UNIVERSITEIT VAN AMSTERDAM

Master Thesis

Advertising in illegal markets
Evidence from Online Gambling in the Netherlands

Marcel Wieting

University of Amsterdam, M.Sc. Economics

Specialization: Public Policy

Student Nr. 12312037

Supervision by

Dr. Jo Seldeslachts

Amsterdam, August 15, 2019

Abstract

This thesis analyzes how operators in the Dutch market for online gambling advertise online - in light of its illegal status. Although online advertisement may be subject to prosecution, I find that some operators do advertise on a larger scale by advertising on websites with little popularity. Some operators even appear to rely on malicious adware. Using Panel Data Regressions and Vector-Autoregression, I find this strategy to be ineffective in terms of inducing website visits. In contrast to the ineffective display ads, I find strong effects for e-mail and social media.

Keywords: online traffic analysis, advertisement regulation, Vector-Autoregression

Statement of Originality

This document is written by Student Marcel Wieting who declares to take full responsibility for the contents of this document.
I declare that the text and the work presented in this document are original and that no sources other than those mentioned in the text and its references have been used in creating it.
The Faculty of Economics and Business is responsible solely for the supervision of completion of the work, not for the contents.

Acknowledgements

I would like to thank Flóra Felsö (Kansspelautoriteit) and my supervisor Jo Seldeslachts for their valuable and helpful comments that have contributed to the writing of this thesis. This thesis was written in collaboration with the Kansspelautoriteit as part of an internship. Lastly, I would like to thank Similarweb to allow me to use their data for the purpose of this analysis. More about Similarweb can be found on http://www.similarweb.com.

Contents

1 Introduction

The very rapid evolution of the internet and associated technologies has had an immense impact on the advertising business. In 2017, the turnover in online advertising has taken over TV advertisement for the first time[1]. Due to the immaterial nature of the Internet, online advertising is available anywhere, anytime and without physical boundaries. As the number of Internet users increases steeply, so does the amount of user data available to advertisers (Bundeskartellamt, 2017). This enables companies to tailor their online advertising more and more accurately to the user (Rochet and Tirole (2003); Evans (2008)). In this respect, this also poses new challenges for regulators, whose primary objective is to protect consumers.

These are important developments with respect to arguably controversial or addictive industries such as alcohol, tobacco or gambling (Youn et al., 2000). Banning such goods altogether, or at least their promotion, is therefore often discussed. With respect to offline advertisement, there is a broad range of studies that study the effect of a ban on advertising (Nelson and Young, 2001). Findings in these studies are mixed and naturally depend on the nature of the regulated good and the exact regulation in place. Empirical studies on the effects of a ban on online advertising, however, appear to be scarce.

This thesis focuses on a market situation in which the good is illegal and its promotion is prosecuted. In particular, this shall be studied by examining the Dutch market for online gambling. In this market, there are no legal grounds for both the operation and promotion of online gambling services. In spite of the lack of legal framework and de facto unlawfulness, there is a broad range of operators offering their services to Dutch consumers[2]. What is more, some operators even advertise on a larger scale by targeting Dutch consumers. In response, regulators have begun to impose heavy fines on companies that online advertise online gambling in the Netherlands (KSA, 2017).

From a general perspective, advertising is a very important aspect in the online gambling business. Large operators usually spend between 15 and 20 percent of their revenue on online advertising alone. Smaller operators may even increase spending on advertising up to 70 percent for a limited period of time (RegulusPartners, forthcoming). Moreover, some users are registered on more than one platform. This makes advertising in this market a highly competitive matter (RegulusPartners, forthcoming). It is therefore very interesting to study this market, where online gambling is illegal and its promotion is prosecuted. This is done in this thesis from two perspectives.

First, from a *regulative* perspective. This thesis is partly the product of several weeks of collaboration with the Dutch

[1] https://www.vox.com/2017/12/4/16733460/2017-digital-ad-spend-advertising-beat-tv

[2] Only the state monopoly-holder *toto.nl* is allowed to offer online gambling services online. Some regulatory specifics may be found in section 3.

regulators for Gambling (*de Kansspelautoriteit*, henceforth KSA). Analyzing volume and origin of online traffic allows me to examine to what extent gambling operators comply with regulation. Specifically, I am interested in how operators advertise and where - despite the illegal status of online gambling. In this regard, the disaggregated structure of the dataset at hand allows me to study advertisement through a variety of channels. The starting point for this thesis is set through the Dutch Senate's recent decision to legalize online gambling and to introduce licenses for online gambling administered by the KSA. Moreover, there has been a specific request by the Dutch senate to the government to investigate the desirability of a ban on online advertising. The main finding from analyzing data on online traffic is that some operators do advertise online on a larger scale, but far off popular websites. In simpler terms, some operators advertise 'in the shadows'.

Second, this thesis is written from an *academic* perspective. Given the insights from advertisement practices, I am interested in the efficiency of advertisement given the regulative situation. In this context, efficiency is understood as to what extent online advertisement generates website visits. Again, I make use of the disaggregated nature of the data and look at different channels in advertisement. Two findings are substantial. First, I find no long-term effect for the most prevalent advertisement channels. Second, I find differences in effect sizes between channels. The largest effect is found for e-mails, while effects for display ads are substantially smaller. Interestingly, I find differences in effects between firms operating illegally and the single legal state-provider.

Taking both perspectives together, regulation and prosecution have driven advertisement away from popular websites to less visible places. Here, I find advertisement to be ineffective in inducing website visits. The mere presence of online advertisement is hardly preventable. As such, regulators have reached their objective to the extent that advertisement was urged into areas of the internet where it is ineffective.

The remainder of this thesis is structured as follows. In the second part I review relevant literature for this thesis. In the third part, I summarize the current regulative situation with respect to gambling in the Netherlands. This is helpful in order to set subsequent empirical results into perspective. In the fourth and fifth part, I describe the data on traffic and different variables obtained. Sixth, I have a descriptive view on advertising traffic for a chosen sample of domains. I analyze traffic both in terms of volume and origin. Seventh, I lay out the empirical methods used in order to measure the effects of advertisement traffic and dynamics. According results follow in the eight part. The last part summarizes and concludes with respect to the regulatory context.

2 Literature Review

This work contributes to three branches of literature. First, literature that examines the effects of a ban on advertising. Second, literature that measures the effects of online advertisement in various channels. Third, literature that specifically examines the effects of advertisement in gambling.

A first branch of literature is concerned with the effects of a ban on advertisement. Overall, effects are mixed across studies and naturally depend on the good and regulation in question. Moreover, there seems to be no study that analyzes the effect of a ban in online advertising. To begin with, Dhar and Baylis (2011) find that a ban on fast-food advertising targeting children significantly reduces the propensity to consume fast-food for the targeted group. Hollingworth et al. (2006) measure positive effects of a simulated ban on alcohol advertising on adult mortality in the US. In a meta study Lancaster and Lancaster (2003), find limited evidence for effects of partial or complete bans on tobacco advertising as the banned advertisement is found to be ineffective. Goldfarb and Tucker (2011a) find that the presence of online advertisement mediates the effects of regulation of offline advertisement in the market for alcoholic beverages. The authors show a substitution effect between on- and offline advertisement such that the effect of a ban in offline advertisement is partly offset by online advertisement. Nelson and Young (2001) study bans on alcohol advertisement in several OECD countries with respect to a variety of outcomes. Overall, the authors do not find evidence for an effect of alcohol advertisement bans on consumption.

A second branch of literature is concerned with the effect of online advertisement. Hereby, the literature builds upon the evidence of effect heterogeneity in offline media (e.g. television, radio; among others Deighton et al. (1994); D'Souza and Rao (1995)) and expands onto online advertisement. Studies examine effects across different channels (e.g. e-mails vs. display ads), synergies between channels or the appearance and content of ads. Similar to the approach in this thesis, in some studies online traffic data is analyzed.

For display ads, Breuer et al. (2011) analyze long-term effects of different online advertisement channels on sales. The authors find a long-term and positive effect of e-mail advertisement, while the effect of display ads is weaker. Braun and Moe (2013) evaluate long-term effects of display ads given the ads an individual has seen previously. Effects on sales are higher if advertisers vary the advertisement content over time. Equally, Sherman and Deighton (2001) find substantially smaller effects for display ads compared to e-mail advertisement. Using a dynamic Poisson Model and Bayesian estimation techniques, Bruce et al. (2017) find varying effects depending on the type (animated or not), content (price vs. product ads) and size of the ad. Moore et al. (2005) examine the heterogenous effects of location and appearance of display ads (Moore et al., 2005). Kireyev et al. (2016) examine synergies between display ads and traffic from search engines using a vector-autoregressive model. The authors find that display ads increase online searches. Goldfarb and Tucker (2011b) examine the effects of obtrusiveness in advertisement. They find that, independently, both obtrusiveness and a good match between ad and publisher have a positive effect on purchase intent. However, if both are combined, the effect vanishes.

Lastly, a third branch of literature examines the effectiveness of advertisement in gambling exclusively. However, there seems to be no study on the effects of advertisement in online gambling. All studies reviewed are concerned with offline gambling, mostly lotteries[3]. Results in this branch of literature are inconclusive and vary between positive effects and no effects (see JLARC (2012); Munoz (2009)). Stone (2000) and Zhang (2004) find positive effects of advertisement expenditures on US state lottery revenues.

To sum up, this thesis investigates advertisement in illegal markets and adds evidence to market situations where advertisement is under prosecution. Lastly, it closes a gap in the literature on advertisement in the online gambling industry.

[3]An extensive review on the literature on advertisement in gambling can be found in Binde (2014).

3 Background

3.1 Regulating Online Gambling in the Netherlands

To put insights from subsequent sections into perspective, it is necessary to briefly discuss the current regulative stance on online gambling and its advertisement in the Netherlands. Here, the applicable law on games of chance dates back to 1964 and does not serve any legal grounds for the operation of online gambling.[4] The holder of the monopoly license for sports betting *Toto* (a subsidiary of the Dutch national lottery), is allowed to offer online gambling services. Beyond, there is no legal ground for provision of online gambling.

Nonetheless, a considerable illegal market for online gambling exists in the Netherlands. Alone in June 2019, there were more than four million Dutch website visits[5]. This poses a general conflict for regulation; An intangible service such as online gambling is technically accessible from anywhere - yet national regulation is aimed at protecting the well-being of its domestic consumers (Laffey et al., 2015). Accordingly, the KSA has been tightening enforcement against illegal operators that target the Dutch market. Since 2017, the KSA has "prioritized" enforcement against operators, which unlawfully provide their services with respect to certain criteria (KSA, 2017). This includes the follow-

[4]While a reform of the current law has been on the political agenda for more than a decade, the Dutch Senate has in February 2019 agreed on a bill that is bound to legalize online gambling by establishing a license regime (KSA, 2019).

[5]Source: Similarweb

ing non-exhaustive list that was taken from the official press release in May 2017 (KSA, 2017):

- Offering gambling services on a website with a *.nl* domain (e.g. as in *toto.nederlandseloterij.nl*)
- The offer of gambling services on a website that can be consulted in the Dutch language
- Advertisement via radio, television or in printed media aimed at the Dutch market
- The use of domain names containing terms that are typical for the Netherlands in combination with indications of games of chance (such as 'red-white-blue-casino')
- Other characteristics from which the focus on the Netherlands can be deduced (e.g. windmills)
- The use of means of payment that are used exclusively or largely by Dutch people (e.g. iDeal)
- The absence of measures to technically restrict website visits from the Netherlands - so called Geo-Blocking

It has to be stressed that this list is non-exhaustive and that other criteria may be considered (KSA, 2017). On the basis of these criteria, a number of operators have recently been fined by the KSA.
Additionally, major technology companies (e.g. Google's and its Ad Network, Apple and its digital payment service) refrain from allowing their services for usage in markets where the regulative situation is unclear (RegulusPartners, forthcoming). Consequently, this poses a barrier for firms to penetrate the market in mass and encourages firms to use somewhat indirect routes to target their customers (RegulusPartners, forthcoming).[6]
To summarize, online gambling in the Netherlands is illegal. Any open online advertisement may thus be subject to prosecution by the regulators at the KSA. Consequently, gambling operators typically have to take "indirect routes" to promote their products online in this market (RegulusPartners, forthcoming). Operators may try to stay off popular websites where advertisement would attract a lot of attention, or even rely on adware and spam. Given the regulative situation, I examine how and where operators in the Dutch market for online gambling advertise online.

4 Data

I fetched data on website visits for 14 operators that provide online games of chance and sports betting. The selection of operators was based on an internal list provided by the KSA. The sample consists

[6]For instance, studying the terms and conditions to Google's Ad network, it becomes clear that there are some legal boundaries. "Google requires that advertisers comply with all applicable laws and regulations in addition to the Google Ads policies (...)" (see Google (2019a)) and further: "We expect all advertisers to comply with the local laws for any area their ads target, in addition to the standard Google Ads policies." (see Google (2019b))

Table 1: Share of Dutch Visits among Total Visits

	Share of Visits with Dutch IP Address
Unibet.eu	94,74%
toto.nl	97,02%
Oranjecasino.com	84,35%
Krooncasino.com	84,35%
MrGreen.com	32,97%
Betway.com	5,78%
Unibet.com	5,14%
888sport.com	2,80%
Bwin.com	2,50%
WilliamHill.com	2,19%
Betfair.com	1,53%
Interwetten.com	1%
Bet-at-home.com	0,28%
Bet365.com	0,09%

Source: Data from http://www.similarweb.com

of daily traffic data between October 1st, 2017 and April 30, 2019. A list of all domains included in the panel and their share of Dutch visits within total visits can be found in Table 1. When looking at the share of Dutch website visits among total website visits, it becomes clear how significant the Dutch market weighs for some operators.

Data is collected for traffic in the Netherlands for the sampled operators[7]. Specifically, I look at website *visits* at respective domain. Traffic is aggregated to one visit if *one or more* page was clicked and inactivity is *less than 30 minutes*. For the scope of this thesis, the term 'online advertising' covers everything that is measurable by traffic data. As such, any promotions obtained within the gambling portals or apps are unobservable (e.g. retention bonuses for long-term customers).

I obtained daily data on online traffic from Similarweb. Data from Similarweb is aggregated from several sources and simulations[8]. First, it includes a global sample of both desktop and mobile devices that directly record traffic activity. Second, Similarweb receives data from Internet Service providers. Third, Similarweb directly measures traffic on websites and apps. This data is finally calibrated and agglomerated using machine learning techniques. Although this yields not into a direct measurement of the actual amount of traffic, it can be considered a reliable estimate and thus eligible for further analysis. Access to the Similarweb database was kindly provided by the KSA for this project. Also, Similarweb was so kind as to allow their data to be used for the purpose of this thesis. Whenever figures on traffic are presented, I refer to the Similarweb data pool. For the sake of brevity, I will not repeat the data source on any occasion.

5 Variables

The subsequent analysis uses data on website visits that is disaggregated onto the level of channel used to access the website. Table 2 and Figure 1 provide an overview on all channels.[9] Similarweb provides disaggregated data on channel level

[7]More specific: Users with a Dutch IP-address

[8]see https://www.similarweb.com/corp/ourdata/

[9]Similarweb provides an additional channel 'Paid' that measures traffic through paid search terms, e.g. on Google. As this channel is not used by the sampled operators, it will be neglected for the scope of further analysis.

only for Desktop data - and currently not for App usage. However, for this analysis this channelization is key. Thus, I solely rely on desktop traffic data.[10] A short description to each channels is given in the subsequent paragraphs.

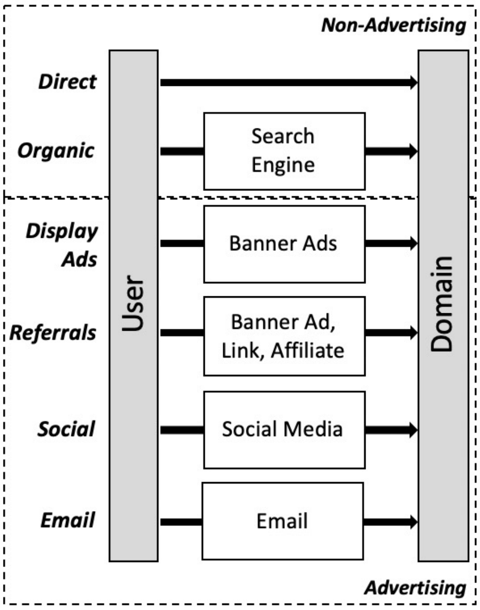

Figure 1: Marketing Channels measured in Similarweb.
Source: Own illustration

Direct

Direct visits through web browser (e.g. Google Chrome, Mozilla Firefox) or through any link from outside the browser (e.g. from a PDF document).[11]

[10]In this market, desktop traffic makes up on average around one third across all operators in the sample within the past 12 months. (Source: Similarweb)

[11]Some words of caution have to be raised about this variable. As confirmed by Similarweb, this variable may be biased by some unknown degree of untraceable adware and spam.

Organic

Website visits through the results from search engines such as Google or Bing.

Display Ads

Website visits where a user has clicked on a display ad (e.g. a banner) that has redirected him or her to the website. Specifically, traffic counts into this channel if an Ad Network is used as intermediary between advertiser and publisher. Advertisers pay to get their ad shown, while publishers are paid to show ads. Ad Networks match advertisers and publishers based on website content of either party such that it maximizes traffic. As such, advertisers are usually billed by the ad network per each click on the ad. The right panel in Figure 2 illustrates this relationship.

E-mail

This channel aggregates traffic that originates from e-mails.[12] A good example for this category, are Newsletters that are sent to clients. This example reveals a major difference to the other channels. Some personal data has to be known in advance in order to reach clients (here the e-mail address). Accordingly, this channel is mainly used to target already existing rather than new clients.

Referrals

This channel aggregates traffic which was redirected from publisher to advertiser.

[12]Specifically, from links in e-mails accessed through web-based applications.

Table 2: List of Variables used in the Analysis

Variable	Description
Non-Advertising Variables	
Direct	Traffic sent from users via: URLs entered directly into a browser, saved bookmarks or any links from outside the browser (e.g. Microsoft Word)
Organic	Traffic sent via the results on search engines (i.e. Google or Bing)
Genuine Interest	Sum of Direct and Organic Traffic without Bounces
Advertising Variables	
Display Ads	Traffic sent from other domains via a known Ad Networks
E-Mail	Traffic sent from web-based mail clients e.g. Newsletters
Referrals	Traffic sent via links from other domains such as affiliates, partners, news coverage, review sites and direct media buying (not through ad networks)
Social Media	Traffic sent from social media
Visit	Aggregated traffic if more than one page clicked and inactivty less than 30 minutes
Bounce Rate	Share of all visits per channel where only one page was clicked

In comparison to the display ads channel, this relation is direct and no Ad Network is used. For referrals, the match between advertiser and publisher is established through bilateral contracts. The content may cover different kinds of advertisement: display ads, redirections from subsidiaries of the operator (e.g. between the Dutch Lottery and *toto.nl*), third parties promoting an operator (e.g. an online blog on gambling), or even traffic that is merely induced by malicious adware. Figure 2 illustrates the difference between the display ads and referrals channel.

Social

This channel aggregates traffic where the publisher is identified to be a recognized social network (e.g. YouTube, Facebook).

Genuine Interest

I further refine previous channelization and distinguish between advertisement (display ads, e-mail, referrals, social) and non-advertisement traffic (Direct and Organic). Furthermore, I obtain data on website visits, where only one page was clicked. In the online marketing language this is often referred to as a *bounce.* Bounce visits can capture website visits that happened accidentally (e.g. by unintentionally clicking a banner ad).

I create a variable for non-advertisement induced traffic that is further reduced by the number of bounces (see equation (1)). Given the data and metrics available, this is the closest proxy in order to capture website visits, which are motivated by genuine interest. In the subsequent analysis, I will refer to this variable as *Genuine Interest.*

$$\begin{aligned} GenuineInterest_{\mathrm{i,t}} = \\ Direct_{\mathrm{i,t}}(1 - BounceRate_{\mathrm{i,t}}) \\ +Organic_{\mathrm{i,t}}(1 - BounceRate_{\mathrm{i,t}}) \end{aligned} \tag{1}$$

In simple terms, I consider a website visit to be induced by some genuine interest if it was either direct or through online search, while the individual clicked more than one page afterwards.

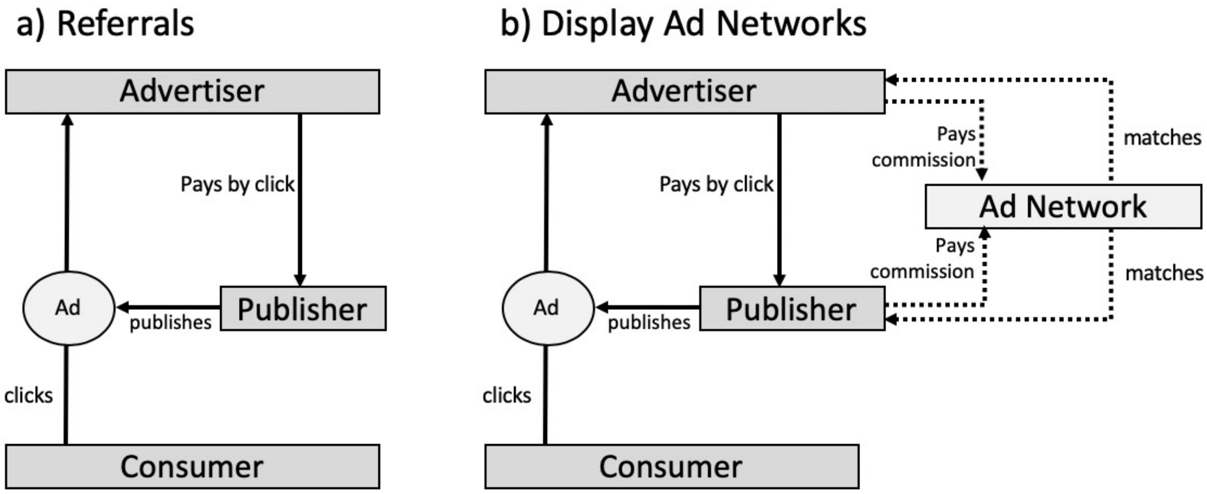

Figure 2: Marketing Channels measured in Similarweb.
Source: Own illustration

6 Descriptive Analysis

In light of the regulative situation outlined in section 3, the purpose of this section is to examine *how* (section 6.1) and *where* (section 6.2) operators advertise online.

6.1 Advertisers

This section provides a descriptive analysis on the volume of traffic and its distribution across channels. An overview of daily average visits per channel and by domain can be found in Table 3 and Figure 3. In terms of average daily visits *unibet.eu* is clearly the leading domain with more than 60.000 visits; outnumbering competitors in direct visits. *mrgreen.com* follows second with roughly a third of the total daily visits. Remaining domains follow behind, while all being on a similar level.
The last row of Table 3, indicates the marketing mix above all domains included. Around 50% of all total daily visits are direct. Display ads and referrals follow second and third with around 20% each. The share of remaining channels is relatively small. It has to be noted that these observations are mainly driven by three operators: *unibet.eu, oranjecasino.com* and *mrgreen.com.* For all remaining competitors, the share of total advertisement traffic is small (see Figure 3). To put the marketing mix in this market into perspective, I compare respective shares with two similar industries: online dating and online marketplaces. This comparison can be found in the appendix in Figure 10. As we see, the shares of both display ads and referrals are substantially higher in the market for online gambling.
Lastly, I am interested in whether advertisement traffic differs across weekdays. In Figure 4, I plot the number of average bounce visits[13] per weekday by advertising channel. Bounce visits are a good indication for unintentional website visits. Presumably, these increase if more advertising is published. We see the same U-shape for social, display ads and referrals.

[13] Visits where only one page was clicked.

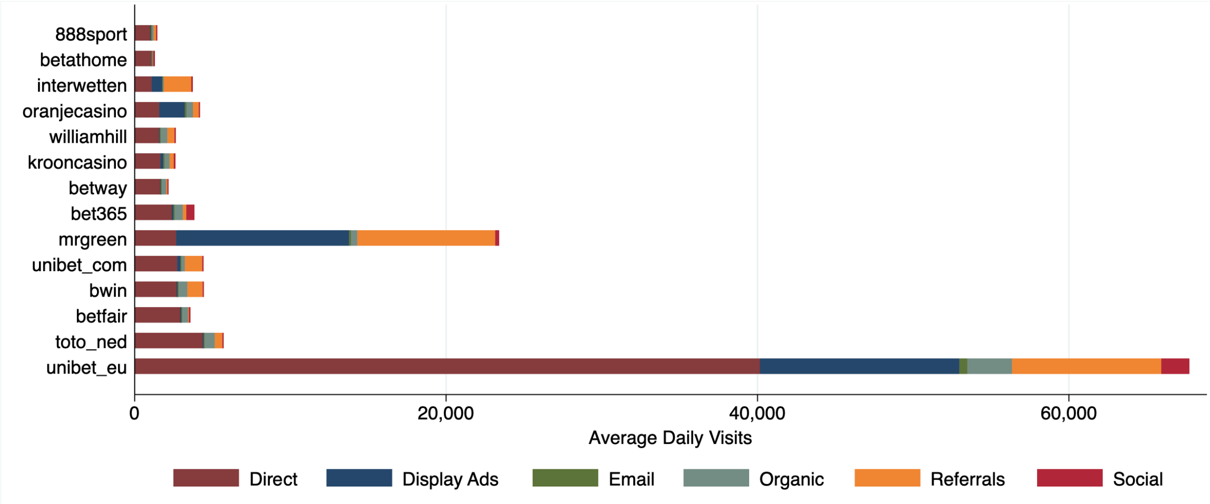

Figure 3: Daily average visits per channel by domain.
Data from http://www.similarweb.com

Nonetheless, it is at this stage unobservable whether this pattern is induced by demand for gambling or supply of advertisement.

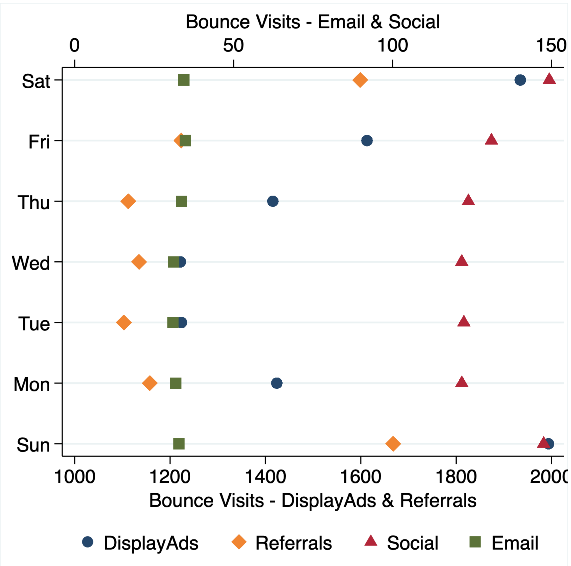

Figure 4: Bounces visits per channel by weekday.
Data from http://www.similarweb.com

Unibet.eu

On August 07, 2018, I observe a sharp drop in display ads and referrals for the domain *unibet.eu* (see Figure 9 in the Appendix). This is of particular importance when considering the immense size of advertisement traffic of this operator relative to competitors. Importantly, for competitors we do not observe a similar development. In this way, it seems that there must have been some strategic corporate decision in ceasing advertising in display ads and referrals by a set date. Finding reasons for such strategic decision is mere speculation and well beyond the scope of this thesis.

Traffic Shares

Figure 5 depicts weekly shares in websites visits. In the left panel, shares across advertisement channels are shown. The right panel shows shares in genuine interest. We recognize the drop for *unibet.eu* on August 07. There are two important lessons to learn from this figure. First, it appears that for *oranjecasino.com* a major ad campaign was launched. Second, there are vir-

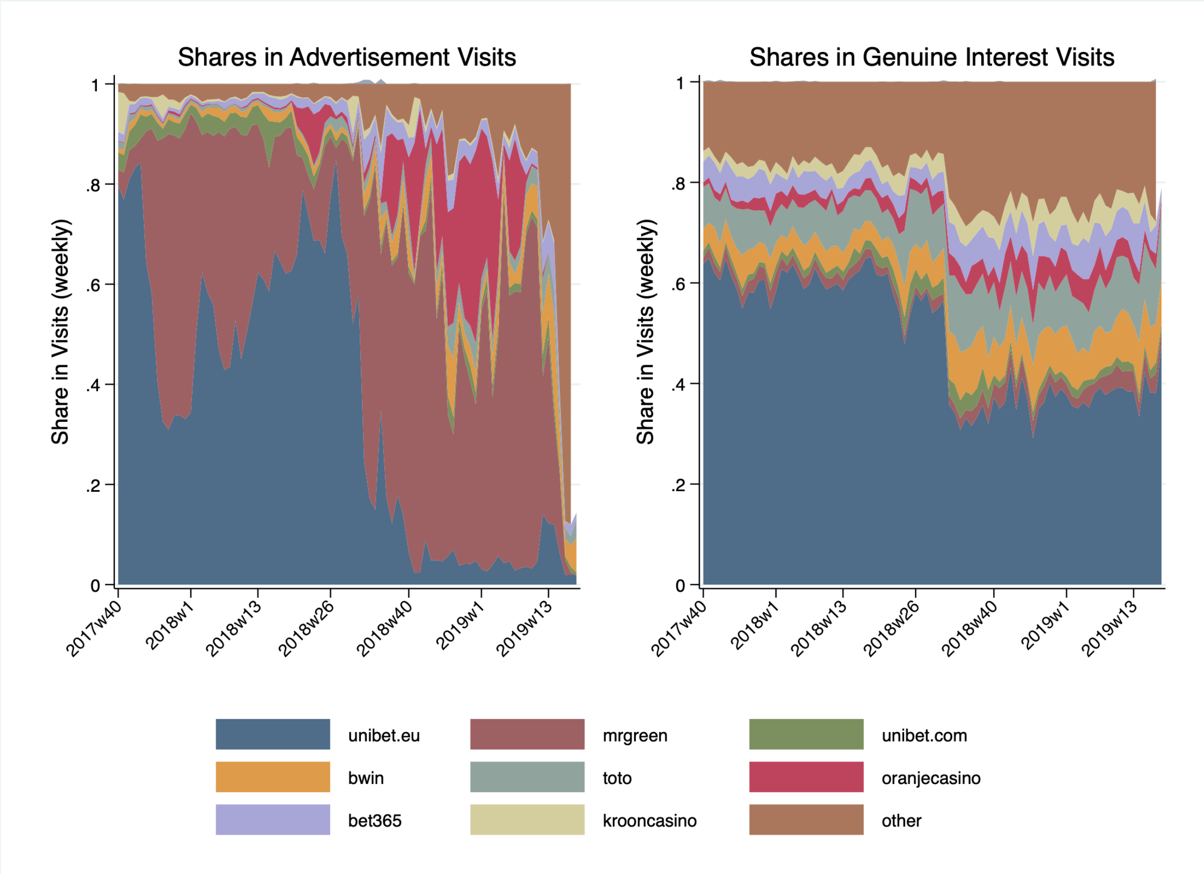

Figure 5: Left: Aggregated shares in visits across advertisement channels -Display Ads, E-mail, Referrals, Social. Right: Shares in non-advertisement (Genuine Interest) visits - Direct and Organic Visits without bounces
Data from http://www.similarweb.com

tually no changes in traffic shares with respect to genuine interest. The sharp drop in *unibet.eu* in the right panel can be explained by the degree of untraceable advertisement in the Direct channel. Presumably, this channel is also subject to the cease in advertisement[14]. If this is taken into account, the stop in advertising of *unibet.eu* has had virtually no effect on shares in genuine interest. In general, it seems that advertisement has no effect on the distribution of traffic shares in genuine interest. This is an important observation for the following sections.

[14]This was confirmed by Similarweb.

6.2 Publishers

As shown in the previous section, albeit the illegal status of online advertising, I find that operators do advertise. For those operators that advertise the most, I now analyze *where* ads are published. This is *mrgreen.com, oranjecasino.com* and *unibet.eu*. The (legal) state license-holder *toto.nl* is further taken as comparison. For all domains, monthly statistics on publishers are obtained through Similarweb[15].

[15]See section 3 and Figure 2 for a helpful distinction between advertiser and publisher.

Display Ads and Referrals

Tables 15 to 22 in the Appendix list the twenty largest publishers in traffic share for *display ads* and *referrals* for each domain.[16] There is one important observation to make with respect to non-license-holders. Note that display ads traffic from illegal providers is in its nature in stark contrast to that of *toto.nl*. The latter advertises on popular Dutch websites (nu.nl, geenstijl.nl, vi.nl). The last column in Tables 15 to 22, gives an indication of the popularity of a certain website. Although the total volume of Ad traffic for *toto.nl* is minuscule in contrast (see Figure 3), it shows that this domain has access to popular websites. Moreover, for illegal operators, publishers seem to not stand in any context to online gambling or related content. What is more, illegal domains seem to make use of malicious adware and spam. This is confirmed by simple online search (see Figure 11 in the appendix). Such publishers are indicated in the tables in bold. Regarding referrals of the state provider *toto.nl*, this is mostly redirected traffic from the parent company, the Dutch state lottery.

In general, these observations are in line with the comments made in section 3. Due to the regulative situation, operators may find indirect routes to their customers and refrain from advertising on popular websites with a broad audience. Instead of using popular Ad Networks, operators rely heavily on bilateral referrals. This is a common observation in low maturity or grey markets where prevalent advertising channels are not available (RegulusPartners, forthcoming).

[16]Sample period is June 2018 to May 2019. The data was fetched on Jun 16, 2019.

Social

In the same fashion as in the previous paragraphs, I study where operators advertise on social media. As depicted in Table 11 in the appendix, this mainly concerns advertisements on the video platform YouTube. In contrast to the little popularity of the publishers detected in the previous section, this channel seems to offer the opportunity to target a broader audience.

To sum up, due to the regulative barriers with respect to advertising, operators seek for indirect ways to find their audience. The threat of enforcement drives online ads to less visible places. Operators advertise on websites with little popularity and even rely on adware or spam. In the next section I examine whether the advertisement strategies outlined above are in fact effective in inducing website visits.

7 Econometric Models

In the previous section, I found that despite the ban on advertisement, operators advertise on websites with very little popularity and some even rely on adware and spam. Given these insights, I am now interested in the efficacy of advertisement in inducing website visits. Given the disaggregated nature of the data, I am also interested in differences between adver-

Table 3: Descriptive Statistics: Daily Average Visits per Domain and Channel

	Direct	Display Ads	E-Mail	Organic	Referrals	Social
888sport.com	1,053.80	3.50	42.86	121.50	167.81	52.00
	406.14	9.92	57.46	85.07	158.15	36.66
bet365.com	2,380.87	102.27	94.12	524.66	218.34	513.36
	1,064.96	75.34	98.00	250.34	192.01	347.09
betathome.com	1,077.32	45.98	6.39	72.65	35.15	17.03
	473.75	42.85	19.87	69.04	56.49	34.02
betfair.com	2,970.90	12.33	72.45	386.86	49.82	87.47
	1,097.61	18.12	82.57	176.74	53.60	64.78
betway.com	1,695.28	2.16	37.00	290.21	82.92	61.66
	602.23	6.28	50.39	158.79	63.85	64.09
bwin.com	2,743.50	7.06	77.76	562.53	988.49	55.08
	1,172.25	17.51	84.36	290.65	1,203.38	36.66
interwetten.com	1,090.73	721.58	11.90	45.86	1,800.52	28.68
	3,813.46	3,936.01	43.81	62.30	5,112.17	119.10
krooncasino.com	1,652.68	186.55	82.21	326.08	308.03	21.67
	1,308.06	796.39	100.04	177.97	1,300.21	24.21
mrgreen.com	2,662.95	11,109.61	116.99	415.98	8,856.33	241.07
	2,111.65	10,838.81	102.19	604.05	9,778.78	165.73
oranjecasino.com	1,582.05	1,646.55	107.38	406.01	384.83	66.18
	1,586.91	2,987.70	109.72	347.00	631.23	63.29
toto.nl	4,409.97	17.92	63.55	655.94	494.37	69.84
	1,970.90	24.63	79.29	514.20	295.89	52.65
unibet.com	2,732.72	241.71	22.15	234.90	1,126.29	49.48
	2,270.81	390.23	35.53	284.12	1,104.94	56.81
unibet.eu	40,154.75	12,811.71	502.73	2,886.03	9,581.64	1,793.81
	28,348.17	13,364.85	343.44	1,607.27	10,017.17	1,292.36
williamhill.com	1,622.60	7.05	34.76	439.76	474.47	40.68
	879.81	15.65	60.14	254.96	893.35	37.88
Total	52.94 %	19.00 %	1.05 %	6.59 %	17.93 %	2.48 %

Note: Mean and standard deviation

tisement channels. I employ two models: First, panel data regressions that exploit fixed-effects to control for unobservables. Second, Vector-Autoregressions that shed more light on longer-term dynamics in advertisement.

7.1 Panel Data Regressions

In need for a suitable model to capture the effect of online advertisement, I refer to the marketing literature. Here, advertisement is often understood as a stock of goodwill $g_{\mathrm{i,t}}$ that can build up over time while being subject to some decay λ. This is called carry-over effect (see among others (Dubé et al., 2005)).

$$g_{\mathrm{i,t}} = \sum_{k=1}^{L} \lambda^{\mathrm{k}} A_{\mathrm{i,t\text{-}k}} \tag{2}$$

As such, keeping advertisement constant, the effect of all past advertisement $A_{\mathrm{t\text{-}k}}$ has an effect on present sales. This effect depreciates over time. This is captured by using lags in both the dependent and independent variables.

In order to find a suitable model specification, I rely on lag selection criteria (e.g. the Akike-Schwarz criterion). The Akike-Schwarz criterion (or AIC) improves with increasing R^2 and penalizes loss in degrees of freedom (Stock and Watson, 2015, p.595). The AIC is shown in equation (3), with p being the chosen lag-length, $SSR(p)$ the sum of squared residuals at lag-length p and T the number of observations per panel. In general, a lower AIC is preferred.

$$AIC(p) = ln\Big(\frac{SSR(p)}{T}\Big) + (p+1)\frac{2}{T} \tag{3}$$

Each panel is estimated separately and the AIC score is calculated.[17] Above all estimations the most common lags were used for the panel specification. An overview with AIC values for different lag length can be found in the appendix in Table 12. Accordingly, I include one lag on the dependent and up to one lag on all independent variables as regressors (in short: ADL (1,1)). This is visualized in Figure 6. As such, genuine interest in period t is affected by genuine interest in $t-1$ and Advertisement in $t-1$. This model will be estimated as a panel, using the domains listed in Table 1. Altogether, this yields the following model

$$\begin{aligned} &GenuineInterest_{\mathrm{i,t}} \\ &= \alpha + \lambda GenuineInterest_{\mathrm{i,t\text{-}1}} \\ &+ \sum_{k}\sum_{t=0}^{1} \beta_{\mathrm{k,t}} Adv^{\mathrm{k}}{}_{\mathrm{i,t}} \\ &+ \sum_{t=0}^{1} \beta_{\mathrm{l,t}} \sum_{l} Comp.Adv^{\mathrm{l}}{}_{\mathrm{i,t}} + v_{\mathrm{i,t}} \end{aligned} \tag{4}$$

while

$$\begin{aligned} k \in \{&DisplayAds, Referrals, \\ &EMail, Social\} \end{aligned} \tag{5}$$

and competitive advertising

$$Comp.Adv^{\mathrm{l}}{}_{\mathrm{i,t}} = \sum_{i\neq j}^{N} Adv^{\mathrm{l}}{}_{\mathrm{i,t}} - Adv_{\mathrm{i,t}} \tag{6}$$

[17] The Stata 15 command *ardl* was used.

and

$$l \in \{DisplayAds, Referrals, Social\} \tag{7}$$

.

For competitive advertising, I exclude e-mail traffic. As laid out previously, traffic from e-mails is presumably targeted at existing clients. As such I assume that e-mail traffic in operator i has no effect on website visits in operator j.

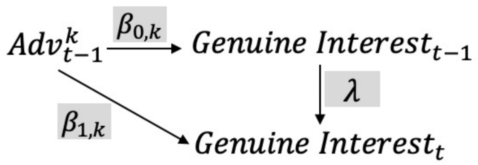

Figure 6: Augmented Distributed Lag Model - Equation 4

Because of the cross-sectional time-series character of the data (where T>>N), we can refrain from more elaborate Dynamic Panel Data techniques and include the lagged dependent variable as an additional regressor.[18]

I carry out several tests in order to investigate the structure of the residuals[19]. First, using a Breusch-Pagan test, I detect cross-sectional dependence in the error terms. The Null-Hypothesis of $Corr(\epsilon_{\mathrm{i,t}}, \epsilon_{\mathrm{j,t}}) = 0$ can be rejected. There is contemporaneous correlation in the residuals between panels.

Second, using a modified Wald-test, I detect panel-specific heteroskedasticity[20]. The Null-Hypothesis of $Var(X) = \sigma_{\mathrm{i}}{}^{2} = \sigma^{2}$ can be rejected.

Lastly, I detect serial correlation of higher order in the residuals. I use the Cumby-Huizinga Test for serial correlation. This test has the advantage of not relying on Homoskedasticity (Baum, 2013). As I have detected heteroskedasticity previously, I rely on this test-statistic rather than e.g. a Breusch-Pagan test. The Null-Hypothesis for no serial-correlation can be rejected for several lags. All mentioned test-statistics can be found in Table 4.

Table 4: Test-Statistics

	Test-Statistic	p-Value
Serial Correlation		
Lag Order 1	354.95	0.00
Lag Order 2	123.74	0.00
Lag Order 3	76.06	0.00
Lag Order 4	54.77	0.00
Groupwise Heteroskedasticity	3,729.31	0.00
Cross-sectional independence	1,034.69	0.00

Note: χ^2 and Wald-Test Statistic

Taking the features of the residuals into account, I decide to use Driscoll-Kraay standard errors.[21] This class of standard errors is especially suitable for cross-sectional time-series with T>>N character and takes all three features into account (Driscoll and Kraay, 1998).

A major obstacle in this exercise is that advertising itself is unobservable. Only

[18] The Nickell bias from including lagged dependent variables without further correcting for the induced endogeneity onto the model is $\frac{1}{7}T$ and thus reaches infinity where T becomes large (Greene, 2000, p.536).

[19] *xttest2, xttest3* and *actest* respectively.

[20] see Greene (2000) for further details.

[21] See Driscoll and Kraay (1998) and Hoechle (2007) for econometric details. I use the *xtscc* command in Stata 15.

data on advertisement traffic can be obtained. It is unknown whether changes in advertising traffic are caused by changes in supply of advertising or changes in demand for gambling. Either way, it is a reasonable assumption that both are event-driven; for instance through Football World Cup 2018 or weekly peaks in traffic on weekends. Demand for gambling increases in light of such events and equally operators may increase advertisement.

By including day-fixed effects, I can alleviate this concern under the assumption that shocks to advertisement supply are mostly subject to upcoming events. Either rigorously by day-fixed effects, or by including weekday-fixed effects to account for the weekly peaks in advertisement over the weekend (see Figure 4). Additionally, a dummy for the Football World Cup 2018 accounts for the overall traffic peak across all domains. Due to the nature of how operators advertise (on unpopular websites unrelated to gambling), an increase in demand for gambling will not have effects on numbers in advertisement traffic. As such, I can focus on accounting for supply-shocks in advertisement.

Additionally, domain-fixed effects are added to the specification. These control for brand perception or endorsement beyond online advertisement. They also serve a second purpose. A potential driver for strategic advertisement decisions are costs of advertising. In display advertisement and social media, the price for advertisement is mainly determined by the popularity of a domain. An online ad is usually billed per each click it generates (Quote). However, costs of advertising are unobservable in this study. Assuming that costs do not vary over time but are different between domains, domain-fixed effects can partly correct for this endogeneity-causing variation.

I further show by Cross-Validation that results including *unibet.eu* are inherently different than without. I estimate equation 4 leaving out each domain once and compare in-sample Root Mean Square Errors (RMSE). We see that leaving out *unibet.eu* yields a substantially lower RMSE compared to the rest. This motivates the decision to leave *unibet.eu* out of the sample and study this domain separately.

Lastly, the distribution of the data also allows to use a non-linear model. The data allows for the usage of a Poisson distribution as it has the nature of count data; observations are discrete and greater or equal than zero, while a larger mass of the distribution lies within the lowest percentiles (Greene, 2000, p.842ff.). Similar as in Bruce et al. (2017), I estimate equation (4) using a Poisson distribution. This is done to see whether the choice of distribution inherently affects the results. Compared to OLS, results from a Poisson model are in semi-elasticities and thus lose ease of interpretation. Given that both distributions yield similar results, OLS is the preferred model. The purpose of this thesis is not to exactly pin down the effect size of each channel. Rather, it is to get a general idea about the order of the effects between channels.

Table 5: Cross Validation - RMSE by leaving out each domain once

Left-out Domain	RMSE
888sport	1,920.64
bet365	1,817.83
betathome	1,921.99
betfair	1,900.19
betway	1,918.30
bwin	1,907.72
interwetten	1,903.90
krooncasino	1,913.11
mrgreen	1,631.41
oranjecasino	1,913.01
toto.nl	1,880.73
unibet.com	1,919.73
unibet.eu	**824.04**
williamhill	1,916.11
None	1,854.89

7.2 Vector-Autoregressive Model

Building up on the previous section, I am interested in longer-term dynamics of a shock in advertisement. Two questions are addressed here. First, is there a long-run effect of advertisement traffic. Second, to what extent do advertisement channels differ in efficacy and dynamics. As such, so called persistence modeling is employed (see among others Dekimpe and Hanssens (2004); Kireyev et al. (2016)). Here, a Vector-Autoregressive model (VAR-model) is employed to measure the impact of a shock in advertisement over time. I rely on Lütkepohl (2005) for the notation and methodology in VAR-models.

In a VAR-model, all variables included are treated as endogenous. As such, dynamics are allowed to go in either direction. Advertisement traffic may influence traffic in genuine interest as well as the other way around. All variables are allowed to influence each other simultaneously (Kireyev et al., 2016). This is sensible, as we can expect firms to change advertisement as a reaction to the number of direct visitors.

In this part of the analysis, I focus on those operators that have engaged in advertising on a larger scale - *unibet.eu, mrgreen.com* and *oranjecasino.com*. Furthermore, I am interested if there is any contrast to the state-operator, *toto.nl*.

This approach follows three steps. First, lag selection, unit root and serial correlation tests are conducted in order to find an adequate model specification. Second, the prior defined system of equations is estimated using OLS. Third, impulse response functions are calculated in order to trace the effect of a shock in advertisement over time. The chosen estimation window allows to investigate effects over several weeks.

(1) Lag selection, unit root and serial correlation

In order for the VAR-model to yield reliable results, all included time-series need to be stationary[22](Lütkepohl, 2005).

I use an augmented Dickey-Fuller test[23] to analyze non-stationarity. This tests fits

[22] "A process x_t: t = 1,2,...m is stationary if for every collection of time indices $1<t_1<t_2<...<t_m$, the joint distribution of (x_{t1}, x_{t2},...x_{tm}) is the same as the joint distribution of (x_{t1h}, x_{t2h},...,x_{tmh}) for all integers $h > 1$" (Wooldridge, 2009, p.378ff.)

[23] The Stata 15 command *dfuller* was used accordingly.

the following model

$$\Delta y_t = \beta y_{t-1} + \gamma_1 \Delta y_{t-1} + ... + \gamma_p \Delta y_{t-p} + \epsilon_t \tag{8}$$

We test against the null hypothesis of non-stationarity

$$H_0 : \beta = 0 \tag{9}$$

This is done for each variable and each time-series separately. As we can see in Table 6, I find stationarity throughout all specifications. This is already obvious from looking at respective series in Figure 7, where no evolving trends are visible. Hence, I can proceed with regular VAR-techniques and may refrain from more elaborate Vector-Error-Correction models that take into account non-stationarity. In order to determine the adequate lag-order of the VAR-model, two metrics are taken into account. First, lag selection criteria such as the AIC. Second, tests for serial correlation. The number of included lags needs to be high enough in order to model the underlying serial correlation in the system of equations. Again, a lower AIC value is preferred. At lag length $L = 10$ and beyond, serial correlation across all operators vanishes. As the AIC increases with lag length, L is set $L = 10$. Respective test statistics can be found in Table 13 in the appendix.

(2) Model Estimation

A vector-autoregressive model of the following structure is estimated for each operator named above

$$\mathbf{y_t} = \phi + \sum_{i}^{L} A_{\mathrm{i}} \mathbf{y}_{\text{t-i}} + \epsilon_{\mathrm{t}} \tag{10}$$

with $\mathbf{y_t}$ being a 5×1 vector of the endogenous variables

$$\mathbf{y_t} = \begin{pmatrix} GenuineInterest_{\mathrm{t}} \\ DisplayAds_{\mathrm{t}} \\ E-Mail_{\mathrm{t}} \\ Referrals_{\mathrm{t}} \\ Social_{\mathrm{t}} \end{pmatrix} \tag{11}$$

and $A_1...A_{\mathrm{p}}$ 5×5 coefficient matrices such that

$$\mathbf{A_i} = \begin{pmatrix} \beta_{11,\mathrm{i}} & \beta_{12,\mathrm{i}} & \beta_{13,\mathrm{i}} & \beta_{14,\mathrm{i}} \\ \beta_{21,\mathrm{i}} & \beta_{22,\mathrm{i}} & \beta_{23,\mathrm{i}} & \beta_{24,\mathrm{i}} \\ \beta_{31,\mathrm{i}} & \beta_{32,\mathrm{i}} & \beta_{33,\mathrm{i}} & \beta_{34,\mathrm{i}} \\ \beta_{41,\mathrm{i}} & \beta_{42,\mathrm{i}} & \beta_{43,\mathrm{i}} & \beta_{44,\mathrm{i}} \\ \beta_{51,\mathrm{i}} & \beta_{52,\mathrm{i}} & \beta_{53,\mathrm{i}} & \beta_{54,\mathrm{i}} \end{pmatrix} \tag{12}$$

ϕ is a 5×1 vector with intercepts

$$\phi = \begin{pmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \\ \beta_{40} \\ \beta_{50} \end{pmatrix} \tag{13}$$

and ϵ_{t} a 5×1 vector of disturbance terms.

$$\epsilon_{\mathbf{t}} = \begin{pmatrix} \epsilon_{\text{Genuine Interest, t}} \\ \epsilon_{\text{Display Ads, t}} \\ \epsilon_{\text{E-Mail, t}} \\ \epsilon_{\text{Referrals, t}} \\ \epsilon_{\text{Social, t}} \end{pmatrix} \tag{14}$$

Parameter L defines the lag-order of the model. Following Lütkepohl (2005), this system of equations can be estimated using OLS.

Table 6: Augmented Dickey-Fuller test for Unit root

	Genuine Interest	DisplayAds	Email	Referrals	Social
mrgreen.com	0.000	0.000	0.000	0.000	0.000
oranjecasino.com	0.000	0.000	0.000	0.000	0.000
toto.nl	0.000	0.000	0.000	0.000	0.000
unibet.eu	0.000	0.000	0.000	0.000	0.000

Note: p-Values against H_0: Unit root

VAR-granger causality tests are conducted in order to examine the explanatory power of the variables with respect to each other. A variable X is said to granger cause a variable Y if, all $Y_{\text{t}}...Y_{\text{t-p}}$ held constant, $X_{\text{t}}...X_{\text{t-p}}$ can jointly predict Y (Lütkepohl, 2005). In order to examine this, F-tests of joint significance on all lags of X are conducted. Specifically, I test the null Hypothesis

$$H_0 : X_{\text{t-1}} = X_{\text{t-2}} = ... = X_{\text{t-q}} = 0 \quad (15)$$

.

I conduct such tests for each variable per equation and each domain. A p-value below the chosen level of significance shows that a variable X and all its included lags granger causes Y. In other words, X today and all past observations have a joint effect on Y today.

(3) Impulse Response Analysis

Lastly, I am interested in the effect of an impulse to advertisement on genuine interest. This elaborates on the idea of Granger causality, examining whether one variable causes another. As all variables mutually affect each other, looking at single coefficients is not really informative with respect to longer-run effects. As such, impulse response functions are calculated for each of the chosen domains. This measures the impact of a one unit increase in one variable on another variable within the estiamtion window. For this task the Stata 15 impulse response function package *irf* is used. Again, I follow Lütkepohl (2005) for methodology in VAR-analysis.[24]

8 Results

8.1 Panel Data Regressions

In order to get a general idea on the size and directions of the effects, I study the correlation matrix between all advertisement, competitors' advertisement[25] and genuine interest. Results are presented in Table 7. There are two things to note with respect to Table 7.

First, the correlation between own advertisement traffic and competitive advertisement traffic is negative for all channels but e-mail. This is presumably picking

[24]Leaving equation (10) as it is, I assume that a shock to one variable may not be accompanied by a shock to another variable in the same period. Further orthogonalization of the shocks by imposing some structure on the coefficient matrix (Structural VAR-model) is beyond the scope of this thesis.

[25]Competitive traffic is estimated according to equation (6).

Table 7: Partial Correlations - Own versus competitive Advertising

	Genuine Interest	Display Ads	E-Mail	Referrals	Social	Comp. Adv. Traffic
Genuine Interest	**1.00**	-0.12	0.15	-0.05	0.08	0.10
DisplayAds	-0.12	**1.00**	0.15	0.73	0.23	-0.12
Email	0.15	0.15	**1.00**	0.19	0.26	0.11
Referrals	-0.05	0.73	0.19	**1.00**	0.27	-0.08
Social	0.08	0.23	0.26	0.27	**1.00**	-0.01
Comp. Adv. Traffic	0.10	-0.12	0.11	-0.08	-0.01	**1.00**

up a certain degree of competition in traffic between operators. An increase in advertisement traffic in one operator leads to a decrease in ad traffic for competitors'. In contrast, the correlation between e-mail and genuine interest is positive. As laid out previously, e-mail advertisement is fundamentally different compared to the other marketing channels. In order to send mass e-mails, at least the e-mail address of the customer has to be known. As such, it is likely to a large extent exclusively used with existing customers and thus less subject to competition.

Second, the correlation between advertisement and genuine interest is found to be negative for referrals and display ads and positive for social and e-mail. A negative correlation is in this context hardly interpretable. Nonetheless, this already hints at different effect sizes between channels.

Table 8 presents estimation results from equation (4). As discussed in section 7.1, both time- and domain-fixed effects are used in order to grasp some degree of unobservable variation in the data. Columns (1) to (3) include day-fixed effects. In column (4) weekday-fixed effects and a dummy for the Football World Cup 2018 are are used for robustness. This appears to have little impact on the results. Domain-fixed effects are added in all columns from column (2) onwards. In the discussion of the results, I focus on column (3).

In general, visits through e-mail, referrals and social have a positive effect on genuine interest in the website. The magnitude differs in between channels. Hereby, e-mail has the highest coefficient. This is in line with findings from the reviewed literature (Breuer et al. (2011); Sherman and Deighton (2001)). A daily increase of 1 visit through e-mail has an immediate effect of 2.1 in genuine interest. An increase of 1 visit through social media, has an effect of 1.4 on genuine interest. The effect of referrals is positive but smaller. The effect of visits in display ads is found to be negative. This is hard to interpret. Potentially, it is either a form of model misspecification or measurement error, as we would expect this coefficient at least to at least be weakly positive. Lagged advertising for e-mail, referrals and social has a negative coefficient. Such result is, again, difficult to interpret. Potentially, this is due to the time-fixed effects not picking up all variation in demand. Furthermore, $fifty$ percent of yesterday's genuine interest translate into present genuine interest.

Table 8: (OLS) Effect of Advertising Traffic on Genuine Interest Traffic

	(1)	(2)	(3)	(4)
	β (se)	β (se)	β (se)	β (se)
L.Genuine Interest	0.805***	0.543***	0.543***	0.549***
	(0.014)	(0.036)	(0.036)	(0.041)
Display Ads	−0.011**	−0.002	−0.003	−0.011**
	(0.005)	(0.005)	(0.005)	(0.005)
L.Display Ads	0.002	0.008*	0.008*	0.014***
	(0.005)	(0.005)	(0.005)	(0.005)
E-Mail	2.297***	2.089***	2.089***	2.090***
	(0.299)	(0.298)	(0.298)	(0.338)
L.E-Mail	−1.738***	−1.413***	−1.413***	−1.356***
	(0.247)	(0.205)	(0.205)	(0.233)
Referrals	0.049***	0.050***	0.050***	0.057***
	(0.010)	(0.011)	(0.011)	(0.011)
L.Referrals	−0.048***	−0.037***	−0.037***	−0.044***
	(0.010)	(0.008)	(0.008)	(0.008)
Social	1.605***	1.379***	1.379***	1.551***
	(0.187)	(0.170)	(0.170)	(0.202)
L.Social	−1.487***	−1.277***	−1.277***	−1.238***
	(0.173)	(0.164)	(0.164)	(0.195)
Comp. Adv. Traffic			−0.000	−0.000
			(0.000)	(0.000)
WM=1				615.392***
				(73.517)
Constant	986.226***	987.014***	609.468***	478.945***
	(24.502)	(42.219)	(46.748)	(71.870)
N	6844	6844	6844	4682
Time FE	1	1	1	0
Domain FE	0	1	1	1
Weekday FE + WorldCup	0	0	0	1

Note: Dependent Variable: Genuine Interest Traffic. All equations include day-fixed effects

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Some words of caution with respect to the size of the effects have to be raised. Some people may only notice an ad and not click on it - but yet directly visit the website afterwards. This may lead to an *underestimation* in the effect of advertisement.
Using a Poisson distribution for robustness, I find similar results in sign and order of the effect sizes. According regression results and comments can be found in the appendix in Table 14. Compared to OLS, results are here in terms of semi-elasticities and thus lose their ease of interpretation. Given that signs and order of the effects are similar to OLS, I refrain from further elaborating on these results.

8.2 Vector-Autoregressive Model

In this section, I focus on those operators that have used advertisement on a larger scale: *unibet.eu*, *oranjecasino.com* and *mrgreen.com*. I compare with the state-provider *toto.nl*. This domain is officially allowed to advertise and may use other means in order to promote its services. Figure 7 shows advertisement traffic for respective domains over time.

Granger Causality Tests

First, I aim at detecting causalities in the estimated model. Granger causality tests are carried out as laid out in section 5.2. Here, I only present results with the direction of the causality going from advertising (display ads, e-mail, referrals, social) onto genuine interest. Test results including all variables for *unibet.eu*, *toto.nl* and *oranjecasino.com* show overall significant results.[26] For these domains, all advertisement variables seem to jointly cause genuine interest. For *mrgreen.com*, I do not find such evidence - neither for all variables jointly, nor separately. For *unibet.eu*, visits through display ads, referrals and social are found to cause genuine interest. For *oranjecasino.com*, e-mail and for *toto.nl*, display ads, e-mail and social are found to cause genuine interest.

Impulse Response Functions

Figure 8 presents impulse response functions after a shock of one unit in the variable mentioned in the title. The response variable is genuine interest in all specifications.[27] In the previous paragraph, I did not find evidence for effects of advertisement for *mrgreen.com*. Hence, this domain will be neglected in this section. In the discussion of the results, I only focus on panels where causality could prior be established (see Table 9).
For instance, the first panel presents the effect of a one unit shock in display ads on genuine interest for the domain *oranjecasino.com*. The second panel shows a one unit shock in referrals for the same domain. The shaded area around the response function indicate 99% confidence intervals. Results from causality tests in Table 9 are indicated in brackets.
First, for *oranjecasino.com*, e-mails appear to not have an effect on genuine inter-

[26] The Stata 15 *vargranger* command was used.
[27] The Stata 15 command *var* in combination with the *irf* package was used.

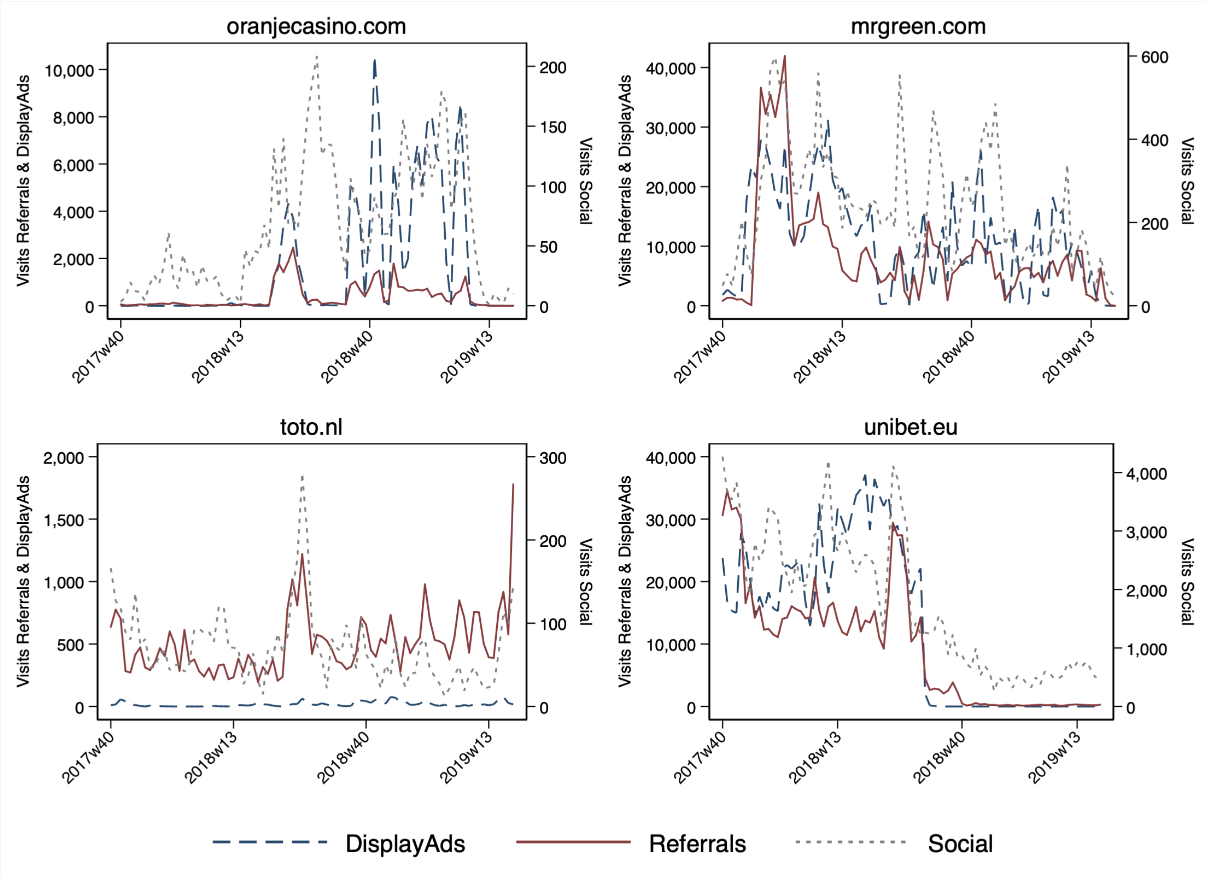

Figure 7: Advertisement traffic over time for chosen domains

est. For *toto.nl* display ads appear to have a temporarily positive effect that washes out after five days. The response function for e-mail is similar, with a positive effect that vanishes after five days. Social media appears to have a positive effect that slowly washes out towards the end of the estimation window. Lastly, display ads and referrals seem to not have an effect on *unibet.eu*. Social media has a temporarily positive effect that vanishes shortly after. To conclude, the magnitudes in these observations are in line with the results from the panel data regressions in Table 8: Effects of social are larger and positive, effects in display ads and referrals are weaker. Interestingly, I do not find effects in display ads and referrals for illegal operators *oranjecasino.com* and *unibet.eu*. Their way of advertisement on unpopular websites and partially relying on adware seems to be ineffective. For the state-provider *toto.nl*, I find at least temporarily positive effects. Social media has (short-term) positive effects for both illegal and legal operators. As I have shown, all operators advertise mainly via YouTube and have here at least technically access to a broader audience.

The null effect of referrals in *toto.nl* can be explained by the nature of the traffic to this domain. Looking at Table 22 we see that referrals here are mostly redirections from the state lottery provider (more than 90% of the traffic). Therefore, traffic in this channel and for this operator cannot

Table 9: VAR-Granger Test, p-Values

	DisplayAds	E-Mail	Referrals	Social	All
mrgreen.com	0.48	0.15	0.20	0.78	0.14
oranjecasino.com	0.17	0.01***	0.17	0.24	0.01***
unibet.eu	0.10*	0.18	0.02**	0.00***	0.00***
toto.nl	0.08*	0.09*	0.15	0.06*	0.00***

Note: p-Values of F-tests against the hypothesis that each of the variables in the columns and all lags do not cause genuine interest. The last column tests against the hypothesis that, all variables jointly, do not cause genuine interest. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

be considered advertising.

Nonetheless, I would have expected to see an even starker contrast in the effect of display ads between *toto.nl* and illegal operators. A possible explanation is that *toto.nl* and its competitors are difficult to compare. *toto.nl* is bound in its scope and volume of advertisement by national law, while competitors are not. Furthermore, being a domestic license-sholder, toto is subject to taxation in the Netherlands, which finally has an effect on the competitiveness of the odds.[28]

9 Summary and Concluding Remarks

In this thesis I have analyzed online advertisement in the Dutch market for online gambling. In this market, the provision of online gambling is illegal for all operators except for the holder of the monopoly license. Advertisement from operators without a license may be subject to prosecution and fines by the regulators. In that respect, I have investigated how operators adapt their advertisement to less obvious places in order to reach their customers.

Using daily data on online traffic, I find that despite the fact that it is risky, operators do advertise. In light of the regulative situation however, operators advertise on unpopular websites and disproportionately rely on bilateral affiliate marketing. Some even rely on spam and adware. However, there is a distinction to make between illegal operators and the single legal state-operator, *toto.nl* The latter is not restricted in advertisement and thus able to explicitly target Dutch clients. Given the insights on how and where operators advertise, I analyze efficiencies in inducing website visits through advertisement.

In general, I find differences in the effects between marketing channels. Effects through e-mail and social media seem to be higher than through display ads and referrals. Moreover, I find no long-run effect of advertising in this market where operators advertise in the shadows. Moreover, for those operators found to run malicious adware (*unibet.eu* and *oranjecasino.com*), I find no effects; neither short- nor long-run. Taking this together, regulation has been successful to the extent that it drove

[28] In section 2 I have laid out the importance of heavy players, who do take odds into account in their preferences for a platform.

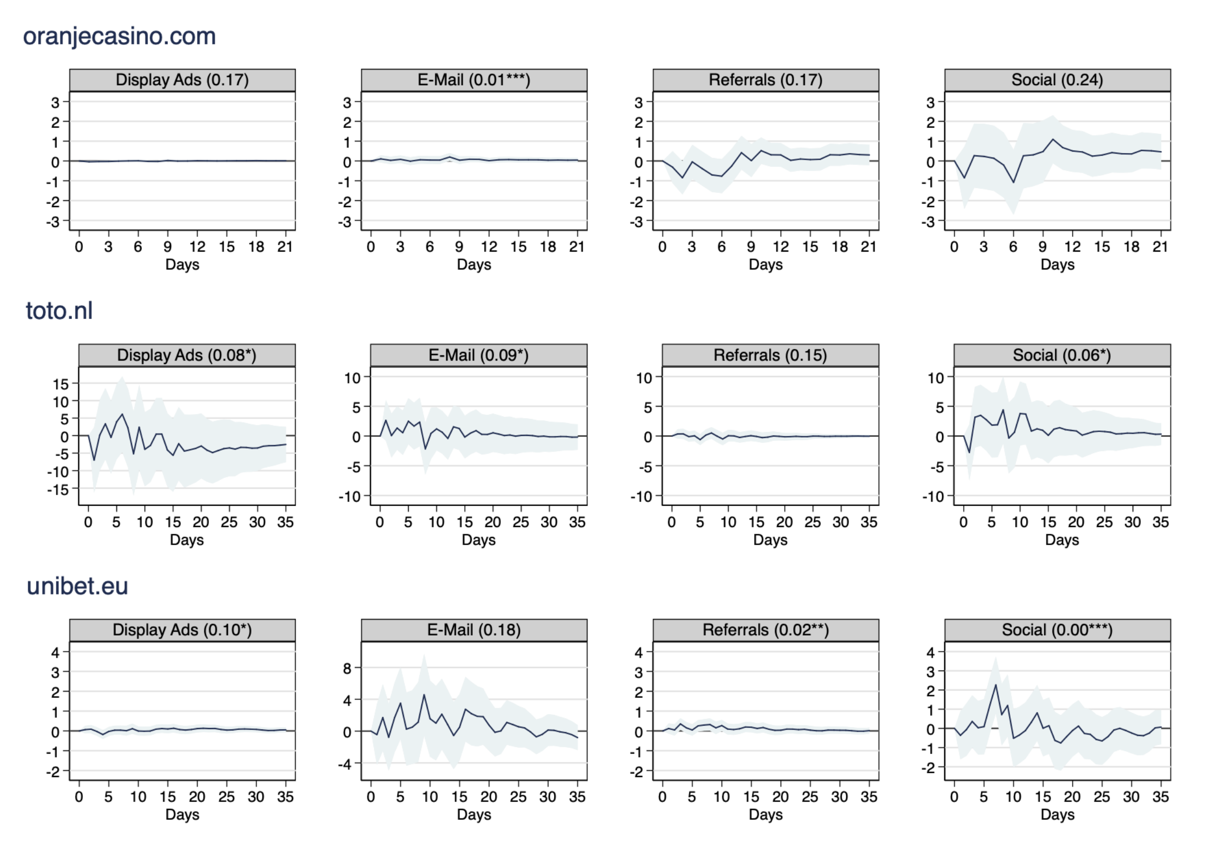

Figure 8: Impulse Response Functions - Effect of one unit shock to Adv. Channel on Genuine Interest. Shaded areas illustrate 99% confidence intervals.

advertisement to less visible places. After all, this is found to be ineffective.

Just recently, the Dutch senate has passed a bill that will introduce a legal framework for the operation of online gambling in the Netherlands. In light of the forthcoming market opening, policy makers and regulators now need to decide to what extent advertisement will be allowed. In light of the previous results, one can discuss definite or partial bans on advertisement under the new regulation.

What we have learned from this thesis is that the illegal status of online gambling together with the prosecution against its promotion yields a situation that is as if advertisement on popular websites was banned. Operators are forced to take 'indirect routes' to advertise their services (RegulusPartners, forthcoming). Operators advertise on less visible or less popular websites. This outcome is very similar to the case of Belgium, where advertising is prohibited on mainstream media (RegulusPartners, forthcoming).

Another aspect of the current regulative situation in the Netherlands is the large share of referrals and affiliate marketing. As we have seen in section 6.2., the unregulated bilateral nature of this channel bears potential for abuse - here in the sense of adware and spam. Evidence from other countries has shown that in regulated markets, the share of referrals marketing falls from around 50% to below 10%.

A definite ban on advertising can also be discussed by taking into account different player types. In general, there are three types of customers in online gambling that differ by activity: Heavy, regular and occasional players (RegulusPartners, forthcoming) (see Table 10). Occasional players have the largest share in total volume. These players need to be activated through advertisement. Hence, advertisement needs to reach these individuals in contexts unrelated to gambling (RegulusPartners, forthcoming). Regular and heavy players, in contrast, consume gambling services even in the total absence of marketing. Consequently, these players can be targeted through e-mails and loyalty bonuses directly in the gambling portal or app. Taking together, heavy and regular players only account for 10% of the total number of players. A definite ban on advertising, prohibits operators to activate occasional players. As such, the distribution will be skewed further towards heavy and regular players - as these are not affected by the absence of online ads. An increase in the number of heavy players may ultimately have an effect on the number of disordered gamblers. This needs to be taken into account when discussing a universal ban on advertising.

As it is the case with any empirical study, this paper has some limitations that invite future research to build upon. First, due to the aggregated nature of the data, I have no means to estimate the explicit effect of exposure to a specific ad. Furthermore, I do not observe any specifications of the ads shown by operators. All inference is based on observations on the aggregate. Also, it could be that individuals see an add without instantly clicking on it, but directly return to the website some time later. As such, estimations are likely to be underestimated. Second, the data used in this study is only based on Desktop usage - that is only a third of the overall traffic. For a complete understanding on advertising practices in this market, a similar analysis on app data would be insightful. Thirdly, a huge part in gambling advertising are loyalty bonuses targeted at existing clients. These are usually transferred within apps or platforms and as such not observable in this study.

Table 10: Types of customer over share and revenue raised

	# of Players	Revenue
Heavy Player	1%	15-20%
Regular Player	9%	40-60%
Occasional Player	90%	25-45%

Source: RegulusPartners (forthcoming)

References

Baum, C.; Schaffer, M. (2013). actest: Stata module to perform cumby-huizinga general test for autocorrelation in time series. *Statistical Software Components, Boston College Department of Economics.*

Binde, P. (2014). Gambling advertising: A critical research review. *Responsible Gambling Trust.*

Braun, M. and Moe, W. W. (2013). Online display advertising: Modeling the effects of multiple creatives and individual impression histories. *Marketing Science*, 32(5):753–767.

Breuer, R., Brettel, M., and Engelen, A. (2011). Incorporating long-term effects in determining the effectiveness of different types of online advertising. *Marketing Letters*, 22(4):327–340.

Bruce, N. I., Murthi, B., and Rao, R. C. (2017). A dynamic model for digital advertising: The effects of creative format, message content, and targeting on engagement. *Journal of marketing research*, 54(2):202–218.

Bundeskartellamt (2017). Online advertising. *Series of papers on "Competition and Consumer Protection in the Digital Economy"*.

Deighton, J., Henderson, C. M., and Neslin, S. A. (1994). The effects of advertising on brand switching and repeat purchasing. *Journal of Marketing Research*, 31(1):28–43.

Dekimpe, M. G. and Hanssens, D. M. (2004). Persistence modeling for assessing marketing strategy performance.

Dhar, T. and Baylis, K. (2011). Fast-food consumption and the ban on advertising targeting children: the quebec experience. *Journal of Marketing Research*, 48(5):799–813.

Driscoll, J. C. and Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80:549–560.

D'Souza, G. and Rao, R. C. (1995). Can repeating an advertisement more frequently than the competition affect brand preference in a mature market? *Journal of Marketing*, 59(2):32.

Dubé, J.-P., Hitsch, G. J., and Manchanda, P. (2005). An empirical model of advertising dynamics. *Quantitative Marketing and Economics*, 3(2):107–144.

Evans, D. S. (2008). The economics of the online advertising industry. *Review of network economics*, 7(3).

Goldfarb, A. and Tucker, C. (2011a). Advertising bans and the substitutability of online and offline advertising. *Journal of Marketing Research*, 48(2):207–227.

Goldfarb, A. and Tucker, C. (2011b). Online display advertising: Targeting and obtrusiveness. *Marketing Science*, 30(3):389–404.

Google (2019a). Advertising policies on gambling.

Google (2019b). Legal requirements.

Greene, W. (2000.). *Econometric Analysis*. New York:Prentice-Hall.

Hoechle, D. (2007). Robust standard errors for panel regressions with cross-sectional dependence. *The Stata Journal*, 7(3):281–312.

Hollingworth, W., Ebel, B. E., McCarty, C. A., Garrison, M. M., Christakis, D. A., and Rivara, F. P. (2006). Prevention of deaths from harmful drinking in the united states: the potential effects of tax increases and advertising bans on young drinkers. *Journal of studies on alcohol*, 67(2):300–308.

JLARC (2012). Lottery marketing and incentive pay: Jackpot and economy, not advertising or beneficiary change, appear to impact ticket sales. *Olympia, WA: State of Washington Joint Legislative Audit and Review Committee (JLARC).*

Kireyev, P., Pauwels, K., and Gupta, S. (2016). Do display ads influence search? attribution and dynamics in online advertising. *International Journal of Research in Marketing*, 33(3):475 – 490.

KSA (2017). Kansspelautoriteit zet nieuwe stap in bestrijden van kansspelen op afstand.

KSA (2019). Eerste kamer stemt in met legalisering online kansspelen.

Laffey, D., Della Sala, V., and Laffey, K. (2015). Patriot games: the regulation of online gambling in the european union. *Journal of European Public Policy*, 23(10):1425–1441.

Lancaster, K. M. and Lancaster, A. R. (2003). The economics of tobacco advertising: spending, demand, and the effects of bans. *International Journal of Advertising*, 22(1):41–65.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis.* Springer Science and Business Media, 2nd edition.

Moore, R. S., Stammerjohan, C. A., and Coulter, R. A. (2005). Banner advertiser-web site context congruity and color effects on attention and attitudes. *Journal of Advertising*, 34(2):71–84.

Munoz, Y. (2009). *An investigation into the sales-advertising relationship: The state lottery case.* PhD thesis, Austin: University of Texas.

Nelson, J. P. and Young, D. J. (2001). Do advertising bans work? an international comparison. *International Journal of Advertising*, 20(3):273–296.

RegulusPartners (forthcoming). Gambling and advertising: an international study of regulatory intervention.

Rochet, J.-C. and Tirole, J. (2003). Platform competition in two-sided markets. *Journal of the european economic association*, 1(4):990–1029.

Sherman, L. and Deighton, J. (2001). Banner advertising: Measuring effectiveness and optimizing placement. *Journal of Interactive Marketing*, 15(2):60–64.

Stock, J. H. and Watson, M. W. (2015). *Introduction to Econometrics.* Pearson Education Limited, 3rd edition.

Stone, H. (2000). An analysis of selected determinants of texas lottery revenue. *San Marcos: Applied Research Project, Texas State University.*

Wooldridge, J. M. (2009). *Introductory Econometrics, Fourth Edition.* South-Western Cengage Learning.

Youn, S., Faber, R. J., and Shah, D. V. (2000). Restricting gambling advertising and the third-person effect. *Psychology & Marketing*, 17(7):633–649.

Zhang, P. (2004). *Over- or Under-Advertising by State Lotteries.* PhD thesis, University of Maryland.

10 Appendix: Additional Figures and Tables

Table 11: Referring Social Networks - Source: Similarweb, Screenshot retrieved June 26, 2019

	unibet.eu	oranjecasino.com	toto.nl	mrgreen.com
Youtube	65.34%	64.70%	62.84%	79.68%
Facebook	17.16%	20.85%	23.53%	8.29%
Twitter	5.64%	6.90%	2.72%	1.93%
WhatsApp Web	5.63%	1.25%	4.45%	3.25%
Others	6.23%	6.30%	6.46%	6.85%

Table 12: Lag selection in the Dynamic Panel Data Model

	Genuine Interest	DisplayAds	Referrals	Email	Social	Comp. Adv.
888sport	1	2	1	0	1	0
bet365	1	1	2	1	0	0
betathome	1	0	2	1	2	0
betfair	1	1	1	0	1	2
betway	1	1	2	0	2	0
bwin	1	2	1	1	1	1
interwetten	1	2	1	0	0	0
krooncasino	2	0	1	0	0	1
mrgreen	1	1	0	1	0	0
oranjecasino	2	2	0	0	0	1
toto.nl	1	1	0	1	0	0
unibet.com	1	2	1	2	1	0
unibet.eu	2	2	2	1	1	0
williamhill	1	0	0	1	0	0

Note: Calculating the AIC test statistic for each panel using the *ardl* command in Stata 15. Indicated for each panel the lag combination with the lowest AIC score.

Table 13: Lag selection for the VAR-model

	Lags	AIC	BIC	Serial Correlation: Chi2	Serial Correlation: p-Value
mrgreen.com	2	78.17	78.43	54.29	0.00
	3	78.01	78.46	42.13	0.02
	4	78.00	78.65	52.31	0.00
	5	78.02	78.86	71.07	0.00
	6	78.02	79.05	34.91	0.09
	7	77.98	79.20	65.90	0.00
	8	77.97	79.39	29.48	0.24
	9	77.93	79.54	24.09	0.51
	10	77.96	79.76	25.64	0.43
oranjecasino.com	2	68.78	69.04	84.06	0.00
	3	68.71	69.17	32.15	0.15
	4	68.63	69.29	47.49	0.00
	5	68.69	69.54	33.68	0.11
	6	68.69	69.74	41.94	0.02
	7	68.74	69.99	43.88	0.01
	8	68.77	70.22	45.37	0.01
	9	68.78	70.43	19.94	0.75
	10	68.78	70.64	27.48	0.33
unibet.eu	2	88.37	88.73	34.77	0.09
	3	88.30	88.96	30.70	0.20
	4	88.33	89.31	39.72	0.03
	5	88.38	89.66	57.52	0.00
	6	88.39	89.98	96.94	0.00
	7	88.16	90.06	38.36	0.04
	8	88.15	90.36	37.84	0.05
	9	88.16	90.69	33.44	0.12
	10	88.17	91.01	28.21	0.30
toto.nl	2	59.58	59.85	75.16	0.00
	3	59.45	59.91	61.40	0.00
	4	59.38	60.02	32.73	0.14
	5	59.36	60.20	75.01	0.00
	6	59.38	60.40	44.51	0.01
	7	59.32	60.54	64.85	0.00
	8	59.27	60.68	31.77	0.16
	9	59.27	60.88	37.46	0.05
	10	59.29	61.08	23.22	0.56

Note: Lag selection criteria and First Order Serial Correlation Tests. For unibet.eu observations before the break are included.

Table 14: (Poisson) Effect of Advertising Traffic on Genuine Interest Traffic

	(1) β (se)	(2) β (se)	(3) β (se)	(4) β (se)
L.Genuine Interest	0.000151***	0.000151***	0.000151***	0.000138***
	(0.000)	(0.000)	(0.000)	(0.000)
DisplayAds	0.000004***	0.000004***	−0.000091***	−0.000002***
	(0.000)	(0.000)	(0.000)	(0.000)
L.DisplayAds	0.000007***	0.000007***	0.000007***	0.000012***
	(0.000)	(0.000)	(0.000)	(0.000)
Email	0.000803***	0.000803***	0.000803***	0.000777***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Email	−0.000734***	−0.000734***	−0.000734***	−0.000645***
	(0.000)	(0.000)	(0.000)	(0.000)
Referrals	0.000031***	0.000031***	−0.000064***	0.000034***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Referrals	−0.000018***	−0.000018***	−0.000018***	−0.000022***
	(0.000)	(0.000)	(0.000)	(0.000)
Social	0.000567***	0.000567***	0.000472***	0.000644***
	(0.000)	(0.000)	(0.000)	(0.000)
L.Social	−0.000463***	−0.000463***	−0.000463***	−0.000423***
	(0.000)	(0.000)	(0.000)	(0.000)
Comp. Adv. Traffic			−0.000095***	−0.000001***
			(0.000)	(0.000)
(max) WM=1				0.217080***
				(0.001)
Constant	6.534732***			
	(0.119)			
N	6844	6844	6844	4682
Time FE	1	1	1	0
Domain FE	0	1	1	1
Weekday FE + WorldCup	1	0	0	1

Note: Dependent Variable: Genuine Interest Traffic. All equations include day-fixed effects. Interpretation: A one unit change in the independent variable causes a change β in the log of the dependent variable, all other regressors held constant. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

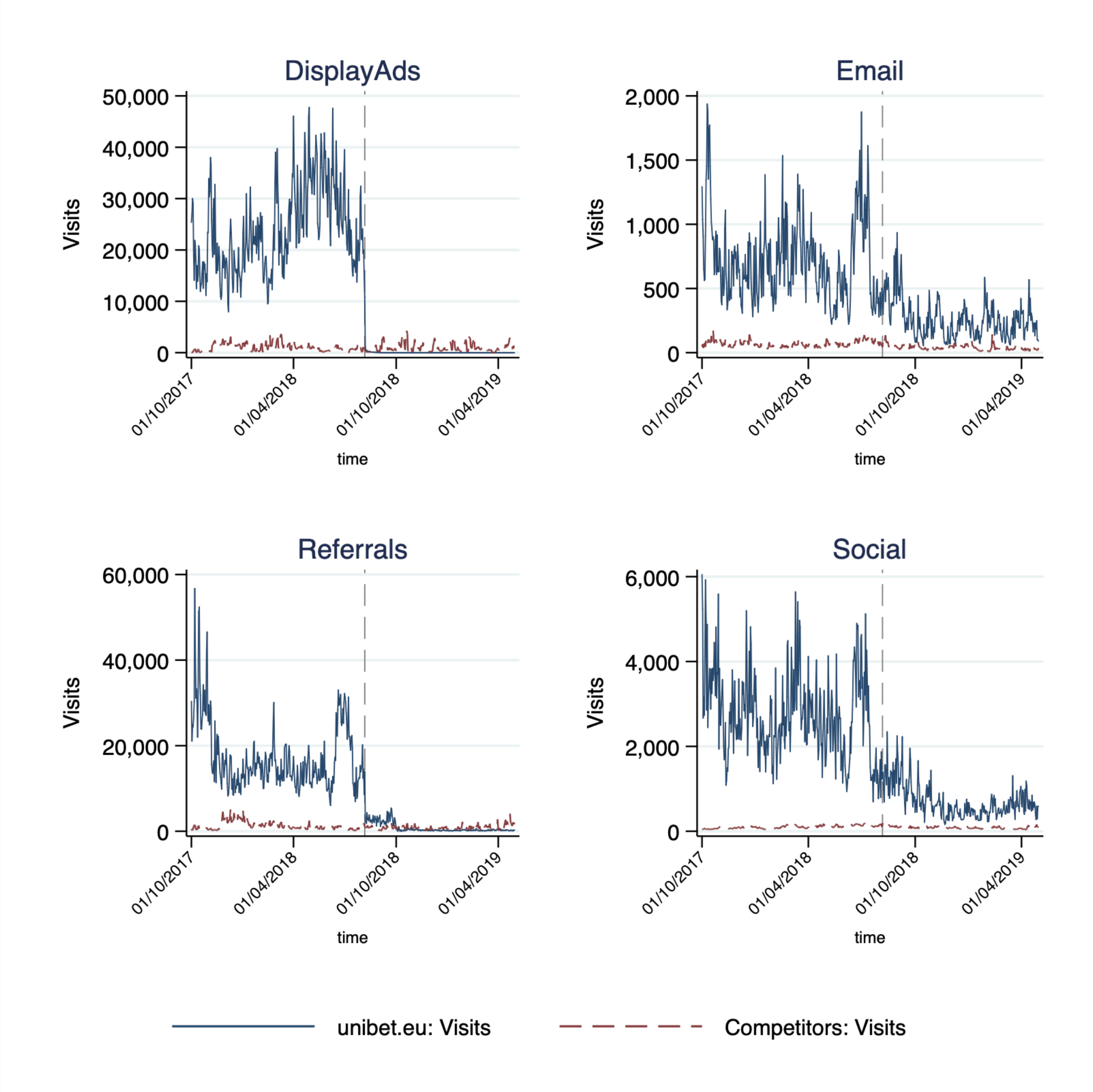

Figure 9: unibet.eu: daily visits across advertisement channels versus competitors

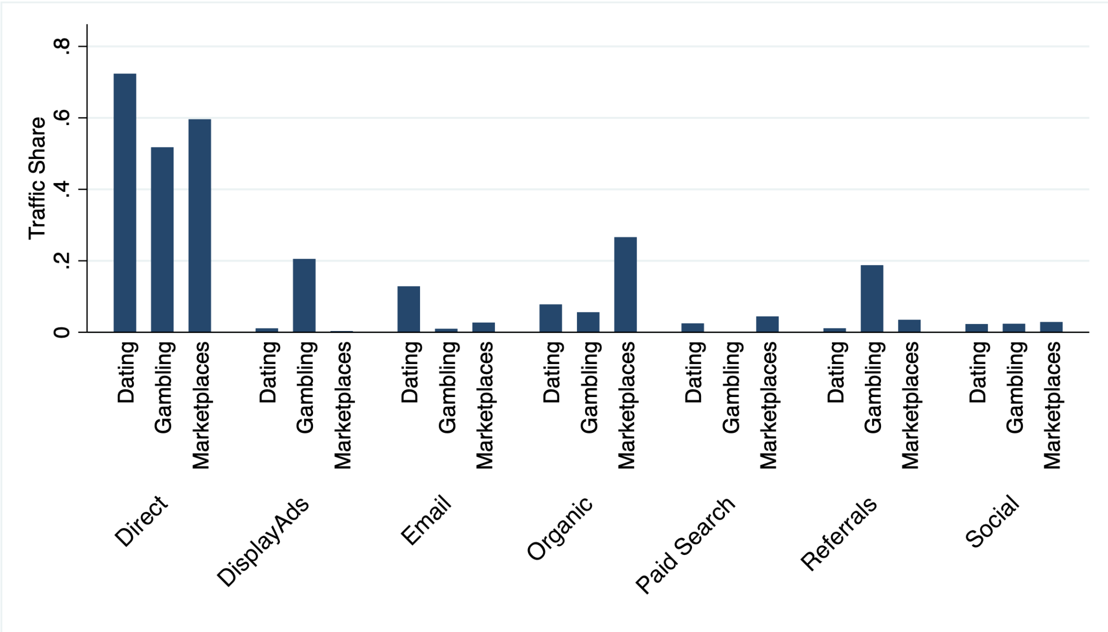

Figure 10: Channel shares for the market for Online Gambling, Online Dating and Online Marketplaces in the Netherlands. Included are the five domains with the most views for each category:
Dating - *parship.nl, relatieplanet.nl, lexa.nl, e-matching.nl elitedating.nl*
Marketplaces - *marktplaats.nl, amazon.de, bol.com, ebay.com, zalando.nl*

Table 15: Display Ads: mrgreen.com

Domain	Category	Traffic Share	Country Rank
oload.download	Computers Electronics and Technology/ File Sharing and Hosting	6,45%	46500
openload.co	Computers Electronics and Technology/ File Sharing and Hosting	5,93%	923
tugaflix.com	Arts and Entertainment/ TV Movies and Streaming	3,06%	8791
watchtheoffice.online	Arts and Entertainment/ Arts and Entertainment	3,05%	6651
anilinkz.to	Arts and Entertainment/ Animation and Comics	2,74%	33191
youtube.com	Arts and Entertainment/ TV Movies and Streaming	2,50%	2
oload.club	Unknown	2,15%	60349
thisismoney.co.uk	News and Media	1,87%	32641
imgur.com	Computers Electronics and Technology /File Sharing and Hosting	1,87%	65
aniwatcher.com	Arts and Entertainment/ Animation and Comics	1,83%	3885
nosteam.ro	Games/ Video Games Consoles and Accessories	1,78%	41400
fili.cc	Arts and Entertainment/ TV Movies and Streaming	1,75%	3820
oload.live	Unknown	1,49%	179743
investopedia.com	Finance/Investing	1,37%	1028
myvidster.com	Adult	1,14%	1492
spaste.com	Computers Electronics and Technology/ File Sharing and Hosting	1,13%	23858
mrworldpremiere.tv	Arts and Entertainment/ TV Movies and Streaming	1,04%	5620
streamlord.com	Arts and Entertainment/ Arts and Entertainment	0,99%	9675
hintfilmcenneti.com	Arts and Entertainment/ TV Movies and Streaming	0,86%	-

Note: Adware is indicated in bold.

Table 16: Display Ads: oranjecasino.com

Domain	Category	Traffic Share	Country Rank
torrentgalaxy.org	Computers Electronics and Technology/ File Sharing and Hosting	28,06%	10658
yuki.la	Adult	11,11%	10513
independent.co.uk	News and Media	5,39%	698
suchen.mobile.de	Unknown	5,27%	-
pathofexile.gamepedia.com	Unknown	4,53%	-
imgur.com	Computers Electronics and Technology/ File Sharing and Hosting	3,97%	65
nuggitgames.com	Gambling/Casinos	3,03%	18631
yourporn.sexy	Adult	3,01%	82802
futbin.com	Games/Video Games	2,93%	314
navigator-lxa.mail.com	Unknown	2,70%	-
jbl.nl	E-commerce and Shopping/ Marketplace	2,62%	3030
dailystar.co.uk	News and Media	2,34%	4693
express.co.uk	News and Media	2,34%	1102
nxctrk.com	Adult	1,74%	39723
worldfootball.net	Sports/Soccer	1,18%	48520
thesimsresource.com	Games/Video Games	1,18%	1034
kissasian.es	Arts and Entertainment	1,18%	-
skyaboveus.com	Sports/Sports	1,18%	273655
messenger.com	Computers Electronics and Technology/ Social Networks and Online Communities	1,18%	547

Note: Adware is indicated in bold.

Table 17: Display Ads: unibet.eu

Domain	Category	Traffic Share	Country Rank
rotumal.com	Unknown	11,17%	-
cobalten.com	Unknown	7,96%	-
kissanime.ru	Arts and Entertainment/ Animation and Comics	7,89%	184
us.baylnk.com	Unknown	3,25%	-
flvto.biz	Arts and Entertainment/ Arts and Entertainment	2,45%	341
clearload.bid	Unknown	2,22%	-
kissmanga.com	Arts and Entertainment/ Animation and Comics	2,06%	1025
youtube.com	Arts and Entertainment/ TV Movies and Streaming	1,92%	2
watchseries.fi	Arts and Entertainment/ TV Movies and Streaming	1,33%	894626
playe.vidto.se	Unknown	1,30%	-
ssl2anyone3.com	Unknown	1,26%	-
animeheaven.eu	Arts and Entertainment/ Animation and Comics	1,23%	56892
hdeuropix.cc	Arts and Entertainment/ TV Movies and Streaming	1,11%	155542
zukxd6fkxqn.com	Unknown	1,06%	-
gorillavid.in	Arts and Entertainment/ TV Movies and Streaming	1,03%	4135
anothere.club	Unknown	0,93%	-
www1.sockshare.net	Unknown	0,90%	-
camvideos.tv	Adult	0,78%	8161
kissasian.ch	Arts and Entertainment/ Arts and Entertainment	0,77%	183890

Note: Adware is indicated in bold.

Table 18: Display Ads: toto.nl

Domain	Category	Traffic Share	Country Rank
nu.nl	News and Media	20,62%	16
geenstijl.nl	Law and Government/ Government	13,72%	94
vi.nl	Sports/Soccer	10,07%	173
youtube.com	Arts and Entertainment/ TV Movies and Streaming	9,21%	2
dumpert.nl	Arts and Entertainment/ TV Movies and Streaming	9,19%	28
voetbalzone.nl	Sports/Soccer	5,17%	86
outlook.live.com	Unknown	4,06%	-
tvgids.nl	Arts and Entertainment/ TV Movies and Streaming	3,39%	132
voetbal.nl	Sports/Soccer	3,33%	3645
voetbalgokken.nu	Gambling/Sports Betting	2,45%	345097
volkskrant.nl	News and Media	2,17%	54
marktplaats.nl	E-commerce and Shopping/ Marketplace	2,17%	12
nederland.fm	Arts and Entertainment/ Music	1,82%	924
rtl.nl	Arts and Entertainment/ TV Movies and Streaming	1,52%	156
encyclo.nl	Reference Materials/ Dictionaries and Encyclopedias	1,51%	284
livescore.com	Sports/Soccer	1,45%	1097
voetbalprimeur.nl	Sports/Soccer	1,39%	73
tvblik.nl	Arts and Entertainment/ Arts and Entertainment	1,39%	1096
buienradar.nl	News and Media	1,36%	20

Table 19: Referrals: mrgreen.com

Domain	Category	Traffic Share	Country Rank
nxctrk.com	Adult	78,01%	39723
cobalten.com	Unknown	2,99%	-
rotumal.com	Unknown	1,58%	-
zukxd6fkxqn.com	Unknown	1,23%	-
bodelen.com	Unknown	0,98%	-
cening-setects.com	Gambling/Casinos	0,91%	75698
dolohen.com	Unknown	0,88%	-
soujoobafoo.com	Unknown	0,69%	-
us.baylnk.com	Unknown	0,69%	-
url.rw	Gambling/Casinos	0,66%	-
eu.baylnk.com	Unknown	0,57%	-
afrtrk.com	Gambling/Gambling	0,54%	436250
poogriry.click	Unknown	0,48%	-
ethikuma.link	Unknown	0,47%	-
jlsyadeysmgghdy.com	Unknown	0,37%	-
o12zs3u2n.com	Unknown	0,36%	-
yllanorin.com	Arts and Entertainment/ Music	0,36%	-
ww2.swatchseries.to	Unknown	0,28%	-
static.swatchseries.to	Unknown	0,24%	-

Note: Adware is indicated in bold.

Table 20: Referrals: oranjecasino.com

Domain	Category	Traffic Share	Country Rank
gokstart.nl	Gambling/Casinos	8,31%	
dolohen.com	Unknown	6,74%	-
bodelen.com	Unknown	5,59%	-
o12zs3u2n.com	Unknown	4,19%	-
soujoobafoo.com	Unknown	3,83%	-
genver.nl	Hobbies and Leisure/ Ancestry and Genealogy	3,63%	29938
5yfi7sy.com	Sports/Sports	3,11%	-
fuxoasim.link	Unknown	2,90%	-
www2.dwatchseries.to	Unknown	2,70%	-
casinotop10.nl	Gambling/Casinos	2,60%	49201
poogriry.click	Unknown	2,49%	-
hox0u3ea48.com	Unknown	2,19%	-
ethikuma.link	Unknown	2,09%	-
www2.gorillavid.in	Unknown	1,73%	-
www2.swatchseries.to	Unknown	1,69%	-
www1.swatchseries.to	Unknown	1,43%	-
kaunairu.net	Unknown	1,38%	-
graucoay.net	Arts and Entertainment/ TV Movies and Streaming	1,30%	197451
orgalso.com	Arts and Entertainment/ TV Movies and Streaming	1,25%	-

Note: Adware is indicated in bold.

Table 21: Referrals: unibet.eu

Domain	Category	Traffic Share	Country Rank
unibet.com	Gambling/Gambling	21,46%	
cobalten.com	Unknown	15,89%	-
rotumal.com	Unknown	11,54%	-
go.afh32lkjwe.net	Unknown	8,39%	-
us.baylnk.com	Unknown	5,75%	-
trk.suprclickers.info	Unknown	4,79%	-
zukxd6fkxqn.com	Unknown	3,85%	-
eu.baylnk.com	Unknown	2,04%	-
clearload.bid	Unknown	1,84%	-
ssl2anyone3.com	Unknown	0,98%	-
ssa.1337x.to	Unknown	0,96%	-
cl96rwprue.com	Unknown	0,94%	-
playe.vidto.se	Unknown	0,93%	-
xqkzsifxgv.com	Unknown	0,88%	-
www2.gorillavid.in	Unknown	0,67%	-
iz682noju02ye5.com	Unknown	0,58%	-
4cj5qu70.top	Unknown	0,57%	-
linkshrink.net	Computers Electronics and Technology/ File Sharing and Hosting	0,57%	-
filter.adright.co	Unknown	0,53%	

Note: Adware is indicated in bold.

Table 22: Referrals: toto.nl

Domain	Category	Traffic Share	Country Rank
nederlandseloterij.nl	Finance/ Financial Planning	35,52%	98
m-toto.nederlandseloterij.nl	Unknown	18,33%	-
staatsloterij.nederlandseloterij.nl	Unknown	15,77%	-
toto-extra.nederlandseloterij.nl	Unknown	13,34%	-
luckyday.nederlandseloterij.nl	Unknown	6,06%	-
eurojackpot.nederlandseloterij.nl	Unknown	3,98%	-
lotto.nederlandseloterij.nl	Finance/ Financial Planning	1,73%	1014
r.srvtrck.com	Unknown	1,22%	-
symbaloo.com	Computers Electronics and Technology/ Search Engines	0,96%	233
checkout.buckaroo.nl	Unknown	0,81%	-
miljoenenspel.nederlandseloterij.nl	Unknown	0,61%	-
mijn-lotto.nederlandseloterij.nl	Unknown	0,33%	-
nu.nl	News and Media	0,30%	16
online-wedden-bookmakers.nl	Sports/Soccer	0,24%	-
totoknvbbeker.nl	Unknown	0,20%	238150
loten-staatsloterij.nederlandseloterij.nl	Unknown	0,06%	-
club-staatsloterij.nederlandseloterij.nl	Unknown	0,06%	-
toto.nl	Gambling/Lottery	0,05%	9435
wielerflits.nl	Sports/Cycling and Biking	0,05%	727

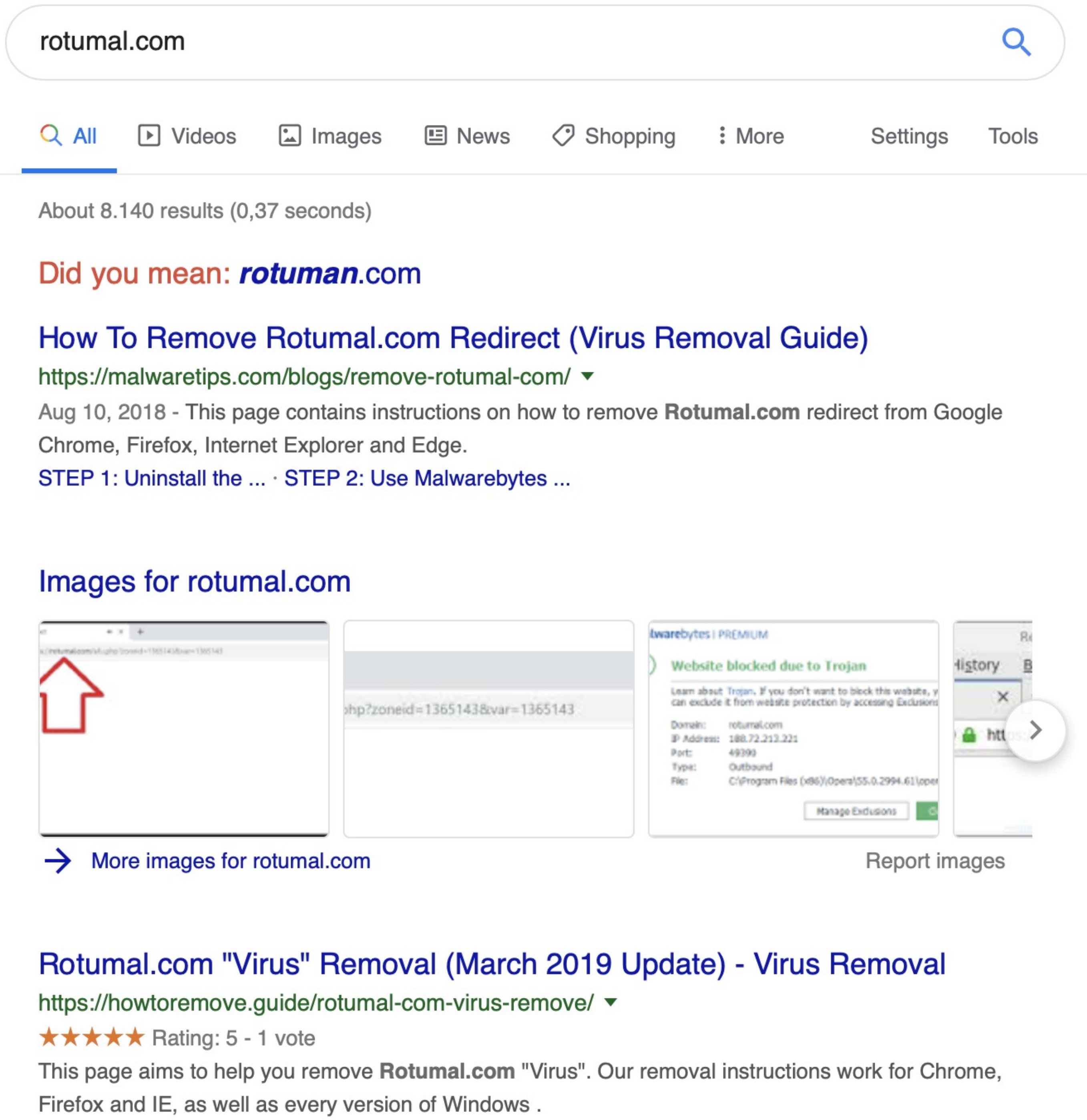

Figure 11: Google search for "roturnal.com". Many entries found for explicit virus and malware removal related to "roturnal.com". Screenshot taken on July 27, 2019.