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BANNING FOREIGN PHARMACIES FROM SPONSORED SEARCH: THE ONLINE CONSUMER RESPONSE

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Banning Foreign Pharmacies from Sponsored Search: The Online Consumer Response
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ABSTRACT

Increased competition from the Internet has raised concerns for the quality of online prescription drugs. Given the illegality of importing unapproved prescription drugs into the U.S. and the pressure from the Department of Justice, Google agreed to ban pharmacies non-certified by the National Association of Boards of Pharmacy (NABP) from sponsored search listings. We study how the ban on non-NABP-certified pharmacies from sponsored search affects consumer search on the Internet. Using click-through data from comScore, we find that non-NABP-certified pharmacies receive fewer clicks after the ban, and this effect is heterogeneous. In particular, pharmacies not certified by the NABP, but certified by other sources (other-certified sites), experience a reduction in total clicks, and some of their lost paid clicks are replaced by organic clicks. In contrast, pharmacies not certified by any of the four major certification agencies suffer a greater reduction in both paid and organic clicks. These results suggest that the ban has increased the search cost for other-certified sites, but at least some consumers overcome the search cost by switching from paid to organic links. In addition to search cost, the ban may have increased concerns for uncertified sites and discouraged consumers from reaching them via both paid and organic links.

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1 Introduction

The Internet has led to a dramatic increase in the number of retailers available to consumers in many industries. The proliferation of competition may benefit consumers in several ways including lower prices. However, there is also the concern that the quality of the new product offerings may be lower, though difficult to discern by consumers. The concern is particularly acute for online prescription drugs, a market where poor product quality may lead to adverse health outcomes.

The high price of brand name prescription drugs has motivated U.S. consumers to search for cheaper supplies from foreign pharmacies, despite the fact that personal importation is illegal. The Federal Food, Drug, and Cosmetic Act (FD&C Act) prohibits the importation of unapproved drugs into the U.S.[1] In particular, section 355(a) states: "No person shall introduce or deliver for introduction into interstate commerce any new drug, unless an approval of an application ... is effective with respect to such drug."[2] The FDA further states that interstate shipment includes importation and the FD&C Act applies to "any drugs, including foreign-made versions of U.S. approved drugs, that have not received FDA approval to demonstrate they meet the federal requirements for safety and effectiveness."[3] Despite the import ban, FDA does not vigilantly enforce the ban on personal drug imports that represent reasonable risk and are intended for personal use of no more than 3-month supply.[4]

Facing online competition from foreign pharmacies, the National Association of Boards of Pharmacy (NABP) emphasizes the illegality of buying foreign drugs and highlights the danger of rogue pharmacies. Independent research, mostly from medical researchers rather than economists, confirmed some of the NABP concerns. In particular, Orizio et al. (2011) reviewed 193 articles about Internet pharmacies, of which 76 were based on original data. The articles with original data suggested that geographic characteristics were concealed in many websites, at least some websites sold drugs without a prescription and an online questionnaire was a frequent tool used to replace a prescription. On drug quality, researchers often found inappropriate packaging and labeling, however, the chemical composition was found to differ from what is ordered in only a minority of studied samples.

Search engines, such as Google, are an important gateway to accessing online pharmacies. When a user submits a query into a search engine, in addition to providing a list of relevant (i.e. organic) links based on the engine's search algorithm, additional links are returned that are based on their

[1] See `http://www.fda.gov/RegulatoryInformation/Legislation/FederalFoodDrugandCosmeticActFDCAct`.

[2] See `http://www.gpo.gov/fdsys/pkg/USCODE-2010-title21/pdf/USCODE-2010-title21-chap9-subchapV-partA-sec355.pdf`.

[3] See `http://www.fda.gov/ForIndustry/ImportProgram/ucm173743.htm`.

[4] To answer the question "Is it legal for me to personally import drugs?", the FDA website states that "... it typically does not object to personal imports of drugs that FDA has not approved under certain circumstances, including the following situation: The drug is for use for a serious condition for which effective treatment is not available in the United States; There is no commercialization or promotion of the drug to U.S. residents; The drug is considered not to represent an unreasonable risk; The individual importing the drug verifies in writing that it is for his or her own use, and provides contact information for the doctor providing treatment or shows the product is for the continuation of treatment begun in a foreign country; and Generally, not more than a 3-month supply of the drug is imported." Source:`http://www.fda.gov/AboutFDA/Transparency/Basics/ucm194904.htm,accessedAugust3,2015`.

relevance to the query and a payment made by the link's owner. These latter results are called sponsored or paid links. An investigation by the DOJ revealed that, as early as 2003, Google was allowing unapproved Canadian pharmacies to purchase sponsored links and target U.S. consumers. While Canadian pharmacies face regulations within Canada, importation of drugs into the U.S. is illegal because the FDA cannot ensure their safety and effectiveness. In addition, some pharmacies that claimed to be based in Canada were actually selling drugs from other foreign countries that may have lacked sufficient regulation. Because of heightened concern to protect consumers, Google agreed to ban non-NABP-certified pharmacies from their sponsored search listings in February 2010. Eighteen months later (August 24, 2011), Google settled with the DOJ by "forfeiting $500 million generated by online ads & prescription sales by Canadian online pharmacies."[5] Other search engines adopted a similar ban on sponsored search listings soon after Google's ban in February 2010 but the settlement with the DOJ is for Google only.

Because the search engine ban only applied to sponsored links for non-NABP-certified pharmacies and these websites potentially continued to appear in the organic search results, the ban provides an excellent opportunity to study how consumers substitute between organic and sponsored links. The goal of this paper is to examine how consumer's organic search activities have changed after the ban of non-NABP-certified pharmacies from sponsored advertising.

The strength of organic substitution depends on a number of factors. First, the sponsored search ban is intended as a warning against consumer use of non-NABP-certified websites. If this warning prompts more consumer concern about drug safety from foreign pharmacy websites, they may discourage consumers from clicking into the banned sites, even if their organic links are readily available. We expect this warning effect to be more salient after the Google-DOJ settlement, as the settlement was reported in the news more widely than the search engine ban itself. In comparison, the search engine ban increases the technical difficulty to access a foreign pharmacy website on the search page: a site that ranked high in the sponsored list before the ban may lose its visibility in sponsored search, and has to compete for consumer attention with hundreds of other search results in the organic section. If that site does not appear highly ranked in the organic search results, consumers may find it difficult to switch to the site's organic link. The technical increase of search cost is a second factor that affects organic substitution. Other factors depend on how search engine users change their behavior to combat this search cost. On the consumer side, some consumers may be willing to spend more time and effort to look for the organic links of the banned websites, especially if the expected benefits from these banned websites (e.g., lower cost drugs and more privacy protection) exceeds the perceived risk (e.g., drug safety concerns, drug efficacy and the stigma of doing something illegal). On the side of pharmacy websites, the banned websites may have strong incentives to "manage" their organic ranks, especially those that disproportionately relied on sponsored ads before the ban.

Keeping these factors in mind, we classify pharmacy sites into three tiers: NABP-certified (tier-A), other-certified (tier-B), and uncertified (tier-C). NABP-certified sites refer to U.S. pharmacies

[5] http://www.justice.gov/opa/pr/2011/August/11-dag-1078.html, retrieved December 28, 2013.

that receive approval from NABP or the NABP-endorsed certifier, LegitScript.[6] NABP-certified sites are free to advertise in sponsored search listings before and after the ban. Other-certified sites refer to foreign or domestic pharmacies that are certified by PharmacyChecker.com or the Canadian International Pharmacy Association (CIPA), but not by NABP or LegitScript. All the rest are classified as uncertified sites. Although both other-certified and uncertified sites are banned from Google's sponsored search after February 2010, we distinguish them for two reasons: first, uncertified sites were prohibited from sponsored listings even before the ban, but the screening was imperfect. In comparison, other-certified websites were allowed to bid for sponsored ads until the ban. Second, other-certified sites may be subject to a higher safety standard in the eyes of consumers that purchase drugs online (as evidenced in Bate et al. 2013) and therefore the ban could trigger different organic substitution patterns for tier-B and tier-C sites. The substitution pattern can also differ between tier-B and tier-C sites because tier-B sites are typically larger in click volume before the ban hence they may have higher organic ranks and are easier to find after the ban.

Using 2008-2012 comScore data, we find that the banned pharmacies experience a reduction in the number of total clicks after the ban, but the effect is heterogeneous. In particular, tier-B sites experience a smaller reduction in total clicks with some of the lost paid click-throughs replaced by organic clicks. These effects do not change significantly after the Google-DOJ settlement. In contrast, tier-C sites receive fewer traffic in both paid and organic clicks, and the reduction is even greater after the DOJ settlement.[7] We also explore whether the effect of the ban depends on a website's total click volume before the ban, its reliance on sponsored clicks before the ban, and consumer's search intention as reflected in specific pharmacy or drug queries. Overall, we conclude that the ban has increased search cost for tier-B sites, but at least some consumers overcome the search cost by switching from paid to organic links. In addition to search cost, the ban may have increased health or safety concerns for tier-C sites, which may explain why consumers are discouraged from switching to their organic links.

The paper proceeds as follows. In section 2, we provide background on the online market for prescription drugs, the role of search engines as gateways to this market, as well as changes to Google's policy regarding sponsored search ads from online pharmacies. We lay out our econometric framework in section 3 and describe the comScore data in section 4. Results are presented in section 5 and section 6 concludes.

2 Background

2.1 The Online Market of Prescription Drugs

A literature review by Orizio et al. (2011) found that the percent of the general population using online pharmacies was often reported to be between 4% and 6%. Although the percentage is

[6] As detailed in Section 2, NABP endorses LegitScript to act on its behalf in screening websites for search engines, so we treat approval from LegitScript the same as certification from NABP.

[7] Paid clicks on tier-C sites should be zero immediately following the ban, though a small number of paid clicks are still observed.

small, the total volume of sales can be huge, given the size of the U.S. prescription drug market.[8] According to Skinner (2006), sales to U.S. consumers from 278 Canadian or seemingly-Canadian pharmacies reached CDN$507 million in the 12-month period ending June 2005.[9] More than half of the sales were on top-selling brand-name prescription drugs consumed primarily by seniors. The $500 million fine that Google agreed to pay in 2011 also indicates the size of the online prescription drug market, as the fine is calculated by the revenue received by Google for selling sponsored ads to Canadian pharmacies and the estimated revenue that Canadian pharmacies got from their sales to U.S. consumers.[10]

One major concern associated with purchasing from online pharmacies is drug safety. As described in NABP (2011) and Orizio et al. (2011), drug safety can be potentially compromised by a relaxed prescription requirement, insufficient medical consultation, incorrect packaging and labeling, wrong ingredients, or no delivery at all.[11] Some rogue websites also aim to steal consumer credit card information for identity theft. Although the FD&C Act prohibits the importation of unapproved drugs, when determining the legality of personal shipments, "FDA personnel may use their discretion to allow entry of shipments of violative FDA regulated products when the quantity and purpose are clearly for personal use, and the product does not present an unreasonable risk to the user."[12] Therefore, a consumer who purchases a drug from a foreign pharmacy for personal use faces some uncertainty regarding the likely reaction by the FDA.

To address safety concerns, the FDA also publicizes anecdotes of unsafe pharmaceuticals on the Internet and warns consumers against rogue websites (which could be foreign or domestic). They also advise consumers to avoid any foreign websites and only make online purchases from the U.S. websites certified by the NABP. The NABP certification ensures that U.S. websites comply with laws in both the state of their business operation and the states they ship medications. As of February 29, 2012, NABP has certified 30 online pharmacies, 12 of which are run by large pharmacy benefits management companies (open to members only) and the rest include national chain pharmacies (such as cvs.com and walgreens.com) and large online-only pharmacies (such as drugstore.com).

Another private certification agency, LegitScript.com,[13] was endorsed by the NABP to screen

[8] Prescription drug sales in the U.S. has grown from $135 billion in 2001 to $307 billion in 2010 (IMS 2011).

[9] This number was measured in standardized manufacturer-level prices and did not include "foot traffic" sales to U.S. consumers through regular "brick-and-mortar" border pharmacies in Canada. Sales measured by final retail prices to U.S. customers was not available but is certainly higher than CDN$507.

[10] CNN report August 24, 2011, accessed at `http://money.cnn.com/2011/08/24/technology/google_settlement/index.htm`.

[11] In particular, the NABP study reviewed 7,430 Internet pharmacies as of December 2010 and found 96.02% of them operating out of compliance with U.S. state and federal laws and/or NABP patient safety and pharmacy practice standards. Among these non-NABP-recommended pharmacies, 2,429 (34%) had server locations in a foreign country, 1,944 (27%) had a physical address out of U.S., 4,005 (56%) did not provide any physical address, 5,982 (84%) did not require a valid prescription, 4,397 (62%) issued prescriptions via online consultation, 3,210 (50%) offered foreign or non-FDA-approved drugs, 5,928 (83%) did not offer medical consultation, and 1,129 (16%) did not have secure sites.

[12] See `http://www.fda.gov/ICECI/ComplianceManuals/RegulatoryProceduresManual/ucm179266.htm`. The FDA defines personal shipments as containing no more than 90-days supply for personal use and does not involve a controlled substance. A controlled substance is a drug that has a high potential for abuse, does not have an accepted medical use, and/or does not meet accepted safety requirements.

[13] LegitScript was founded by a former White House aide named John Horton.

pharmacy websites after the Google ban. As of March 5, 2012, LegitScript monitored 228,419 Internet pharmacies among which 40,233 were active. Within active websites, LegitScript found 221 legitimate (0.5%), 1,082 potentially legitimate (2.7%) and 38,929 not legitimate (96.8%). Their certification criterion includes a valid license with local U.S. jurisdictions, valid registration with the U.S. Drug Enforcement Administration (DEA) if dispensing controlled substances, valid contract information, valid domain name registration, requiring a valid prescription, only dispensing FDA approved drugs, and protecting user privacy according to the HIPAA Privacy Rule (45 CRF 164). There are more LegitScript-certified websites than NABP-certified websites, probably because the NABP requires interested websites to apply and pay verification fees while LegitScript's approval is free and does not require website application. Because the NABP endorses the use of LegitScript by domain name registrars to assist in identifying illegally operating websites, throughout this paper we treat LegitScript the same as NABP and label websites certified by either agency as NABP-certified.

The other two private certifiers – PharmacyChecker.com and the Canadian International Pharmacy Association (CIPA) – are fundamentally different from NABP/LegitScript. CIPA is a trade association of Canadian pharmacies and only certifies Canadian websites that comply with Canadian laws, while PharmacyChecker.com covers U.S., Canada, and many other countries. Upon voluntary application (with a fee), PharmacyChecker certifies that any approved website has a valid pharmacy license from its local pharmacy board, requires a prescription for U.S. purchase if the FDA requires a prescription for the medication, protects consumer information, encrypts financial and personal information, and presents a valid mailing address and phone number for contact information. As of March 9, 2012, PharmacyChecker has approved 73 foreign websites and 51 U.S. websites. PharmacyChecker also charges fees for an approved website to be listed on PharmacyChecker.com beyond a short period of initial approval. Consequently, those listed on PharmacyChecker's Pharmacy Ratings page are only a selected list of PharmacyChecker-approved websites. Because PharmacyChecker is unwilling to share their complete list of approvals, we are not able to conduct a full comparison between approvals by PharmacyChecker and those by the NABP, LegitScript or the CIPA. Of the 37 websites listed on the Pharmacy Ratings page of PharmacyChecker.com, only three are labeled U.S. while all the others are either listed under one foreign country or a number of foreign countries plus U.S. This list overlaps incompletely with the list of approvals from the NABP, LegitScript and the CIPA. Among the four certification agencies, PharmacyChecker is the only one that provides head-to-head drug price comparison across online pharmacies. As detailed below, Google used to contract with PharmacyChecker to filter websites listed in its sponsored search page, but switched to NABP/LegitScript after it agreed to ban non-NABP-certified pharmacies in February 2010.

In an audit study, Bate, Jin and Mathur (2013) purchased samples of five popular brand-name prescription drugs from NABP/LegitScript-certified websites (tier-A), PharmacyChecker/CIPA-certified websites (tier-B), and websites that were not certified by any of the four certifiers (tier-C). After comparing the purchased samples with authentic versions, they found similar drug quality between tier-A and tier-B samples, but the cash price of tier-B samples were 49.2% cheaper than tier-A samples after controlling for other factors. In comparison, tier-C websites were 54.8% cheaper than tier-A sites, but eight tier-C samples failed the authenticity test as compared to zero failures in the tier-A and tier-B samples.[14]

Consistent with Bate, Jin and Mathur (2013), other studies also suggest that a lower price for brand-name prescription drugs is an important incentive for U.S. consumers to shop online. According to Gurau (2005), the most frequent reasons quoted by interviewees for buying or intending to buy online were convenience and saving money, followed by information anonymity and choice. Skinner (2005) estimated that Canadian prices for the 100 top-selling brand-name drugs were on average 43% below U.S. prices for the same drugs.[15] Quon et al. (2005) compared 12 Canadian Internet pharmacies with three major online U.S. drug chain pharmacies and found that Americans can save an average of approximately 24% per unit of drug on the 44 most-commonly purchased brand-name medications from Canada.[16]

Fox (2004) reported that the most frequent drugs bought online were for chronic conditions (75%), followed by weight loss and sexual performance substances (25%). Consistently, Skinner (2006) found resemblance between the top five therapeutic categories used by U.S. seniors and the top five therapeutic categories in the cross-border online sales from Canada to the U.S. This suggests that seniors are an important source of demand for Canadian pharmacies. Bate, Jin and Mathur (2013) reported an online survey of RxRights members. Because RxRights is a non-profit organization that pays attention to the cost of prescription drugs, their members are likely more price sensitive than the general population. Among 2,907 respondents who purchase prescription medication for either themselves or family members, 54.8% admitted to purchasing at least one category of the drugs online at some time in the past year, 72.4% of online shoppers purchased from foreign websites only, and an overwhelming majority (91.1%) cited cost savings to be one of the reasons for buying from foreign websites. Surprisingly, most respondents had medical insurance and/or some prescription drug coverage, and the percentage of being insured was not lower among online shoppers. Comments left by respondents suggested that incomplete coverage on prescription drugs, in the form of high deductibles, high coinsurance rates, or the donut hole in the Medicare Part D coverage, was one of the factors that motivated the insured to shop online.

The survey reported in Bate, Jin and Mathur (2013) also highlighted how respondents searched for pharmacies. Conditional on shopping online, 53.1% used Internet search, 40.4% checked with a credential agency such as PharmacyChecker, 22.4% used personal referrals, and only 12.7% looked

[14]The price difference was mostly driven by non-Viagra drugs. There was no significant price difference across tiers for Viagra, but all the tier-C failures were Viagra.

[15]This number has been adjusted for currency equivalency. Skinner (2005) also reported that the 100 top-selling generic drugs are on average priced 78% higher in Canada than in the U.S. This explains why most cross-border sales from Canada to the U.S. are brand-name drugs.

[16]The large price difference between the U.S. and Canada has motivated not only individual Americans to order brand name prescription drugs from foreign pharmacies, but also a large number of bills introduced by state or federal legislators in favor of legalizing or facilitating the cross-border drug trade with Canada. According to Skinner (2006), the number of state and federal bills on this topic increased from three in 2002 to 84 in 2005. Recent articles in the press also argue against the ban on unapproved foreign drugs, but the FDA maintains that drugs sold via unapproved pharmacies are often not equivalent to those sold legally in the U.S. See a New York Times Opinion article: `http://www.nytimes.com/2014/03/25/opinion/scare-tactics-over-foreign-drugs.html` and the FDA's response: `http://www.nytimes.com/2014/04/03/opinion/unsafe-foreign-drugs.html`.

for the cheapest deal. Consistently, most online shoppers restrict themselves to one primary website, sometimes with supplements from other websites. This suggests that many consumers, especially those that need an economic solution for a long-term supply of chronic drugs, are aware of credential agencies for foreign online pharmacies and use them as one way to discern the quality of online pharmacies. This behavior is consistent with a perceived quality difference between tier-B and tier-C sites, which motivates us to examine whether the ban of non-tier-A sites from sponsored listings has a differential effect on tier-B and tier-C sites.

2.2 Search Engine Policy on Online Pharmacies

As summarized in Table 1, Google used to contract with PharmacyChecker to ensure that every pharmacy website listed in Google's sponsored search page is legitimate according to PharmacyChecker's certification standard. Despite this policy, the FDA found in July 2009 that some online pharmacies advertising on Google had not been approved by PharmacyChecker.[17] Shortly after (November 2009), the FDA issued 22 warning letters to website operators.[18] At about the same time (August 2009), a study published by LegitScript.com and KnuhOn.com criticized Microsoft Bing for allowing rogue online pharmacy to advertise on its search engine. The study found that "89.7% (of the advertising websites) led to 'rogue' Internet pharmacies that do not require a prescription for prescription drugs, or are otherwise acting unlawfully or fraudulently."[19] While 89.7% is an impressive number, one should note that LegitScript will "not approve websites sourcing prescription drugs in a way that the FDA has indicated is contrary to U.S. law (meaning, 'Canadian' or other foreign pharmacy websites)."[20] In contrast, PharmacyChecker certifies some foreign pharmacies that would not be certified by LegitScript.

Figure 1 presents a screen shot of Google search page following the query "liptor" in 2008. On the left hand side are organic links including brand-name websites such as lipitor.com and information-oriented websites such as wikipedia.org. At the top of the whole page is a sponsored link for lipitor.com from the brand's U.S. manufacturer (Pfizer). On the right hand side are other sponsored links, of which the top two are clearly foreign pharmacies (canadapharmacy.com and canadadrugpharmacy.com).

In response to the highlighted concern of drug safety, on February 9, 2010, Google announced two changes regarding its pharmacy advertising policy. The first change is to only accept ads from U.S. online pharmacy websites that are certified by the NABP and from Canadian websites that are certified by CIPA. The second change is that the NABP-certified websites can only target their ads to Google users in the U.S. and the CIPA-certified websites can only target Google users in

[17] `http://www.nytimes.com/2011/05/14/technology/14google.html?_r=0`.

[18] `http://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/ucm191330.htm`. The current FDA website hosting safety information of online purchase of drugs: `http://www.fda.gov/Drugs/ResourcesForYou/Consumers/BuyingUsingMedicineSafely/BuyingMedicinesOvertheInternet/default.htm`.

[19] The report `http://www.cnn.com/2009/TECH/08/20/internet.drugs/index.html` posts the link `http://www.legitscript.com/BingRxReport.pdf`, but it is unavailable to access on December 25, 2012. The report is also available here: `http://www.legitscript.com/download/BingRxReport.pdf`.

[20] `http://www.legitscript.com/services/certification`.

Canada. The new policy is only applicable to U.S. and Canada.[21] Two months later (April 21, 2010), LegitScript announced assistance to Google in implementing Google's Internet pharmacy advertising policy in place of PharmacyChecker.[22] On June 10, 2010, both Microsoft and Yahoo! started to require NABP certification for online pharmacy advertisers.[23]

In May 2011, Google announced in its quarterly report that "in connection with ... an investigation by the United States Department of Justice into the use of Google advertising by certain advertisers, we accrued $500 million for the three month period ended March 31, 2011."[24] On August 24, 2011, the DOJ made it official that "Google Forfeits $500 Million Generated by Online Ads & Prescription Drug Sales by Canadian Online Pharmacies." The press release states that "Under the terms of an agreement signed by Google and the government, Google acknowledges that it improperly assisted Canadian online pharmacy advertisers to run advertisements that targeted the United States ..."[25]

Figure 2 presents a screen shot of Google search page following the query "lipitor" in 2013. In contrast to Figure 1, there are no sponsored links on the page except for lipitor.com at the top. The void of sponsored links on the right hand side is filled by a drug fact label of lipitor with links to official information about the drug's side effects, warnings and user guidance from the National Library of Medicine. The drug fact label started on June 22, 2010 under a partnership between Google and the National Institute of Health (NIH),[26] and probably has diverted some click traffic following drug name queries after the ban.

In light of these events, we define three regimes for our empirical analysis as shown in Table 2. Regime 0 refers to a 17-month period up to January 2010, right before Google adopted the ban. Regime 1 ranges from March 2010 to July 2011, covering a period after the Google ban but before the Google-DOJ settlement. The 13-month period after the Google-DOJ settlement is referred to as Regime 2. Because our data are monthly but both the Google ban and the Google-DOJ settlement occurred in the middle of a month, our sample excludes the two event months (February 2010 and August 2011).[27]

In our main analysis, we consider consumer search behavior from all search engines. This is partly because other search engines adopted a similar policy change soon after the Google ban, partly because the Google-DOJ settlement is an effective warning to all search engines. As a robustness

[21] `http://adwords.blogspot.com/2010/02/update-to-pharmacy-policy-in-us-and.html`.

[22] `http://blog.legitscript.com/2010/04/legitscript-to-help-google-implement-internet-pharmacy-ad-policy/`.

[23] `https://www.nabp.net/news/microsoft-and-yahoo-now-require-vipps-accreditation-for-online-pharmacy-advertisers`.

[24] `http://sec.gov/Archives/edgar/data/1288776/000119312511134428/d10q.htm` .

[25] `http://www.justice.gov/opa/pr/2011/August/11-dag-1078.html`.

[26] `http://venturebeat.com/2010/06/22/google-health-search-adds-drug-info-upping-pharma-ad-spend`.

[27] Because we define regimes 1 and 2 by time only, the difference between regimes 1 and 2 could be driven by a general trend or heightened consumer awareness. To address this concern, we count the number of searchers per month for queries related to pharmacy certification. This number fluctuates month to month, but starts to pick up an upward trend in the middle of 2011. We regress the log of this count on regime dummies and quarter dummies (to control for seasonality). The coefficient on the regime 2 dummy is 1.175 (with stdev=0.391, p-value<0.01). In comparison, the coefficient on the regime 1 dummy is 0.272 (with stdev=0.37, p-value=0.465). This suggests that the average monthly count of searchers that query pharmacy certification terms has increased significantly in regime 2, but not in regime 1.

check, we also rerun the analysis for Google only and report corresponding results in the Appendix.

2.3 Organic and Sponsored Search

Internet search engines, such as Google, are one avenue consumers use to reach Internet pharmacies. Upon submitting a query, a user is presented with organic and sponsored results. If the user clicks on a sponsored link, the link owner pays the search engine the next highest bid or the reserve price if there are no other bids. An example of a Google search results page is shown in Figure 1.

The ban of non-NABP-certified pharmacies from search engines' sponsored links may be less effective if links to those same pharmacies appear in the organic links of a results page.

A rising literature has shown that sponsored links accounted for 15% of all clicks (Jansen and Sprink 2009), consumers have a preference against sponsored links (Jansen and Resnick 2006), consumers appreciate sponsored links as advertisements if they are relevant (Jansen, Brown and Resnick 2007), and organic and sponsored links from the same website of a national retailer were complements in consumer clicks (Yang and Ghose 2010). Two studies released by Google painted a somewhat different picture. Chan, et al. (2012) found that 81% of sponsored impressions and 66% of sponsored clicks occurred in the absence of an associated organic link on the first page of search results. This suggests that most sponsored links are from websites that are not easy to find in organic search. Chan, et al. (2011) examined 446 incidences between October 2010 to March 2011 where advertisers temporarily paused their sponsored ads to determine their effectiveness. From these incidences, they found that 89% of the traffic generated by sponsored ads was not replaced by organic clicks (leading to the same destination website) when the ads were paused. This suggests that organic and sponsored traffic are not necessarily substitutes.

In contrast, Blake, Nosko and Tadelis (2014) run a series of controlled field experiments in eBay, Inc. and found strong substitution between its organic and sponsored listings. In particular, when eBay stopped its sponsored ad for the keyword "eBay", consumers simply substituted to eBay's (unpaid) organic search links. Sponsored ads for non-branded keywords were also found to be ineffective on average for a large and well-known brand like eBay.

Above all, the existing literature suggests that whether organic and sponsored results substitute or complement each other depends on the organic rank of the site. In our context, if a non-NABP-certified pharmacy appears high on the first page of the organic results, the ban of its sponsored listing may redirect consumer clicks to its organic link. But for many non-NABP-certified pharmacies that do not appear in high ranked organic results, the ban of their appearance in sponsored listings could be an effective tool to minimize consumer clicks on them in organic search. Our data do not contain organic rank of each pharmacy site, but the overall click traffic before the ban is higher for tier-B than for tier-C sites, which implies that the ban on sponsored listings could generate a differential effect on tier-B and tier-C sites.

In addition to the above-mentioned similarity, our context also differs from the literature in the incentives for or against organic substitution. In the literature, a pause of sponsored ads is often driven by an internal decision from the advertising website, which does not necessarily carry any explicit message on the quality of the website. However, in our context, the ban of sponsored ads is imposed by search engines due to safety and legal concerns. This action alone may change consumer willingness to access the organic link of a banned website as well as the website's incentive to manage its organic link in response to the ban. These two incentives may generate another differential effect on tier-B and tier-C sites, if consumers believe tier-B are more trustworthy than tier-C or if tier-C relied more on sponsored ads before the ban and therefore became more eager to increase its organic rank after the ban.

2.4 Other Related Literature

Our study is indirectly related to two other literatures. At first glance, the sponsored search ban is a form of a minimum quality standard. A number of empirical studies have attempted to test the theory of minimum quality standards by examining price, quantity, quality, and market structure, but all of them assumed that the standard is well enforced in reality. This assumption does not hold for online pharmacies: after the ban, consumers can still access non-NABP-certified pharmacies through organic search. Moreover, the ban affected only one channel through which consumers can gather safety information about online pharmacies. Other channels of information include consumer experience, word of mouth, and alternative certification agencies. With organic links and alternative information channels, this denial is likely incomplete for online pharmacies, which offers us an excellent opportunity to study how pharmacies compliant with the minimum quality standard (NABP-certified pharmacies) coexist or even compete with the banned pharmacies in organic search.

Our study also contributes to the literature on the effectiveness of advertising and the ability and willingness of consumers to switch to alternative information channels when one channel is removed. Much of the literature on the effects of advertising focuses on either the market expanding effects (e.g., Stigler (1961) and Grossman and Shapiro (1984)) or the business stealing effects (e.g., Becker and Murphy (1993) and Stigler and Becker (1977)) while Ackerberg (2001) tries to distinguish the two effects for different types of products. More recently, Goldfarb and Tucker (2011) consider how offline advertising bans are effected by the simultaneous exposure of online ads and show that government bans of offline ads are less effective in the presence of online ads. Chiou and Tucker (2011) show that, following the removal of search advertising for certain pharmaceutical drugs, consumers searching for information on medical conditions were less likely to click on the drug company's website, but more likely to click on non-FDA regulated websites such as Canadian pharmacies.[28]

Similar to Chiou and Tucker (2011), we study how the ban on sponsored search advertisements for online pharmacies affects consumer search. This could lead to the opposite of the market expanding effect as consumers avoid certain pharmacies due to safety concerns. It could also lead to substitution between different-tiered pharmacies. Our data are unique in that it allows us to

[28]In addition, Manchanda, et al (2006) focus only on online banner advertisements and show that ads increase the probability of purchase for current customers. Chatterjee et al (2003) find that repeated exposure to banner ads reduces click probabilities especially for consumers with a higher innate tendency to click on ads.

analyze these effects through the ban's impact on both sponsored and organic clicks.

3 Conceptual and Econometric Framework

Our empirical analysis follows the typical differences-in-differences (DID) framework. In this section, we first define treatment and control groups, and then present the main specification. At the end, we discuss how we detect heterogenous effects in a few extended specifications.

3.1 Treatment and Control Groups

We aim to study how consumers substitute between organic and sponsored links. Because the sponsored search ban applies to tier-B and tier-C pharmacies, these two tiers belong to the treatment group. One may argue that tier-A pharmacies should belong to the control group, because they are not directly subject to the search engine ban. However, tier-A competes with tier-B and tier-C, and all tiers can be affected by the sponsored search ban and the Google-DOJ settlement. In light of this, we classify tier-A pharmacies in the treatment group as well, but allow the three tiers to have differential effects from the regime changes.

A key challenge is to find a control group that exhibits similar trends as the treated pharmacy websites, but is immune to the search engine ban on sponsored pharmacy links. To meet this challenge, we turn to clicks on non-pharmacy websites from health queries. Health queries refer to searches on health conditions, drug manufacturers, and health related regulators, but exlude searches on specific drug names (e.g., lipitor) or searches related to pharmacies (e.g., canadapharmacy, pharmacychecker, or "cheapdrug Canada"). Before the sponsored search ban, 98-99% of all the clicks into tier-A, tier-B and tier-C sites (via search engines) came from drug queries or pharmacy queries, and only 1-2% came from health queries. In contrast, 57% of clicks into health-related non-pharmacy websites originated from health queries. Hence, clicks on non-pharmacy websites from health queries are by and large independent of the sponsored search ban on pharmacy websites. To ensure comparability between treatment and control websites, we test for differential time trends before the search engine ban, and check the robustness of our main results by allowing a time trend in the main specification.

3.2 Main Specification

With treatment and control groups defined above, we now present the main specification. Our data source, comScore, reports organic and paid clicks separately. For each measure of clicks (organic, paid and total), we are interested in the effect of the sponsored search ban and the Google-DOJ settlement on two margins: on the extensive margin, the regime changes may have made a website more or less likely receive any clicks in a given month; on the intensive margin, a website may get more or fewer clicks after the regime changes, conditional on receiving positive clicks.

We distinguish the extensive and intensive margins for two reasons. First, comScore codes the number of clicks as censored if the website receives too few clicks. We do not have specific information on the censoring rule, so we treat any censored clicks as zero. In a robustness check, we separately code zero clicks and censored clicks for the extensive margin analysis and the results are similar. More importantly, the distribution of clicks per website-month is characterized by a spike at zero and a bell-shape positive distribution skewed to the right. To best capture this data pattern, we choose a two-part model where the first part focuses on whether the number of clicks is zero or not and the second part specifies a log-normal distribution conditional on observing a positive number of clicks.[29]

We prefer the two-part model to Tobit because Tobit assumes a specific functional form on the underlying distribution and requires that distribution to fit both the probability of censoring and the shape of the data distribution conditional on being uncensored. Our two-part model relaxes this assumption thus allowing more flexibility to fit the censored and uncensored data separately. When we analyze our data in a Tobit model, we find it to be significantly worse than the two-part model as measured by likelihood ratio test.[30] We have also tried a Heckman selection model. Because we do not know comScore's censoring rules, there is no observable factor that affects the censoring, but not the underlying distribution. As a result, by using the same set of control variables in both stages, the inverse Mills ratio computed from the first stage of the Heckman model is collinear with the control variables in the second stage.[31]

We estimate the two-part model in two equations. The first equation investigates the extensive margin using a logit regression:

$$\begin{aligned} Prob(Y_{it}^{AllQueries} > 0) &= \Phi(\alpha + \sum_{k\in\{A,B,C\}} \beta_k * Tier_k + \sum_{r=1}^{2} \gamma_r * Regime_r \\ &+ \sum_{k\in\{A,B,C\}} \sum_{r=1}^{2} \theta_{kr} * Tier_k * Regime_r), \end{aligned} \tag{1}$$

where $Y_{it}^{AllQueries}$ denotes the paid/organic/total clicks that website i received in month t, $Tier_k$ *are* indicator variables for the type of pharmacy (tier A, B, or C) accessed at website i, and $Regime_r$ refers to the time period to which month t belongs (regime 0, 1, or 2).

The intensive margin is assessed using a simple OLS model conditional on a website receiving positive clicks:

[29] Two-part models used to analyze such data patterns are well discussed in the health literature when examining health expenditures (Mullahy (1998) and Manning (1998)).

[30] The log likelihood from the two-part model and Tobit model are -284,731 and -332,007 respectively with 11 degree of freedom differences. Twice the log likelihood difference between the two models is -189,104, far greater than $\chi^2_{0.005}(11) = 26.757$.

[31] To check for multicollinearity of the inverse Mills ratio and the other regressors in the second stage of the Heckman two-step model, we calculate the variance inflation factor (VIF) with and without the inverse Mills ratio. The mean VIF is 2.02 without the inverse Mills ratio and increases to well beyond 10 if including the inverse Mills ratio. This suggest that the inverse Mills ratio is highly colinear with other control variables in the second stage, and hence the Heckman model is not well identified. In addition, using Vuong's test for the null hypothesis that the two models are similar in terms of fit, we estimate a t-statistic of 456.79, so we strongly reject the Heckman model in favor of the two-part model.

$$(ln(Y_{it}^{AllQueries})|Y_{it}^{AllQueries} > 0) = \delta_i + \sum_{r=1}^{2} \lambda_r * Regime_r + \sum_{k \in \{A,B,C\}} \sum_{r=1}^{2} \vartheta_{kr} * Tier_k * Regime_r + \epsilon_{it}, \quad (2)$$

where δ_i denotes website fixed effects. Because website fixed effects absorb the tier dummies, $Tier_k$ only appears in the interaction with $Regime_r$. We do not include website fixed effects in equation (1) because a non-linear regression with fixed effects may introduce an incidental parameter problem. In both specifications, the DID coefficients (θ_{kr} and ϑ_{kr}) measure the conditional differential effect of regime 1 and regime 2 for tier-A, tier-B and tier-C websites compared with the control group of non-pharmcy websites in regime 0.

By definition, when the dependent variable is the number of paid clicks, the DID coefficients should be negative for both tier-B and tier-C sites, because tier-B was not allowed to advertise in sponsored search after the ban and the prohibition on tier-C sponsored ads was not fully enforced until the ban.

In comparison, when the dependent variable is the number of organic clicks, the DID coefficients can be positive for tier-B or tier-C because of the organic substitution effect, or negative if the ban has motivated consumers to avoid all non-NABP-certified websites. Either way, the effect of the ban can be different before and after the Google-DOJ settlement because it calls attention to the potential safety and legal concerns about foreign pharmacies, while the ban on sponsored ads alone primarily increases the cost to find the banned pharmacy websites on a search page. We also expect the organic substitution effect to be different for tier-B and tier-C sites for several reasons: consumers may perceive tier-B sites to be safer than tier-C sites due to tier-B's certification status, thus less likely to avoid the organic links of tier-B sites. Moreover, a tier-B site typically enjoys more overall traffic before the ban and therefore it may be easier to find tier-B sites than tier-C sites in the organic search results.

We do not have clear predictions for tier-A sites. As competitors, they should benefit from the sponsored search ban on tier-B and tier-C sites if consumers become more concerned about foreign pharmacies or face higher search costs in locating these banned pharmacies in the organic results. However, consumers that preferred visiting foreign pharmacy websites before the ban did so for a reason. The ban itself does not make prescription drugs from tier-A websites more affordable, and the high cost of drugs in the U.S. may drive price-sensitive consumers to use fewer prescription drugs, rather than switching to tier-A. Which force dominates is an empirical question.

3.3 Heterogeneous Effects

The main specification has incorporated the across-tier and across-regime differences in the DID coefficients. To better understand these differences, especially the tier-B versus tier-C comparison, we explore three types of heterogeneous effects.

The first heterogeneous effect relates to a website's organic visibility and we use a website's total clicks as a proxy. When a website is removed from the sponsored links, it may experience a strong or weak organic substitution effect depending on its organic rank. Unfortunately, comScore does not provide data on a website's organic rank. Moreover, it is difficult to infer organic rank from organic clicks before the ban because consumers may click on the site's sponsored link even if its organic link was highly ranked (as in the eBay study by Blake et al. 2014). Moreover, at least in Google, the rank of a sponsored link depends on the organic relevance of the website, leading to a positive correlation between organic and sponsored clicks in our data. For these reasons, we proxy a website's organic visibility by its monthly total clicks across all queries in the first six months of our sample ($Volume_{i,init}$).

As shown in the next section, on average tier-B websites have greater $Volume_{i,init}$ than tier-C sites before the ban and therefore are more likely to have higher organic visibility after the ban if search engines do not change their organic algorithms. Hence we may expect stronger organic substitution for tier-B, simply because tier-B sites have higher $Volume_{i,init}$. To isolate this from other explanations, we need to condition our main analysis on $Volume_{i,init}$.

The second heterogeneous effect relates to a website's reliance on sponsored ads before the ban. Consider a website i that receives x organic clicks and y sponsored clicks in the first nine months of regime 0. Then we can define $FracSponsored_{i,init} = \frac{y}{x+y}$ as its reliance on sponsored clicks before the ban. A greater value of $FracSponsored_{i,init}$ implies a greater negative shock from the ban. Whether that shock translates into a larger or smaller organic substitution effect depends on several factors. On the one hand, the organic substitution effect can be larger for sites with a higher $FracSponsored_{i,init}$ because a bigger fraction of searchers are forced to seek alternative links to click and the website's organic link is one such alternative. On the other hand, foreign pharmacy websites with higher $FracSponsored_{i,init}$ are used to receiving traffic from sponsor links and may not do as well in promoting their organic links. However, at the same time, they may have stronger incentives to manage search engine optimization in order to obtain greater organic substitution after the ban. We explore this heterogeneity by conditioning the analysis sample on $FracSponsored_{i,init}$.

A third type of heterogeneous effect relates to a searcher's willingness to substitute sponsored ads with organic links, as it determines how much time and effort the searcher will spend in looking for the organic link of a banned website. This willingness in turn depends on the searcher's expected benefit and cost of using a tier-B or tier-C website. The ban and the Google-DOJ settlement may have raised the perceived health, legal and technical cost of using a foreign pharmacy website, but searchers that expect overwhelming cost-saving or privacy benefits from these sites may continue to search for these websites. In contrast, those that do not expect high enough benefits from these sites may be persuaded by the warning message to avoid such websites. This logic motivates us to look for heterogeneity in searchers' expected benefits from foreign pharmacy websites. Existing literature suggests that cost saving and privacy are the most cited reasons for using online/foreign pharmacies before the ban, thus consumers that target chronic or lifestyle drugs may expect higher benefits from the banned websites and are more willing to continue using their organic links after the ban.[32] Similarly, those that search for the exact name of a foreign pharmacy or a discount pharmacy query (such as "cheap drug in Canada") indicate their preference for cost-saving and should be more likely to engage in organic substitution. These arguments suggest that we should analyze queries about chronic/lifestyle drugs separately from other drug queries.

More specifically, for the first two heterogeneous effects, we denote $X_{i,init}$ as the classification variable that measures website i's heterogeneity in $Volume_{i,init}$ or $FracSponsored_{i,init}$. We then split the data into subsamples according to the value of $X_{i,init}$ and rerun the main specifications for each subsample. Because tier-A sites are very different from tier-B and tier-C sites in $Volume_{i,init}$ and $FracSponsored_{i,init}$, these specifications exclude tier-A sites, but still use non-pharmacy sites from health queries as the control group. The control group is subject to the same cutoff in $Volume_{i,init}$ and $FracSponsored_{i,init}$ as the treatment group when we construct subsamples. Similarly, for the third heterogeneity, we define X_g as a dummy variable queries that indicate a stronger intention to search for foreign pharmacy websites (such as a search for a chronic drug). We then split the sample by X_g and compare tier-B and tier-C organic clicks after the ban. One caveat is that specifications based on X_g are conditional on drug or pharmacy queries and therefore we can no longer use the non-pharmacy websites from health queries as the control group. Therefore, we focus on a direct comparison of tier-B and tier-C sites. The coefficient magnitudes of this estimation are not comparable to those from the main specification, but it still captures the net difference between tier-B and tier-C sites.

4 Data Summary

Our primary datasource is comScore.[33] ComScore tracks the online activity of over two million persons worldwide, one million of whom reside in the U.S. ComScore extrapolates the observed activity in the households it tracks and by using various demographic weights, it determines the aggregate activity of all U.S. Internet users. We obtained access to click-through data from U.S. households. ComScore data have been used to study internet search behavior by a number of economists including Chen and Waldfogel (2006), Chiou and Tucker (2011), and George and Hogendorn (2013).

4.1 Click and Search Data

We use data from comScore's Search Planner suite of tools, which provides click-through data on queries submitted to five large search engines - Google, Yahoo!, Bing, Ask, and AOL. The click

[32] Following the Oxford English dictionary, we define a lifestyle drug as "a drug prescribed to treat a condition that is not necessarily serious or life-threatening but that has a significant impact on the quality of life." See `http://www.oed.com/view/Entry/108129`. In addition, one medical article by Gilbert, Wally and New in the *British Medical Journal*, describes a drug in this category as "one used for 'non-health' problems or for problems that lie at the margins of health and well being." Viagra is a prominent example of a lifestyle drug.

[33] http://www.comscore.com/.

data (available on comScore's "term destinations" report) are organized by query-month-engine and include the number of queries (searches), searchers, and clicks in a given month. In addition, clicks are also broken down into organic versus paid and by destination URL.[34] At times, due to small sampling of some queries, click activity is censored because comScore is unable to reliably extrapolate the observed activity to the whole population.[35] We observe 49 months of data from September 2008 to September 2012. In addition to click activity following each query, we also We also observe the share of clicks following a query that are received by each of the five search engines.

Figure 3 shows an example of the term destination report for Lipitor in January 2012. The report lists the total clicks, divided between organic and paid, following queries for Lipitor in January 2012. Because we selected "match all forms", the click counts include queries for Lipitor alone as well as Lipitor plus other keywords. This report shows clicks on all five search engines combined, but separate reports were also run on individual search engines. The click counts under the key metrics section is comScore's estimate of the total number of clicks by users in the U.S. on all websites following the query. In addition, the clicks are broken down by specific entity.[36] Each entity name is also assigned to one or more categories, such as, health, government, or pharmacy. It is important to note that the clicks we observe on an entity all originate from a search engine. We do not know how many clicks a website receives via direct navigation, bookmarks, etc.

4.2 Query List and Website Classification

To extract clicks data on a given website, a list of queries must be submitted to comScore to extract query-level data. To create a list of drug and pharmacy related terms, we use several resources. The first one is a list of brand names from the FDA's Orange Book of all approved drugs.[37] The second resource is a list of drug manufacturers from Kantar Media.[38] We also include three government website names that provide drug information (FDA, NIH, and CDC), and four website names that certify online pharmacies (NABP, LegitScript, PharmacyChecker, and CIPA). The resulting list of queries is supplemented by the names of online pharmacies, which is based on comScore's own categorization of the websites in their data.[39] Running our list of drug names on comScore, we

[34] A query is the actual text that a searcher enters on a search engine. Our data include click activity on websites following the exact query, but also clicks following queries where the text appears somewhere in the search box, potentially along with other words. Plural forms of the query are also included. comScore refers to this as "match-all-forms" queries as opposed to "exact" queries that return the clicks on the query text exactly as entered on the search engine.

[35] Our data has a limitation in regard to censoring. When a click count is censored by comScore, the name of the website entity appears in the database with a click count of -1. This means there were positive clicks on the website during that month, but extrapolation to the population would not produce a reliable estimate. We treat these websites as having zero clicks in our analysis.

[36] Usually an entity name is a URL, but comScore also aggregates clicks on websites with common ownership and lists them under a different entity level (e.g., property, media title, channel, etc). We collect click data at the finest level available to avoid double counting.

[37] http://www.accessdata.fda.gov/scripts/cder/ob/default.cfm.

[38] http://kantarmediana.com/intelligence.

[39] Since the search engine ban only applies to online pharmacies that sell prescription drugs, our analysis is restricted to this set of pharmacies. We cannot directly infer whether a pharmacy sells prescription drugs from its site name or comScore classification, so we check by clicking into each pharmacy website to verify that prescription drugs are sold

can identify the top pharmacy website names in the comScore "Pharmacy" category.[40] This list, plus any pharmacy names that we can find on any of the four certifying websites, comprise our preliminary list of pharmacy websites.

To address the possibility that searchers may reach drug and pharmacy related websites by searching for a medical condition, symptom, or another non-drug and non-pharmacy term, we supplement the query list with data from Keywordspy.com. This website collects information on keywords that companies bid on for sponsored ads on a search engine. It also reports a list of keywords that more likely lead to organic clicks on a certain website.[41] This allows us to identify a list of organic keywords that are popular searches when the destination is ultimately an online pharmacy. We also add all keywords that the FDA bid on to appear in an engine's sponsored ads.

The combination of all these sources led to over 8,000 queries, far too many to download from comScore given time constraints. Therefore, we restricted the list of drugs to only those that were advertised (in the Kantar media data) and/or prescribed by a physician from 2006-2009.[42] We also ran the complete list of queries through comScore twice on two time windows in 2009 and 2012 and restricted our sample to queries that accounted for the top 90% of clicks in either window. This left us with 690 queries. Because comScore reports the clicks both for the query exactly as it appears and variations of the query (e.g., clicks following a search for "canada online pharmacy" are included in a search for "canada pharmacy"), we only use queries that are not variations of another to avoid double counting. This further restricts our sample to 528 queries. Each query was then submitted to comScore and monthly reports from each search engine were downloaded for the analysis.

Each of the 528 queries are then classified into different query types (see Table 3). Along with drug queries, pharmacy queries are further classified according to their certify-status (tier A, B, or C) as well as general and discount pharmacy keywords. In particular, we first separate out the queries that are the exact name of the online pharmacy websites and classify them according to the pharmacy tiers. Queries that target pharmacies that sell cheap or discount drugs, and those operate in foreign countries are classified into discount pharmacy search terms.[43] The remaining pharmacy queries are all general search terms for pharmacies.[44] Queries that are not drug or pharmacy related are classified as health queries. As described above, the control group in most specifications is defined as non-pharmacy websites originated from health queries.

Table 3 shows the total query count in each category of query. Among the 528 queries, drug

on the website at the time of our study.

[40] The "Pharmacy" category ID on comScore is 778268. A website may have multiple classifications, but any site with this ID we classify as a pharmacy.

[41] This is similar to the Keyword Tool in Google's Adwords.

[42] The latter comes from the National Ambulatory Medical Care Survey (NAMCS).

[43] Among 46 discount pharmacy queries, 11 contain the words "canada", "international" and "europe", 5 contain word "online", and 17 contain words "cheap", "discount", "low cost", "free", "deal", and "coupon".

[44] In the general pharmacy terms, there are three queries "pharmacy in", "pharmacy on" and "the pharmacy" carrying exactly the same observations, so we dropped the first two. To check if "the pharmacy" counts all clicks from the query that contains only the word "pharmacy", we calculate the total number of clicks by all queries with "pharmacy" in it except for "the pharmacy". We find that "the pharmacy" always records a larger number of clicks and conclude that "the pharmacy" includes all clicks for queries with "pharmacy" in it. We kept the query "the pharmacy", but subtract the from it the total number of clicks by queries containing the complete word "pharmacy".

and pharmacy queries are more likely to lead to online pharmacy websites. In regime 0, drug and pharmacy queries account for 98.3%, 99.0%, and 98.1% of the clicks on tier-A, tier-B, and tier-C websites respectively. In comparison, drug and pharmacy queries account for 57% of clicks on non-pharmacy sites, while the other 43% come from health queries. Figure 4 shows that the number of searchers and searches evolve similarly by broad query groups Pharmacy search queries experience a spike in the last few months of each year because some pharmacy queries include large retail stores (e.g., walmart and target) with seasonal demand. We control for seasonality in robustness checks of our results.[45]

All empirical results present below pool data from all five search engines. Robustness check for Google only is presented in the Appendix.

5 Empirical Results

5.1 Descriptive Statistics

Before the ban, drug and pharmacy queries led to 98-99% of click traffic (from search engines) into all three tiers of pharmacy websites.[46] Hence Table 4 focuses on drug and pharmacy queries only. More specifically, for each type of drug and pharmacy query, Table 4 summarizes the number of searches and the number of clicks into pharmacy websites. The ratio of total pharmacy clicks to total searches (column 3) indicates the difficulty in finding any pharmacy website following certain queries. If pharmacy websites do not appear in the paid links or do not rank high in the organic results, consumers may not click on any pharmacy website, leading to a low number of pharmacy clicks per search. Another way to show the relevance of pharmacy websites is the ratio of pharmacy clicks to the total of pharmacy and non-pharmacy clicks (column 4). Pharmacy clicks per search and percent of pharmacy clicks are highly correlated, as both depend on the relevance of pharmacy websites to the studied queries.

In general, pharmacy queries lead to many more clicks into pharmacy websites than drug queries. Queries on tier-B names are very likely to lead to pharmacy websites (93-98%), followed by tier-A names (78-81%), and discount pharmacy keywords (59-67%).[47] Queries on tier-C pharmacy names are associated with the lowest percentage of pharmacy clicks among all pharmacy name queries and this percentage drops sharply from 39.8% in regime 0 to 31.4% in regime 1 and 7.1% in regime 2. In contrast, the percentage of pharmacy clicks is stable or even increasing for Tier-B pharmacy names after the ban. Compared with pharmacy queries, drug queries have a much lower percentage of pharmacy clicks (22.1%) and that percentage plummets after the ban (to 2-4%). This is probably

[45] Since the search engine ban only applies to online pharmacies that sell prescription drugs, our analysis is restricted to this set of pharmacies. We cannot directly infer whether a pharmacy sells prescription drugs from its site name or comScore classification, so we check by clicking into each pharmacy website to verify that prescription drugs are sold on the website at the time of our study.

[46] The percent of clicks from non-drug and non-pharmacy health queries drops further after the ban for all tiers of pharmacy websites, except for a slight increase for tier-C websites in regime 2.

[47] The average clicks per search and the percent pharmacy clicks are first calculated at the query level and then averaged.

because many drug queries target information websites rather than pharmacies and the searchers that target a pharmacy website using a drug query cannot find the pharmacy site via sponsored links following the ban.

The remaining columns of Table 4 report paid and organic clicks separately by pharmacy tier. After the ban, paid clicks dropped dramatically for tier-B and tier-C sites. Few paid clicks still linger for tier-C sites after the ban, probably because some tier-C sites may give an impression of dispensing nutritional supplements and over-the-counter drugs rather than prescription drugs and therefore are not perfectly screened by the ban. The organic clicks to Tier-B and Tier-C sites have increased after the ban for almost all pharmacy and drug queries, suggesting some substitution to organic results when sponsored links are no longer available.

To better illustrate potential organic substitution after the ban, Table 5 summarizes the organic and paid click volume by regime and treatment/control group. For tier-A pharmacies, the number of paid clicks growed steadily after the ban, while the number of organic clicks first dropped slightly after the ban and then increased susbtantially after the Google-DOJ settlement. The fraction of paid clicks to total clicks increases slightly from 8% in regime 0 to 9.7% in regimes 1 and 2. In contrast, tier-B pharmacies were accessed mostly via paid clicks in regime 0, with an average of 6,338 monthly paid clicks and 1,795 monthly organic clicks. The ban results in almost 100% loss in paid clicks, but part of the loss is offset by a large increase in organic clicks, suggesting that searchers are substituting organic for paid links. For tier-C websites, the average number of paid clicks falls as expected and the average organic clicks rose in regime 1, but fell in regime 2, consistent with substitution to organic links in regime 1 and more awareness of the risks associated with these sites in regime 2.

The differential changes in organic clicks on tier-B and tier-C websites after the ban can also be seen in Figure 5, where we plot the monthly number of paid and organic clicks for each pharmacy tier and for the control group of non-pharmacy websites. Organic clicks on tier-B websites gradually increases after the sponsor link ban while organic clicks on tier-C websites experience no increase after the ban.

Using non-pharmacy websites as a control, we can see that organic clicks trend up throughout regime 0 for both the control websites and each tier of pharmacy sites. To further assess whether these trends are comparable, we use the 17-months of data before the ban and regress organic clicks on a full set of tier dummies, time (counted by month since the beginning of data), and the interaction of each tier dummy and time. Consistent with our main specifications, the dependent variables in this pre-treatment test are (1) whether a website receives any positive organic click in a month and (2) the log of the total organic clicks conditional on receiving any positive organic clicks. As the shown in Table 6, results suggest that a general linear trend applies to all treatment and control groups, but there is no statistically different trend between the control websites and each pharmacy tier.

The last three columns of Table 5 show the distribution of number of websites active in each regime. With the same set of queries in each regime, the number of online pharmacy websites that are recorded as having any clicks in comScore is relatively stable for tier-A and tier-B pharmacies, but declines 33% for tier-C from 138 to 92. This decline could be due to both health concerns and search costs. The decline in the number of tier-C websites may have several implications. For pharmacy competition, this may benefit the remaining tier-C pharmacies if consumers preferring tier-C pharmacies continue to buy from them. However, if consumers are shifting from tier-C to tier-B or tier-A pharmacies, we will observe clicks on tier-C websites decline as a whole.

Overall, these statistics suggest a similar pre-treatment trend between our control websites and each pharmacy tier, which validates our main DID specifications. There is also a similar trend in searches across drug and pharmacy queries, but click patterns are different for tier-A, tier-B and tier-C websites. In general, we observe more paid and organic clicks on tier-A pharmacies, a greater substitution from paid clicks to organic clicks for tier-B pharmacies after the ban, and a reduction in organic clicks for tier-C pharmacies after the ban.

5.2 Regression Results

5.2.1 Main Specification

Our first set of regressions focus on clicks received by pharmacy website i in month t from all queries, as compared to clicks received by non-pharmacy sites from health queries. As detailed in Section 3, this main specification reflects the overall effect of the regime changes on pharmacy websites clicks.

Table 7 reports five columns. The first three focus on total clicks and the last two focus on organic clicks. Within total clicks, column (1) examines whether website i received any clicks in month t (censored or uncensored); column (2) examines whether website i received any uncensored clicks in month t. Both columns (1) and (2) refer to the extensive margin, following the logit specification in equation (1). On the intensive margin, column (3) uses equation (2) to examine the log of the number of clicks, conditional on a website receiving positive clicks in the month. Because click traffic of many websites is too low to have non-censored clicks, especially for non-pharmacy websites, the number of observations drops significantly from columns (1) and (2) to column (3). The direction of the results for "any click" and "any positive click" are similar, so for organic clicks we only report regressions for "any positive organic click" (column 4) and log positive organic clicks conditional on having positive organic clicks (column 5). All columns use non-pharmacy sites as the excluded baseline group.

The first three columns suggest that, after the ban, tier-C sites suffer more on the extensive margin while tier-B sites suffer more on the intensive margin. In particular, the probability of a tier-C site receiving any clicks falls 2.5 percentage points in regime 1 and 5.3 percentage points in regime 2, as compared to non-pharmacy health related clicks in the control group. In contrast, there is no significant change in the probability of a tier-B site receiving any click. Conditional on receiving any positive clicks, the amount of total clicks received by a tier-B site falls 65.3% in regime 1 and 84.1% in regime 2. At the same time, the ban does not have a significant effect on tier-A sites in regime 1, but increased the propensity of a tier-A site being clicked in regime 1 by

2.2 percentage points. However, there is also a reduction on the intensive margin for tier-A sites compared to the control group.

Focusing on organic clicks only, the last two columns of Table 7 indicate a strong organic substitution effect for tier-B sites: there is an 85.1% increase of organic clicks in regime 1 and 87.2% increase in regime 2. Combined with the fall in total clicks, this suggests that the loss of paid clicks on tier-B sites was partially offset by organic substitution. Total clicks still fall significantly, as an average tier-B site received 78% of its clicks from sponsored ads before the ban and the organic substitution is insufficient to replace all the lost paid clicks. Moreover, the organic substitution effect is similar across the two regimes. In contrast, tier-C sites suffer a reduction in organic (and total) clicks on the extensive margin. The magnitude of the reduction is greater in regime 2 than in regime 1, though the difference is not statistically significant. These differential effects suggest that the ban generates search frustration and some, but not all, consumers switch from paid to organic links for tier-B sites.

We have estimated auxiliary models to assess the robustness of the organic substitution results. Although treatment and control groups follow a similar linear trend before the ban, it is possible that the simple control of regime dummies is not sufficient to account for the temporal changes common to all groups. To address this, we add a linear trend in the main specification and rerun the analysis for organic clicks. Results are similar in magnitude and significance. We also check for the impact of seasonality by including a dummy variable for the holiday months of November and December for all sites. Neither of these specifications impacted the qualitative results.[48]

Because the sponsored search ban on tier-B and tier-C pharmacies was imperfect (as shown in figure 5), we also conducted robustness checks on the starting date of regime 1 in two ways. First, we used a new regime 1 cut-off corresponding to the actual month when paid clicks on non-NABP certified pharmacies fell to nearly zero (September 2010). Second, we performed a placebo test by adding a hypothetical regime cut-off in June 2009 (well before the ban). The first strategy does not affect the qualitative results and the second shows no change in organic and paid clicks in the hypothetical treatment period before the actual ban. In the first strategy, we also tried dividing regime 1 into two halves corresponding to before and after September 2010. We find the coefficients similar for these two periods, except that the reduction in total clicks on tier-C websites at the extensive margin is deepened in the second half of regime 1.

5.2.2 Heterogeneous Effects

So far we find that both tier-B and tier-C pharmacy sites experienced a significant reduction in total clicks after the ban, but the mechanisms are different: the reduction for tier-B sites is concentrated on the intensive margin and partially offset by organic substitution; in comparison, the reduction for tier-C sites is driven by the extensive margin and occurs for both total and organic clicks. One explanation is that the search engine ban and the Google-DOJ settlement have heightened the health concerns of uncertified pharmacies and therefore consumers may perceive tier-C as having

[48]Estimates for all robustness checks are available from the authors upon request.

higher health risks than tier-B sites. However, another possible explanation is that tier-C websites were ranked low in organic results and their organic ranks became even lower over time as consumers had difficulty finding them after the ban.

To distinguish these two explanations, we first check whether consumers can differentiate tier-B and tier-C websites when searching for online pharmacies. If consumers cannot distinguish tier-B from tier-C sites, it is unreasonable to argue that tier-B and tier-C sites generate different health concerns. One way to determine the certification tier of a pharmacy is searching for pharmacy certifiers on the Internet. Therefore, we aggregate the total number of searches using pharmacy-certifier-related queries. As reported in Table 8, LegitScript's monthly searches increased from 18 in regime 0 to 278 in regime 1 and 1,275 in regime 2. Similarly, the monthly search for "NABP" and "VIPPS" (the certification program of NABP) have more than tripled from 6,895 in regime 0 to 27,098 in regime 2. Searches for queries containing "pharmacy check", "pharmacy rating" and "pharmacychecker" increased from 731 in regime 0 to 1,685 in regime 1 and 4,127 in regime 2. The only exception is that queries for the Canadian certifier, "CIPA" have fallen over time, , probably because the first organic result for CIPA is Children's Internet Protection Act (which was edited in 2011) rather than the Canadian Internet Pharmacy Association. These patterns are consistent with the hypothesis that at least some consumers are either aware or concerned of the certification differences between online pharmacies and actively search more for certification status after regime 0.

To further uncover mechanisms that drive the differential changes in tier-B and tier-C websites, we compare clicks on tier-B and tier-C websites using subsets of the data based on the organic visibility of the website, a website's sponsored click fraction, and clicks from the types of queries that may imply a stronger intention to reach foreign pharmacies.

In the first set of heterogeneous results, we classify websites by the total number of clicks on the website in the first six months of our sample. We identify the common support of total clicks for the control group, tier-B, and tier-C websites and divide websites into three bins based on total clicks in the first six months of the data:[49]

- bin 1 includes websites with 8,000 to 20,000 clicks,
- bin 2 includes websites with 20,000 to 60,000 clicks, and
- bin 3 includes websites with 60,000 to 155,000 clicks.

The bin cutoffs are unevenly spaced because the number of tier-B and tier-C websites drops significantly in bins with larger number of clicks. We choose these cutoffs to ensure a large enough sample in each bin.

Tier-B websites receive more clicks than tier-C websites on average. If the differences between tier-B and tier-C are all driven by the potential organic rank a website can obtain after the ban, comparing websites with similar total clicks volumes before the ban should erase the different effect

[49] Tier-A sites are excluded because they are typically much larger in the absolute click volume than tier-B and tier-C sites.

of the ban on tier-B and tier-C websites. The bin-by-bin results in Table 9 does not support this prediction. In fact, we observe positive organic substitution for tier-B sites in all three bins, and the increase in tier-B organic clicks appears even stronger for smaller websites (in bin 1) than for bigger websites (in bins 2 and 3). In contrast, no significant organic substitution effect is observed for tier-C sites in all three bins. This suggests that there are reasons other than website size that drive the tier-B and tier-C differences in organic substitution.

Our second check of heterogeneous effects focuses on websites that derive a high fraction of their traffic from sponsored links before the ban. The reliance on sponsor links depends on a website's strategy in choosing sponsor bids or search engine optimization (SEO), and this choice in turn sheds light on the website's comparative advantage in optimizing their paid or organic ranking. A website with almost all its clicks coming from sponsored links may have a low organic rank, and may find it hard to boost its organic ranking after the ban. As a result, it may not experience organic substitution after the ban. On the other hand, organic substitution is not well defined unless there are substantial sponsored clicks to from which to substitute.

To explore this heterogeneity, we run the DID specification conditional on subsamples of websites with similar $FracSponsored_{initial}$ before the ban. In the raw data, tier-B websites have a higher $FracSponsored_{initial}$ than tier-C websites. The average fraction of sponsored clicks is 66% for tier-B sites and 27% for tier-C sites. Because very few tier-B websites have $FracSponsored_{initial}$ below 50%, we focus on two subsamples, one with $FracSponsored_{initial}$between 50% and 85% (medium fraction), and the other above 85% (high fraction). As shown in Table 10, compared with the baseline non-pharmacy websites, the tier-B websites that relied heavily on sponsored clicks before the ban received higher organic clicks in regime 2, whereas tier-C websites in the same subsample do not experience a significant rise in organic clicks in both regimes. Moreover, for the medium fraction websites, tier-B sites experience high organic clicks in both regime 1 and regime2, and tier-C websites also gain significantly higher clicks in regime 2. Again, the tier-B and tier-C differences condition on the same fraction of sponsored clicks suggest that there might be reasons beyond consumer search costs that drives the different organic substitution effect for tier-B and tier-C sites. Moreover, the larger magnitude of organic substitution in the medium fraction results suggest that the difficulty to manage organic ranking may play a role in forestalling organic substitution for tier-C websites that relied heavily on sponsored links before the ban.

The last check of heterogeneous effects targets consumers' differential incentives to substitute organic clicks for sponsored ads. Consumers that care more about cost-savings from foreign pharmacies should have stronger incentives to spend time and effort finding the organic links of banned websites despite the ban. To assess this heterogeneous effect, we examine the source of clicks as reflected in consumer search queries. The queries consumers use may suggest a consumer's intention to search and her potential benefit from search. Consumers who are willing to spend time and effort to find foreign pharmacies may also directly search for the name of tier-B and tier-C pharmacies. Besides the pharmacy queries, clicks on pharmacy websites following drug queries may also reveal a searcher's preference for tier-B and tier-C websites. For example, consumers who intended to buy drugs treating chronic conditions or those buying lifestyle drugs may find the cost saving and privacy benefit of foreign pharmacies attractive despite the heightened search cost and safety warning.

Among the different pharmacy queries, we classify discount pharmacy searches and tier-B and tier-C name searches as targeted pharmacy searches, and the other general pharmacy queries as non-targeted pharmacy searches. In terms of drugs queries, we define a drug query as chronic if the drug was on average prescribed five or more times a year per patient in the nationally representative 2010 Medical Expenditure Panel Survey (MEPS). A drug query is defined non-chronic if the average prescription frequency is below 3.5 per patient per year. In total, we have identified 73 chronic drug queries.[50] In addition, we define lifestyle drugs as those that target ED (5 queries), birth control (11 queries), weight loss (3 queries), facial skin problems (11 queries), or smoking cessation (3 queries). We also include drugs that are designated as controlled substances by the U.S. government (23 queries).[51]

Table 11 compares how organic clicks into tier-B and tier-C websites change after the ban conditional on whether the clicks come from a targeted pharmacy query. The coefficients for the cross product of tier-B and regime dummies show that the increase in organic clicks is larger for tier-B websites than for tier-C websites for both targeted and non-targeted search, and the increase in clicks for tier-B websites is greater through targeted searches. In addition, the coefficients for regime 1 and regime 2 indicate that tier-C websites experienced a shakeout after the ban, as the number of websites attracting a positive number of clicks is decreasing while the number of clicks rises for those remaining active tier-C websites.

Conditional on different drug queries, Table 12 shows that for chronic and lifestyle drug queries, tier-C pharmacies did not experience any significant increase in organic clicks. In fact, they had a significant decrease in the extensive margin in regime 2. This reduction is directionally similar to that from targeted pharmacy queries. In comparison, for chronic/lifestyle drug queries, tier-B pharmacies had a marginally significant increase of organic clicks in regime 2 at the intensive margin, while the effect on the extensive margin is not different from zero.

To summarize, the heterogeneous effects presented above suggest that the differential organic substitution for tier-B sites is not just driven by the fact that tier-B sites are on average larger and relied more on sponsored links than tier-C sites. Rather, the ban and the Google-DOJ settlement have increased searches for online pharmacy certification and tier-B sites enjoyed positive organic substitution even when compared with tier-C websites of similar click volume or those that have a similar fraction of sponsored clicks before the ban. Moreover, the organic substitution is stronger for tier-B sites if we focus on searchers that look for chronic/lifestyle drugs or target foreign pharmacies.

[50] Appendix Table 2 provides a list of the top 10 chronic queries and top 10 non-chronic queries ranked by the number of pharmacy-related clicks following each query.

[51] Some, but not all, sleep aid, ADHD and muscle relaxant drugs are controlled substances.

6 Conclusion

We have shown that following the ban on non-NABP-certified pharmacies from sponsored search, there is a reduction in total clicks into the banned pharmacies. However, this effect is differential in several dimensions.

The websites certified by non-NABP agencies, referred to as tier-B sites, experience a reduction in total clicks, though some of their lost paid clicks are replaced by organic clicks. The organic substitution effect does not change significantly before or after the Google-DOJ settlement. In contrast, pharmacies not certified by any of the four major certification agencies, referred to as tier-C sites, suffer the greatest reduction in both paid and organic clicks, and the reduction is exacerbated after the Google-DOJ settlement.

Overall, we conclude that the ban has increased search cost for tier-B sites, but at least some consumers overcome the search cost by switching from paid to organic links. In addition to search cost, our results suggest that the ban may have increased health concerns for tier-C sites and discouraged consumers from reaching them via both paid and organic links. It is also possible that tier-C sites are buried deeper in organic results than tier-A and tier-B sites, and the extra obscurity adds difficulty for consumers to switch to organic links for tier-C sites. However, a more careful look at the data suggests that this cannot fully explain the differential organic substitution effect for tier-B sites. After the ban and the Google-DOJ settlement, consumers have searched more for online pharmacy certification and tier-B sites enjoyed positive organic substitution even when compared with websites of similar organic visibility. The organic substitution is also found to be stronger for tier-B sites that relied more on sponsored ads before the ban and for searchers that look for chronic/lifestyle drugs or target foreign pharmacies.

One caveat of our study is the limit of comScore data to clicks via search engines only. Due to the lack of individual click-through data, we do not know whether consumers switch between drug, pharmacy and other queries after the ban. Nor do we know whether the banned pharmacies have engineered their organic results or the NABP-certified pharmacies have increased price or changed their advertising strategy after the ban. These supply-side questions warrant further study.

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Figures and Tables

Figure 1: Google Search Screenshot, Before the Ban

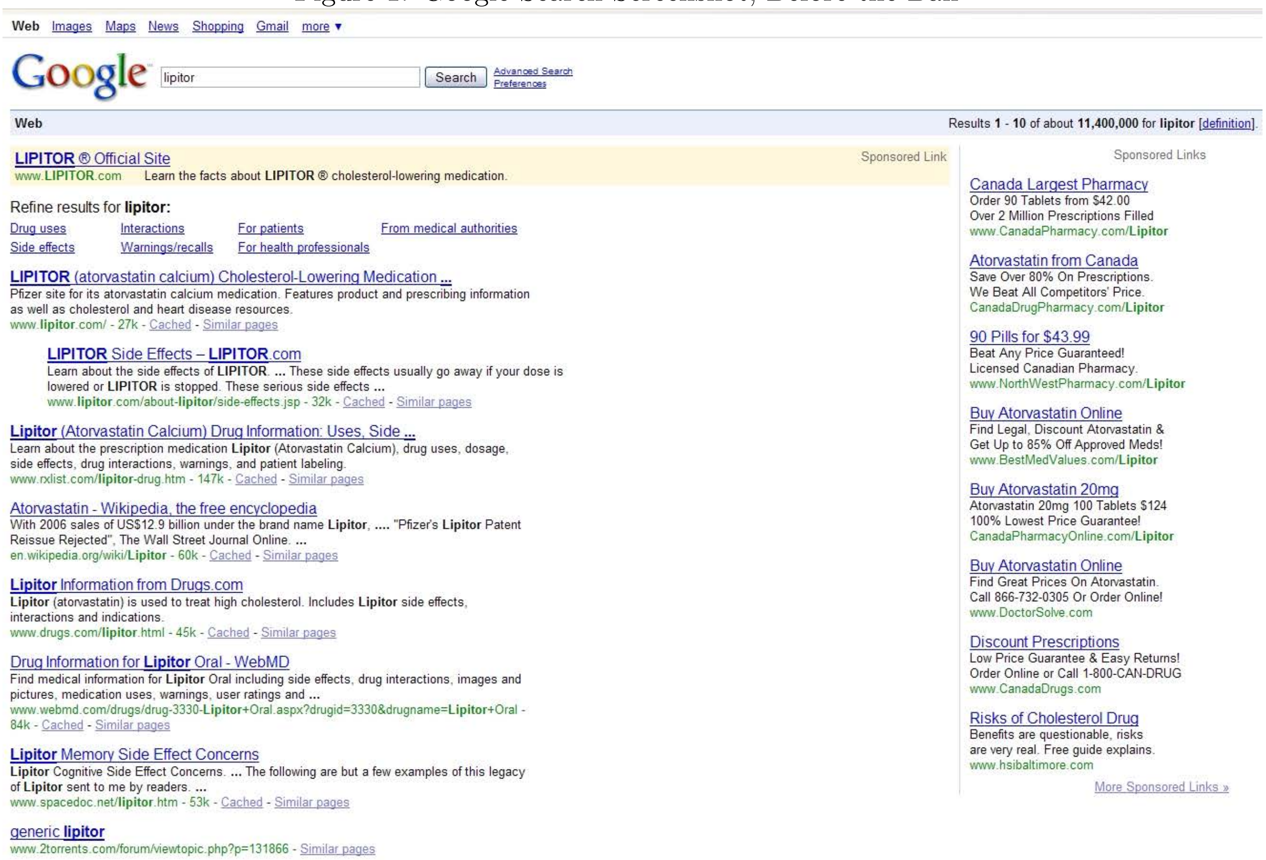


Figure 2: Google Search Screenshot, After the Ban

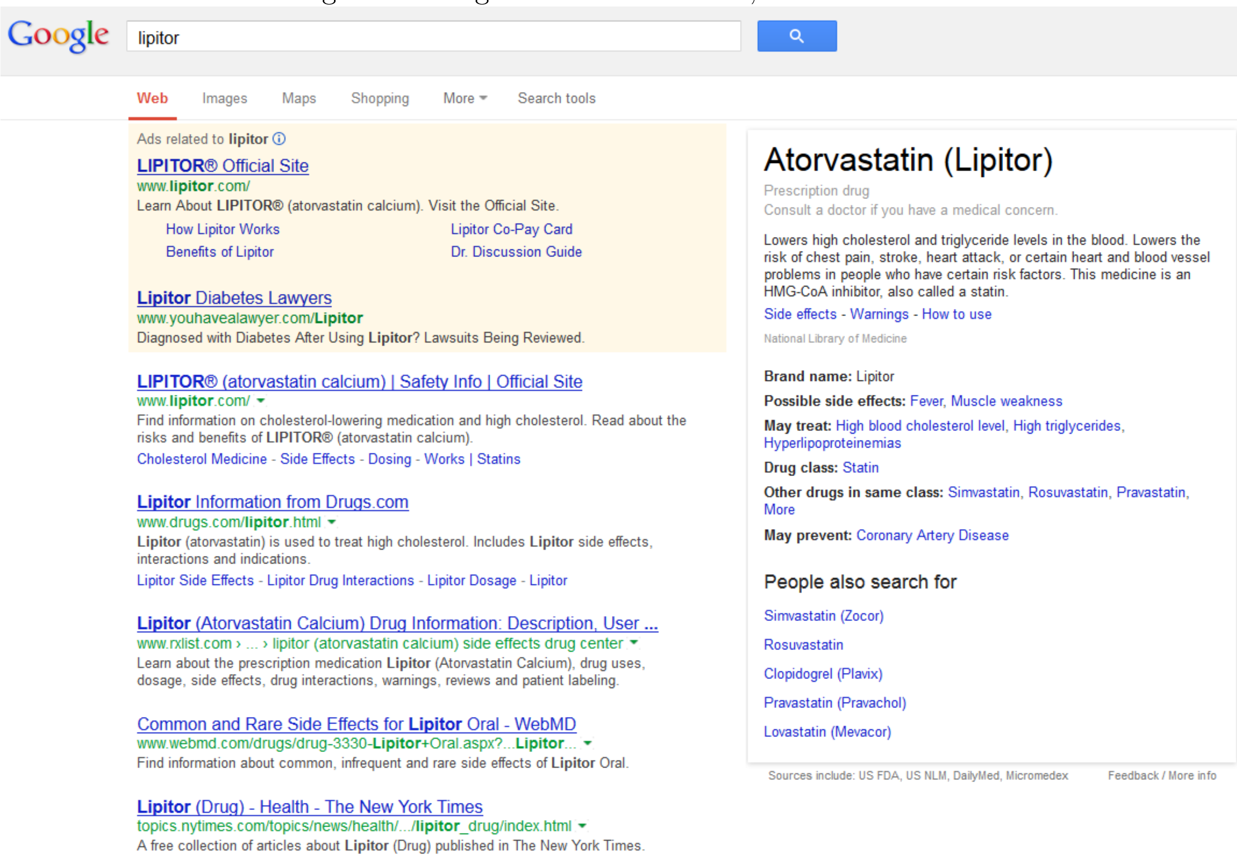
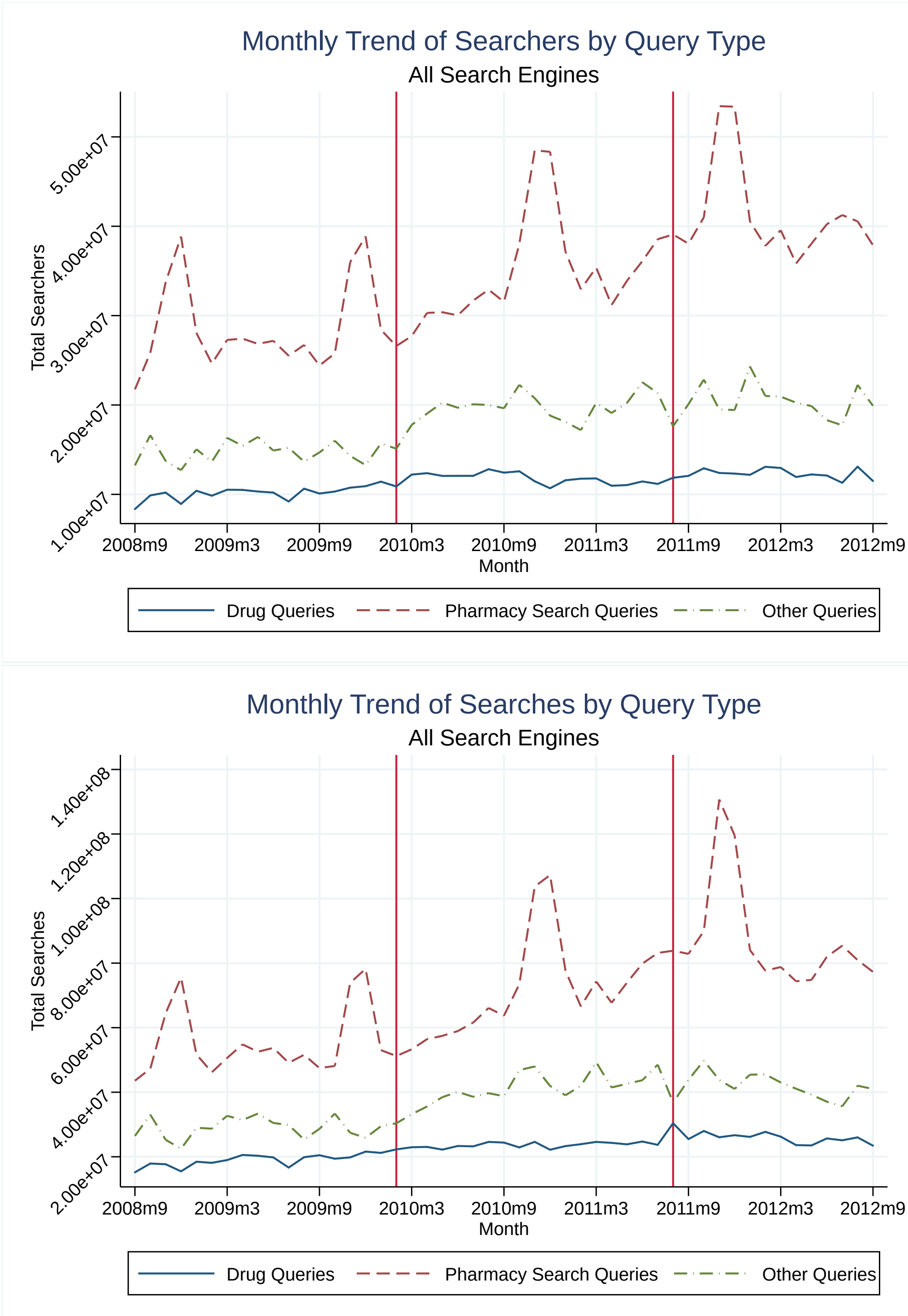


Figure 3: Example ComScore Data

Report:	Term Destinations			
Query:	Lipitor			
Date:	January 2012			
Engine:	All			
Match Option:	Match All Forms			
Key Metrics				
Total Clicks	169,156			
Paid Clicks	38,670			
Organic Clicks	130,486			
Site Clicks				
Entity Name	lipitor.com	Wal-Mart	walmart.com	...
Entity Level	Property	Property	Media Title	...
SubCategory	778218	778230	778230,778281	...
Organic Clicks	27,228	10,713	10,713	...
Paid Clicks	34,420	2,861	2,861	...

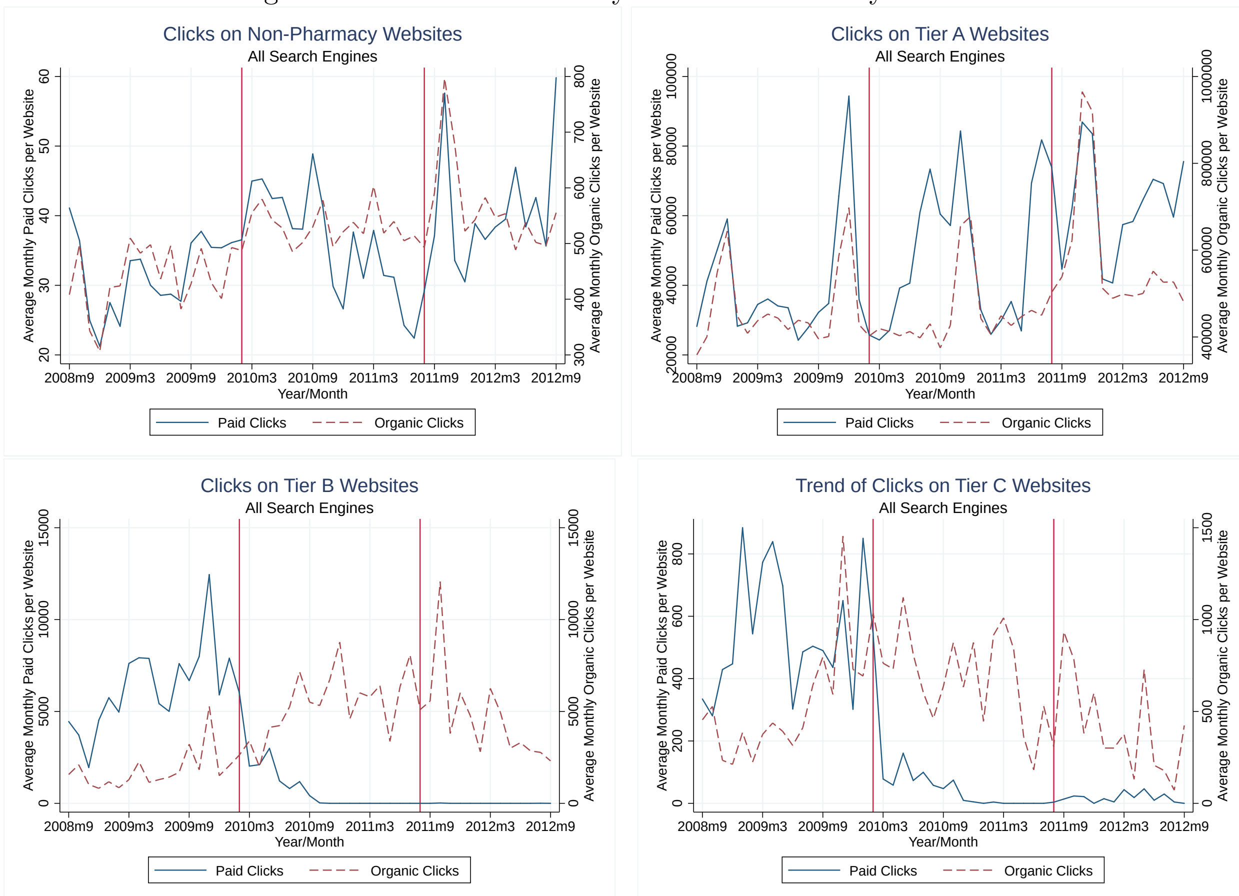
Report:	
Query:	
Date:	
Engine:	
Match Option:	
Key Metrics	
Searches	
Searchers	
Searches per Searcher	
Demographics	
Title	
Level	
Reach	

Figure 4: Searchers and Searches by Broad Query Type



Notes: The top figure plots the total number of searchers of each query type in each month. The bottom figure plots the total number of searches of each query type in each month.

Figure 5: Clicks On Pharmacy and Non-Pharmacy Websites



Notes: 1. The figures plot the total monthly paid and organic clicks of each tier of online pharmacy website. 2. For non-pharmacy websites, we calculate total clicks by aggregating click traffic from all types of health queries excluding drug and pharmacy queries. For pharmacy websites, we calculate total clicks by aggregating click traffic from all types of health queries. 3. If the ban on sponsored links has been perfectly implemented, we should observe zero paid clicks for tier-B and tier-C websites in regimes 1 and 2. However, because screening is imperfect, we still observe a small volume of paid clicks on these websites.

Table 1: List of Events

Time	Event
before 2009	Google contracted with PharmacyChecker to filter out uncertified websites
July 2009	Some pharmacies advertising on Google were found to be uncertified by PharmacyChecker
August 2009	LegitScript.com and KnuhOn.com criticized Microsoft for allowing rogue pharmacies to advertise on Bing
November 2009	FDA issued 22 warning letters to website operators
February 9, 2010	Google began to ban non-NABP-certified pharmacies from sponsored ads for U.S. consumers
April 21, 2010	Google contracted with LegitScript to implement the ban
June 10, 2010	Microsoft and Yahoo! started to ban non-NABP-certified pharmacies from sponsored ads for U.S. consumers.
June 22, 2010	Google partnered with the National Institute of Health (NIH) and expanded its search tool to include drug facts with NIH links. This is only available to U.S. consumers.
August 24, 2011	DOJ announced its settlement with Google

Table 2: Regimes

Regime	Time	Policy
Regime 0	September 2008 - January 2010	Google used PharmacyChecker to filter online pharmacy ads
Regime 1	March 2010 - July 2011	Google required NABP-certification and switched to LegitScript in place of PharmacyChecker
Regime 2	September 2011 - September 2012	Google reached an official settlement with DOJ

Notes: February 2010 and August 2011 are excluded because the imposition of the ban and the announcement of the settlement occurred in these two months.

Table 3: Query List

Query Group	Query Type	Count	Examples	Source
Pharmacy	General Pharmacy Keywords	6	pharmacy at	Keywordspy.com
	Discount Pharmacy Keywords	46	cheap drugs	Keywordspy.com
	TierA Pharmacy Names	9	cvs	comScore, cert. websites
	TierB Pharmacy Names	13	jandrugs	comScore, cert. websites
	TierC Pharmacy Names	19	canadamedicineshop	comScore, cert. websites
	Certifier Search	8	vipps	cert. websites
Drug	Prescription Drug Names	263	lipitor	FDA Orange Book, Keywordspy.com
Other	Drug Manufacturer	59	pfizer	Kantar Media
	Information/Gov.	5	fda	comScore
	Information/Info Sites	17	webmd	comScore
	Information/Health Terms	8	panic-anxiety	comScore
	Other Drugs/Non-Online Rx	17	renvela	FDA Orange Book
	Other Drugs/OTC Related	58	prevacid	FDA Orange Book
	Total Count	528		

Table 4: Query Statistics: Overall Number of Searches and Clicks

		Total	PharmClicks/	%Pharmacy	Paid Clicks			Organic Clicks		
Query Type	Reg	Searches*	Search	Clicks	Tier-A	Tier-B	Tier-C	Tier-A	Tier-B	Tier-C
Pharmacy Queries										
General Pharmacy Search	*0*	832.6	9.6	27.9%	94,325	20,843	6,692	306,419	6,312	13,792
	1	1,156.6	8.3	39.7%	72,707	2,483	1,390	259,706	16,445	18,972
	2	1,208.7	6.5	21.0%	88,117	0	222	268,329	10,373	17,160
Discount Pharmacy Search	*0*	9.0	38.9	66.5%	932	5,889	776	3,673	2,900	3,815
	1	11.8	33.4	58.5%	1,825	815	19	3,097	10,353	5,184
	2	11.7	26.3	62.4%	1,512	1	0	3,571	10,370	3,166
Tier-A Pharmacy Names	*0*	5,546.1	49.8	80.6%	230,232	71	20	2,883,102	55	183
	1	7,167.0	51.1	78.2%	283,555	0	0	2,794,803	105	217
	2	8,853.2	45.1	78.8%	380,141	0	0	3,793,243	794	568
Tier-B Pharmacy Names	*0*	2.4	50.2	92.9%	632	366	98	2,088	652	96
	1	4.7	52.9	93.0%	721	64	0	1,695	3,319	0
	2	3.9	50.2	97.9%	958	0	0	740	3,543	0
Tier-C Pharmacy Names	*0*	1.4	47.2	39.8%	0	0	160	0	0	250
	1	0.6	47.8	31.4%	0	0	104	113	0	684
	2	0.6	0.0	7.1%	0	0	0	0	0	15
Certifier Search	*0*	2.8	117.0	6.5%	59	0	0	77	0	0
	1	2.2	0.9	1.3%	0	0	0	44	0	0
	2	4.1	3.9	1.5%	109	0	0	0	0	0
Drug Queries	*0*	71.9	14.1	22.1%	273	1,039	1,092	6,348	63	578
	1	89.9	2.2	2.6%	329	238	121	1,750	535	1,439
	2	97.6	2.6	3.5%	559	2	111	2,171	713	1,344

* in thousands

Notes: 1. All statistics in this table are averages across queries within each query type×month and the statistics related to clicks are conditional on queries that resulted in positive clicks on any pharmacy website. "Total Searches" is the average monthly searches per query. "PharmClicks/Search" is the average monthly (Pharmacy Website Clicks/Searches) ratio per query. "%Pharmacy Clicks" is the average monthly ratio of clicks on pharmacy websites relative to all clicks following each query. Columns for paid clicks and organic clicks show the number of monthly clicks that lead to each tier of pharmacy. 2. The large number of searches on tier-A pharmacy names is due to the discount chains that also sell general products besides drugs. 3. The pharmacy clicks to search ratio for tier-C queries in regime 2 is not precisely zero, but we cannot calculate the ratio due to censoring.

Table 5: Pharmacy and Control Website Statistics

		Mean		Median		StdDev		25 percentile		75 percentile		N	N	N
	Regime	*paid*	*organic*	*paid*	*organic*	*paid*	*organic*	*paid*	*organic*	*paid*	*organic*	*active*	*(Paid>0)*	*(Organic>0)*
TierA	0	40,538	466,980	0	627	138,298	2,078,990	0	0	412	7,566	47	23	36
	1	48,571	452,544	0	680	206,487	2,075,955	0	0	132	8,071	50	19	39
	2	62,696	586,653	0	567	228,356	2,820,957	0	0	175	5,119	48	19	34
TierB	0	6,338	1,795	735	217	10,168	3,640	0	0	7,929	2,058	26	17	17
	1	633	5,476	0	824	1,105	10,870	0	108	1,137	3,712	27	13	24
	2	2	4,652	0	1,078	8	7,376	0	0	0	5,201	25	2	17
TierC	0	544	522	0	0	2,593	1,495	0	0	0	189	138	28	74
	1	39	694	0	0	244	2,932	0	0	0	56	132	14	59
	2	18	417	0	0	223	1,787	0	0	0	0	92	2	40
Non-	0	50	525	0	0	1,307	21,909	0	0	0	0	27663	1750	7421
pharmacy	1	62	683	0	0	2,187	28,046	0	0	0	0	29885	1582	7562
	2	65	723	0	0	1,666	25,602	0	0	0	0	21867	1182	5405

Notes: 1. The click counts in the table are at the month×website level and the statistics are calculated for each website type×regime. We keep the balanced sample of websites, (57 tier-A websites, 28 tier-B websites, and 181 tier-C websites) in calculating the statistics. 2. We define active websites as websites having received either censored or positive clicks from the set of queries in our data. The last three columns report the number of websites in each regime that are active, have positive (non-censored) paid clicks, and have positive (non-censored) organic clicks.

Table 6: Test of Pre-trends in Regime 0

	(1)	(2)
	$I(OrgClicks > 0)$	$ln(Orglicks)$
t	0.0212***	0.00908***
	(0.00153)	(0.00234)
TierA$\times$ t	0.00531	-0.00226
	(0.0116)	(0.0142)
TierB$\times$ t	-0.0168	0.0458
	(0.0224)	(0.0331)
TierC$\times$ t	-0.00718	0.0214
	(0.0133)	(0.0178)
TierA	2.994***	.
	(0.235)	.
TierB	2.870***	.
	(0.329)	.
TierC	1.473***	.
	(0.158)	.
Constant	-3.305***	7.509***
	(0.0245)	(0.00109)
Observations	484,211	18,077
FE		website

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

Notes: 1. The regression only includes regime 0 observations. 2. t corresponds to the month in the data and ranges from -24 to 24. 3. We exclude the dummy variables for the control group, non-pharmacy websites, and pre-treatment period, regime0. 4. The dependent variable in column (1) is if a website has any *non-censored* positive organic clicks in a given month, and the dependent variable in column (2) is the number of non-censored positive organic clicks on a website when the number of clicks is non-censored and positive. 5. Standard errors are clustered at the website level for all regressions.

Table 7: Regression Results: Clicks on Online Pharmacy Websites Compared with Control Websites

	(1)	(2)	(3)	(4)	(5)
	I(Any Click>0)	*I(Total Click>0)*	*ln(Total Clicks)*	*I(Organic Clicks>0)*	*ln(Organic Clicks)*
TierA×Regime1	0.104	0.0630	-0.0356	0.0571	-0.0311
	(0.0777)	(0.0734)	(0.110)	(0.0733)	(0.115)
TierB×Regime1	0.259	-0.167	-0.653***	0.0756	0.851***
	(0.245)	(0.201)	(0.241)	(0.183)	(0.230)
TierC×Regime1	-0.274***	-0.416***	-0.175	-0.263*	0.0986
	(0.0995)	(0.146)	(0.177)	(0.136)	(0.159)
TierA×Regime2	0.243**	0.169	-0.259*	0.167	-0.264**
	(0.120)	(0.113)	(0.139)	(0.112)	(0.130)
TierB×Regime2	0.350	0.108	-0.841***	0.407**	0.872***
	(0.246)	(0.207)	(0.230)	(0.186)	(0.236)
TierC×Regime2	-0.580***	-0.676***	-0.278	-0.498**	-0.0170
	(0.143)	(0.211)	(0.200)	(0.197)	(0.196)
TierA	2.233***	2.953***		2.991***	
	(0.225)	(0.235)		(0.234)	
TierB	2.438***	3.111***		2.865***	
	(0.294)	(0.331)		(0.329)	
TierC	1.375***	1.629***		1.470***	
	(0.120)	(0.157)		(0.158)	
Regime1	-0.0206**	-0.0378***	0.212***	-0.0318**	0.230***
	(0.00862)	(0.0145)	(0.0184)	(0.0147)	(0.0189)
Regime2	-0.279***	-0.309***	0.410***	-0.316***	0.410***
	(0.0120)	(0.0217)	(0.0269)	(0.0220)	(0.0280)
Constant	-2.107***	-3.254***	7.719***	-3.300***	7.602***
	(0.0124)	(0.0238)	(0.0113)	(0.0244)	(0.0117)
Marginal Effect					
TierA×Regime1	0.0095	0.0021		0.0019	
	(0.0071)	(0.0025)		(0.0024)	
TierB×Regime1	0.0238	-0.0057		0.0025	
	(0.0225)	(0.0068)		(0.0059)	
TierC×Regime1	-0.0252***	-0.0141***		-0.0086*	
	(0.0091)	(0.0049)		(0.0044)	
TierA×Regime1	0.0223**	0.0057		0.0054	
	(0.011)	(0.0038)		(0.0036)	
TierB×Regime2	0.0321	0.0037		0.0132	
	(0.0226)	(0.007)		(0.006)	
TierC×Regime2	-0.0532***	-0.0229***		-0.0162**	
	(0.0131)	(0.0072)		(0.0064)	
Observations	1,338,701	1,338,701	47,825	1,338,701	45,748
FE	-	-	Website	-	Website

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: 1. We exclude the dummy variables for control group, non-pharmacy websites, and pre-treatment period, regime0. 2. Each observation is at a website×month level. 3. The dependent variable in column (1) is whether a website had any clicks, paid or organic, *including censored clicks*, in a given month. Dependent variables in columns (2) and (4) are if a website has any *non-censored* positive total or organic clicks in a given month, respectively. Dependent variables in columns (3) and (5) are the number of non-censored positive total and organic clicks (respectively) on a website when the number of clicks is non-censored and positive. 4. Standard errors are clustered at the website level for all regressions. 5. In counting the total number of clicks into pharmacy websites, we include clicks from all types of queries - pharmacy queries, drug queries and health queries. In counting the total number of clicks into non-pharmacy websites, we only include clicks from health queries.

Table 8: Search Trends for Pharmacy Certifiers

Query	Regime 0	Regime 1	Regime 2
check pharmacist license	0	0	309
cipa	18,955	6,852	4,052
legitscript	18	278	1,275
nabp	6,369	10,121	23,996
national pharmacy certification	6	15	0
pharmacy check	226	727	1,686
pharmacy ratings	174	327	391
pharmacychecker	332	631	1,742
vipps	490	1,651	3,102

Notes: This table documents the monthly level of searches of all online pharmacy certifier related queries.

Table 9: Organic Click Analysis Grouped by Website's Initial Click Volume in Regime 0

	(1)	(2)	(3)	(4)	(5)	(6)
	Bin 1		*Bin 2*		*Bin 3*	
	I(Organic Clicks>0)	*ln(Organic Clicks)*	*I(Organic Clicks>0)*	*ln(Organic Clicks)*	*I(Organic Clicks>0)*	*ln(Organic Clicks)*
TierB×Regime1	0.317**	0.857**	-0.233	0.165*	-15.50***	0.861*
	(0.129)	(0.411)	(0.278)	(0.0996)	(1.092)	(0.509)
TierC×Regime1	-0.106	-0.214	-0.898***	0.118	1.581***	0.320
	(0.302)	(0.411)	(0.266)	(0.236)	(0.52)	(0.607)
TierB×Regime2	1.063***	0.677**	0.679*	1.380***	-14.61	1.157***
	(0.232)	(0.317)	(0.408)	(0.486)	(0)	(0.325)
TierC×Regime2	0.0569	-0.175	-1.353**	-0.131	0.412	0.418
	(0.480)	(0.260)	(0.555)	(0.305)	(0.981)	(0.454)
TierB	0.259		-0.169		15.55***	
	(0.786)		(0.728)		(0.658)	
TierC	0.0280		-0.286		-3.908***	
	(0.541)		(0.378)		(0.348)	
Regime1	-0.653***	0.186***	-0.689***	0.158***	-1.720***	-0.0557
	(0.0583)	(0.0474)	(0.0782)	(0.0418)	(0.258)	(0.0697)
Regime2	-1.286***	0.401***	-1.388***	0.136**	-2.497***	-0.177
	(0.0890)	(0.0610)	(0.113)	(0.0632)	(0.311)	(0.119)
Constant	0.435***	7.551***	1.267***	8.088***	3.075***	9.160***
	(0.0883)	(0.0292)	(0.131)	(0.0282)	(0.327)	(0.0526)
Marginal Effect		*s.e.*		*s.e.*		*s.e.*
TierB×Regime1	0.0738**	(0.0299)	-0.0509***	(0.0609)	-2.3316***	(0.2717)
TierC×Regime1	-0.0246	(0.0704)	-0.1966*	(0.0582)	0.2378***	(0.084)
TierB×Regime2	0.2475***	(0.0529)	0.1486**	(0.0892)	-2.1983	(0.2037)
TierC×Regime2	0.0133	(0.1118)	-0.2962	(0.1212)	0.0619	(0.1478)
Observations	11,234	4,992	9,266	5,674	3,116	2,397
FE	-	Website	-	Website	-	Website

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: 1. Bin 1 contains websites with 8,000 to 20,000 clicks in six months between September 2008 and February 2009; bin 2 websites have 20,000 to 60,000 clicks and bin 3 websites have 60,000 to 155,000 clicks. 2. We exclude the dummy variable for the control group, non-pharmacy websites, for the pre-treatment period, regime0. 3. Dependent variables in columns (1), (3), (5) are whether a website has any non-censored positive organic clicks on a website and the dependent variable in columns (2),(4), (6) are the number of organic clicks given a website has some non-censored organic clicks. 4. Standard errors are clustered at the website level.

Table 10: Organic Click Analysis Grouped by Website's Initial Fraction of Sponsored Clicks

	(1)	(2)	(3)	(4)
	High Fraction		Medium Fraction	
	I(Organic Clicks>0)	*ln(Organic Clicks)*	*I(Organic Clicks>0)*	*ln(Organic Clicks)*
TierB×Regime1	0.159	0.547	-0.397	0.738***
	(0.421)	(0.470)	(0.243)	(0.223)
TierC×Regime1	-0.408	0.214	-0.107	0.772
	(0.405)	(0.369)	(0.554)	(0.660)
TierB×Regime2	0.586**	0.537*	0.302	0.776***
	(0.282)	(0.315)	(0.206)	(0.280)
TierC×Regime2	-0.751	0.149	0.0252	0.788**
	(0.699)	(0.551)	(0.665)	(0.359)
TierB	-0.415***	0.432**	-0.544***	0.189***
	(0.101)	(0.209)	(0.0610)	(0.0583)
TierC	-0.892***	0.814***	-1.045***	0.278***
	(0.170)	(0.233)	(0.0874)	(0.0825)
Regime1	2.522***		1.472***	
	(0.712)		(0.552)	
Regime2	1.124***		-0.469	
	(0.293)		(0.648)	
Constant	-1.811***	6.525***	0.173*	7.836***
	(0.156)	(0.0807)	(0.102)	(0.0305)
Marginal Effect		*s.e.*		*s.e.*
TierB×Regime1	0.0163	(0.043)	-0.0922	(0.0567)
TierC×Regime1	-0.0417	(0.0412)	-0.0248	(0.1285)
TierB×Regime2	0.0599**	(0.029)	0.0702	(0.0475)
TierC×Regime2	-0.0767	(0.0706)	0.0058	(0.1544)
Observations	7,003	914	9,870	4,299
FE	-	Website	-	Website

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: 1. "High Fraction" are websites with greater than 85% clicks coming from sponsor links in six months between September 2008 and February 2009; and "Medium Fraction" are websites with this number between 50% and 85%. 2. We exclude the dummy variable for control group, non-pharmacy websites, and for the pre-treatment period, regime0. 3. Dependent variables in columns (1) and (3) are whether a website has any non-censored positive organic clicks on a website, and the dependent variable in columns (2) and (4) are the number of organic clicks given a website has some non-censored organic clicks. 4. Standard errors are clustered at the website level.

Table 11: Organic Click Analysis Conditional on Heterogeneous Pharmacy Queries

	(1)	(2)	(3)	(4)
	From Targeted Query		From Non-Targeted Query	
	I(Organic Clicks>0)	*ln(Organic Clicks)*	*I(Organic Clicks>0)*	*ln(Organic Clicks)*
TierB	1.852***		1.258***	
	(0.389)		(0.368)	
Regime1	-0.168	0.0300	-0.200	0.669***
	(0.212)	(0.257)	(0.156)	(0.188)
TierB×Regime1	0.189	1.300***	0.306	0.524**
	(0.285)	(0.337)	(0.255)	(0.242)
Regime2	-0.769**	-0.0473	-1.130***	1.220***
	(0.326)	(0.354)	(0.254)	(0.237)
TierB×Regime2	0.969***	1.529***	0.993***	-0.0941
	(0.371)	(0.456)	(0.347)	(0.289)
Constant	-2.707***	7.441***	-2.424***	6.141***
	(0.210)	(0.103)	(0.207)	(0.0662)
Marginal Effect		*s.e*		*s.e.*
TierB×Regime1	0.0141	(0.0209)	0.0236	(0.0198)
TierB×Regime2	0.072***	(0.0278)	0.0767***	(0.0285)
Observations	7,896	729	7,896	710
FE	-	Website	-	Website

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: 1. Targeted pharmacy queries include tier-B names, tier-C names and queries that imply a search for inexpensive drugs. 2. Tier-C and regime 0 serve as the comparison group. 3. Dependent variables in columns (1) and (3) are whether a website has any non-censored positive organic clicks on a website through given type of queries, and the dependent variable in columns (2) and (4) are the number of organic clicks conditional on a website having some non-censored organic clicks. 4. Standard errors are clustered at the website level.

Table 12: Organic Click Analysis Conditional on Heterogeneous Drug Queries

	(1)	(2)	(3)	(4)
	LS/Chron Durg Query		Non-LS/Chron Durg Queriy	
	I(Organic Clicks>0)	*ln(Organic Clicks)*	*I(Organic Clicks>0)*	*ln(Organic Clicks)*
TierB	0.723*		0.341	
	(0.436)		(0.530)	
Regime1	-0.227	0.342	-1.038***	0.881**
	(0.208)	(0.269)	(0.367)	(0.356)
TierB×Regime1	-0.164	0.467	1.038*	0.206
	(0.328)	(0.382)	(0.544)	(0.931)
Regime2	-0.937***	0.279	-1.307**	1.173***
	(0.281)	(0.330)	(0.585)	(0.281)
TierB×Regime2	0.509	0.725*	1.002	0.642
	(0.392)	(0.427)	(0.874)	(0.702)
Constant	-2.347***	7.059***	-3.298***	6.186***
	(0.209)	(0.103)	(0.301)	(0.164)
Marginal Effect		*s.e*		*s.e.*
TierB×Regime1	-0.0116	(0.0237)	0.0245*	(0.0139)
TierB×Regime2	0.036	(0.0271)	0.0237	(0.021)
Observations	7,379	574	7,379	180
FE	-	Website	-	Website

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: 1. This sets of regression examines clicks on pharmacy websites through different drug queries. We classify drug queries into chronic drugs, lifestyle drugs and other drugs. 2. Tier-C and regime 0, and non-chronic and non-lifestyle drug queries serve as the comparison group. 3. Dependent variables in columns (1) and (3) are whether a website has any non-censored positive organic clicks, and the dependent variable in columns (2) and (4) are the number of organic clicks conditional on a website having some non-censored organic clicks. 4. Standard errors are clustered at the website level.

Appendix

Table A1: Robustness Check using Google's Search Engine Only

	(1)	(2)	(3)	(4)	(5)
	$I(AnyClicks)$	$I(TtlClicks > 0)$	$ln(TtlClicks)$	$I(OrgClicks > 0)$	$ln(Orglicks)$
TierA×Regime1	0.0535	0.0540	-0.0478	0.0491	-0.0768
	(0.0801)	(0.0710)	(0.120)	(0.0744)	(0.117)
TierB×Regime1	0.00969	-0.561**	-0.136	-0.0656	1.228***
	(0.235)	(0.253)	(0.331)	(0.246)	(0.262)
TierC×Regime1	-0.401***	-0.498***	-0.0124	-0.202	0.121
	(0.118)	(0.188)	(0.201)	(0.170)	(0.196)
TierA×Regime2	0.174	0.102	-0.215*	0.111	-0.294**
	(0.136)	(0.119)	(0.124)	(0.120)	(0.120)
TierB×Regime2	0.437*	0.112	-0.210	0.621***	1.092***
	(0.232)	(0.226)	(0.331)	(0.233)	(0.322)
TierC×Regime2	-0.771***	-0.822***	-0.174	-0.507**	-0.0542
	(0.165)	(0.232)	(0.216)	(0.215)	(0.216)
TierA	2.296***	2.947***		2.965***	
	(0.229)	(0.242)		(0.241)	
TierB	2.291***	3.041***		2.577***	
	(0.325)	(0.349)		(0.350)	
TierC	1.389***	1.642***		1.373***	
	(0.131)	(0.169)		(0.178)	
Regime1	-0.00969	-0.0224	0.217***	-0.0173	0.230***
	(0.00931)	(0.0156)	(0.0199)	(0.0158)	(0.0208)
Regime2	-0.262***	-0.291***	0.453***	-0.300***	0.452***
	(0.0131)	(0.0240)	(0.0294)	(0.0242)	(0.0307)
Constant	-2.174***	-3.344***	7.635***	-3.380***	7.537***
	(0.0134)	(0.0263)	(0.0123)	(0.0268)	(0.0129)
TierA×Regime1	0.0047	0.0017		0.0015	
	(0.007)	(0.0022)		(0.0023)	
TierB×Regime1	0.0008	-0.0177**		-0.002	
	(0.0205)	(0.008)		(0.0075)	
TierC×Regime1	-0.0352***	-0.0157***		-0.0061	
	(0.0103)	(0.0059)		(0.0052)	
TierA×Regime1	0.0153	0.0032		0.0034	
	(0.0119)	(0.0037)		(0.0037)	
TierB×Regime2	0.0383*	0.0035		0.0189***	
	(0.0203)	(0.0071)		(0.0071)	
TierC×Regime2	-0.0676***	-0.0259***		-0.0155***	
	(0.0144)	(0.0073)		(0.0066)	
Observations	1,172,368	1,172,368	38,819	1,172,368	37,384
FE	-	-	Website	-	Website

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table replicates Table 7 in the paper using data only from Google's search engine.

Table A2: Examples of Top Chronic and Lifestyle Drugs

Top 10 Chronic Drugs

Rank	Query	Total Clicks[a]	Tier-BC Ratio[b]	Prescription Freq.[c]	May Treat
1	lexapro	1,053,639	0.0%	5.5	depression
2	zoloft	817,323	0.1%	5.1	depression
3	effexor	656,777	0.5%	5.3	depression
4	cymbalta	648,823	0.3%	6.3	depression
5	oxycontin	553,726	15.9%	5.1	pain, controlled substance
6	synthroid	529,037	0.4%	5.7	hypothyroidism
7	metoprolol	516,298	0.0%	5.7	high blood pressure
8	gabapentin	507,686	1.0%	5.6	seizures
9	pristiq	440,084	2.3%	5.0	depression
10	seroquel	438846	0.8%	6.2	schizophrenia

Top 10 Lifestyle Drugs

Rank	Query	Total Clicks[a]	Tier-BC Ratio[b]	May Treat
1	viagra	2,890,258	36.6%	ED*
2	phentermine	2,140,199	51.7%	over weight, controlled substance
3	xanax	1,866,525	20.3%	depression, insomnia, controlled substance
4	cialis	1,056,012	23.3%	ED*
5	oxycodone	829,212	5.1%	pain, controlled substance
6	ambien	697,907	6.4%	sleep aid, controlled substance
7	oxycontin	553,726	15.9%	pain, controlled substance
8	botox	420,769	0.7%	wrinkle, face lift
9	levitra	367,965	13.9%	ED*
10	soma	327,303	6.9%	pain and stiffness of muscle spasms

* ED stands for erectile dysfunction.

Notes: [a] Total Clicks is the total number of clicks on online pharmacy websites following the search query from September 2008 to September 2011. The drugs in each category are ranked by the total number of clicks. [b] Tier-B,C ratio is the percentage of total clicks from each query that led to Tier-B and Tier-C sites in the first nine months of the sample (2008/09 - 2009/05). [c] Prescriptions Freq.(frequency) is the average number of prescriptions for each patient in a given year. It is calculated from 2010 Medical Expenditure Panel Survey and is weighted to reflect the national representative statistics. When the average number of prescriptions is higher than 5, we define the drug as chronic, while if it is below 3.5, we define the drug as non-chronic.