Impressions	-.9010274	.2721158	-3.31	0.001	-1.434365	-.3676902
Device_impression	14.94686	4489.278	0.00	0.997	-8783.876	8813.77
Facebook_display_d1	-24.78331	2.74e+09	-0.00	1.000	-5.37e+09	5.37e+09
Facebook_display_d2	-41.68292	2.56e+09	-0.00	1.000	-5.01e+09	5.01e+09
Facebook_targ_d1	-1.806893	3.525112	-0.51	0.608	-8.715985	5.102198
Facebook_targ_d2	-.2971461	2.212499	-0.13	0.893	-4.633565	4.039272
Facebook_targ_d3	1.022699	1.355709	0.75	0.451	-1.634442	3.67984
Facebook_targ_d4	1.317996	1.846909	0.71	0.475	-2.30188	4.937871
_cons	-12.43981	4489.278	-0.00	0.998	-8811.263	8786.384
/lnalpha	-1.001285	.1151351	-8.70	0.000	-1.226945	-.7756241
alpha	.3674071	.0423014			.2931868	.4604164

Annex 12 - STATA results of zero-inflated negative binomial, social media regression model of variable *conversions* with control variable *log_clicks1*.

```
Zero-inflated negative binomial regression      Number of obs     =        213
                                                Nonzero obs       =         48
                                                Zero obs          =        165

Inflation model = logit                         LR chi2(8)        =      76.95
Log likelihood  =  -144.403                     Prob > chi2       =     0.0000
```

Conversions	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Conversions						
Log_Clicks1	.8319155	.1907528	4.36	0.000	.4580469	1.205784
Device_impression	-.4765796	.255735	-1.86	0.062	-.977811	.0246517
Facebook_display_d1	-.9724459	.6846658	-1.42	0.156	-2.314366	.3694744
Facebook_display_d2	-2.210179	.4551534	-4.86	0.000	-3.102263	-1.318094
Facebook_targ_d1	.6026509	.4146357	1.45	0.146	-.2100201	1.415322
Facebook_targ_d2	1.275376	.5159063	2.47	0.013	.2642182	2.286534
Facebook_targ_d3	.452135	.3812672	1.19	0.236	-.2951349	1.199405
Facebook_targ_d4	2.0611	.2656238	7.76	0.000	1.540487	2.581713
_cons	-3.486956	1.12956	-3.09	0.002	-5.700853	-1.273059
inflate						
Log_Clicks1	-.4190166	.8235647	-0.51	0.611	-2.033174	1.195141
Device_impression	44.08172	3672.863	0.01	0.990	-7154.598	7242.762
Facebook_display_d1	42.94762	3672.856	0.01	0.991	-7155.717	7241.612
Facebook_display_d2	-12.9362	1391.285	-0.01	0.993	-2739.804	2713.931
Facebook_targ_d1	27.95366	2649.812	0.01	0.992	-5165.582	5221.489
Facebook_targ_d2	-.907928	2.512921	-0.36	0.718	-5.833163	4.017307
Facebook_targ_d3	-4.28971	15.4792	-0.28	0.782	-34.62839	26.04896
Facebook_targ_d4	-3.955824	17.10887	-0.23	0.817	-37.48859	29.57694
_cons	-41.72761	3672.878	-0.01	0.991	-7240.436	7156.981
/lnalpha	-1.786554	.6378171	-2.80	0.005	-3.036652	-.5364552
alpha	.1675365	.1068577			.0479953	.5848176

Annex 13 - STATA results of zero-inflated negative binomial social media regression of variable *conversions* with control variable *log_clicks*.

```
Zero-inflated negative binomial regression      Number of obs     =        187
                                                Nonzero obs       =         48
                                                Zero obs          =        139

Inflation model = logit                         LR chi2(8)        =      77.60
Log likelihood  = -143.9334                     Prob > chi2       =     0.0000
```

Conversions	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Conversions						
Log_Clicks	.8224667	.0943053	8.72	0.000	.6376316	1.007302
Device_impression	-.4781058	.2411348	-1.98	0.047	-.9507213	-.0054903
Facebook_display_d1	-1.001306	.4795417	-2.09	0.037	-1.94119	-.0614214
Facebook_display_d2	-2.20346	.4440699	-4.96	0.000	-3.073821	-1.333099
Facebook_targ_d1	.603678	.4093578	1.47	0.140	-.1986485	1.406005
Facebook_targ_d2	1.271748	.4338202	2.93	0.003	.4214765	2.12202
Facebook_targ_d3	.4528439	.3532186	1.28	0.200	-.2394518	1.14514
Facebook_targ_d4	2.061679	.258182	7.99	0.000	1.555651	2.567706
_cons	-3.428001	.5944898	-5.77	0.000	-4.593179	-2.262822
inflate						
Log_Clicks	-.3445222	.3494305	-0.99	0.324	-1.029393	.340349
Device_impression	49.23738	7238.222	0.01	0.995	-14137.42	14235.89
Facebook_display_d1	47.90398	7238.222	0.01	0.995	-14138.75	14234.56
Facebook_display_d2	-15.83287	4161.679	-0.00	0.997	-8172.574	8140.908
Facebook_targ_d1	31.87223	5666.885	0.01	0.996	-11075.02	11138.76
Facebook_targ_d2	-.8701954	1.798743	-0.48	0.629	-4.395667	2.655276
Facebook_targ_d3	-14.69676	2681.544	-0.01	0.996	-5270.426	5241.032
Facebook_targ_d4	-14.30089	1049.22	-0.01	0.989	-2070.735	2042.133
_cons	-47.25189	7238.223	-0.01	0.995	-14233.91	14139.4
/lnalpha	-1.791296	.6307227	-2.84	0.005	-3.02749	-.5551019
alpha	.166744	.1051692			.0484371	.5740137