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Goggles on Google

The effect of observational cues on stigmatizing Google search behaviour

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Abstract

This thesis uses Google Trends data to examine search behaviour for stigmatized Google search terms in the United States and the United Kingdom. The study aims to test the *evolutionary legacy hypothesis*, that suggests an automatic, prosocial response resulting from alterations of perceived anonymity. In our study, this alteration occurs when online searchers are exposed to observational cues in the Google logo. Our work builds on previous and inconclusive research on eye exposure and expands the study to a real-life setting. We discover no evidence for change in behaviour. Our follow-up analyses make us confident that at least two of our search categories are stigmatizing enough to provoke a reaction to alterations of actual anonymity, adding strength to our conclusion.

Keywords: observational cues, strong reciprocity, evolutionary legacy hypothesis, prosociality, Google Trends.

This thesis relies on contributions from several people. First and foremost, we wish to thank our supervisor Mathias Ekström for constructive feedback and encouragement throughout the semester. We also want to thank friends and family for support and valuable input during the work with our thesis.

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1. Introduction

Neoclassical economic theory rests on the assumption that decision-makers are profit-maximizing, rational and have narrow self-interest (Alchian, 1950). Although such models enable us to quantify the considerations of a decision-maker in a simple and comprehensible manner, their description of human behaviour is far from the reality. Neoclassical models provide little to no explanation as to why someone would donate anonymously to charity, help others financially or contribute voluntarily to the public good. This is, quite obviously, not always in line with what we see in real life.

As a consequence, these assumptions have been challenged by behavioural economic theories that take into account a range of deviations from the behaviour assumed in neoclassical economic theory. The presence of behavioural anomalies is proven by a large number of studies and research. An example of such a deviation is the fact that people tend to be generous toward others, even to genetically unrelated strangers (Camerer and Fehr, 2006). A suggested reason for this is the motivation to maintain a good reputation (Alexander, 1987; Roberts, 1998). People take observers into account when future interaction is likely and good behaviour today could benefit the decision-maker at some point in the future.

This effect can also arise in situations where there are no expectations of repeated interaction or direct reciprocity (Gintis, 2000). For instance, people often tip unknown taxi drivers in large cities while being alone. The probability of meeting the driver again is virtually zero, and reputational concerns would therefore be non-existent in the world of traditional economic models (Camerer and Fehr, 2006). These types of altruistic behaviour in situations without social consequences have previously been explained by the term *strong reciprocity*: the predisposition to cooperate even when there is no apparent benefit in doing so. Thus, people who demonstrate strong reciprocity care less about the benefits or costs of such altruistic behaviour (Gintis, 2000; Gintis et al., 2003; Fehr and Henrich, 2003).

However, several additional contributions to this subject indicate that strong reciprocity cannot fully explain such prosocial behaviour. A number of studies, with Haley and Fessler (2005) in the forefront, show that even though respondents are told and believe that they are anonymous, they demonstrate a pro-social response to subtle implicit cues of being watched in dictator and trust games (Burnham and Hare, 2007; Burnham, 2003; Haley and Fessler, 2005; Nettle et al., 2013). Burnham and Hare (2007) explain this phenomenon using *the evolutionary legacy hypothesis*. The theory suggests that people automatically detect faces and eyes to evaluate the level of privacy. Such an automatic activation also occurs with pictures of faces and eyes, with no connection to either actual observation or future payoffs. This leads to an automatic behavioural response equivalent to a situation where one is actually observed, and reputation is at stake. Burnham and Hare's experiment showed exactly this, an increase in prosociality even when the eyes belonged to Kismet, a robot on a computer. Their study indicated a 29% increase in public contribution when subjects were assisted through the experiment by Kismet. Such a substantial growth in contribution demonstrates the potentially strong effect of observational cues. This has also been the case for naturalistic field experiments where a simple picture of eyes has increased donations for both coffee and charities (Powell et al., 2012; Ekström, 2012; Bateson et al., 2006).

We want to further explore the presence of this automatic response to images of eyes. Research is inconclusive, as several studies uncover weak or negative results (Fehr and Schneider, 2009; Nettle et al., 2013). In addition, a lot of the research is based on game settings in a laboratory. Dictator Games have previously shown to be problematic because of demand effects, and laboratory experiments in general face framing effects, self-selected participation and anonymity issues (Camerer and Fehr, 2006; Powell et al., 2012; Ekström, 2012). Moreover, the previous naturalistic field experiments have struggled to create fully anonymous settings and eliminate social multiplier effects (Ekström, 2012).

Based on the previous literature, we will neither do a laboratory nor a field experiment, but rather a study using existing big data provided by Google. Occasionally, the Google logo is replaced by pictures containing eyes, and we will use these alterations to examine whether the presence of eyes in the logo affects the search volume for stigmatizing terms.

Previous literature has examined the effects of observational cues on positive behaviour, for instance donations in a game or a naturalistic setting. This study will try to uncover whether the same effects could reverse stigmatizing behaviour that affects one's reputation. Also, in previous research, respondents are exposed to the eyes before they make their decision. We are using Google search data, where people have generally decided what to Google in advance. We can therefore see if the automatic observational response is strong enough to reverse a decision. Additionally, in our setting the subjects do not have to think about the direct consequences of their choices on other people in the same way as in a dictator or trust game. Seeing pictures of eyes and faces can remind the respondents that there indeed is a human counterpart affected by the decision. This issue is reduced in our analysis, as searching for something has no immediate impact on another human being. The fact that there are no obvious economic aspects or third-party involvement allows us to research if the eye cues really trigger an automatic response in humans. We further argue that most people sit alone when searching for stigmatized phrases. Google searches is something we hold very personal, and most of us are brutally honest while sitting at our computer (Stephens-Davidowitz and Pinker, 2017). This implies that people believe it is a fairly anonymous setting without any real-life consequences. Our setting gives us the anonymous environment that Ekström (2012) shows is crucial for social cues to be effective. Without a lot of other people around, the only extra set of eyes are on the computer, which could increase the effect of our observational cues (Ekström, 2012).

To summarize, this study aims to take advantage of Google's natural alteration of perceived anonymity in order to assess whether people react to the presence of eyes. This will be done through looking at the volume of stigmatized search queries on days where the Google logo is altered so that the searcher is met with a logo containing a pair of eyes. Based on the previous literature on presence of eyes in behavioural studies, there are reasons to believe that this could lead to a reduction in queries for stigmatized phrases, as the exposure of such search behaviour could affect one's reputation.

Thus, the main hypothesis of the current investigation can be summarized as follows: *Exposure to doodles containing eyes leads to a decrease in the search volume for stigmatized searches.*

Based on data from the tool Google Trends, we are able to analyse search behaviour over the course of two 1350-day periods, one stretching from 2008 to 2011, and one from 2014 to 2017. Using the Google doodle archive, we have collected and categorized the alterations of the Google logo that have taken place throughout these periods and used these to categorize the strength of any observational cues in the Google logo. Thus, we are able to analyse search behaviour in response to different types of Google logos.

In chapter 2, we will describe the conceptual framework for this thesis, presenting our data types and the limitations that have impacted our data collection. In chapter 3, we will go through the process of selecting dependent (search terms) and independent (doodle and control) variables, before we present our final dataset and descriptive statistics in chapter 4. In chapter 5, we present the OLS model we will use to analyse the hypothesis, before we present our results in chapter 6 and discuss them in detail in chapter 7. In chapter 8, we carry out a follow-up analysis to examine whether the prerequisite of sufficient stigma of our search terms are met. We will discuss the internal and external validity in chapter 9, before we finally present our conclusion in chapter 10.

2. Conceptual framework

To test if observational cues in the Google logo has an effect on the search volume for stigmatizing phrases, we will use data from Google on search volume and alterations to the Google logo. In this chapter, we will present the framework we use to carry out this analysis. This includes presenting our data sources, Google Trends and Google's doodle archive, and the limitations that come with the use of this data. In addition, we will present issues that had to be addressed in order to choose suitable countries and time periods to analyze. The framework presented in this chapter will later be used to select the final datasets for our analysis.

2.1 Doodles

The Google doodles are the first core element of our analysis. This is where the observational cues appear on several occasions. The doodles are alterations to the Google homepage logo that were introduced in 1998 (Google, 2013). Three doodles were published in 1998, and five in 1999, before the number increased rapidly to 33 doodles worldwide in year 2000. In recent years, the number of doodles per year has generally been between 50 and 100 in the United States, and somewhat lower in other countries (Google, 2018a). They are typically published on special occasions, such as birthdays of famous people, national days, sports events, and holidays. The presence of any given doodle stretches from visibility only in one country at a time to worldwide alterations, depending on the relevance of the content of the doodle.

Doodles come in many different forms. Sometimes, the doodles contain still life drawings, other times they contain humans or animals. They can also be animated, contain real-life videos, or even consist of an interactive game. An example of a doodle celebrating the anniversary of Sesame Street can be seen in figure 2.1, next to the regular Google logo in the same time period.

Figure 2.1 – Example of a doodle (left) and the regular Google logo (right)

Doodles appear when one enters www.google.com from a computer or mobile device, and on the homepage in the Google search app (see appendix A.1, figures A.1 to A.7). The doodles do not appear at the opening of a new tab in other browsers than Google Chrome, or when one uses the address bar to search either on mobile devices or in a computer browser. They do, however, appear substantially smaller and in the corner of the webpage, once one has carried out an initial search and entered the search result website (see appendix A.1, figures A.3 and A.7), in browsers both on smartphones and computers. This smaller logo does not appear after one carries out a search using the app (see appendix A.1, figure A.5). The transition to smartphones combined with the ability to search using the address bar in internet browsers is important to have in mind when choosing the time period to analyze. We will address this issue in section 2.3.

Google has published all previous doodles in an archive on their Google Doodles website, allowing a systematic review of historical doodles. Here, we can see which of the doodles that contained observational cues. The archive also indicates which countries they have been published in, and the date each doodle was published.

2.2 Google Trends and search data

The second core element of our analysis is the search data on stigmatizing phrases. Google Trends, a freely accessible tool from 2009, allows third parties to download data about the popularity of queries worldwide or in a set geographical range, from 2004 until 36 hours before the time of retrieval (Google, 2018b). The service also lists related searches to the term one is looking at. These are the searches that are highly connected to the phrase and often searched for in the same Google session. For example, if our search term was [chess], then [Magnus Carlsen] could be a natural related search. Although Google gives us easy access to data from all over the world, there are some important limitations we have to keep in mind throughout our analysis.

The first one is that Google Trends does not allow the download of absolute search volumes. Instead, they index their data based on the popularity of a search term relative to the total volume of Google searches on that given day. The highest relative search volume within the chosen time period gets a value of 100, and the other observations are represented as a share of this maximum.

Expressed mathematically, we have t = day, j = term and $SVratio_{jt}$ = the search volume ratio of term j on day t, which gives us the following formula:

$$SVratio_{jt} = \frac{No.\,of\,queries\,for\,term\,j\,on\,day\,t}{Total\,no.\,of\,Google\,queries\,on\,day\,t} \tag{2.1}$$

The search volume ratio is calculated for each day, and the highest ratio throughout the period is given a value of 100. All other search volume ratios are then given a value as a share of this maximum $SVratio_{jt}$, henceforth called the SVI (Search Volume Index), where:

$$SVI_{jt} = \frac{SVratio_{jt}}{Max.\,SVratio\,in\,period} * 100 \tag{2.2}$$

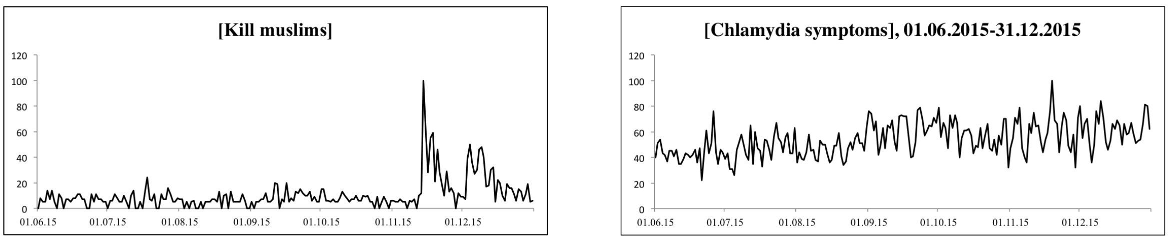
It is important to note that the value of 100 within each period not necessarily means that this day has the highest absolute number of queries for the given phrase, but rather that the number of searches for the phrase on this day accounted for the highest *share of total daily searches* within the given period. Furthermore, if the relative volume of a search phrase is either too small compared to the maximum or falls below a level in terms of absolute search volume set by Google, the value of the observation becomes zero. This limit is referred to as *The Privacy Threshold*, and is meant to preserve the privacy of people searching for rare terms. The privacy threshold thus has to be taken into account during the data selection process, as search phrases that do not exceed the threshold are useless in our analysis.

The second limitation is the length of our datasets. Although one can get monthly search data from present times all the way back to 2004 in one CSV datafile, Google Trends only lets third parties download adjusted data for daily searches for 1350 days at a time. As doodles change on a daily basis, we are dependent on daily data. Our available time periods for analysis are therefore bound by this 1350-day limit.

The final limitation is the Search Volume Index's challenge with outliers. If the maximum search volume ratio differs significantly from the rest, it follows from equation 3.2 that the rest of the observations will be assigned low values. This will further lead to low variance among the remaining observations. If the dataset less the outlier only has a range of values going from 1 to 3, for instance, there is a very limited amount of information to be retrieved from it as it only picks up large fluctuations in search volume.

An example of this can be seen in figure 2.2, where we have compared the prevalence of the terms [kill muslims] and [chlamydia symptoms] in late 2015. Because of the vast surge in searches for [kill muslims] following the Paris attacks in November, despite the 100 index point range for the whole period, the SVI in the period before the attacks only ranges between 0 and 24. The SVI for [chlamydia symptoms], however, has a range of 78 and consistent variation. This means that changes in the SVI for [kill muslims] must be substantially larger than those for [chlamydia symptoms] in order to have an effect in the dataset. We do not have any way to deal with how outliers affect the rest of the dataset as simply removing them would not solve the problem. In order to capture sufficient day-to-day variation to expect any results, we must therefore identify search terms that do not show the same outlier tendencies as [kill muslims].

Figure 2.2 – [Kill muslims] vs [Chlamydia symptoms], United States, June-December 2015



2.3 Time periods and countries

During the 2000s search behaviour has changed drastically, especially because of the rapid expansion of smartphone ownership. The smartphone penetration rate in the United

States has gone from 20.2% of the population in 2010 to 67.3% in 2017 (Ofcom, 2018). The development has been similar in the United Kingdom (eMarketer, 2017), where smartphone adoption went from 29% in 2011 to 76% of the population in 2017. In addition, we have seen an increasing focus on digital privacy and surveillance in the recent years. We therefore find it necessary to look at both an early time period before the popularity of smartphones exploded and a late time period where people are more digitally aware. This lets us test at least one period where we are confident that the searches are exposed to the doodles and observational cues. As mentioned, we can only download a maximum of 1350 days of indexed data at a time. Therefore, each of our periods will be exactly 1350 days long. It is important that the periods we choose have enough relevant doodles and observational cues to give us a sufficient basis for analysis. After looking through Google's Doodle Archive, our first period is from 01.02.2008 to 12.10.2011. January 2008 did not have a substantial amount of doodles, and as a consequence, we have chosen to start in February 2008 instead. Our second period goes from 01.01.2014 to 11.09.2017.

English is the most popular language used on the internet (W3Techs, 2018). It is therefore natural for us to use search phrases in English and look at countries with English as their native language. For the early period, we will use data from the US only. This is due to the privacy threshold, which makes retrieving data on rare search phrases virtually impossible in other countries than the US between 2008 and 2011. For the late time period, we will use data from both the US and the UK. These countries both have a relatively high volume of data and doodles. Other English-speaking countries were excluded, again because of their failure to exceed the privacy threshold for stigmatizing queries.

3. Selection of doodles and stigmatized content

In the previous chapter, we established the sources from which we will retrieve our data and the limitations we need to consider when selecting our data. In this chapter, we will first establish an objective identification process within the framework and use this to select our search terms and doodle variables. Then, we argue for the use of cyclical, country and time variables.

3.1 Dependent variables

3.1.1 Selection criteria for search terms

Since there is no pre-existing literature defining stigmatizing Google search terms, we have decided to target terms that meet three criteria: degree of stigma, intention, and cultural versatility.

Degree of stigma

In order to reverse a negative act, we need one to begin with. We must therefore identify searches that people, if observed, would be less likely to perform. One type of searches is then extra appealing: those that are associated with stigma.

There is a reason why stigmatizing searches are done privately: people are afraid of being caught breaking social norms. According to theory presented on reputational concerns, people react more strongly to eyes when they can expect some sort of social consequence of their choice (Haley and Fessler, 2005; Bateson et al., 2006). We therefore believe that people will be more inclined towards changing their search behaviour due to eye exposure when searching for something stigmatizing and abnormal than when asking Google how to boil spaghetti.

In order to select truly stigmatizing terms, we must define what stigma is and what makes one type of search behaviour more stigmatizing than another. Goffman (1963) defines stigma as *"an attribute that is deeply discrediting"* (Goffman, 1963,p. 13), and distinguishes between three types of potential stigma (Goffman, 1963,p. 13):

1. *"Abominations of the body"*: physical deformities.

2. *"Blemishes of individual character perceived as weak will (...) unnatural passions, (...) dishonesty [etc]*: homosexuality, addiction, mental health issues, unemployment, suicide attempts.

3. *"Tribal attributes"*: religious or racial minorities.

If a person is affected by physical deformities or tribal attributes, these are generally already known to the public and can be categorized as visible, as opposed to other *concealable* stigmas (Smart and Wegner, 1999). The revelation of Google queries on Goffman's topic 1 and 3 would for that reason generally not expose anything beyond the stigma already imposed on the person in question.

Thus, we will focus on the second category of stigma. Such blemished character traits are easier to hide in everyday life. A revelation of searches related to these traits would therefore add to the bearer's level of stigma, implying a negative change in society's perception of him. Hence, we have a negative trait that will be revealed if he is exposed, and that has the potential to make him reverse his actions when anonymity is altered.

Evidence also points towards a high level of anxiety among people with concealable stigmas due to the fear of being exposed (Smart and Wegner, 1999). It is reasonable to assume that this anxiety would contribute to a higher sensitivity towards the feeling of being observed, underscoring the use of concealable stigma as the basis for our selection of queries. In *Everybody Lies* (2017), Stephens-Davidowitz uses Google searches to present evidence that people lie about their porn habits in real life (p. 110), admit regrets to Google about having children (p. 111), and are more likely to confess their homosexuality to Google than what is publicly enclosed (pp. 114-116). Thus, we have an indication that people do, in fact, open up more about such concealable stigma to Google than in the real world.

Intent

As a second criterion, our terms must demonstrate a degree of intent of looking for something stigmatized. For instance, a search for "get drugs online" demonstrates a higher degree of intent than "online drug trade US", because the latter has a higher chance of being used simply in a research context. Clearly, we do not expect observational cues to affect searches for professional purposes and we therefore focus on terms that indicate an intention.

It is worth mentioning that the intention behind search terms can be revealed by the related search overview that Google Trends provides us with when searching for a phrase. If the related searches point towards other search terms that demonstrate a high degree of intent, this can underscore the relevance of the original term.

Culture

As a last criterion, the terms must be viewed as stigmatizing in both the US and UK. This is in order to ensure that any revelation of search behaviour causes similar consequences across our two countries. Many stigmatizing search terms are based on slang, making it difficult to make cross-country comparisons. Such terms include "fag", which in the UK, in addition to being a condescending phrase for gay people, is a slang term for "cigarette". As previously mentioned, a person using a query in order to find something innocent will, according to our hypothesis, react in a different manner to one actually looking for something stigmatizing. Thus, including search terms whose meaning is culturally dependent has the potential to harm our analysis.

3.1.2 Selection of search terms

Based on the three criteria, we have narrowed down the search terms to four main categories: pedophilia, sexuality (regular porn and niche porn), health and relationships. We will describe them more closely in the following section.

Pedophilia

In the world of stigmatizing behaviour, sexual attraction towards children cannot be ignored. Due to a combination of criminal sanctions and condemnation by society if such interests are revealed, it stands out as a particularly interesting topic to analyse in the light of our research question. Pedophiles are viewed in a highly unfavourable manner by the public (Levenson et al., 2007), for instance through overestimation of the probability of carrying out sexual abuse of children (Jahnke, 2018). Thus, the reputational consequences of public disclosure of sexual interest in children, we argue, will be large and its reception dominated by a high degree of extremely negative characterizations. Internet searches for sexual content involving children therefore falls well within the borders of our previously stated definition of stigmatizing behaviour.

In terms of demonstrated intent, explicit terms such as [preteen sex] would be preferable, but the privacy threshold limits the amount of data available for these terms. However, even when looking at the seemingly broad term [preteen] in Google Trends for the US and the UK, terms such as [jailbait][1], which is also included as a term in our model, [PTHC] (abbreviation for "pre-teen hardcore"), and [lolita model] are among the related searches. Such related searches suggest that the subsequent activities of these searchers tend not to be of an innocent character.

Because of the way the terms seem to capture such activities, we have therefore included the terms [preteen] and [jailbait] in our pedophilia variable.

Sexuality

There are a limited number of alternative reasons as to why a person would enter a porn query other than the quest for fulfilment of their sexual needs. This is therefore an interesting category for us to research. The vast amount of porn searches, Pornhub being the sixth most popular Google search in the US in 2018 (Tim Soulo, 2018), certainly gives us a large amount of pornographic search data to work with. We will therefore look at both [porn] and [pornhub] searches.

[1] Slang term for "a girl under the age of consent with whom sexual intercourse is unlawful and constitutes statutory rape" (Merriam-Webster, 2018)

However, with Pornhub's 81 million visits per day (Pornhub Insights, 2018), there is a high probability that your neighbours, classmates or co-workers also use this type of sites. People do not judge to the same degree when they themselves are just as guilty, which makes porn searches less stigmatizing. In addition, research finds that 30% of porn users watch it as a habit or addiction (Pizzol et al., 2016). Habits are harder to change (Verplanken and Wood, 2006), and as a consequence, we do not expect observational cues to affect them to the same degree as rarer search terms.

We have therefore chosen to include more narrow porn terms as well, more specifically [gay porn], [hardcore porn], and [rape sex]. These terms would, following our argument of the trade-off between normalcy and stigma, be more stigmatizing than [pornhub] and [porn]. Evidence shows that a considerable percentage of the searches for [gay porn] are made by closeted gay men in intolerant states (Stephens-Davidowitz and Pinker, 2017). This adds a fear of exposure and stigma from both the closest ones and the community. When it comes to the term [hardcore porn], the name in itself insinuates an extra element of violence and hostile sexual acts. [Rape sex] often consists of reenactments of criminal actions such as forced intercourse and violence. This type of material is often considered both aggressive and degrading towards women (Whisnant, 2010). Viewers could therefore face stigma from others.

Although the level of stigma varies, we have included all five porn related queries in two different categories. The pornography variable consists of [porn] and [pornhub], and the niche pornography variable includes [gay porn], [hardcore porn] and [rape sex].

Health

Health issues are an important source of stigma for their sufferers - and something people frequently turn to Google to resolve. The issues can generally be split into two categories: those that you cannot influence and those you can. Or more importantly in our case, those that are perceived as unavoidable and those that are not. The former consists mostly of innate conditions, like type 1 diabetes and asthma, while the latter includes diseases such as mental illness and STDs.

Patients suffering from mental illnesses such as schizophrenia and depression report a higher degree of consequences of stigma than patients suffering from cardiac conditions (Lai et al., 2001). Depressive patients are often perceived as, among others, *emotionally weak* and *lazy* (Lai et al., 2001,p. 113), while its heaviest sufferers who have attempted suicide can be labeled *bad* people (Lai et al., 2001,p. 114). We have therefore included [I want to die] and [commit suicide], two queries that are frequent enough to exceed the privacy threshold. The number of searches for [commit suicide] is positively correlated with American suicide rates (Gunn and Lester, 2013), and [I want to die] must be assumed not to be searched for very often by those not wanting to die. Thus, these can be good indicators of stigmatizing searches in the mental health category.

Sexually transmitted diseases also carry a high level of stigma and shame (Sales et al., 2007). Abnormal diseases would be ideal, but the privacy threshold reduces the range of queries to choose from in this category. We have therefore chosen to include searches for [chlamydia symptoms], as it is demonstrating a worry-driven intentional search to get information about a common, but still stigmatized disease. Duncan et al. (2001) show that their subjects perceive a chlamydia diagnosis as stigmatizing, associating sufferers from the disease with irresponsibility and promiscuity. Although these results are from Ireland, we assume that the cultural differences in this respect are marginal and that it can indicate the level of stigma in the United Kingdom. Although little recent research is available for the United States, similar results have been uncovered in the Netherlands (Theunissen et al., 2015) as well. Arguing that results from these countries are transferable to the US, we believe that chlamydia, or the fear of it, can be considered stigmatizing in both our selected countries.

Thus, we have chosen to include the terms [I want to die], [commit suicide], and [chlamydia symptoms] to represent our health category.

Relationships

Almost all American couples, married or not, expect sexual exclusivity of one another (Treas and Giesen, 2000). It is assumed that people are monogamous, and activities that refrain from this are frowned upon by both partners and society. With over 82% of Americans believing that polygamy is morally wrong, there is no doubt that it carries a certain social stigma with it (Gallup, 2018). We have therefore decided to include two infidelity search terms, [I cheated] and [Adultfriendfinder].

A Google search for [I cheated] clearly shows intent and potential guilt over the action. One can imagine that the ultimate fear of a cheater is being caught by their partner. This carries with it both reputational consequences and a high risk of wrecking the relationship. Although infidelity is quite common in relationships (Mark et al., 2011), and therefore faces a decreasing degree of stigma from society in general, research also shows that only 5% believe their partner have or would cheat on them (Watkins and Boon, 2016). We therefore argue that the stigma one could face from their partner after searching [I cheated] is substantial.

Another type of relationship searches that is relevant to look at is that of adult dating sites. Adultfriendfinder is, according to themselves, one of the world's largest adult dating sites (Adultfriendfinder, 2018). It has its focus on affairs and other sexual activities such as orgies and swinger-parties. A search for this site shows an intent of engaging in untraditional sexual activity. In addition to facing the consequences of your partner finding out about potential infidelity, there is also a bigger social stigma attached to swinger-communities, orgies and other less common sexual activities. A portion of the users on Adultfriendfinder might even be in open relationships and swinger-communities and engage in this activity together with their partner. We therefore believe this search term faces a high level of potential stigma both from partners and outsiders of the relationship.

Considering that both [I cheated] and [adultfriendfinder] involve unwanted and abnormal behaviour in a relationship, we have decided to combine them as our indicator for stigmatized relationship-related queries.

Final dependent variables

In table 3.1, we have summarized the terms that will be used to define our final dependent variables. For simplicity, we have generated the variables as average SVI of the terms included in the category. As a consequence, the results in our analysis can be compared directly between the categories.

Table 3.1 – Summary of all five search variables

Topic	**Terms**
Health	$\frac{[chlamydia\,symptoms] + [commit\,suicide] + [i\,want\,to\,die]}{3}$
Niche Pornography	$\frac{[gay\,porn] + [hardcore\,porn] + [rape\,sex]}{3}$
Pedophilia	$\frac{[jailbait] + [preteen]}{2}$
Relationships	$\frac{[adultfriendfinder] + [i\,cheated]}{2}$
Porn	$\frac{[porn] + [pornhub]}{2}$

3.2 Independent variables

3.2.1 Doodle variables

We use dummy variables to represent the presence of doodles in each country on each day. After a review of all doodles in the Doodle Archive and observational cues used in previous relevant literature, we have chosen to divide them into three categories: *strong observational cue, weak observational cue* and *eyeless doodle.* Looking at figure 3.1, we see some examples of previously used observational cues that have yielded significant results. They vary between human eyes, human-looking figures and very subtle indications of eyes. Based on this, we do not see the need to divide between human and non-human observational cues.

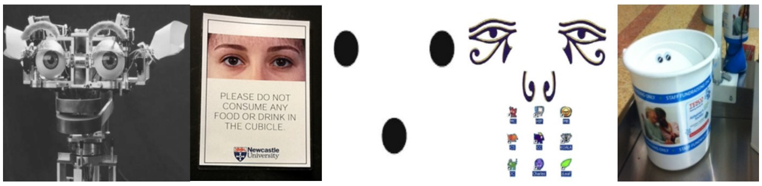


Figure 3.1 – Observational cues from Burnham and Hare (2007), Nettle et al. (2013), Rigdon et al. (2009), Haley and Fessler (2005) and Powell et al. (2012)

Nettle et al. (2013) used pictures of both female and male eyes in their Dictator Game experiment and found no difference between them. We will therefore not differentiate between genders when categorizing the doodles. The dictator game results from Haley and Fessler (2005) indicated a stronger effect of a direct eye gaze than skewed eyes, and as a consequence, the majority of our doodles in the strong observational cue category consist of logos containing a direct gaze. Weak observational cues, on the other hand, often contain skewed eyes. We note that almost all the previous experiments use close-up pictures of eyes, and it is logical that the closer and more in focus the eyes are, the easier it is to isolate the eye effect. We have therefore put doodles with large eyes and limited background noise in the strong observational cue category.

All other previous experiments have used control images without eyes. In our study, the original Google logo provides us with a natural control image. In addition, we have created a category for eyeless doodles to account for any effect these might have on search behaviour. We have few good suggestions as to how this effect will play out, but find it reasonable to suspect that doodles themselves could have an effect on search volume even when no eyes are present.

The figures below show two examples each of doodles in the three different categories.

1. Strong observational cue: A doodle containing staring eyes up close

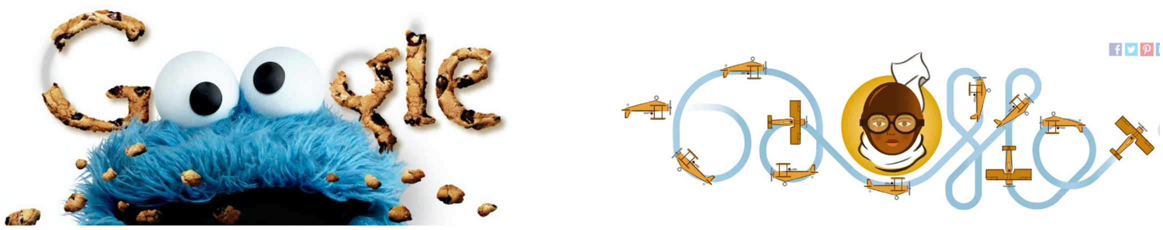


Figure 3.2 – Examples of doodles in Category (1): Strong observational cue

2. Weak observational cue: A doodle containing non-staring eyes and/or distant eyes

Figure 3.3 – Examples of doodles in Category (2): Weak observational cue

3. Eyeless doodle: A doodle not containing eyes

Figure 3.4 – Examples of doodles in Category (3): Eyeless doodle

3.2.2 Control variables

Cyclical variables

Most of our dependent variables show clear cyclical tendencies. This is especially true in our porn search terms. Porn searches show a surge during both weekends and holidays. We therefore see a considerable difference of volume each Saturday and Sunday compared to the other weekdays. This is also the case for the summer months from mid-May to August, Thanksgiving weekend and during Christmas. This can be explained by the fact that people Google our selected terms more often in their spare time, and the majority have the weekend and regular holidays off. We have therefore included dummy variables indicating days of the week, months, public holidays and summer holidays, in order to control for their effect on the search volume.

Country variable

Using data from two countries gives us a better fundament for our analysis. The two countries have different search trends, cultures, laws, holidays and doodles on different days. In figure 3.5, we have illustrated the expected behaviour of SVI on days when there is an observational cue in the Google logo. When there is a doodle with an observational cue present in both countries, we expect both SVI_{UK} and SVI_{US} to fall. When a doodle with an observational cue is only present in one country, the other country will continue its regular trend while SVI will fall in the country exposed to the doodle. If our analysis can uncover this effect, the probability that our results are causal is higher than if we analyze only one country. We have therefore added a country variable to one of our late time period analyses, where we have included both the US and the UK. This variable is not included in the 2008-2011 analysis because this analysis only includes American search data.

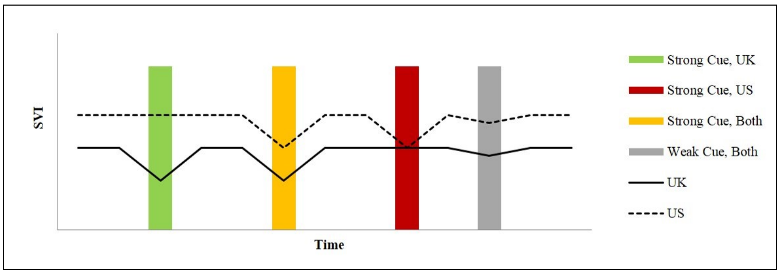


Figure 3.5 – Expected SVI for different doodle categories across countries

Time trend variable

We expect most of our search terms to show clear trends over our long time period. It is therefore necessary for us to account for trends in our analysis. We have chosen to include a daily time trend in our analysis. Since these trends might vary between the two countries, we will also include an interaction term between time trend and country in the two-country analysis in the last period.

4. Descriptive statistics

In this chapter, we will first present the development of the search volume index and summary statistics for our selected variables in the two time periods. We will then describe the development of frequency and the prevalence of different types of doodles.

4.1 Search terms

The charts in figures 4.1 and 4.2 show the development of search volume over time for our search category variables in the early and late periods. It is clear that search terms show similar behaviour across the two countries between 2014 and 2017. The most prominent trend is the exponentially decreasing search volumes for our pedophilia terms in the late period for both the UK and the US. Our last period begins shortly after the revelation of the National Security Agency's surveillance of internet use, and the trend can therefore be seen in relation to increasing digital surveillance, punishments and use of digital evidence (Department Of Justice, 2016). Because of this trend, we have decided to use the natural logarithm of the pedophilia variable in our analysis. The rest of the dependent variables generally show signs of linear or stable trends with some cyclical variations.

Figure 4.1 – Development of respective search terms in the US, 2008-2011

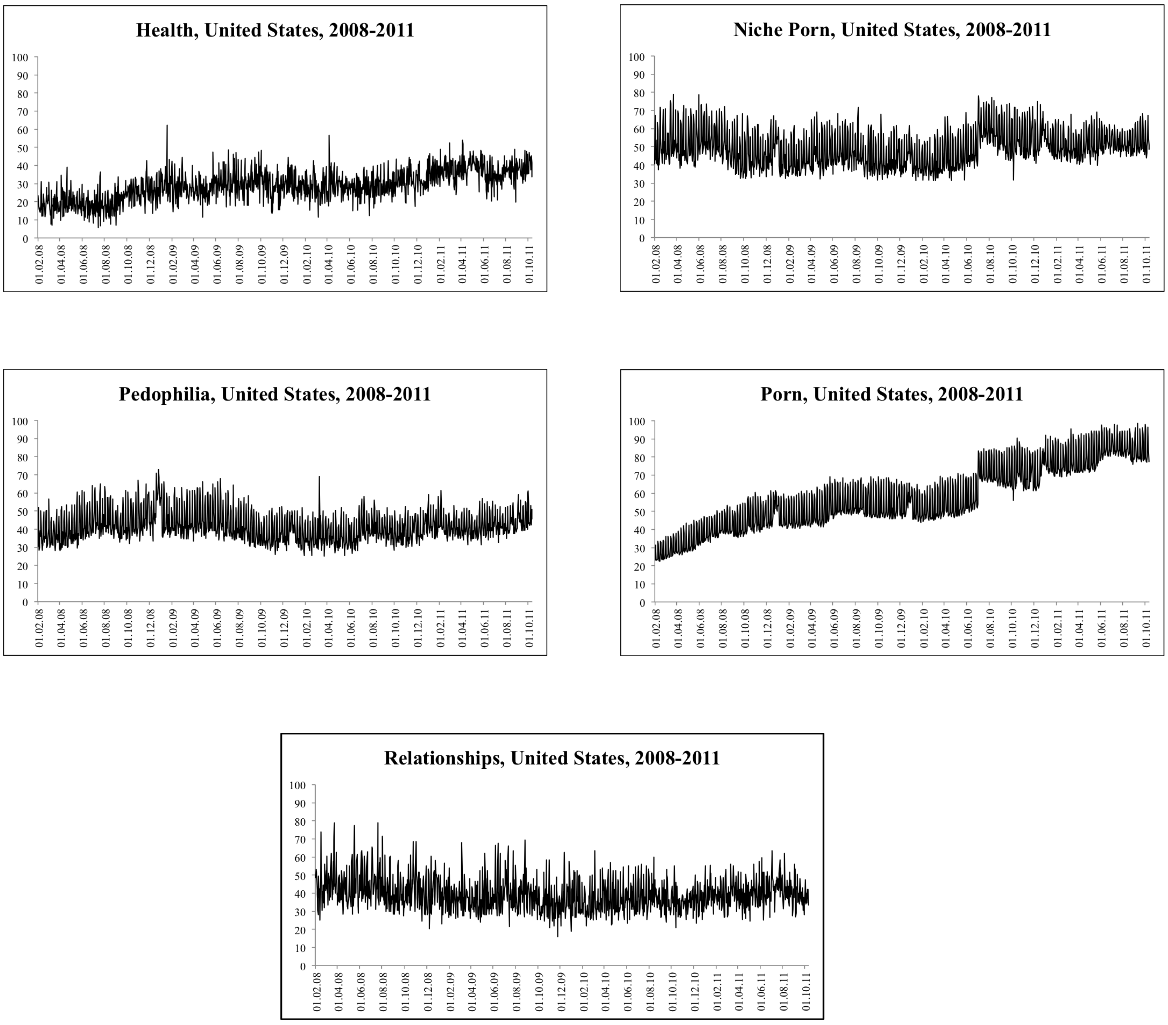


Figure 4.2 – Development of search volume for our search term variables in the US and the UK, 2014-2017

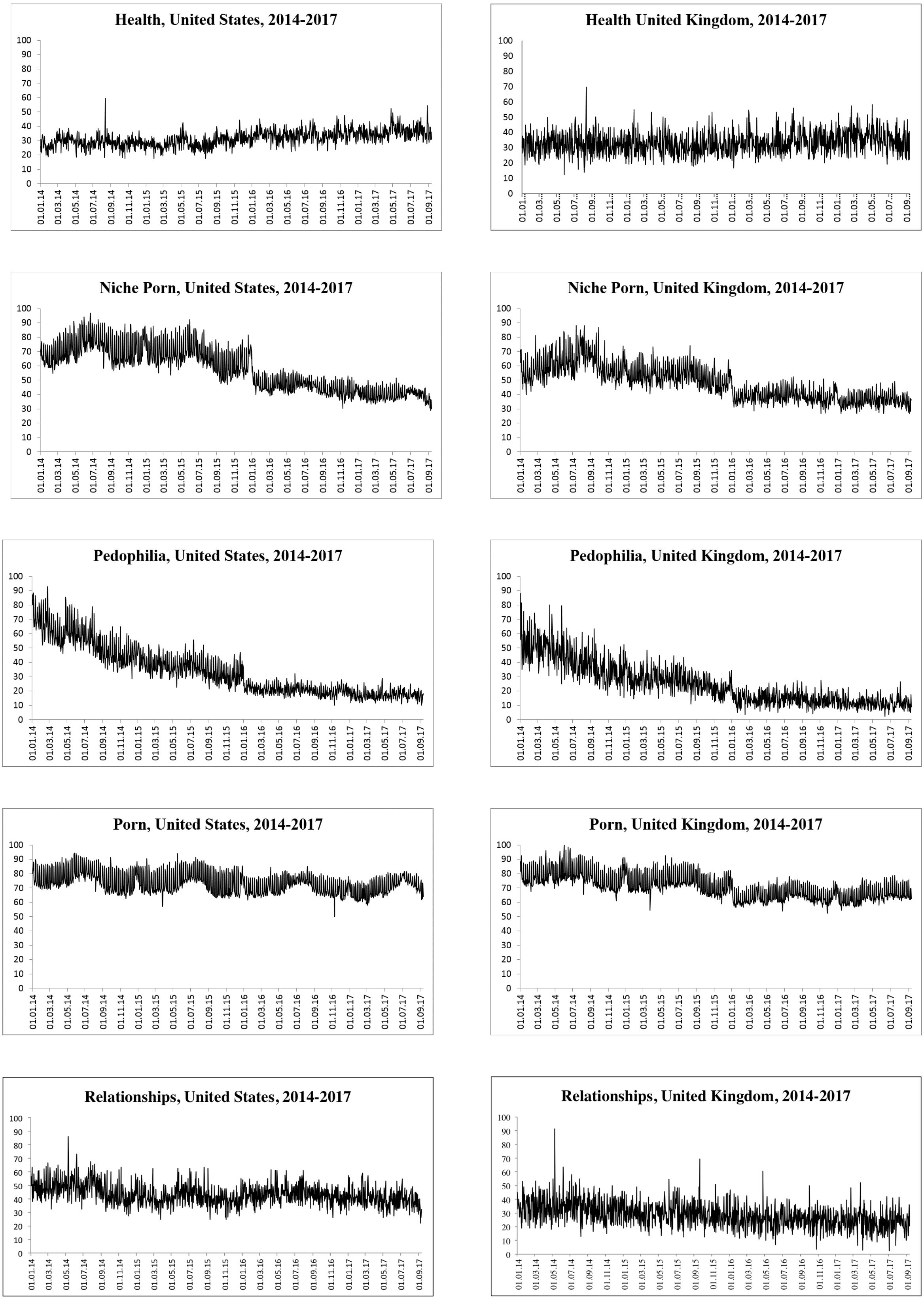


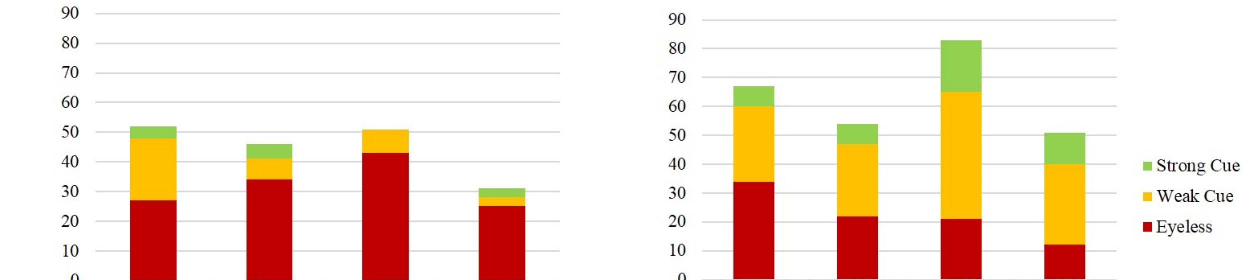
Table 4.1 shows summary statistics for our dependent variables. Porn searches have the highest mean and a relatively low variation. The large increase in popularity of the porn terms gives us an unusual variation of 17.87 SVI points for porn, which is also seen in the trend chart. The large drop of 7.77 points for mean and 11.25 points for median in the pedophilia variable from the early to the late period is also worth mentioning. This is due to a consistent decrease in the popularity of such searches between 2014 and 2017. The high variation of 17.19 and 14.78 SVI points tells us that it continues to drop throughout our late dataset, as seen in the trend graphs. We can also recognize the large variation in niche porn from the decreasing trend graphs in the late period.

Table 4.1 – Summary statistics for the dependent variables

	Mean	**Median**	**St. dev.**
2008-2011			
US			
Pedophilia	41.45	40.00	8.35
Niche Porn	48.87	47.33	9.98
Porn	57.68	53.50	17.87
Relationships	39.30	38.00	9.02
Health	28.95	29.00	8.54
2014-2017			
US			
Pedophilia	33.68	28.75	17.19
Niche Porn	57.30	56.67	15.26
Porn	73.27	72.50	7.43
Relationships	43.10	42.00	7.51
Health	31.50	31.33	5.56
UK			
Pedophilia	24.80	21.00	14.78
Niche Porn	47.94	46.67	12.21
Porn	70.67	70.00	8.65
Relationships	28.43	27.75	9.04
Health	33.24	32.67	7.07

4.2 Doodles

Figure 4.3 shows the development of frequency of doodles by type in the United States in our early and late periods respectively. Over the years, the frequency of doodles, and the share of doodles that contain strong observational cues, have increased. There are 83 doodles in 2016, the highest number overall. This is mainly driven by Google presenting the Doodle Fruit Games with 17 consecutive interactive doodles worldwide in August, as well as the football World Cup with a new doodle each day of the championship. 2008 had a relatively large amount of weak observational cues. This is because each day during the summer Olympics, a sport was represented in the Google logo. The overall number of doodles is seemingly unexpectedly low in 2011 and 2017, but this can be explained by the fact that our dataset does not cover the entire last year of each time period. This leaves out 3-4 months of potential doodle observations in 2011 and 2017. Note that we have also left out the first month in 2008.



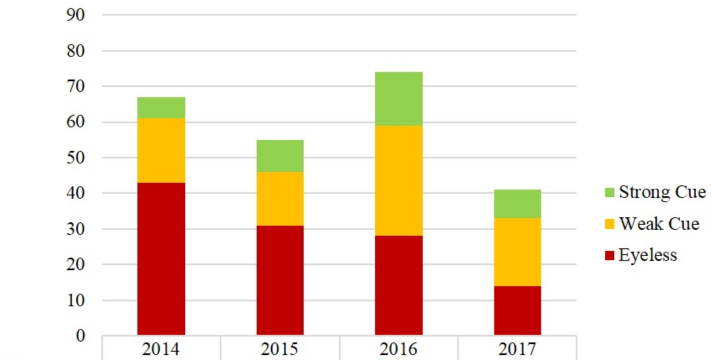
	2008	2009	2010	2011
Strong Cue	4	5	0	3
Weak Cue	21	7	8	3
Eyeless	27	34	43	25

	2014	2015	2016	2017
Strong Cue	7	7	18	11
Weak Cue	26	25	44	28
Eyeless	34	22	21	12

Figure 4.3 – Development and distribution of Doodles in the US over the two periods: 2008-2011 (left) and 2014-2017 (right)

We also see an increasing number of observational cues in our later dataset. This is in line with our expectations due to the increased quantity and complexity of the doodles over the years, in addition to a shift from celebrating holidays to honouring people, often represented by detailed portraits. Eyeless doodles and weak observational cues constitute the largest share of our observations by far. Still, there are 51 doodles containing some type of observational cue in the early period.

Because we include the UK in our late time period analysis only, we only have data from the UK from the period between 2014 and 2017. An overview of doodles over time in the UK is shown in figure 4.4. We can see a decrease in the number of eyeless doodles from 2014 to 2017, while we simultaneously see an increase in observational cues.



	2014	2015	2016	2017
Strong Cue	6	9	15	8
Weak Cue	18	15	31	19
Eyeless	43	31	28	14

Figure 4.4 – Development and distribution of Doodles in the UK, 2014-2017

Comparing the datasets from the late period for the two countries, it is clear that the US has a slightly higher number of weak observational cues, strong observational cues and doodles in general. The US has 255 doodles in total during our late period, while the UK has 237. For a full list of doodles categorized by weak and strong observational cues used in this thesis, see appendices A.5-A.7.

5. Empirical strategy

For the first time period, 01.02.2008 - 12.10.2011, we have 1350 observations for each of the five dependent variables we have chosen, i.e. one per day. As mentioned earlier, we will only analyze the United States in this period. We will run five separate Ordinary Least Squares (OLS) regressions to answer our hypothesis, one for each dependent variable. The key identifying assumption for this analysis is that conditional on the trend, the day of the holidays, the day of the month and the day of the week, the doodle is uncorrelated with other factors that drive underlying search behaviour except for the effect of the doodle itself.

For the second time period, 01.01.2014 - 11.09.2017, we have added the United Kingdom and therefore have 2700 observations for each of the five dependent variables. We then have two observations per day in the cross-country analysis, one for each country. We will also here apply Ordinary Least Squares regressions to examine the relationship between SVI of the stigmatizing search terms and a set of independent variables. For the cross-country analysis the key identifying assumption is the common trend assumption: that we would expect the same change in search behaviour in the UK and the US absent country-specific doodles. We will also run regressions for both the UK and US separately. This is to break the analysis down even further and gain the opportunity to look at the potential differences between the two countries.

For both our periods, we have the following regression model for search term j in country i on day t:

$$SVI_{ijt} = \beta_0 + \delta_1 StrongCue_{it} + \delta_2 WeakCue_{it} + \delta_3 EyelessDoodle_{it} + \beta_x + \varepsilon_{ijt} \quad (5.1)$$

StrongCue takes a value of 1 if the doodle falls within the aforementioned strong observational cue category and 0 if not. *WeakCue* takes a value of 1 if the doodle falls within the weak observational cue category and 0 if not. *EyelessDoodle* takes a value of 1 if there is a doodle present that does not contain any eyes, and 0 if there is no doodle or a doodle containing eyes.

δ_1 is our main variable of interest and gives us the total effect of strong observational cues relative to no doodle. δ_2 gives us the total effect of weak observational cues relative to no doodle, and δ_3 allows us to control for the potential effect of a doodle with no eyes relative to days with no doodle.

By combining or subtracting the coefficients, we can get further insight from our regression model. $\delta_1 - \delta_3$ captures the effect of strong observational cues on top of the eyeless effect. $\delta_1 - \delta_2$ captures the effect of strong observational cues on top of the weak observational cues. $\delta_1 + \delta_2$ captures the effect of any form of observational cues.

β_x in the regression model consists of x representing our control variables, and β representing the effect of the respective variables. These consist of dummy variables indicating weekdays (7 weekday dummies in total, omitting Sunday in the analysis), months (12 monthly dummies in total, omitting December in the analysis) and Holidays (2 dummies in total, turning 1 during public and summer holidays, and taking a value of 0 the rest of the time). This is in order to control for the previously mentioned cyclical behaviour of our Search Volume Indexes. The control variables also include our daily time trend variable (t).

In the OLS regressions for our second time period from 2014 to 2017, we will also add the aforementioned country variable in the cross-country analysis to control for the differences between the US and UK.

6. Results

In this chapter, we will summarize the results from the OLS regressions described in the previous chapter. First, we will go through the results for one example term (niche porn) and walk through the process of adding control variables, before we use the final model to establish the results for all search terms. We will comment briefly on this final model, first for the US-only analyses in the 2008-2011 and 2014-2017 periods, before we add data from the UK to our late-period analysis and present the combined results.

6.1 Example: Niche porn, United States

In this section, we will demonstrate the effect of adding our control variables (weekdays, months, holidays, and time trend), as well as robust and clustered standard errors, on our observational cue results for the niche porn category. In doing so, we will explain the process through which we have landed on our final model to use on all search terms.

Tables 6.1 and 6.2 include six analyses of our niche porn category for the US in 2008-2011 and 2014-2017, respectively. We will start by going through the results from the early period before moving on to see whether the results in the late period show the same development.

6.1.1 Early period, 2008-2011

The early period results for our niche porn variable can be found in table 6.1. For *strong observational cues*, we have a negative coefficient in column (1) with no control variables. This is the effect we expect based on our hypothesis. However, when controlling for weekdays, the insignificant negative sign turns positive with a 1.012 SVI point increase of search volumes on niche porn, as seen in column (2). There are twice as many strong observational cues on average per weekday (Monday-Friday) than during the weekends (Saturday-Sunday), see appendix A.2, figure A.8, while niche porn searches tend to be substantially higher during the weekends. Our results in column (2) therefore make it clear that the negative coefficient from column (1) can be explained by the search volumes on different days of the week rather than the strong observational cues. When controlling for months in column (3), our insignificant positive coefficient from column (2) increases somewhat to a coefficient of 1.027. The same mechanism has therefore taken place again: months with a low search volume seem to coincide with months containing a high number of doodles. Not adding monthly variables would lead to a failure of capturing this effect. In column (4) we add our holiday variables, one representing public holidays (Thanksgiving, Christmas and 4th July), and one representing the summer holidays (15th June-15th August every year). The coefficient increases from 1.027 in column (3) to 1.328 in column (4), again due to the same mechanism. When adding the daily time trend (t) in column (5), the coefficient increases yet again, from 1.328 in column (4) to 1.587 in column (5). Thus, if not controlling for the time trend, the effect of coinciding high search volumes and low doodle frequency would not be captured.

The same intuition follows with *weak observational cues*. Here however, we start with a positive coefficient of 1.169, suggesting that days with weak observational cues increases search volumes of niche porn. This coefficient gets even higher and significant when controlling for weekdays in column (2). Looking at the coefficients for the different weekdays, it is clear that we have a high variation of search volume on the different days. When taking this weekday-effect into account, we still have positive significant search volumes on days with weak observational cues. The weekday differences can therefore not fully explain the significantly positive effect we see. When controlling for months and holidays in column (3) and (4), this effect is reversed and the coefficient decreases. The mechanism is reversed yet again for the time trend in column (5), where we get a higher positive coefficient and a higher level of significance. The significantly positive coefficient of 3.034 holds through both robust standard errors and clustered robust standard errors. Thus, it goes against our hypothesis by indicating that a weak observational cue increases searches for niche porn in the early period, compared to days without doodles.

For *eyeless doodles* we get negative coefficients throughout all 7 specifications. When controlling for the time trend and robust standard errors, we even get significant results suggesting that a doodle without observational cues decreases searches for niche porn.

This result turns insignificant in column (7) on the other hand, which implies that the use of clustered standard errors allows us to capture a weekly effect that we did not capture earlier. This indicates that we should, indeed, use clustered standard errors to get correct results.

Table 6.1 – Regression results, Niche Porn 2008-2011, United States: Model without control variables in column (1), controls in column (2), (3) and (4) for weekdays, months and holidays respectively. Column (5) adds the time trend, while robust results are shown in column (6). Finally, clustered standard errors are added in column (7). t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Nicheporn 2008 - 2011, US						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strong observational cue	-0.968 (-0.33)	1.012 (0.53)	1.027 (0.57)	1.328 (0.75)	1.587 (0.92)	1.587 (1.19)	1.587 (1.08)
Weak observational cue	1.169 (0.72)	2.810* (2.63)	2.556* (2.52)	2.331* (2.34)	3.034** (3.09)	3.034** (3.20)	3.034** (3.36)
Eyeless Doodle	-1.332 (-1.44)	-0.941 (-1.55)	-0.775 (-1.34)	-1.085 (-1.89)	-1.161* (-2.07)	-1.161* (-2.04)	-1.161 (-1.57)
Monday		-15.11*** (-22.67)	-15.11*** (-24.07)	-15.04*** (-24.36)	-15.06*** (-24.92)	-15.06*** (-22.65)	-15.06*** (-24.02)
Tuesday		-16.90*** (-25.36)	-16.95*** (-27.00)	-16.80*** (-27.21)	-16.81*** (-27.80)	-16.81*** (-27.23)	-16.81*** (-41.83)
Wednesday		-16.83*** (-25.23)	-16.91*** (-26.89)	-16.77*** (-27.12)	-16.77*** (-27.71)	-16.77*** (-27.42)	-16.77*** (-40.43)
Thursday		-16.56*** (-24.79)	-16.63*** (-26.41)	-16.64*** (-26.89)	-16.64*** (-27.47)	-16.64*** (-27.50)	-16.64*** (-39.89)
Friday		-15.06*** (-22.60)	-15.08*** (-24.02)	-15.18*** (-24.59)	-15.19*** (-25.13)	-15.19*** (-24.32)	-15.19*** (-35.42)
Saturday		1.080 (1.62)	1.076 (1.71)	1.051 (1.70)	1.068 (1.77)	1.068 (1.56)	1.068* (2.27)
January			-4.195*** (-4.64)	-2.713** (-2.96)	-2.791** (-3.11)	-2.791** (-3.07)	-2.791** (-3.22)
February			-3.843*** (-4.43)	-2.170* (-2.44)	-1.710 (-1.96)	-1.710 (-1.89)	-1.710* (-2.14)
March			-2.924*** (-3.45)	-1.236 (-1.42)	-0.902 (-1.06)	-0.902 (-1.03)	-0.902 (-1.13)
April			-1.683* (-1.97)	0.0192 (0.02)	0.271 (0.32)	0.271 (0.32)	0.271 (0.33)
May			-0.684 (-0.81)	1.024 (1.17)	1.155 (1.35)	1.155 (1.34)	1.155 (1.07)
June			1.288 (1.51)	2.001* (2.06)	2.042* (2.15)	2.042* (2.15)	2.042* (2.11)
July			3.674*** (4.34)	3.281** (2.82)	3.244** (2.85)	3.244** (2.83)	3.244* (2.22)
August			1.378 (1.63)	2.204* (2.32)	2.013* (2.17)	2.013* (2.13)	2.013 (1.59)
September			-0.472 (-0.55)	1.228 (1.40)	0.973 (1.13)	0.973 (1.10)	0.973 (0.94)
October			-2.325** (-2.65)	-0.634 (-0.70)	-0.691 (-0.78)	-0.691 (-0.77)	-0.691 (-0.67)
November			-2.348* (-2.57)	-1.519 (-1.67)	-1.398 (-1.58)	-1.398 (-1.59)	-1.398 (-1.37)
Public Holidays				6.568*** (6.54)	6.572*** (6.68)	6.572*** (5.75)	6.572*** (4.50)
Summer Holidays				1.828* (2.35)	1.813* (2.38)	1.813* (2.45)	1.813 (1.51)
t					0.00323*** (7.66)	0.00323*** (7.86)	0.00323*** (4.09)
Constant	48.97*** (167.78)	60.20*** (127.26)	61.12*** (79.83)	59.42*** (74.60)	0.503 (0.07)	0.503 (0.07)	0.503 (0.03)
Observations	1350	1350	1350	1350	1350	1350	1350

6.1.2 Late period, 2014-2017

At first glance, the later period (Table 6.2) looks more promising. We have large negative coefficients for *strong observational cues* and smaller negative coefficients for *weak observational cues.*

We initially start with a significant negative coefficient of 6.914 SVI points for *strong observational cues* in column (1). The coefficient is still negative after controlling for weekdays, months and holidays, which suggests that the cyclical variations in SVI cannot fully explain our decrease in search terms on days with strong observational cues. After controlling for our time trend on the other hand, the significance disappears, and our coefficient increases from -6.346 to -1.483. This can be explained by the combination of decreasing search volume over time and increased frequency of strong observational cues in the later parts of our dataset. It is worth mentioning, however, that p-values in columns (6) and (7) are only marginally above 5%, and that we should therefore not dismiss them completely.

For *weak observational cues* we have negative and insignificant coefficients until column (4), where we control for holidays. Here, we have significant results and the holidays, monthly differences and weekdays cannot explain our negative search volume of weak observational cues. However, as with strong observational cues, when we control for the decreasing time trend, the results turn insignificant.

Eyeless doodles starts out positive and turns significant, implying that doodles without observational cues leads to higher search volumes. As with both strong and weak observational cues, the time trend has a large impact, turning the results insignificant. It is clear that the decreasing number of eyeless doodles in the later part of our dataset (see figure 4.3) combined with a negative time trend affects the results.

Table 6.2 – Regression results, Niche Porn 2014 - 2017, United States: Model without control variables in column (1), controls in column (2), (3) and (4) for weekdays, months and holidays respectively. Column (5) adds the time trend, while robust results are shown in column (6). Finally, clustered standard errors are added in column (7). t statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Nicheporn 2014 - 2017, US						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Strong observational cue	-6.914**	-5.691*	-5.985**	-6.346**	-1.483	-1.483	-1.483
	(-2.93)	(-2.57)	(-2.70)	(-2.86)	(-1.66)	(-1.96)	(-1.96)
Weak observational cue	-2.538	-2.464	-2.671	-3.043*	-0.152	-0.152	-0.152
	(-1.76)	(-1.81)	(-1.96)	(-2.22)	(-0.28)	(-0.27)	(-0.26)
Eyeless Doodle	3.552*	4.588**	4.230**	3.681*	0.584	0.584	0.584
	(2.12)	(2.92)	(2.68)	(2.32)	(0.91)	(1.02)	(0.93)
Monday		-9.772***	-9.734***	-9.734***	-9.888***	-9.888***	-9.888***
		(-6.72)	(-6.73)	(-6.74)	(-16.99)	(-14.42)	(-17.43)
Tuesday		-11.84***	-11.83***	-11.83***	-12.00***	-12.00***	-12.00***
		(-8.14)	(-8.18)	(-8.19)	(-20.62)	(-18.97)	(-25.69)
Wednesday		-12.46***	-12.48***	-12.51***	-12.51***	-12.51***	-12.51***
		(-8.58)	(-8.63)	(-8.67)	(-21.51)	(-20.27)	(-27.49)
Thursday		-12.64***	-12.66***	-12.72***	-12.61***	-12.61***	-12.61***
		(-8.69)	(-8.74)	(-8.80)	(-21.63)	(-20.35)	(-30.93)
Friday		-11.35***	-11.34***	-11.38***	-11.31***	-11.31***	-11.31***
		(-7.82)	(-7.85)	(-7.89)	(-19.45)	(-17.74)	(-26.28)
Saturday		0.119	0.126	0.106	0.216	0.216	0.216
		(0.08)	(0.09)	(0.07)	(0.37)	(0.31)	(0.82)
January			-3.552	-2.314	-7.279***	-7.279***	-7.279***
			(-1.83)	(-1.15)	(-8.95)	(-8.08)	(-4.66)
February			-5.679**	-4.240*	-8.063***	-8.063***	-8.063***
			(-2.86)	(-2.05)	(-9.64)	(-8.80)	(-5.35)
March			-4.258*	-2.818	-5.540***	-5.540***	-5.540***
			(-2.19)	(-1.38)	(-6.75)	(-6.57)	(-3.59)
April			-3.278	-1.857	-3.535***	-3.535***	-3.535*
			(-1.67)	(-0.91)	(-4.28)	(-4.29)	(-2.29)
May			-1.826	-0.389	-1.194	-1.194	-1.194
			(-0.94)	(-0.19)	(-1.46)	(-1.32)	(-0.59)
June			-0.194	0.0416	0.421	0.421	0.421
			(-0.10)	(0.02)	(0.45)	(0.46)	(0.26)
July			-1.829	-2.714	-1.199	-1.199	-1.199
			(-0.94)	(-1.00)	(-1.09)	(-1.18)	(-0.61)
August			-4.591*	-4.286	-2.076*	-2.076*	-2.076
			(-2.36)	(-1.90)	(-2.28)	(-2.53)	(-1.31)
September			-6.629**	-5.181*	-5.286***	-5.286***	-5.286**
			(-3.25)	(-2.44)	(-6.17)	(-6.53)	(-3.29)
October			-3.834	-2.440	-4.096***	-4.096***	-4.096**
			(-1.84)	(-1.13)	(-4.70)	(-5.30)	(-2.73)
November			-2.083	-1.351	-2.139*	-2.139*	-2.139
			(-0.99)	(-0.64)	(-2.51)	(-2.46)	(-1.26)
Public Holidays				5.638*	5.822***	5.822***	5.822***
				(2.36)	(6.06)	(5.13)	(3.56)
Summer Holidays				2.148	2.018**	2.018**	2.018
				(1.17)	(2.73)	(3.16)	(1.64)
t					-0.0335***	-0.0335***	-0.0335***
					(-82.74)	(-90.43)	(-53.08)
Constant	57.52***	65.68***	68.89***	67.55***	752.8***	752.8***	752.8***
	(125.39)	(63.18)	(38.96)	(36.37)	(90.53)	(98.71)	(57.20)
Observations	1350	1350	1350	1350	1350	1350	1350

6.2 All terms

Based on our results from the niche porn examples, we have decided to include all the control variables in our model, while also using robust standard errors clustered on week number (as in column (7) in tables 6.1 and 6.2). Having established this final model to apply to all terms, we will in the following subsections present the final results for all our search categories in the US in 2008-2011 and 2014-2017, as well as for the combined model in the latter period.

6.2.1 United States, 2008-2011

Table 6.3 shows all our different search terms in the early period for the US (full regressions including all control variables can be found in appendix A.1). None of the variables show any significant reaction to *strong observational cues*. The health and pedophilia variables show a negative relationship between strong observational cues and SVI, in line with what we expected, but the results are not significant. The niche porn, porn and relationship categories however, have positive coefficients that are inconsistent with our hypothesis. According to our hypothesis, we would also expect the coefficients for the *weak observational cues* to show a smaller negative reduction in SVI than those representing the strong cues. This is only the case for our health variable, which is not significant for either strong or weak observational cues. We even have a significant result suggesting that that the SVI for niche porn searches increases by 3.034 points on days with weak observational cues. For *eyeless doodles* we have no significant coefficients, although they are all negative.

Table 6.3 – Regression results final model, 2008 - 2011: All search terms, United States. Using robust standard errors clustered on week number. t-statistics are given in parentheses. We indicate significance by: * p < 0.05, ** p < 0.01, *** p < 0.001.

	(1) Health	(2) Niche Porn	(3) Pedophilia	(4) Porn	(5) Relationships
Strong observational cue	-0.528 (-0.28)	1.587 (1.08)	-0.475 (-0.48)	1.165 (1.16)	1.610 (0.71)
Weak observational cue	-0.315 (-0.24)	3.034** (3.36)	2.550 (1.55)	1.554 (1.44)	0.725 (0.50)
Eyeless Doodle	-0.230 (-0.42)	-1.161 (-1.57)	0.0330 (0.06)	-0.783 (-1.28)	-0.824 (-1.02)
t	0.0139*** (26.97)	0.00323*** (4.09)	-0.00151* (-2.61)	0.0399*** (117.36)	-0.00345*** (-5.80)
Constant	-221.9*** (-23.25)	0.503 (0.03)	78.74*** (7.36)	-660.3*** (-107.10)	107.7*** (9.77)
Observations	1350	1350	1350	1350	1350
Weekday dummies	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes
Holiday dummies	Yes	Yes	Yes	Yes	Yes

Table 6.4 – Regression results final model, 2014 - 2017: All search terms, United States. Using robust standard errors clustered on week number. t-statistics are given in parentheses. We indicate significance by: * p < 0.05, ** p < 0.01, *** p < 0.001.

	(1) Health	(2) Niche Porn	(3) Pedophilia (ln)	(4) Porn	(5) Relationships
Strong observational cue	-0.119 (-0.19)	-1.483 (-1.96)	-0.0114 (-0.43)	0.0939 (0.21)	1.601 (1.57)
Weak observational cue	-0.270 (-0.74)	-0.152 (-0.26)	-0.0261 (-1.92)	-0.113 (-0.37)	0.328 (0.60)
Eyeless Doodle	0.731 (1.31)	0.584 (0.93)	0.0142 (0.87)	0.625* (2.42)	0.382 (0.59)
t	0.00784*** (17.52)	-0.0335*** (-53.08)	-0.00119*** (-68.29)	-0.00741*** (-22.52)	-0.00684*** (-12.11)
Constant	-129.7*** (-14.21)	752.8*** (57.20)	27.90*** (78.71)	230.5*** (33.47)	182.2*** (15.89)
Observations	1350	1350	1350	1350	1350
Weekday dummies	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes
Holiday dummies	Yes	Yes	Yes	Yes	Yes

6.2.2 United States, 2014-2017

The results from the late period for the US are presented in table 6.4 (full regression can be found in appendix A.2). Although we have negative coefficients for *strong observational cues* in the health, niche porn and pedophilia categories, none of them are significant. For *weak observational cues* the three mentioned variables are still negative, in addition to porn turning negative as well. There are no significant results here either. For our *eyeless doodles*, all our coefficients are positive. In addition, our porn variable is even significant and indicating a 0.625 SVI increase in response to eyeless doodles. We thus see a correlation between porn searches and the presence of doodles not containing observational cues. This effect does not appear for the other search variables.

6.2.3 Combined model: United States and United Kingdom, 2014-2017

In the previous models, we have only analyzed one country, and thus only compared a day with a doodle to another day without a doodle. By including the UK in this analysis, we can compare the same date in two different countries, with or without the same doodle (as explained in chapter 3.2.2). This serves as a better control for our analysis as we now, on several occasions, have one country where an observational cue is present and one where it is not. We can therefore see how SVI in the two countries behaves on the same date. The results from this analysis can be seen in table 6.5.

For *strong observational cues*, we see no changes in significance level or sign for the coefficients for any of our variables when we add the UK to the analysis. For *weak observational cues*, the health and porn categories, that were both negative in the US only model, are now positive. This implies a large difference between the coefficients for the US and UK, where the UK have higher positive coefficients for these two variables. The rest of the coefficients keep the same sign as in the US only analysis, and still, none of them are significant. We find the biggest difference in the *eyeless doodles*. Both pedophilia and relationships have changed to negative signs in the combined model. In addition, the porn variable is no longer significant. This implies that the significant increase in porn searches on days with eyeless doodles was restricted to the US only. Table A.4 (see appendix A.3), that shows the regression results for the UK, confirms this. Here, we see that the porn variable is insignificant and has a much lower coefficient. All in all, the UK in itself does not have any significant results and after adding the UK to our analysis we still have no significant reaction to our observational cues in the late period.

Table 6.5 – Regression results final model, 2014 - 2017: All search terms, US and UK combined. Using robust standard errors clustered on week number. t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Health	(2) Niche Porn	(3) Pedophilia (ln)	(4) Porn	(5) Relationships
Strong observational cue	-0.442	-0.722	-0.0222	0.462	0.557
	(-0.68)	(-1.10)	(-0.60)	(1.19)	(0.62)
Weak observational cue	0.0927	-0.145	-0.00235	0.111	0.482
	(0.23)	(-0.26)	(-0.13)	(0.37)	(0.99)
Eyeless Doodle	0.465	0.269	-0.00295	0.373	-0.235
	(1.01)	(0.58)	(-0.18)	(1.78)	(-0.44)
Country	-95.77***	168.8***	-2.754***	-151.9***	-62.01***
	(-7.30)	(13.26)	(-5.33)	(-26.81)	(-4.41)
t	0.00327***	-0.0259***	-0.00135***	-0.0150***	-0.0106***
	(5.61)	(-37.15)	(-47.32)	(-43.53)	(-19.31)
Country $\times t$	0.00461***	-0.00782***	0.000152***	0.00757***	0.00376***
	(7.15)	(-12.72)	(6.02)	(27.27)	(5.50)
Constant	-34.06**	585.8***	30.69***	384.6***	247.4***
	(-2.86)	(40.61)	(52.94)	(53.39)	(21.99)
Observations	2700	2700	2700	2700	2700
Weekday dummies	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes
Holiday dummies	Yes	Yes	Yes	Yes	Yes

6.3 Summary of results

Overall, we find some marginally insignificant results in the analysis of our niche porn category, and only two significant results in the rest of our analyses for observational cues on stigmatizing Google searches. The significant results are also the opposite of what we expected. A weak observational cue allegedly increases searches for niche porn with 3.034 SVI points in the US in the early period and an eyeless doodle increases porn searches with 0.635 SVI points in the US in the late period.

7. Discussion

In this chapter, we will discuss the previously presented results from our observational cue analysis for both the early and late time period in the US, UK and combined. Then, we will discuss the potential reasons behind our null-findings.

7.1 Doodle analysis

For us to be able to claim that there is an observational cue effect, some key relationships must be in place. First of all, the strong observational cues must show a significant and negative relationship with the SVI. Given such a relationship, we expect a smaller, or insignificant effect of our weak observational cues and potentially an unknown effect of the eyeless doodles.

We also expect the relationship to be stronger in the early period. This is because the rapid increase in smartphone ownership and development of web browsers after our early period makes it likely that more people in the later years access Google through channels that do not expose them to doodles (for instance by searching using the address bar in the browser on their computer or on their smartphone). This has a direct effect on the design of our study, and we therefore expect a stronger effect between 2008 and 2011. If these relationships, a negative impact of strong cues on SVI, a relatively smaller impact of weak cues on SVI, and a stronger relationship in the early period are in place, we can be confident that people do, in fact, react to the presence of eyes in the doodles.

As mentioned earlier, the strong observational cue coefficients for niche porn between 2014 and 2017 in the US are only marginally insignificant and could therefore not be dismissed completely. There are two issues related to this, however. The first is the fact that the coefficient jumps from -6.436 to -1.483 by adding a time trend. Such a large difference means that there is a probability that some of this time trend might not have been captured completely by adding the time variable. Secondly, in order to be able to draw a general conclusion, our other terms would have to demonstrate similar behaviour.

This is not the case. We rather find a significant effect suggesting a 3.259 point increase in the SVI for niche porn searches in response to *weak observational cues* in the early period. It is unclear why exposure to a weak observational cue would significantly increase the searches for niche porn. This is not the case for any of our other dependent variables. We do not see any evidence for the incremental increase in effect based on the strength of observational cues for the niche porn variable either. Moreover, the results for niche porn in the late period do not show the same tendencies. This implies that there must be a relationship between days with weak observational cues and niche porn searches in the early period only. We do not have any good suggestions as to what this relationship could be, and therefore believe that this is not actually a result of the weak observational cues. The same applies to our results suggesting that days with an eyeless doodle significantly increases porn searches by 0.635 SVI points in the US in the late period. This could imply that we actually see an effect of doodles without observational cues, but since the eyeless doodles fail to demonstrate an effect for any of our other search variables, we cannot draw a conclusion about this effect either.

Without our controls, the pedophilia and niche porn categories in the late period show intriguing results. These are, however, eliminated at the introduction of a time trend. This is consistent with the reduction we see in the search terms' behaviour in figures 4.1 and 4.2, where they both show a consistent decline throughout our time period. As we have no fundament to question the impact of the time trend on the development of SVI for these variables, we cannot use these results as evidence for a doodle effect.

With our use of controls, robust and clustered standard errors as well as the cross-country analysis, we believe that observational cues in the Google logo does not decrease the search volume of stigmatizing searches. Given adequate validity of this study, there are two main potential explanations for this result. With respect to our hypothesis, the first that comes to mind is that the evolutionary legacy hypothesis presented by Burnham and Hare (2007) is wrong. Alternatively, it could be because our search terms are simply not stigmatizing enough to cause a reaction in response to the observational cues. This view is possible to test further and will be discussed in the next chapter, where we conduct a follow-up analysis of our search terms to examine if this is the case.

8. Follow-up analysis: response to privacy scandals

In this chapter, we will try to eliminate the probability that our null-findings in the observational cue analysis stem from the fact that our selected search queries are not stigmatizing enough to encourage behavioural alteration at all. We will do this by testing whether our search terms react to news that may have altered their perception of online anonymity.

8.1 Motivation and basis for analysis

Going back to our hypothesis, a prerequisite for our study to yield any results is that people searching for our terms would have altered their behaviour if they were actually being observed. If they would not alter their behaviour, the null findings from the eye exposure analysis do not stem from a lack of reactions to eyes, but simply that people do not consider the search terms stigmatizing enough to make them react. If, however, they do care about the anonymity of their search behaviour but do not react to doodles, our conclusions from the observational cue analysis are strengthened.

Marthews and Tucker (2017) used the development of 282 Google search terms across 11 countries in the time before and after the revelation of the National Security Agency's (NSA) PRISM surveillance system to uncover what they called a "chilling effect". This effect gave significantly negative Google search volumes for phrases that could get you into trouble with the government, and mixed results for searches that would only get you into trouble with family and friends. This indicates that there is, in fact, some behavioural reaction to such news. We will therefore carry out a study similar to theirs in order to test if our search terms follow the same pattern. This will be done by examining SVI before and after the PRISM revelation (2013) and the Ashley Madison data breach (2015).

8.1.1 NSA leaks

On Thursday 6th June 2013, the Guardian (Greenwald and MacAskill, 2013) revealed information on the PRISM program, owned and used by the US National Security Agency. The Program lets the NSA monitor the digital activities of any users of the companies under surveillance. This, according to the article, had been the case for Google since 2009, despite Google's claim of not being aware of any such activity. The revelations created a media storm all over the world. Because this scandal affected such a wide range of topics, we will analyse the search volume of all our search categories before and after the scandal, using weekly data stretching from 01.01.2011 to 31.12.2015.

8.1.2 The Ashley Madison data breach

In July 2015, a group named "The Impact Team" hacked Ashley Madison, a popular affair dating site for married people. They retrieved user information of more than 37 million users. Four weeks later, in mid-August 2015, a leakage of user data was confirmed in the Guardian (Gibbs, 2015). The story got a vast amount of attention in the news, and quickly became an international sensation (Mansfield-Devine, 2015). The case stood out due to its magnitude and the level of detail about its victims, revealing full names, credit card information and sexual fantasies of the site's users to the public.

An analysis of the Ashley Madison data breach can provide us with additional information about post-scandal search behaviour. While the NSA scandal exposed government surveillance, the Ashley Madison data breach meant that information about the site's users was published on the internet. Assuming that people care more if their wives find out about their cheating than if the NSA does, we expect the people in our relationship category that might not respond to the NSA scandal to respond to this news story. As seen in appendix A.4, figure A.11, the lowest SVI value for [adultfriendfinder] in the US between 2012 and 2016 takes place shortly after the hack, suggesting that there was, in fact, an effect of it. In this analysis, we will therefore use weekly datasets stretching from 01.01.2012 to 31.12.2016 to test whether this was part of a systematic decline after the data breach.

8.2 OLS Model - Response to privacy news

We will use an OLS model to run our subsidary analysis. The model can be summarized by the following equation representing the search volume index for query i in country j in week t:

$$SVI_{ijt} = \beta_0 + \delta_1 Scandal_t + \beta_x + \varepsilon_{ijt} \tag{8.1}$$

δ_1 indicates the effect of the scandal, represented by a scandal dummy variable $Scandal_t$ turning from 0 to 1 at the point where the given scandal was made public. β_x represents our control variables. In this analysis, these consist of dummies indicating the corresponding periods to our treatment periods in the years preceding and following the two scandal years (2013 and 2015), and a time variable.

8.3 Results and brief discussions

8.3.1 PRISM scandal

In tables 8.1 and 8.2, we have presented the cross-country effect of the NSA scandal across all our search terms in the US and the UK combined. Using the week after 6th June 2013 as a starting point, we have looked at a short-term effect of 5 weeks and a long-term effect of 26 weeks. Note that the pedophilia category uses a different long-term indicator than the others (see explanation in table 8.2) and is not included in the short-term analysis. This is because of the extreme long-term reduction in searches for such terms in the wake of the scandal (see appendix A.4, figure A.10).

Apart from the relationship category, where the US drives the long-term post-PRISM growth (see appendix, tables A.7 and A.8), the results are similar in the two countries. In the long run, the pedophilia category shows a clear reduction in search volume after the PRISM scandal. This is in line with our expectations. We also discover a significant surge in searches for regular porn, niche porn and relationships across our two countries following the PRISM revelations. The first two are also significant in the short term. This is an unexpected result in the light of our hypothesis, selection of search terms and previous literature (Marthews and Tucker, 2017), but could also provide an explanation

Table 8.1 – NSA Scandal, US & UK: 5-week effect using panel. Here, we present one short-run regression for each term except pedophilia. The five-week effect is indicated by a dummy variable turning 1 in the 5 weeks following 6th June 2013. The control variable is represented by a dummy that turns 1 for the five-week period following 6th June each year. We use robust standard errors in all regressions. t-statistics are given in parentheses. We indicate significance by: * p < 0.05, ** p < 0.01, *** p < 0.001.

	NSA Scandal, US & UK: Short-term effect using panel data			
	(1) Health	(2) Niche Porn	(3) Porn	(4) Relationships
Short term	1.667	4.408**	10.69***	-0.550
	(1.75)	(3.03)	(8.97)	(-0.22)
Control	-2.141***	3.736***	2.222**	2.173*
	(-3.69)	(3.46)	(2.85)	(2.16)
Country	26.36	219.5***	23.36	-174.1***
	(1.66)	(9.37)	(1.11)	(-8.30)
t	-0.00179***	0.0117***	0.00150	-0.0161***
	(-3.42)	(12.75)	(1.85)	(-23.76)
Country $\times t$	-0.00128	-0.0114***	-0.00129	0.00819***
	(-1.59)	(-9.37)	(-1.21)	(7.65)
Constant	76.17***	-155.8***	52.90**	386.4***
	(7.47)	(-8.77)	(3.30)	(29.11)
Observations	522	522	522	522

Table 8.2 – NSA Scandal, US & UK: 26-week effect using panel. Here, we present one long-run regression for each term. The 26-week effect is indicated by a dummy variable that turns 1 in the 26 weeks following 6th June 2013. The control variable is represented by a dummy that turns one for the 26-week period following the week containing 6th June each year. The permanent effect of the pedophilia variable is indicated by a dummy that turns 1 in the week after 6th June 2013, and stays 1 throughout the entire rest of the period. We use robust standard errors in all regressions. t-statistics are given in parentheses. We indicate significance by: * p < 0.05, ** p < 0.01, *** p < 0.001.

	NSA Scandal, US & UK: Long-term effect using panel data				
	(1) Health	(2) Niche Porn	(3) Pedophilia	(4) Porn	(5) Relationships
Permanent effect			-17.31***		
			(-7.19)		
26-week effect	0	4.450***		9.159***	2.930**
	(0.00)	(4.39)		(10.16)	(3.01)
Control	-0.630	-1.172		-1.002	0.801
	(-1.43)	(-1.92)		(-1.84)	(1.36)
Country	26.36	219.5***	-57.07	23.36	-174.1***
	(1.72)	(10.34)	(-1.28)	(1.24)	(-8.54)
t	-0.00171**	0.0118***	-0.0320***	0.00139*	-0.0163***
	(-3.08)	(15.26)	(-12.54)	(2.04)	(-21.97)
Country $\times t$	-0.00128	-0.0114***	0.00259	-0.00129	0.00819***
	(-1.64)	(-10.46)	(1.13)	(-1.34)	(7.85)
Constant	74.76***	-155.7***	690.1***	55.04***	389.3***
	(6.89)	(-10.34)	(14.10)	(4.12)	(26.94)
Observations	522	522	522	522	522

for the absence of a doodle effect in these categories. We should, however, note that these terms demonstrate tendencies to non-linear behaviour (see appendix figure A.10) and that the results could therefore be biased. Such an effect could, however, also stem from a general decrease in Google searches overall following the scandal combined with sustained demand for the terms in our categories. If such persistent demand after anonymity alterations were the explanation, then this could be the reason behind the null-findings in our observational cue analysis.

To summarize, these findings can indicate that the only phrases that people actually react to in terms of search behaviour at the revelation of government surveillance are those in the pedophilia category. All other terms show no, or positive, results at the threat of government surveillance.

8.3.2 Ashley Madison data breach

In order to measure the effect of the Ashley Madison data breach, we have chosen to test only the [adultfriendfinder] term from our relationship category. The reason is that while it is reasonable to expect that several of our terms would react to the PRISM scandal, we have no such expectation for the Ashley Madison scandal. As [adultfriendfinder] is the only term that can be assumed to be relatively directly affected by the hack in terms of anxiety amongst its enquirers, this is the term we have chosen to test.

We use the week beginning on 16th August as the starting point for our analysis, as this was the peak week for the scandal in terms of public attention (see figure A.12 in the appendix for development of the term [ashley madison] in the US, indicating the public attention the news story received). Looking at table 8.3, we can see that [adultfriendfinder] drops significantly both in the US and the UK in the short term, and in the US in the long term. This indicates that people actually reacted to the Ashley Madison hack. The insight also underscores our theory suggesting that people care less about NSA officials than people in close proximity to them when searching for terms that cause stigma from friends and family. Thus, the fact that some of our terms do not react to the NSA news does not necessarily mean that these terms would not react to revelations about anonymity that actually felt threatening to them.

Table 8.3 – **Ashley Madison Revelation**: Here, we have listed three short-run and three long-run models. We use the corresponding time frame - the five (for the short-term) and 26 (for the long-term) weeks following the week containing 19th August - in each year, as a control variable. We have also included the time trend (and country-specific time trend for panel data) in order to capture the long-term development of the popularity of [adultfriendfinder]. Column (1) and (4) test the combination of the two countries, replicating the panel used in our doodle analysis. In column (2) and (5), we run short- and long-term regressions for the United States, while specifications (3) and (6) show the United Kingdom.We use robust standard errors in all regressions. t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Ashley Madison Revelations, 2015					
	(1: Panel)	(2: US)	(3: UK)	(4: Panel)	(5: US)	(6: UK)
5-week hack effect	-5.977***	-6.495***	-5.458*			
	(-3.97)	(-4.17)	(-2.55)			
Corresponding time	2.753**	0.947	4.559***			
	(2.93)	(0.78)	(3.38)			
26-week hack effect				-3.164***	-6.228***	-0.100
				(-3.55)	(-5.00)	(-0.09)
Corresponding time				-0.898	-0.763	-1.032
				(-1.42)	(-0.86)	(-1.14)
Country	145.5***			145.5***		
	(6.29)			(6.35)		
Country-specific trend	-0.00813***			-0.00813***		
	(-7.06)			(-7.13)		
t	-0.0305***	-0.0304***	-0.0387***	-0.0299***	-0.0294***	-0.0385***
	(-38.10)	(-38.06)	(-46.32)	(-38.39)	(-38.11)	(-43.41)
Constant	672.3***	671.6***	818.6***	661.6***	651.6***	817.1***
	(41.88)	(41.85)	(48.85)	(42.28)	(42.11)	(45.92)
Observations	524	262	262	524	262	262

8.4 Summarizing discussion and implications for the observational cue analysis

Uncovering an effect of doodles in our research context depends on two things: (i) search terms that are stigmatizing enough to provoke a reaction to changes in actual anonymity, and (ii) a reaction to observational cues in the Google logo given reaction (i).

Our initial doodle analysis gives us no evidence to support point (ii) about reactions to observational cues. Analysis of point (i) about actual anonymity has therefore been done for all categories in order to eliminate an insufficient level of stigma as the reason behind the null-findings in our observational cue analysis. We see a sharp drop in searches for pedophilia terms post-PRISM and a reduction in [adultfriendfinder] searches after the Ashley Madison hack. That means that we have a significant reaction from the entire pedophilia category, and from one of the two terms in our relationship category, to alterations in actual anonymity. Thus, the failure of these categories, and especially the pedophilia category, to demonstrate a reaction to observational cues strengthens our conclusion from the observational cue analysis.

Due to a lack of scandals, we cannot carry out an individual follow-up analysis for the health, niche porn, and porn categories. Because these terms are unlikely to get you into problems with the government, however, it is reasonable to believe that these, too, would react more strongly to a threat of public exposure than to the PRISM scandal. Thus, we cannot eliminate the possibility that these meet the prerequisite of reactions to alterations in actual anonymity based solely on the results from our PRISM analysis.

Having confirmed point (i) about a reaction to anonymity alterations for the pedophilia and to some extent the relationship categories, we believe that the lack of significant results in the observational cue analysis (ii) is due to a lack of reaction to observational cues in the Google logo. Assuming that the health, niche porn, and porn categories would also react to public exposure, this evidence is strengthened. Whether the null-findings in our observational cue analysis reflect evidence against the evolutionary legacy hypothesis, or if they are simply due to particular circumstances to this context, will be discussed further in chapter 9.

9. Validity

In this chapter, we will discuss the internal and external validity of our study. The section on internal validity will discuss whether our fundament was good enough to actually test what we wanted, while the section on external validity will discuss whether our results can be assumed to apply to situations beyond the scope of our study.

9.1 Internal validity

When assessing the internal validity, we want to discuss whether our framework has been good enough to test our hypothesis. Our main concern is whether our research design is sufficient to allow us to believe that the doodles in this context could realistically have an effect on the SVI for stigmatizing terms.

First of all, our terms have to be truly stigmatizing. The privacy threshold has been a large obstacle in the choice of stigmatizing search terms. We argue that the doodle effect will be more prevalent the more stigmatizing the search terms are. The fact that queries such as [preteen sex] and [pthc] must be left out because of their failure to exceed the privacy threshold thus decreases the probability that our terms give us the stigma needed to provoke any effects. Another issue related to stigma is the fact that the perception and definition of stigmatizing behaviour is highly subjective. A person watching porn defined as "niche" in this thesis might be so used to this type of videos that they do not consider it stigmatizing, while someone else definitely would. However, based on our follow-up analysis, we have clear indications that people react to at least some of our terms. Although we could have gotten a stronger effect by including narrower phrases, we do have terms that could be expected to provoke an eye effect.

Moreover, as Google upholds full anonymity, it is not possible for us to check the number of different people responsible for our searches. If our dataset consists of a few people accounting for the majority of searches, we might experience a reduced effect of the observational cues. For a person searching for pedophilia or rape sex twice a week for several years, we could expect the observational cue to have the largest effect the first times, with a decreasing effect of each new cue as they become used to the cues and their own behaviour. Although there is a chance that stigmatizing searches are affected by this, we have such a high volume of searches in different categories that we do not consider the problem big enough to have major implications for our study.

Although we have tried to use universally stigmatizing terms, there are definitely geographical differences in the level of stigma our terms imply. This is, for instance, the case for [gay porn] and [chlamydia symptoms], where the level of stigma could be significantly affected by how liberal the society the searcher lives in is. We have not been able to carry out a follow-up analysis on the above mentioned terms. We have however, separated the two countries in our observational cue analysis and thereby accounted for some of the differences.

There are also issues concerning the design of browsers that make it difficult to know whether people are actually exposed to doodles before they carry out searches. There are three reasons behind this: the vast increase in smartphone usage, the opportunity for carrying out searches using the address bar, and the design of the Google website. The first and second problem have been reduced by the inclusion of the time period between 2008 and 2011. At this point smartphones popularity was substantially lower than between 2014 and 2017 (Ofcom, 2018; eMarketer, 2017). Address bar searches were introduced for most browsers in the late 2000s, but it is safe to assume that their popularity has increased over time. Figures A.1 to A.7 in the appendix show the Google website design and our third issue. Although the doodle is very striking on the startpage or when opening a new tab, as soon as one enters their first search and is sent to the search results page, the figure shrinks considerably. Thus, unless our search phrases capture people at the first stage of their potential series of searches, the doodle effect could be weakened by the reduction in doodle size. It is unfortunately not possible for us to get data that differentiates between the various origins of Google searches.

With respect to the structure of our study, there is also a difference between ours and studies that have yielded positive results in the past. The settings the respondents are put into in the other studies can make them more alert, observant and open for influences.

It is an unusual setting where they make a standpoint on decisions they have not faced before. These decisions often have tangible and direct consequences. The first time one plays a dictator or trust game, one would probably think about the consequences of each option and take some time for reflection. In such a situation, people are vulnerable for impact. We, on the other hand, have tested the effect of observational cues in settings that are very normalized for the respondents. This makes them less likely to think actively about their decision and take elements of their environment into account when searching. This might contribute to our null-findings.

It might also be that the observational cues in Google's doodles are not strong enough to promote an effect. This could especially be true in the early period where there are few doodles in general and ever fewer with eyes. However, based on the strength of our observational cues in comparison to effective pictures such as that of Kismet in Burnham and Hare (2007), this is unlikely to have been a major problem in our study.

9.2 External validity

When assessing external validity, our main question is whether our results apply to other groups than those we have included in our study.

Ideally, this study would have taken into account search terms from a wide range of countries in order to cross-check effects of doodles on different days. This, however, was impossible for most search terms under consideration for this thesis because of the privacy threshold. Thus, it is difficult to know whether our study will show the same results in other countries than the US and the UK.

Targeting the group of people searching for these stigmatizing terms might also weaken our external validity. These people could have a different mindset and weaker reaction to social consequences than the rest of the population. If this is true, any results would only be conclusive for a small unrepresentative minority of the population. This is especially important for the darkest search terms such as pedophilia and rape sex. Because of this, we have included other more normal search terms as well, such as porn, health and relationships.

9.3 Suggestions for further research

Most limitations in this study are related to the lack of access to more extensive and detailed data. The ideal study of this research question would involve the access to a breakdown of search data including the means through which the searches were performed. In this way, one could separate the doodle-exposed searchers from those who were not exposed. Also, access to non-indexed, absolute numbers would allow for a more detailed analysis. Ideally, this data would not be limited by the privacy threshold. Getting access to such data, however, is virtually impossible for anyone except Google.

Considering the fact that we have results that go against the evolutionary legacy hypothesis and an automatic response to eyes, it would definitely be interesting to explore this further. The automatic reaction might very well exist, but we do not know how far it stretches or when it kicks in. Identifying this would imply experiments within a larger variety of settings than we have today. Experiments in a naturalistic setting are in a minority, especially those involving total anonymity and lack of people around. Several more studies on observational cues decreasing negative behaviour, and not only promoting positive, are also needed.

10. Conclusion

The aim of this thesis was to explore the effect of observational cues in real life settings and add empirical evidence to previous inconclusive results. This was done with the use of Google Doodles and historic Google Trends data. More specifically, the thesis seeked to explore if *exposure to doodles containing eyes leads to a decrease in the search volume for stigmatized searches*. Our analysis provides us with no evidence to support our hypothesis. Our follow-up analysis strengthens this conclusion by eliminating the probability that our lack of results are due to too little stigmatizing terms. Based on this, it is clear that the results are due to a lack of changes in search volume when there are observational cues in the Google logo. Our study therefore provides no support for the evolutionary legacy hypothesis.

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Appendix

A.1 Doodles in different browsers

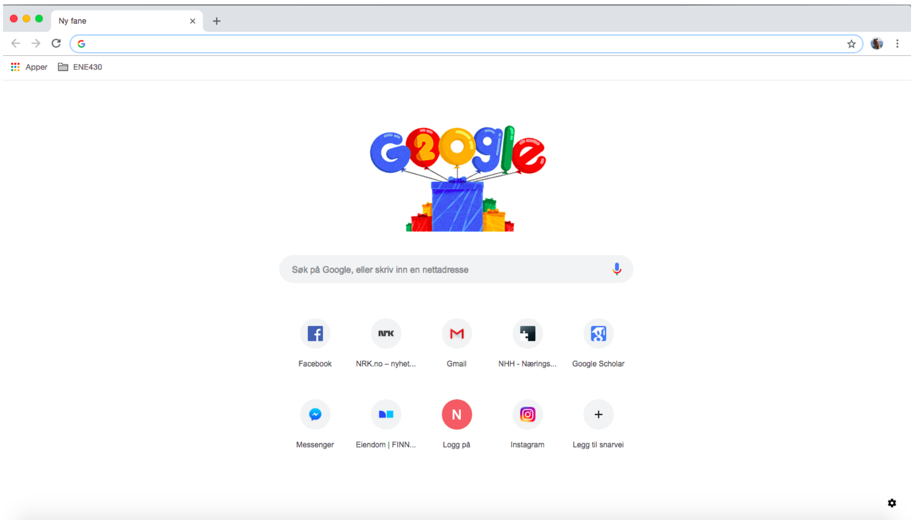


Figure A.1 – Doodle exposure when opening a new tab in Google Chrome on a day with a doodle.

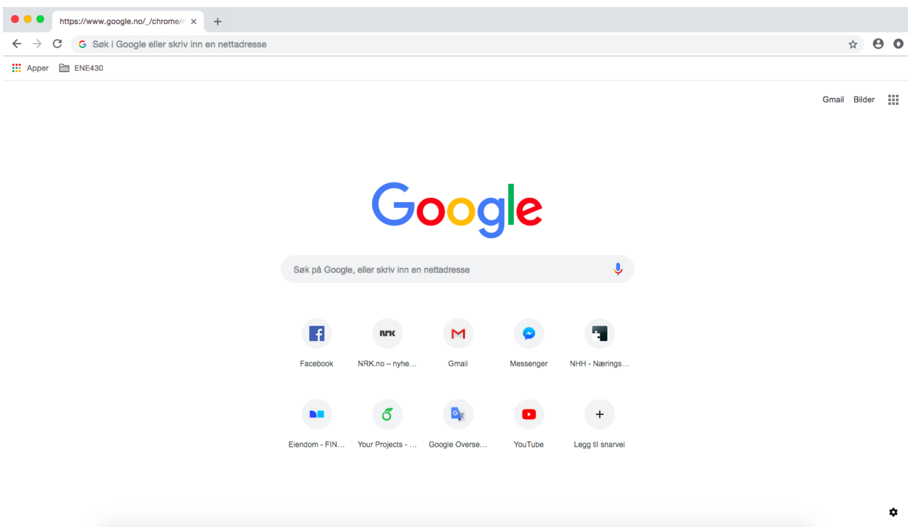


Figure A.2 – Regular logo exposure when opening a new tab in Google Chrome on a day without a doodle.

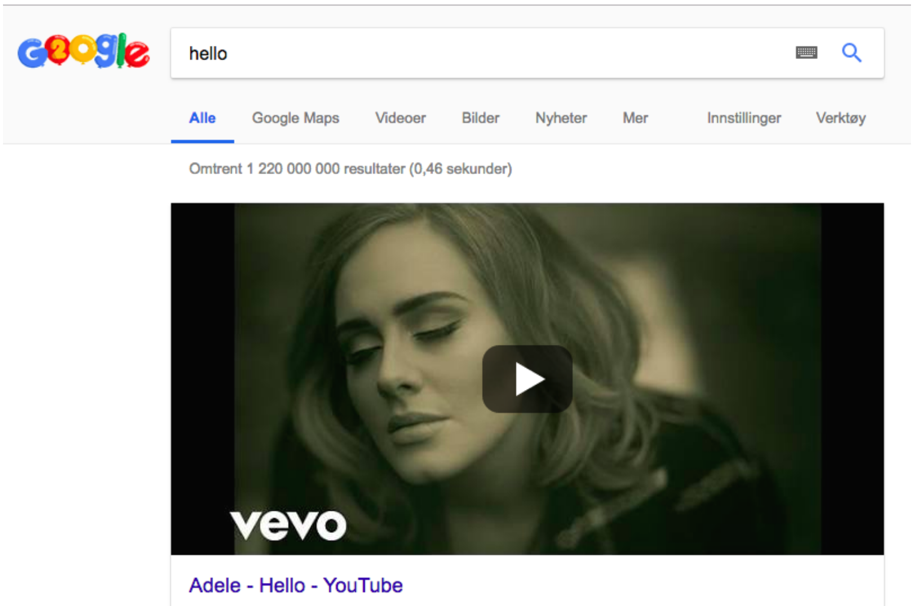


Figure A.3 – Doodle exposure after entering a Google search on a day with a doodle.

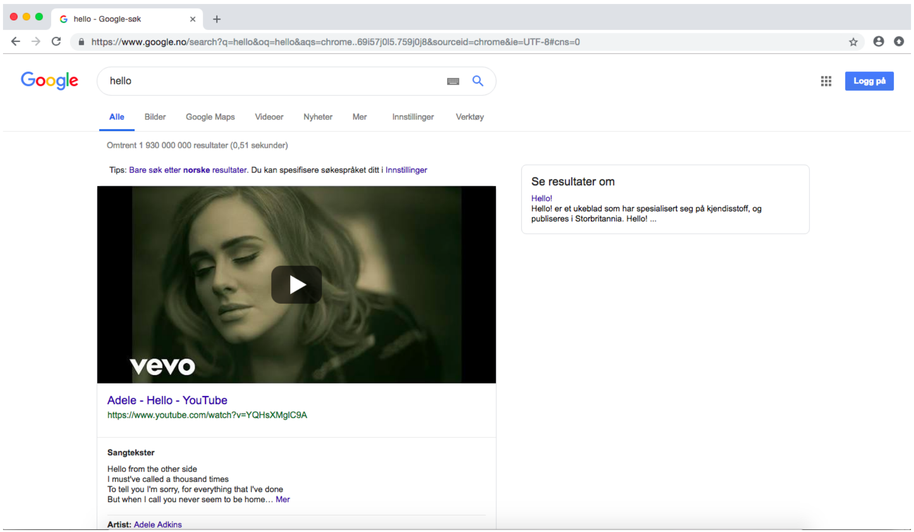


Figure A.4 – Regular logo exposure after entering a search in Google Chrome on a day without a doodle.

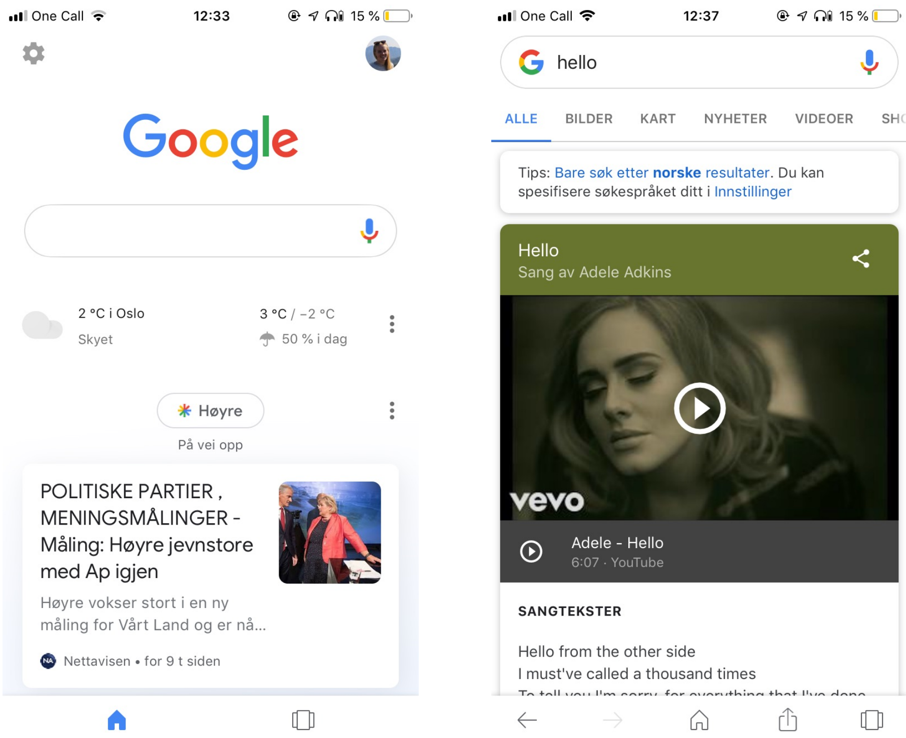


Figure A.5 – Homepage (left) and appearance once one has entered a search (right) in the Google app for iPhone. Unfortunately, we do not have any screenshots of the Google app on a day when there is a doodle present.

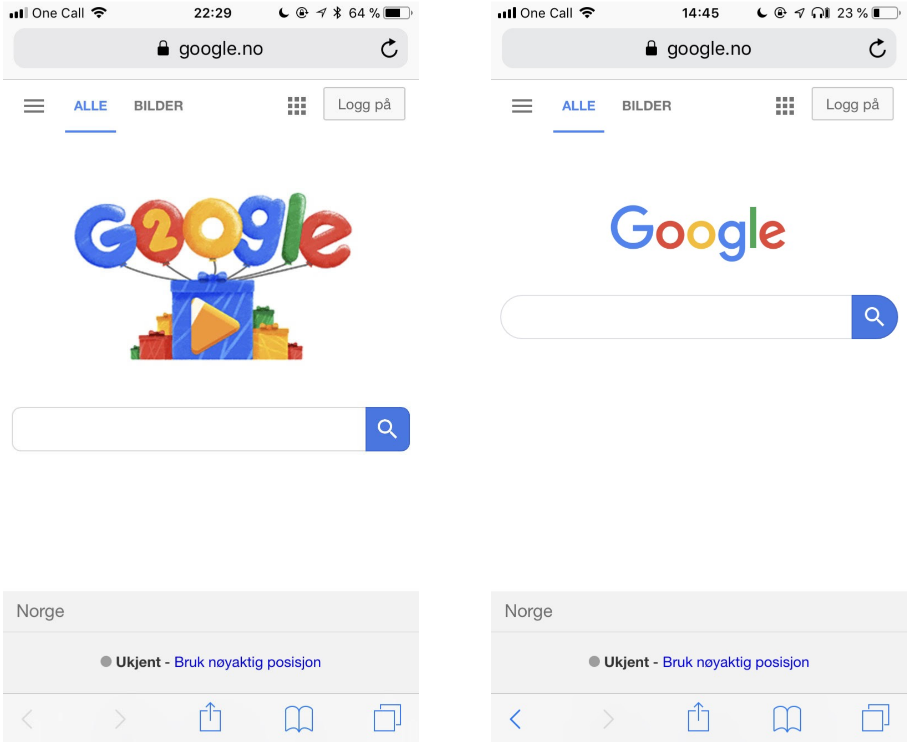


Figure A.6 – Doodle (left) and regular logo (right) exposure on the Google homepage using a smartphone.

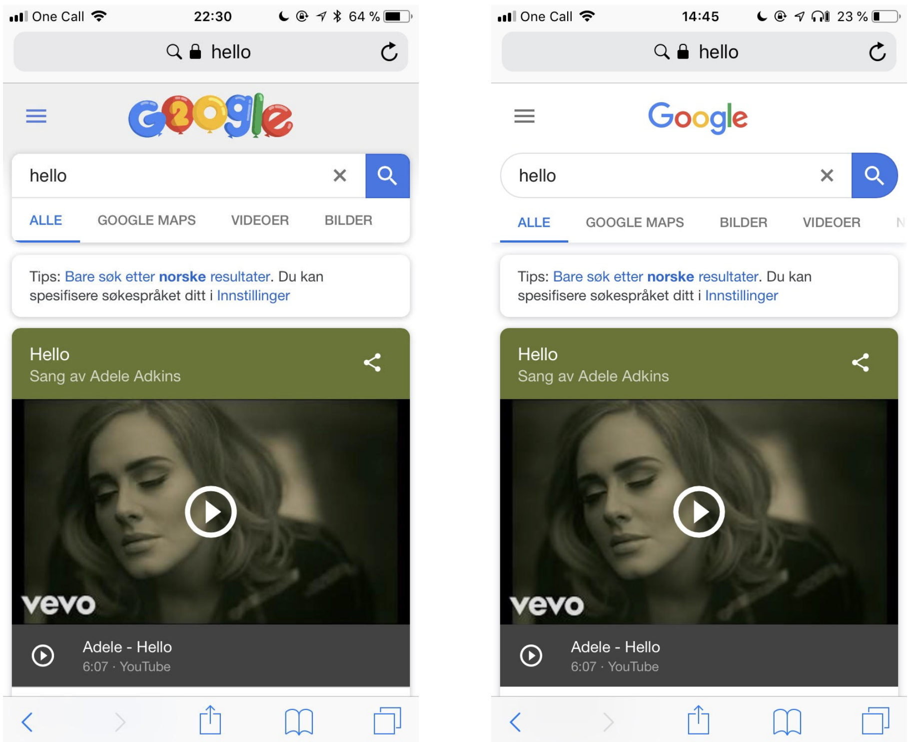


Figure A.7 – Doodle (left) and regular logo (right) exposure after entering a search using a smartphone.

A.2 Doodle distribution throughout the week

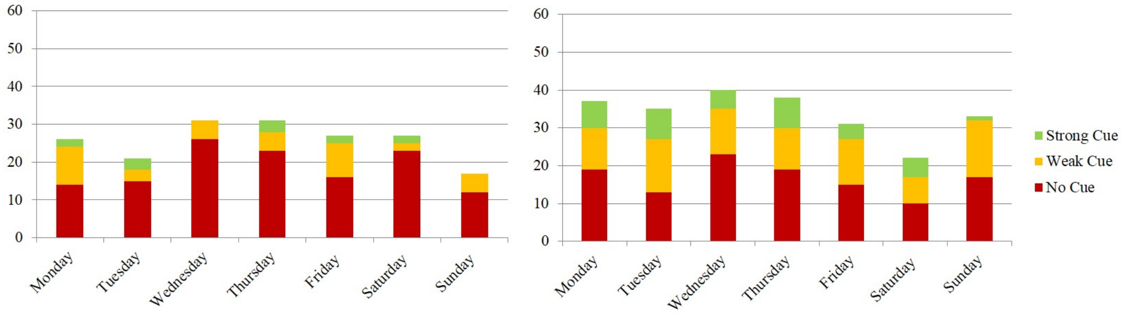


Figure A.8 – Distribution of doodles throughout the week for the United States in 2008-2011 (left) and in 2014-2017 (right).

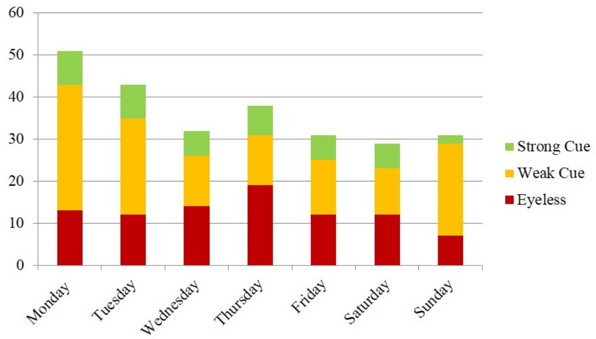


Figure A.9 – Distribution of doodles throughout the week for the United Kingdom, 2014-2017.

A.3 Full regressions of all search terms

Table A.1 – Regression results final model with controls, United States 2008 - 2011: All search terms. Using robust standard errors clustered on week number. t-statistics are given in parentheses. We indicate significance by: * p < 0.05, ** p < 0.01, *** p < 0.001.

	(1) Health	(2) Niche Porn	(3) Pedophilia	(4) Porn	(5) Relationships
Strong observational cue	-0.528	1.587	-0.475	1.165	1.610
	(-0.28)	(1.08)	(-0.48)	(1.16)	(0.71)
Weak observational cue	-0.315	3.034**	2.550	1.554	0.725
	(-0.24)	(3.36)	(1.55)	(1.44)	(0.50)
Eyeless Doodle	-0.230	-1.161	0.0330	-0.783	-0.824
	(-0.42)	(-1.57)	(0.06)	(-1.28)	(-1.02)
Monday	-2.844***	-15.06***	-12.00***	-13.37***	-9.806***
	(-4.30)	(-24.02)	(-23.33)	(-32.56)	(-11.50)
Tuesday	-1.197	-16.81***	-13.64***	-14.51***	-11.07***
	(-1.97)	(-41.83)	(-33.85)	(-58.10)	(-16.51)
Wednesday	-2.424***	-16.77***	-13.83***	-14.38***	-11.10***
	(-3.99)	(-40.43)	(-31.61)	(-52.66)	(-14.57)
Thursday	-2.496***	-16.64***	-13.49***	-14.00***	-10.63***
	(-3.76)	(-39.89)	(-35.05)	(-53.69)	(-14.31)
Friday	-0.3599***	-15.19***	-12.11***	-12.00***	-9.539***
	(-5.61)	(-35.42)	(-27.60)	(-47.46)	(-13.30)
Saturday	-1.846**	1.068*	0.998*	2.263***	-0.153
	(-2.91)	(2.27)	(2.59)	(11.10)	(-0.18)
January	1.921*	-2.791**	-0.695	-0.448	1.220
	(2.43)	(-3.22)	(-0.67)	(-0.65)	(1.32)
February	0.0766	-1.710*	-2.288*	-2.724**	0.371
	(0.10)	(-2.14)	(-2.18)	(-3.46)	(0.34)
March	-0.772	-0.902	-2.195	-2.550***	3.271**
	(-1.03)	(-1.13)	(-1.98)	(-3.68)	(3.29)
April	0.471	0.271	-1.738	-2.111**	0.529
	(0.67)	(0.33)	(-1.65)	(-3.44)	(0.59)
May	-0.126	1.155	-1.408	-1.073	2.077*
	(-0.19)	(1.07)	(-1.06)	(-1.05)	(2.30)
June	-2.154*	2.042*	-0.819	0.207	3.953***
	(-2.32)	(2.11)	(-0.71)	(0.26)	(4.21)
July	-2.226*	3.244*	0.368	3.209**	7.026***
	(-2.11)	(2.22)	(0.25)	(3.31)	(5.50)
August	-2.090**	2.013	0.150	2.382**	3.940***
	(-3.23)	(1.59)	(0.13)	(2.94)	(4.64)
September	-0.364	0.973	-0.484	1.059	1.088
	(-0.38)	(0.94)	(-0.43)	(1.47)	(1.18)
October	0.494	-0.691	-2.225	1.151	0.359
	(0.64)	(-0.67)	(-1.97)	(1.44)	(0.37)
November	-0.741	-1.398	-1.737	-0.318	-1.153
	(-0.67)	(-1.37)	(-1.54)	(-0.49)	(-0.92)
Public Holidays	-0.829	6.572***	7.571***	5.825***	3.273
	(-0.72)	(4.50)	(5.28)	(6.17)	(1.60)
Summer holiday	-0.116	1.813	0.432	1.090	-0.791
	(-0.16)	(1.51)	(0.52)	(1.64)	(-1.22)
t	0.0139***	0.00323***	-0.00151*	0.0399***	-0.00345***
	(26.97)	(4.09)	(-2.61)	(117.36)	(-5.80)
Constant	-221.9***	0.503	78.74***	-660.3***	107.7***
	(-23.25)	(0.03)	(7.36)	(-107.10)	(9.77)
Observations	1350	1350	1350	1350	1350

Table A.2 – Regression results final model with controls, United States 2014 - 2017: All search terms. Using robust standard errors clustered on week number. t-statistics are given in parentheses. We indicate significance by: * p < 0.05, ** p < 0.01, *** p < 0.001.

	(1) Health	(2) Niche Porn	(3) Ln Pedo	(4) Porn	(5) Relationships
Strong observational cue	-0.119	-1.483	-0.0114	0.0939	1.601
	(-0.19)	(-1.96)	(-0.43)	(0.21)	(1.57)
Weak observational cue	-0.270	-0.152	-0.0261	-0.113	0.328
	(-0.74)	(-0.26)	(-1.92)	(-0.37)	(0.60)
Eyeless Doodle	0.731	0.584	0.0142	0.625*	0.382
	(1.31)	(0.93)	(0.87)	(2.42)	(0.59)
Monday	1.903***	-9.888***	-0.198***	-9.885***	-3.508***
	(4.41)	(-17.43)	(-12.66)	(-19.82)	(-6.86)
Tuesday	3.095***	-12.00***	-0.234***	-11.57***	-4.154**
	(8.07)	(-25.69)	(-20.00)	(-30.28)	(-7.41)
Wednesday	3.064***	-12.51***	-0.261***	-11.78***	-4.988***
	(7.04)	(-27.49)	(-18.19)	(-30.52)	(-8.66)
Thursday	2.539***	-12.61***	-0.285***	-11.97***	-5.202***
	(6.73)	(-30.93)	(-22.49)	(-34.38)	(-9.03)
Friday	1.578***	-11.31***	-0.245***	-10.18***	-4.917***
	(4.11)	(-26.28)	(-22.26)	(-29.30)	(-9.54)
Saturday	0.630	0.216	-0.0204	1.415***	-0.500
	(1.71)	(0.82)	(-1.88)	(7.20)	(-0.80)
January	-0.134	-7.279***	-0.0982***	-0.614	4.476***
	(-0.20)	(-4.66)	(-5.16)	(-0.51)	(4.33)
February	-1.241*	-8.063***	-0.134***	-1.993	3.151**
	(-2.15)	(-5.35)	(-6.15)	(-1.81)	(3.42)
March	-0.314	-5.540***	-0.117***	-0.677	3.174***
	(-0.53)	(-3.59)	(-5.83)	(-0.60)	(5.08)
April	0.615	-3.535*	-0.0843***	0.730	3.963***
	(0.77)	(-2.29)	(-3.96)	(0.66)	(6.92)
May	0.0953	-1.194	-0.0471*	3.271*	4.735***
	(0.13)	(-0.59)	(-2.20)	(2.35)	(4.96)
June	-1.807*	0.421	-0.0256	5.064***	4.966***
	(-2.13)	(0.26)	(-1.09)	(4.64)	(5.48)
July	-1.616	-1.199	-0.0137	5.364***	7.123***
	(-1.31)	(-0.61)	(-0.46)	(4.31)	(5.74)
August	-1.242	-2.076	-0.0220	3.925**	5.624***
	(-1.42)	(-1.31)	(-1.08)	(3.30)	(7.86)
September	-1.081	-5.286**	-0.0989***	-0.161	1.958**
	(-1.57)	(-3.29)	(-5.50)	(-0.13)	(3.02)
October	-2.058**	-4.096**	-0.108***	-1.593	1.498*
	(-3.38)	(-2.73)	(-5.84)	(-1.43)	(2.44)
November	0.112	-2.139	-0.0910***	-1.636	0.383
	(0.19)	(-1.26)	(-4.33)	(-1.45)	(0.36)
Public Holidays	-2.565***	5.822***	0.0573	4.808***	1.829
	(-5.50)	(3.56)	(1.33)	(4.76)	(1.57)
Summer Holidays	0.624	2.018	0.0432*	1.939***	-0.178
	(0.68)	(1.64)	(2.07)	(3.68)	(-0.19)
t	0.00784***	-0.0335***	-0.00119***	-0.00741***	-0.00684***
	(17.52)	(-53.08)	(-68.29)	(-22.52)	(-12.11)
Constant	-129.7***	752.8***	27.90***	230.5***	182.2***
	(-14.21)	(57.20)	(78.71)	(33.47)	(15.89)
Observations	1350	1350	1350	1350	1350

Table A.3 – Regression results final model with controls, UK & US combined 2014 - 2017: All search terms. Using robust standard errors clustered on week number. t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Health	(2) Niche Porn	(3) Ln Pedo	(4) Porn	(5) Relationships
Strong observational cue	-0.442	-0.722	-0.0222	0.462	0.557
	(-0.68)	(-1.10)	(-0.60)	(1.19)	(0.62)
Weak observational cue	0.0927	-0.145	-0.00235	0.111	0.482
	(0.23)	(-0.26)	(-0.13)	(0.37)	(0.99)
Eyeless Doodle	0.465	0.269	-0.00295	0.373	-0.235
	(1.01)	(0.58)	(-0.18)	(1.78)	(-0.44)
Country	-95.77***	168.8***	-2.754***	-151.9***	-62.01***
	(-7.30)	(13.26)	(-5.33)	(-26.81)	(-4.41)
Monday	0.926*	-9.644***	-0.208***	-10.85***	-4.239***
	(2.247)	(-25.94)	(-12.86)	(-32.26)	(-7.72)
Tuesday	1.425**	-11.25***	-0.216***	-11.96***	-4.639**
	(3.28)	(-28.91)	(-19.00)	(-41.50)	(-8.07)
Wednesday	1.181**	-11.54***	-0.245***	-11.99***	-5.754***
	(3.07)	(-37.10)	(-18.32)	(-40.91)	(10.68)
Thursday	0.281	-11.56***	-0.247***	-11.90***	-5.601***
	(0.72)	(-35.56)	(-19.98)	(-48.32)	(-11.37)
Friday	-0.510	-10.92***	-0.224***	-11.39***	-5.561***
	(-1.38)	(-35.11)	(-17.89)	(-43.07)	(-11.95)
Saturday	-0.980*	-0.677**	-0.0224	-0.342*	-1.449**
	(-2.66)	(-2.96)	(-1.60)	(-2.21)	(-2.78)
January	0.804	-7.285***	-0.103***	-2.347*	2.298*
	(1.15)	(-5.50)	(-3.82)	(-2.21)	(2.63)
February	0.128	-6.551***	-0.108***	-3.100***	1.504*
	(0.20)	(-5.07)	(-3.52)	(-3.13)	(2.40)
March	0.985	-4.830***	-0.103***	-1.822	1.270*
	(1.86)	(-3.98)	(-3.83)	(-1.88)	(2.29)
April	1.173	-2.776*	-0.0460	-0.171	1.912**
	(1.58)	(-2.37)	(-1.47)	(-0.18)	(3.13)
May	0.963	-1.065	-0.0202	1.695	2.232***
	(1.49)	(-0.71)	(-0.77)	(1.47)	(4.31)
June	-0.839	0.105	-0.0179	2.935**	2.874***
	(-1.28)	(0.09)	(-0.67)	(3.17)	(3.80)
July	-0.120	-0.388	0.0128	3.191**	4.058***
	(-0.18)	(-0.28)	(0.44)	(3.18)	(4.70)
August	-0.593	-0.877	-0.000438	1.894	3.064***
	(-0.76)	(-0.68)	(-0.02)	(1.95)	(3.91)
September	0.127	-2.159	-0.0556*	-0.346	1.914**
	(0.18)	(-1.75)	(-2.12)	(-0.32)	(3.05)
October	-0.368	-2.896*	-0.0944***	-2.338*	0.162
	(-0.50)	(-2.40)	(-3.84)	(-2.48)	(0.31)
November	-0.0784	-2.403*	-0.0671*	-2.848**	0.623
	(-0.14)	(-2.05)	(-2.38)	(-3.09)	(0.94)
Public Holidays	-0.902	5.729***	0.114*	5.299***	0.816
	(-1.31)	(4.98)	(2.59)	(5.61)	(0.91)
Summer Holidays	0.361	3.030***	0.0460***	2.465***	0.766
	(0.78)	(4.77)	(3.69)	(6.67)	(1.09)
t	0.00327***	-0.0259***	-0.00135***	-0.0150***	-0.0106***
	(5.61)	(-37.15)	(-47.32)	(-43.53)	(-19.31)
Country $\times t$	0.00461***	-0.00782***	0.000152***	0.00757***	0.00376***
	(7.15)	(-12.72)	(6.02)	(27.27)	(5.50)
Constant	-34.06**	585.8***	30.69***	384.6***	247.4***
	(-2.86)	(40.61)	(52.94)	(53.39)	(21.99)
Observations	2700	2700	2700	2700	2700

Table A.4 – Regression results final model with controls, United Kingdom 2014 - 2017: All search terms. Using robust standard errors clustered on week number. t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

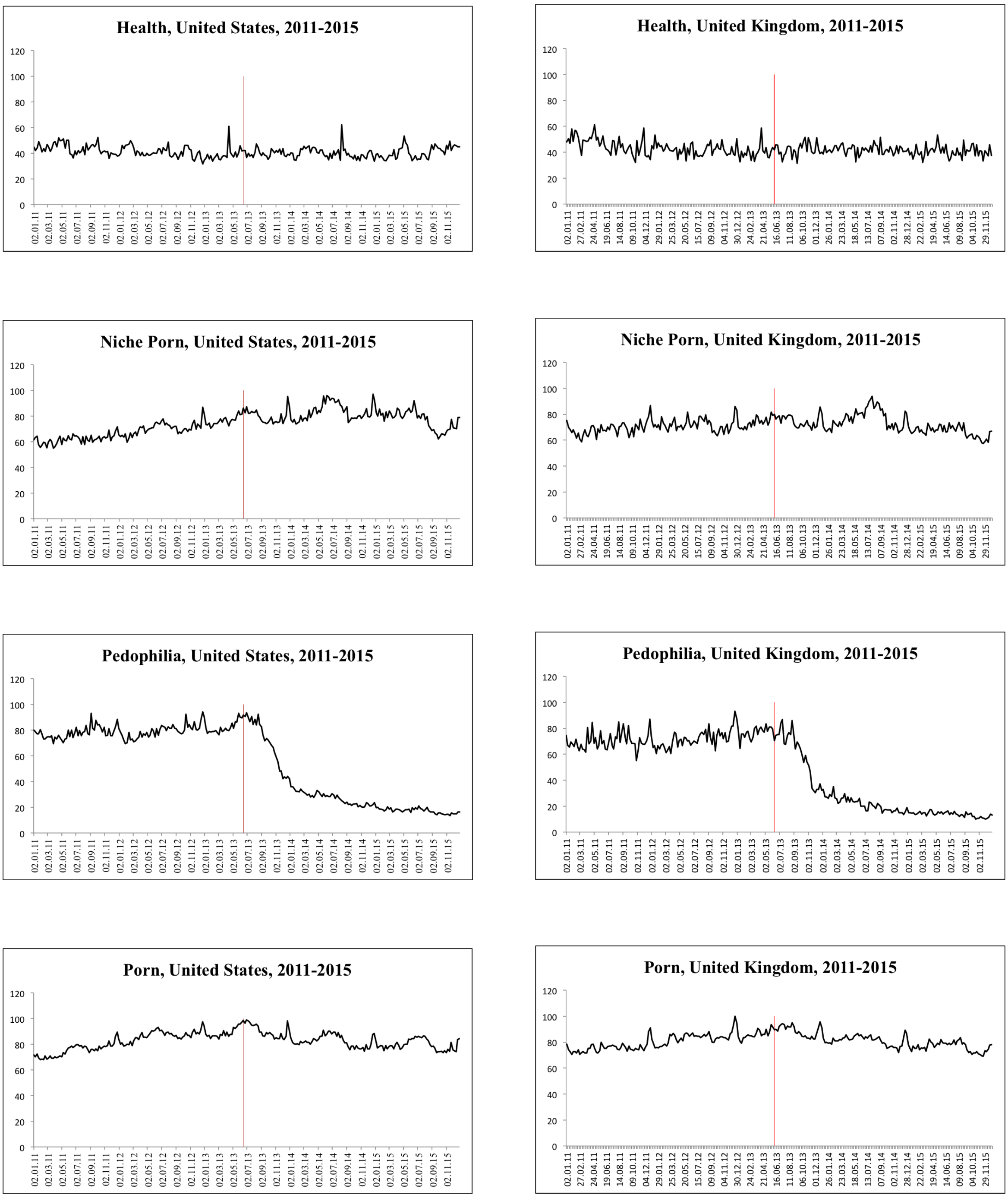
	(1) Health	(2) Niche Porn	(3) Ln Pedo	(4) Porn	(5) Relationships
Strong observational cue	-0.799	-0.241	-0.0354	0.675	-0.662
	(-0.80)	(-0.25)	(-0.56)	(1.16)	(-0.46)
Weak observational cue	0.846	-0.177	0.0313	0.372	0.910
	(1.12)	(-0.26)	(0.91)	(0.73)	(1.11)
Eyeless Doodle	0.210	-0.0237	-0.0133	0.0274	-0.704
	(0.33)	(-0.05)	(-0.53)	(0.10)	(-0.90)
Monday	-0.0694	-9.390***	-0.219***	-11.82***	-4.956***
	(-0.11)	(-23.92)	(-7.49)	(-32.19)	(-5.85)
Tuesday	-0.221	-10.51***	-0.197***	-12.33***	-5.138***
	(-0.31)	(-22.46)	(-8.70)	(-38.77)	(-5.44)
Wednesday	-0.678	-10.58***	-0.230***	-12.19***	-6.538***
	(-1.09)	(-26.25)	(-9.64)	(-36.94)	(-7.85)
Thursday	-1.955**	-10.51***	-0.208***	-11.82***	-6.030***
	(-3.00)	(-26.04)	(-8.57)	(-41.13)	(-7.89)
Friday	-2.610***	-10.52***	-0.202***	-12.60***	-6.231***
	(-4.08)	(-26.38)	(-8.09)	(-42.53)	(-7.82)
Saturday	-2.585***	-1.587***	-0.0248	-2.114***	-2.426**
	(-3.85)	(-3.97)	(-0.89)	(-8.89)	(-3.27)
January	1.587	-7.269***	-0.108*	-4.058***	0.349
	(1.59)	(-6.07)	(-2.66)	(-3.84)	(0.36)
February	1.291	-5.017***	-0.0839	-4.187***	0.0870
	(1.51)	(-4.13)	(-1.83)	(-4.06)	(0.11)
March	2.030**	-4.085***	-0.0937*	-2.958**	-0.407
	(2.71)	(-4.23)	(-2.21)	(-3.14)	(-0.56)
April	1.479	-1.990*	-0.0129	-1.090	0.153
	(1.38)	(-2.19)	(-0.29)	(-1.23)	(0.19)
May	1.607	-0.901	0.00357	0.127	-0.0176
	(1.97)	(-0.83)	(0.09)	(0.13)	(-0.02)
June	-0.263	0.403	-0.0119	1.131	1.500
	(-0.32)	(0.38)	(-0.30)	(1.25)	(1.47)
July	0.831	1.657	0.0501	1.890	2.003
	(0.95)	(1.52)	(1.17)	(1.93)	(1.63)
August	-0.691	1.331	0.0315	0.758	0.924
	(-0.46)	(0.91)	(0.61)	(0.77)	(0.61)
September	1.104	1.070	-0.00954	-0.374	2.091*
	(1.09)	(1.06)	(-0.22)	(-0.33)	(2.22)
October	1.135	-1.682	-0.0820	-3.065**	-0.909
	(1.07)	(-1.65)	(-1.93)	(-3.26)	(-1.32)
November	-0.210	-2.648*	-0.0353	-3.945***	0.936
	(-0.25)	(-2.47)	(-0.76)	(-4.12)	(1.17)
Public Holidays	-0.110	5.760***	0.161**	5.871***	0.691
	(-0.10)	(5.25)	(2.68)	(4.55)	(0.74)
Summer Holidays	0.717	2.585**	0.0330	1.843***	1.074
	(1.07)	(2.89)	(1.03)	(3.69)	(0.79)
t	-0.00329***	-0.0260***	-0.00135***	-0.0150***	-0.0107***
	(5.42)	(-36.33)	(-47.54)	(-43.32)	(-19.62)
Constant	-33.66**	587.2***	30.72***	386.8***	250.8***
	(-2.70)	(39.90)	(52.91)	(53.46)	(22.34)
Observations	1350	1350	1350	1350	1350

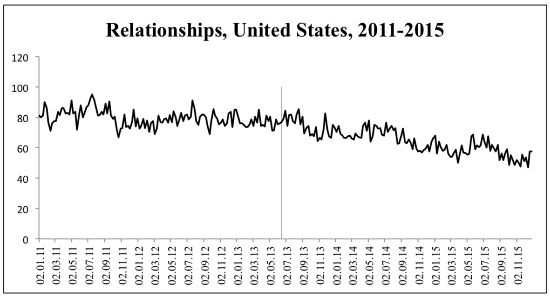
A.4 Privacy Scandals

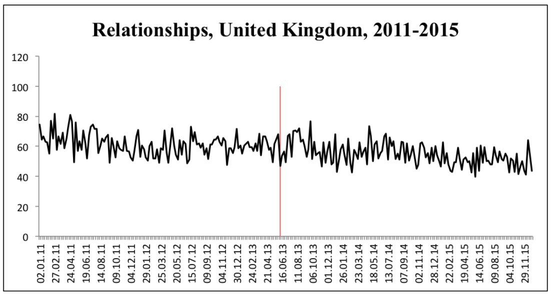
A.4.1 Descriptive statistics

NSA

Figure A.10 – Development of search terms in the US and the UK, before and after the PRISM revelation. Date of revelation is marked with a vertical red line for all search terms.







Ashley Madison

Figure A.11 – Development of [adultfriendfinder] before and after Ashley Madison, UK and US. The week with the release of the most important news stories about the Ashley Madison hack is marked with a red, vertical line.

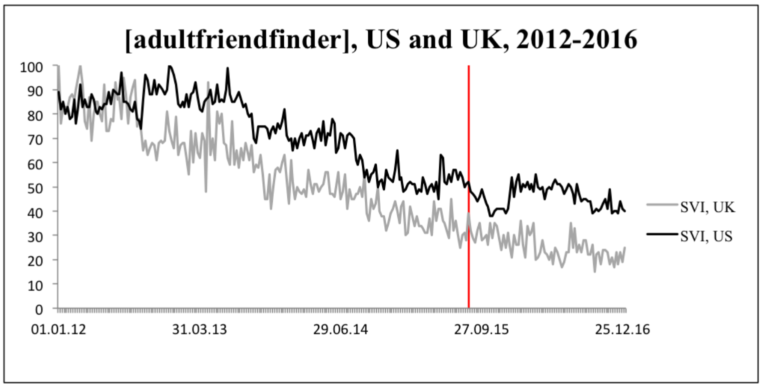
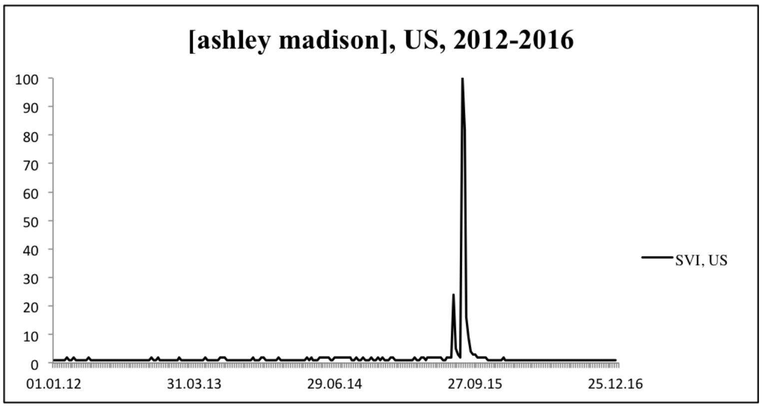


Figure A.12 – Development of [ashley madison] in the US between 01.01.2012 and 31.12.2016.



A.4.2 All results, NSA analysis

Table A.5 – NSA Scandal United Kingdom, Short term. Using robust standard errors. t represents the weekly time variable. t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Nicheporn	(2) Porn	(3) Relationships	(4) Health
Short term	4.333**	9.650***	-4.050	1.767
	(2.71)	(8.06)	(-1.13)	(1.14)
Control	1.477	0.465	0.744	-2.001*
	(1.18)	(0.48)	(0.42)	(-2.09)
t	0.000377	0.000207	-0.00792***	-0.00307***
	(0.48)	(0.30)	(-9.53)	(-4.96)
Constant	64.04***	76.54***	212.7***	102.5***
	(4.19)	(5.61)	(13.05)	(8.39)
Observations	261	261	261	261

Table A.6 – NSA Scandal United Kingdom, Long Term. Using robust standard errors. t represents the weekly time variable. t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Pedo	(2) Niche Porn	(3) Porn	(4) Relationships	(5) Health
Permanent	-19.63***				
	(-3.89)				
Long term		2.933**	9.279***	1.856	0.359
		(2.77)	(10.01)	(1.07)	(0.33)
Control long term		0.00937	-1.939**	0.722	-0.918
		(0.01)	(-2.82)	(0.81)	(-1.42)
t	-0.0275***	0.000300	0.000211	-0.00805***	-0.00297***
	(-6.47)	(0.40)	(0.33)	(-9.64)	(-4.82)
Constant	597.1***	65.46***	76.73***	214.7***	100.7***
	(7.36)	(4.44)	(6.08)	(13.15)	(8.31)
Observations	261	261	261	261	261

Table A.7 – NSA Scandal United States, Short term. Using robust standard errors. t represents the weekly time variable. t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Nicheporn	(2) Porn	(3) Relationships	(4) Health
Short term	4.483*	11.73***	2.950	1.567
	(2.34)	(10.45)	(1.66)	(1.42)
Control	5.994***	3.979***	3.603***	-2.280***
	(3.66)	(3.53)	(4.12)	(-3.49)
t	0.0118***	0.00151	-0.0161***	-0.00179***
	(12.81)	(1.87)	(-24.04)	(-3.42)
Constant	-156.1***	52.62**	386.1***	76.20***
	(-8.83)	(3.32)	(29.44)	(7.47)
Observations	261	261	261	261

Table A.8 – NSA Scandal United States, Long Term. Using robust standard errors. t represents the weekly time variable. t-statistics are given in parentheses. We indicate significance by: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) Pedo	(2) Niche Porn	(3) Porn	(4) Relationships	(5) Health
Permanent	-14.99** (-2.78)				
Long term		5.968*** (4.90)	9.038*** (7.87)	4.005** (3.26)	-0.359 (-0.52)
Control long term		-2.354** (-2.63)	-0.0646 (-0.08)	0.881 (1.21)	-0.342 (-0.58)
t	-0.0339*** (-7.43)	0.0119*** (13.57)	0.00129 (1.68)	-0.0163*** (-24.05)	-0.00174** (-3.26)
Constant	726.2*** (8.34)	-157.3*** (-9.26)	56.71*** (3.74)	389.8*** (29.45)	75.16*** (7.24)
Observations	261	261	261	261	261

A.5 Observational cues 2008-2011, US

US Early Period Table 1

Date	**Doodle Name**	**Doodle Category**
28.02.2008	Leap Year 2008	Strong Observational Cue
03.03.2008	Alexander Graham Bell's 161st Birthday	Weak Observational Cue
10.05.2008	Mother's Day 2008	Weak Observational Cue
29.05.2008	Anniversary of the First Ascent of Mount Everest	Weak Observational Cue
06.06.2008	Diego Velázquez's Birthday	Weak Observational Cue
07.07.2008	Marc Chagall's Birthday	Weak Observational Cue
28.07.2008	Beatrix Potter's Birthday	Strong Observational Cue
08.08.2008	2008 Beijing Olympic Games - Opening Ceremony	Strong Observational Cue
10.08.2008	2008 Beijing Olympic Games - Weight Lifting	Weak Observational Cue
11.08.2008	2008 Beijing Olympic Games - Diving	Weak Observational Cue
12.08.2008	2008 Beijing Olympic Games - Rhythmic Gymnastics	Weak Observational Cue
13.08.2008	2008 Beijing Olympic Games - Rings	Weak Observational Cue
14.08.2008	2008 Beijing Olympic Games - Basketball	Weak Observational Cue
15.08.2008	2008 Beijing Olympic Games - Badminton	Weak Observational Cue
18.08.2008	2008 Beijing Olympic Games - Table Tennis	Weak Observational Cue
19.08.2008	2008 Beijing Olympic Games - Swimming	Strong Observational Cue
20.08.2008	2008 Beijing Olympic Games - Athletics	Weak Observational Cue
22.08.2008	2008 Beijing Olympic Games - Martial Arts	Weak Observational Cue
13.10.2008	Paddington Bear's 50th Birthday	Weak Observational Cue
31.10.2008	Halloween 2008 designed by Wes Craven	Weak Observational Cue
21.12.2008	Happy Holidays from Google 2008 - 1	Weak Observational Cue
22.12.2008	Happy Holidays from Google 2008 - 2	Weak Observational Cue
23.12.2008	Happy Holidays from Google 2008 - 3	Weak Observational Cue
24.12.2008	Happy Holidays from Google 2008 - 4	Weak Observational Cue
25.12.2008	Happy Holidays from Google 2008 - 5	Weak Observational Cue
01.01.2009	Happy New Year 2009!	Weak Observational Cue
19.01.2009	Dr Martin Luther King Day 2009	Strong Observational Cue

US Early Period Table 2

Date	Doodle Name	Doodle Category
20.03.2009	First Day of Spring 2009	Weak Observational Cue
22.05.2009	Mary Cassatt's Birthday	Weak Observational Cue
21.06.2009	Father's Day 2009	Weak Observational Cue
02.10.2009	Birthday of Mohandas Karamchand Gandhi	Weak Observational Cue
05.11.2009	40th Anniversary of Sesame Street - Cookie Monster	Strong Observational Cue
06.11.2009	40th Anniversary of Sesame Street - Bert & Ernie	Strong Observational Cue
07.11.2009	40th Anniversary of Sesame Street - Oscar the Grouch	Strong Observational Cue
09.11.2009	40th Anniversary of Sesame Street - Count von Count	Weak Observational Cue
10.11.2009	40th Anniversary of Sesame Street	Weak Observational Cue
22.12.2009	Happy Holidays from Google 2009 - 2	Strong Observational Cue
18.01.2010	Dr Martin Luther King Day 2010	Weak Observational Cue
14.02.2010	Valentine's Day/2010 Vancouver Olympic Games - Pairs Skating	Weak Observational Cue
07.05.2010	Pyotr Ilyich Tchaikovsky's 170th Birthday	Weak Observational Cue
11.06.2010	World Cup 2010 Opening Day/Jacques Cousteau's 100th Birthday	Weak Observational Cue
30.09.2010	Flintstones' 50th Anniversary	Weak Observational Cue
31.10.2010	Halloween 2010	Weak Observational Cue
13.11.2010	Robert Louis Stevenson's 160th Birthday	Weak Observational Cue
01.12.2010	55th Anniversary: Rosa Parks refuses to move	Weak Observational Cue
17.01.2011	Dr Martin Luther King Day 2011	Weak Observational Cue
24.03.2011	Harry Houdini's 137th Birthday	Strong Observational Cue
21.06.2011	First Day of Summer by Takashi Murakami	Strong Observational Cue
05.09.2011	Freddie Mercury's 65th Birthday	Strong Observational Cue
24.09.2011	Jim Henson's 75th Birthday	Strong Observational Cue
12.10.2011	Art Clokey's 90th Birthday	Weak Observational Cue

A.6 Observational cues 2014-2017, US

US Late Period Table 1

Date	Doodle Name	Doodle Category
01.01.2014	New Year's Day 2014	Strong Observational Cue
07.01.2014	Zora Neale Hurston's 123rd Birthday	Weak Observational Cue
20.01.2014	Martin Luther King Jr. Day 2014	Weak Observational Cue
01.02.2014	Celebrating Harriet Tubman	Strong Observational Cue
24.03.2014	Dorothy Irene Height's 102nd Birthday	Weak Observational Cue
11.04.2014	Percy Julian's 115th Birthday	Weak Observational Cue
11.05.2014	Mother's Day 2014 (International)	Weak Observational Cue
27.05.2014	Rachel Louise Carson's 107th Birthday	Weak Observational Cue
13.06.2014	World Cup 2014 #3	Weak Observational Cue
16.06.2014	World Cup 2014 #13	Weak Observational Cue
17.06.2014	World Cup 2014 #14	Strong Observational Cue
20.06.2014	World Cup 2014 #20	Weak Observational Cue
21.06.2014	World Cup 2014 #22	Weak Observational Cue
24.06.2014	World Cup 2014 #29, #30	Weak Observational Cue
25.06.2014	World Cup 2014 #31	Weak Observational Cue
28.06.2014	World Cup 2014 #38	Weak Observational Cue
29.06.2014	World Cup 2014 #40	Strong Observational Cue
01.07.2014	World Cup 2014 #46	Weak Observational Cue
05.07.2014	World Cup 2014 #53	Weak Observational Cue
09.07.2014	World Cup 2014 #57, #58	Weak Observational Cue
18.07.2014	Nelson Mandela's 96th Birthday	Strong Observational Cue
25.08.2014	Althea Gibson's 87th Birthday	Weak Observational Cue
09.09.2014	Leo Tolstoy's 186th Birthday	Weak Observational Cue
28.10.2014	Jonas Salk's 100th Birthday	Weak Observational Cue
31.10.2014	Halloween 2014	Weak Observational Cue

US Late Period Table 2

Date	Doodle Name	Doodle Category
02.11.2014	Day of the Dead 2014	Weak Observational Cue
11.11.2014	Veteran's Day 2014	Strong Observational Cue
27.11.2014	Thanksgiving 2014	Strong Observational Cue
11.12.2014	Annie Jump Cannon's 151st Birthday	Weak Observational Cue
21.12.2014	Winter Solstice 2014 (Northern Hemisphere)	Weak Observational Cue
23.12.2014	Holidays 2014 (Day 1)	Weak Observational Cue
24.12.2014	Holidays 2014 (Day 2)	Weak Observational Cue
19.01.2015	Martin Luther King, Jr. Day 2015	Weak Observational Cue
07.02.2015	Laura Ingalls Wilder's 148th Birthday	Strong Observational Cue
19.02.2015	Lunar New Year 2015	Weak Observational Cue
05.03.2015	Momofuku Ando's 105th Birthday	Weak Observational Cue
08.03.2015	International Women's Day 2015	Weak Observational Cue
17.03.2015	St. Patrick's Day 2015	Strong Observational Cue
31.03.2015	126th Anniversary of the public opening of the Eiffel Tower	Weak Observational Cue
14.04.2015	155th anniversary of the Pony Express	Weak Observational Cue
21.04.2015	81st anniversary of the Loch Ness Monster's most famous photograph	Weak Observational Cue
04.05.2015	Bartolomeo Cristofori's 360th Birthday	Weak Observational Cue
05.05.2015	Nellie Bly's 151st Birthday	Strong Observational Cue
10.05.2015	Mother's Day 2015	Weak Observational Cue
26.05.2015	Sally Ride's 64th Birthday	Weak Observational Cue
21.06.2015	Father's Day 2015 (Multiple Countries)	Weak Observational Cue
04.07.2015	Fourth of July 2015	Weak Observational Cue
06.07.2015	FIFA Women's World Cup 2015 Winner (US)	Weak Observational Cue
07.07.2015	Eiji Tsuburaya's 114th Birthday	Strong Observational Cue
24.08.2015	Duke Kahanamoku's 125th Birthday	Strong Observational Cue
10.09.2015	Google Gameday Doodle Kickoff	Weak Observational Cue
13.09.2015	Google Gameday Doodle #1	Weak Observational Cue
20.09.2015	Google Gameday Doodle 2	Weak Observational Cue

US Late Period Table 3

Date	Doodle Name	Doodle Category
23.09.2015	First Day of Autumn 2015 (Northern Hemisphere)	Weak Observational Cue
27.09.2015	Google Gameday Doodle 3	Weak Observational Cue
29.09.2015	Evidence of water found on Mars	Strong Observational Cue
04.10.2015	Google Gameday Doodle 4	Weak Observational Cue
09.11.2015	Hedy Lamarr's 101st birthday	Weak Observational Cue
11.11.2015	Veterans Day 2015	Weak Observational Cue
30.11.2015	Lucy Maud Montgomery's 141st Birthday	Weak Observational Cue
14.12.2015	BKS Iyengar's 97th Birthday	Weak Observational Cue
17.12.2015	Celebrating Ludwig van Beethoven's 245th Year	Strong Observational Cue
23.12.2015	Holidays 2015 (Day 1)	Weak Observational Cue
25.12.2015	Holidays 2015 (Day 3)	Weak Observational Cue
31.12.2015	New Year's Eve 2015	Weak Observational Cue
01.01.2016	New Year's Day 2016	Weak Observational Cue
11.01.2016	Alice Paul's 131st Birthday	Weak Observational Cue
12.01.2016	Charles Perrault's 388th Birthday	Weak Observational Cue
18.01.2016	Martin Luther King Jr. Day 2016	Weak Observational Cue
22.01.2016	Wilbur Scoville's 151st Birthday	Strong Observational Cue
26.01.2016	90th Anniversary of the first demonstration of Television	Strong Observational Cue
01.02.2016	Celebrating Frederick Douglass	Weak Observational Cue
08.02.2016	Lunar New Year 2016	Weak Observational Cue
14.02.2016	Valentine's Day 2016	Weak Observational Cue
29.02.2016	Leap Year 2016	Weak Observational Cue
08.03.2016	International Women's Day 2016	Weak Observational Cue
09.03.2016	Clara Rockmore's 105th Birthday	Weak Observational Cue
20.03.2016	First Day of Spring 2016 (Northern Hemisphere)	Weak Observational Cue
23.04.2016	Celebrating William Shakespeare	Strong Observational Cue

US Late Period Table 4

Date	Doodle Name	Doodle Category
28.04.2016	Hertha Marks Ayrton's 162nd birthday	Weak Observational Cue
03.05.2016	Teachers' Day 2016 (US)	Weak Observational Cue
04.05.2016	Jane Jacobs' 100th birthday	Strong Observational Cue
06.05.2016	Sigmund Freud's 160th Birthday	Weak Observational Cue
19.05.2016	Yuri Kochiyama's 95th Birthday	Strong Observational Cue
09.06.2016	Phoebe Snetsinger's 85th birthday	Weak Observational Cue
20.06.2016	Summer Solstice & Strawberry Moon	Strong Observational Cue
04.07.2016	Fourth of July 2016	Weak Observational Cue
05.07.2016	Juno Reaches Jupiter	Weak Observational Cue
07.07.2016	Nettie Stevens' 155th birthday	Weak Observational Cue
06.08.2016	2016 Doodle Fruit Games – Day 2	Weak Observational Cue
07.08.2016	2016 Doodle Fruit Games – Day 3	Weak Observational Cue
08.08.2016	2016 Doodle Fruit Games – Day 4	Strong Observational Cue
09.08.2016	2016 Doodle Fruit Games – Day 5	Weak Observational Cue
10.08.2016	2016 Doodle Fruit Games – Day 6	Weak Observational Cue
11.08.2016	2016 Doodle Fruit Games – Day 7	Weak Observational Cue
12.08.2016	2016 Doodle Fruit Games – Day 8	Weak Observational Cue
13.08.2016	2016 Doodle Fruit Games – Day 9	Strong Observational Cue
14.08.2016	2016 Doodle Fruit Games – Day 10	Weak Observational Cue
15.08.2016	2016 Doodle Fruit Games – Day 11	Strong Observational Cue
17.08.2016	2016 Doodle Fruit Games – Day 13	Strong Observational Cue
18.08.2016	2016 Doodle Fruit Games – Day 14	Weak Observational Cue
19.08.2016	2016 Doodle Fruit Games – Day 15	Strong Observational Cue
20.08.2016	2016 Doodle Fruit Games – Day 16	Weak Observational Cue
21.08.2016	2016 Doodle Fruit Games – Day 17	Weak Observational Cue
01.09.2016	37th Anniversary of The Neverending Story's First Publishing	Weak Observational Cue
05.09.2016	Labor Day 2016 (US)	Weak Observational Cue

US Late Period Table 5

Date	Doodle Name	Doodle Category
13.09.2016	Yma Sumac's 94th birthday	Strong Observational Cue
22.09.2016	First Day of Autumn 2016 (Northern Hemisphere)	Strong Observational Cue
26.09.2016	US Voter Registration Day Reminder	Weak Observational Cue
24.10.2016	Antoni van Leeuwenhoek's 384th Birthday	Weak Observational Cue
31.10.2016	Halloween 2016	Weak Observational Cue
04.11.2016	Walter Cronkite's 100th Birthday	Weak Observational Cue
06.11.2016	United States Elections 2016 Reminder (Day 1)	Weak Observational Cue
07.11.2016	United States Elections 2016 Reminder (Day 2)	Weak Observational Cue
08.11.2016	United States Elections 2016	Weak Observational Cue
11.11.2016	Veterans Day 2016	Weak Observational Cue
14.11.2016	Sir Frederick Banting's 125th Birthday	Weak Observational Cue
18.11.2016	James Welch's 76th Birthday	Strong Observational Cue
29.11.2016	Louisa May Alcott's 184th Birthday	Weak Observational Cue
30.11.2016	Jagadish Chandra Bose's 158th Birthday	Strong Observational Cue
18.12.2016	Steve Biko's 70th Birthday	Strong Observational Cue
21.12.2016	Winter Solstice 2016 (Northern Hemisphere)	Strong Observational Cue
23.12.2016	Holidays 2016 (Day 1)	Weak Observational Cue
24.12.2016	Holidays 2016 (Day 2)	Strong Observational Cue
25.12.2016	Holidays 2016 (Day 3)	Weak Observational Cue
29.12.2016	Charles Macintosh's 250th Birthday	Strong Observational Cue
31.12.2016	New Year's Eve 2016	Weak Observational Cue
01.01.2017	New Year's Day 2017	Weak Observational Cue
16.01.2017	Martin Luther King Jr. Day 2017	Weak Observational Cue
23.01.2017	Ed Roberts' 78th Birthday	Strong Observational Cue
26.01.2017	Bessie Coleman's 125th Birthday	Strong Observational Cue
30.01.2017	Fred Korematsu's 98th Birthday	Weak Observational Cue
01.02.2017	Celebrating Edmonia Lewis	Weak Observational Cue
11.02.2017	Valentine's Day 2017 (Day 1)	Weak Observational Cue

US Late Period Table 6

Date	Doodle Name	Doodle Category
12.02.2017	Valentine's Day 2017 (Day 2)	Weak Observational Cue
13.02.2017	Valentine's Day 2017 (Day 3)	Weak Observational Cue
14.02.2017	Valentine's Day 2017 (Day 4)	Weak Observational Cue
23.02.2017	Seven Earth-Size Exoplanets Discovered!	Strong Observational Cue
25.02.2017	Ida Lewis' 175th Birthday	Weak Observational Cue
28.02.2017	Abdul Sattar Edhi's 89th Birthday	Weak Observational Cue
06.03.2017	37th Anniversary of Komodo National Park	Weak Observational Cue
08.03.2017	International Women's Day 2017	Weak Observational Cue
13.03.2017	Holi Festival 2017	Weak Observational Cue
20.03.2017	First Day of Spring 2017 (Northern Hemisphere)	Weak Observational Cue
31.03.2017	Doodle 4 Google 2017 – US Winner	Strong Observational Cue
03.04.2017	Fazlur Rahman Khan's 88th birthday	Strong Observational Cue
08.04.2017	Mary Pickford's 125th birthday	Weak Observational Cue
18.04.2017	Esther Afua Ocloo's 98th birthday	Weak Observational Cue
26.04.2017	Cassini Spacecraft Dives Between Saturn and its Rings!	Strong Observational Cue
09.05.2017	Teachers' Day 2017 (United States)	Weak Observational Cue
14.05.2017	Mother's Day 2017	Weak Observational Cue
22.05.2017	Richard Oakes' 75th Birthday	Strong Observational Cue
31.05.2017	Celebrating Zaha Hadid	Weak Observational Cue
03.06.2017	Josephine Baker's 111th Birthday	Strong Observational Cue
13.06.2017	Celebrating the ICC Champions Trophy 2017	Weak Observational Cue
17.06.2017	Susan La Flesche Picotte's 152nd Birthday	Weak Observational Cue
18.06.2017	Father's Day 2017	Weak Observational Cue
21.06.2017	Summer Solstice 2017 (Northern Hemisphere)	Weak Observational Cue
30.06.2017	Celebrating Victor Hugo	Strong Observational Cue
17.07.2017	Celebrating the ICC 2017 Women's Cricket World Cup	Weak Observational Cue
21.07.2017	Marshall McLuhan's 106th Birthday	Weak Observational Cue
28.07.2017	100th Anniversary of the Silent Parade	Weak Observational Cue
03.08.2017	Celebrating Dolores del Río	Weak Observational Cue
21.08.2017	Great American Eclipse 2017	Strong Observational Cue

A.7 Observational Cues 2014-2017, UK

UK Late Period, Table 1

Date	**Doodle Name**	**Doodle Category**
01.01.2014	New Year's Day 2014	Strong Observational Cue
09.01.2014	Simone de Beauvoir's 106th Birthday	Strong Observational Cue
31.01.2014	Chinese New Year 2014	Weak Observational Cue
06.03.2014	Elizabeth Browning's 208th Birthday	Weak Observational Cue
30.03.2014	Mother's Day 2014 (UK)	Weak Observational Cue
16.05.2014	Maria Gaetana Aghesi's 296th Birthday	Strong Observational Cue
18.07.2014	Nelson Mandela's 96th Birthday	Strong Observational Cue
27.05.2014	Rachel Louise Carson's 107th Birthday	Weak Observational Cue
13.06.2014	World Cup 2014 #3	Weak Observational Cue
16.06.2014	World Cup 2014 #13	Weak Observational Cue
17.06.2014	World Cup 2014 #14	Weak Observational Cue
20.06.2014	World Cup 2014 #20	Weak Observational Cue
21.06.2014	World Cup 2014 #22	Weak Observational Cue
24.06.2014	World Cup 2014 #30	Weak Observational Cue
25.06.2014	World Cup 2014 #31	Weak Observational Cue
16.08.2014	Diana Wynne Jones' 80th Birthday	Weak Observational Cue
28.08.2014	Sheridan Le Fanu's 200th Birthday	Weak Observational Cue
09.09.2014	Leo Tolstoy's 186th Birthday	Weak Observational Cue
06.10.2014	Thor Heyerdahl's 100th Birthday	Strong Observational Cue
28.10.2014	Jonas Salk's 100th Birthday	Weak Observational Cue
31.10.2014	Halloween 2014	Weak Observational Cue
21.12.2014	Winter Solstice 2014 (Northern Hemisphere)	Weak Observational Cue
23.12.2014	Holidays 2014 (Day 1)	Weak Observational Cue
24.12.2014	Holidays 2014 (Day 2)	Weak Observational Cue
07.02.2015	Laura Ingalls Wilder's 148th Birthday	Strong Observational Cue
19.02.2015	Lunar New Year 2015	Weak Observational Cue
05.03.2015	Gerardus Mercator's 503rd Birthday	Weak Observational Cue

UK Late Period, Table 2

Date	Doodle Name	Doodle Category
06.03.2015	Holi Festival 2015	Weak Observational Cue
08.03.2015	International Women's Day 2015	Weak Observational Cue
15.03.2015	Mother's Day 2015	Weak Observational Cue
17.03.2015	St. Patrick's Day 2015	Strong Observational Cue
31.03.2015	126th Anniversary of the public opening of the Eiffel Tower	Weak Observational Cue
14.04.2015	B. R. Ambedkar's 124th Birthday	Strong Observational Cue
21.04.2015	81st Anniversary of the Loch Ness Monster's most famous photograph	Weak Observational Cue
23.04.2015	St. George's Day 2015	Weak Observational Cue
04.05.2015	Bartolomeo Cristoferi's 360th Birthday	Weak Observational Cue
23.05.2015	Eurovision Song Contest 2015 Final	Strong Observational Cue
15.06.2015	800th Anniversary of the Magna Carta	Weak Observational Cue
21.06.2015	Father's Day 2015 (Multiple Countries)	Weak Observational Cue
07.07.2015	Eiji Tsuburaya's 114th Birthday	Strong Observational Cue
24.08.2015	Duke Kahanamoku's 125th Birthday	Strong Observational Cue
26.08.2015	La Tomatina 70th Anniversary	Weak Observational Cue
23.09.2015	First Day of Fall 2015 (Northern Hemisphere)	Weak Observational Cue
29.09.2015	Evidence of water found on Mars	Strong Observational Cue
30.11.2015	Saint Andrew's Day 2015	Strong Observational Cue
14.12.2015	BKS Iyengar's 97th Birthday	Weak Observational Cue
17.12.2015	Celebrating Ludwig van Beethoven's 245th Year	Strong Observational Cue
23.12.2015	Holidays 2015 (Day 1)	Weak Observational Cue
25.12.2015	Holidays 2015 (Day 3)	Weak Observational Cue
31.12.2015	New Year's Eve 2015	Weak Observational Cue
01.01.2016	New Year's Day 2016	Weak Observational Cue
09.01.2016	41st Anniversary of the Discovery of the Mountain of the Butterflies	Weak Observational Cue
12.01.2016	Charles Perrault's 388th birthday	Weak Observational Cue
22.01.2016	Wilbur Scoville's 151st birthday	Strong Observational Cue
26.01.2016	90th Anniversary of the first demonstration of television	Strong Observational Cue
08.02.2016	Dmitri Mendeleev's 182nd birthday	Weak Observational Cue

UK Late Period, Table 3

Date	Doodle Name	Doodle Category
14.02.2016	Valentine's Day 2016	Weak Observational Cue
17.02.2016	Rene Lannec's 235th birthday	Weak Observational Cue
29.02.2016	Leap Year 2016	Weak Observational Cue
08.03.2016	International Women's Day 2016	Weak Observational Cue
09.03.2016	Clara Rockmore's 105th birthday	Weak Observational Cue
16.03.2016	Caroline Herschel's 266th birthday	Weak Observational Cue
20.03.2016	First Day of Spring (Northern Hemisphere)	Weak Observational Cue
22.04.2016	Earth Day 2016	No Observational Cue
23.04.2015	Celebrating William Shakespeare and St. George's Day 2016	Strong Observational Cue
28.04.2016	Hertha Marks Ayrton's 162nd birthday	Weak Observational Cue
09.06.2016	Elizabeth Garrett Anderson's 180th birthday	Weak Observational Cue
10.06.2016	UEFA Euro 2016	Weak Observational Cue
06.08.2016	2016 Doodle Fruit Games – Day 2	Weak Observational Cue
07.08.2016	2016 Doodle Fruit Games – Day 3	Weak Observational Cue
08.08.2016	2016 Doodle Fruit Games – Day 4	Strong Observational Cue
09.08.2016	2016 Doodle Fruit Games – Day 5	Weak Observational Cue
10.08.2016	2016 Doodle Fruit Games – Day 6	Weak Observational Cue
11.08.2016	2016 Doodle Fruit Games – Day 7	Weak Observational Cue
12.08.2016	2016 Doodle Fruit Games – Day 8	Weak Observational Cue
13.08.2016	2016 Doodle Fruit Games – Day 9	Strong Observational Cue
14.08.2016	2016 Doodle Fruit Games – Day 10	Weak Observational Cue
15.08.2016	2016 Doodle Fruit Games – Day 11	Strong Observational Cue
16.08.2016	2016 Doodle Fruit Games – Day 12	Strong Observational Cue
17.08.2016	2016 Doodle Fruit Games – Day 13	Strong Observational Cue
18.08.2016	2016 Doodle Fruit Games – Day 14	Weak Observational Cue
19.08.2016	2016 Doodle Fruit Games – Day 15	Strong Observational Cue
20.08.2016	2016 Doodle Fruit Games – Day 16	Weak Observational Cue
21.08.2016	2016 Doodle Fruit Games – Day 17	Weak Observational Cue
01.09.2016	37th Anniversary of the Neverending Story's first publishing	Weak Observational Cue
22.09.2016	First Day of Autumn 2016 (Northern Hemisphere)	Strong Observational Cue

UK Late Period, Table 4

Date	Doodle Name	Doodle Category
24.10.2016	Antoni von Leeuwenhoek's 384th birthday	Weak Observational Cue
31.10.2016	Halloween 2016	Weak Observational Cue
14.11.2016	Sir Frederick Bonting's 125th birthday	Weak Observational Cue
29.11.2016	Louisa May Alcott's 184th birthday	Weak Observational Cue
07.12.2016	340th anniversary of the determination of speed of light	Weak Observational Cue
18.12.2016	Steve Biko's 70th birthday	Strong Observational Cue
21.12.2016	Winter Solstice (Northern Hemisphere)	Strong Observational Cue
23.12.2016	Holidays 2016 (Day 1)	Weak Observational Cue
24.12.2016	Holidays 2016 (Day 2)	Strong Observational Cue
25.12.2016	Holidays 2016 (Day 3)	Weak Observational Cue
29.12.2016	Charles Macintosh's 250th birthday	Strong Observational Cue
31.12.2016	New Year's Eve 2016	Weak Observational Cue
01.01.2017	New Year's Day 2017	Weak Observational Cue
07.01.2017	Sandford Fleming's 190th birthday	Weak Observational Cue
11.02.2017	Valentine's Day 2017 (Day 1)	Weak Observational Cue
12.02.2017	Valentine's Day 2017 (Day 2)	Weak Observational Cue
13.02.2017	Valentine's Day 2017 (Day 3)	Weak Observational Cue
14.02.2017	Valentine's Day 2017 (Day 4)	Weak Observational Cue
23.02.2017	Seven earth-size exoplanets discovered!	Strong Observational Cue
28.02.2017	Abdul Sattar Edhi's 89th birthday	Weak Observational Cue
08.03.2017	International Women's Day 2017	Weak Observational Cue
20.03.2017	First day of spring 2017 (Northern Hemisphere)	Weak Observational Cue
26.03.2017	Mother's Day 2017	Weak Observational Cue
31.03.2017	Sergei Diaghilev's 145th birthday	Weak Observational Cue
03.04.2017	Fazlur Rahman Khan's 88th birthday	Strong Observational Cue
18.04.2017	Esther Afua Ocloo's 98th birthday	Weak Observational Cue
26.04.2017	Cassini spacecraft dives between Saturn and its rings!	Strong Observational Cue
09.05.2017	Ferdinand Monoyer's 181st birthday	Weak Observational Cue
31.05.2017	Celebrating Zaha Hadid	Weak Observational Cue

UK Late Period, Table 5

Date	Doodle Name	Doodle Category
18.06.2017	Father's Day 2017	Weak Observational Cue
21.06.2017	Summer solstice 2017 (Northern Hemisphere)	Weak Observational Cue
30.06.2017	Celebrating Victor Hugo	Strong Observational Cue
01.07.2017	Amy Johnson's 114th birthday	Weak Observational Cue
21.07.2017	Marshall McLuhan's 106th birthday	Weak Observational Cue
28.08.2017	James Wong Howe's 118th birthday	Weak Observational Cue
04.09.2017	Edward Khil's 83rd birthday	Strong Observational Cue
06.09.2017	Celebrating British sign language and the Braidwood Academy	Strong Observational Cue
07.09.2017	Sir John Cornforth's 100th birthday	Strong Observational Cue