How Does the Use of Trademarks by Third-Party Sellers A ect Online Search?

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Abstract

Firms that sell via a direct channel *and* via indirect channels have to decide whether to allow third-party sellers to use the trademarked brand name of the product in their advertising. This question has been particularly controversial for advertising on search engines. In June 2009, Google started allowing any third-party reseller for a product to use a trademark, such as `Doubletree,' in the text of its ad, even if the reseller did not have the trademark holder's permission. We study the e ects of this change empirically within the hotel industry. We nd some evidence that allowing third-party sellers to use a trademark in their online search advertising weakly reduced the likelihood of a consumer clicking on a trademark holder's paid search ads. However, the decrease in paid clicks was outweighed by a large increase in consumers clicking on the unpaid links to the hotelier's website within the main search results. Our evidence shows that when third-party sellers focus on the trademarked brand in their ads, their ads become less distinct, and customers are more likely to ignore the advertised o ers and buy from the direct channel.

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1 Introduction

Suppose a consumer wants to book a room at a Doubletree hotel and searches for `Doubletree' on a search engine. Next to the main search results there will be a separate set of paid search ads that each contain a link to a website. These ads will not only be for the direct channel (Doubletree.com), but also for third-party resellers such as www.HotelReservations.com. Should Doubletree allow third-parties to use the `Doubletree' trademark in the text of their ads? If the use of the trademark legitimizes the third-party seller as an alternative outlet for the brand, the trademark holder may lose money. Doubletree will have to pay 10% commission to the agent, which it could have avoided had the customer not been diverted from Doubletree's own websites. Even worse, a travel agency website may lead the consumer to book a room at a competing hotel. Such fears have led legal analysts to estimate losses of $400 million annually for the hotel industry due to use of trademarks to trigger ads and in ad-copy by third-party sellers (Ripin, 2007); such practices have been referred to as `poaching' (Sayedi et al., 2011).

The advertising literature has a di erent prediction. Koch and Ullman (1985); Itti (2005)'s work on visual distinctness suggest that the salience of a paid search ad is not determined solely by its own design but also by the extent to which it is distinct from paid search ads. Similarity in ad features leads to competitive ad clutter (Kent and Allen, 1993; Pieters et al., 2007; Danaher et al., 2008; Goldfarb and Tucker, 2011b), which reduces the e cacy of advertising. If third-party sellers ads highlight the same trademark, they risk becoming less distinct, and consumers may choose instead the non-advertised path to the direct channel. Therefore, the empirical consequences of the use of trademarks by third-party sellers are not clear-cut, making this an empirical question.

In June 2009, Google began allowing advertisers to use trademarks in the text of their paid search ads even if they did not have the permission of the trademark holder. Paid search ads appear in a separate column next to the main search results when consumers query a specific search term. Firms must pay for clicks on links in their paid ads but do not pay for clicks on the link in the main result.

We compare changes in click behavior by customers who used a search engine to query major US hotel brand trademarks before and after the policy change. We use aggregate data from comScore that describes which websites US consumers visited after searching Google or Yahoo! using a trademarked search term from April to August 2009. We compare how clicks changed on Google (where the policy change occurred) to Yahoo! (where there was no such change in policy).

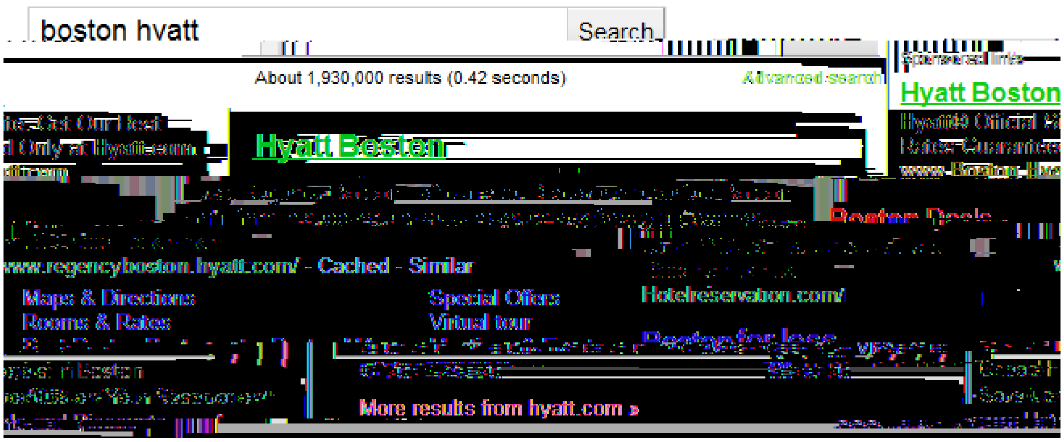
We find little evidence of harm to the trademark's direct channel. The trademark holder's website did receive (marginally) fewer clicks on its paid search ads after the change in policy. However the decrease was outweighed by a large increase in the number of clicks on the non-paid link to the trademark holder's website within the main search results. When third-party ads started displaying the trademark, search engine users started clicking directly on the main link to the trademark holder's website.

Our finding is robust to different functional forms, specifications, and control groups. We show that no such effect occurred in the previous year or for related searches that were unaffected by the policy change. We also replicate our results in the controlled conditions of an online survey, and we show that when advertising is already indistinct, no such effect occurs from the addition of trademarks. Furthermore, when a larger number of ads contribute to the clutter, the positive spillover effects are stronger.

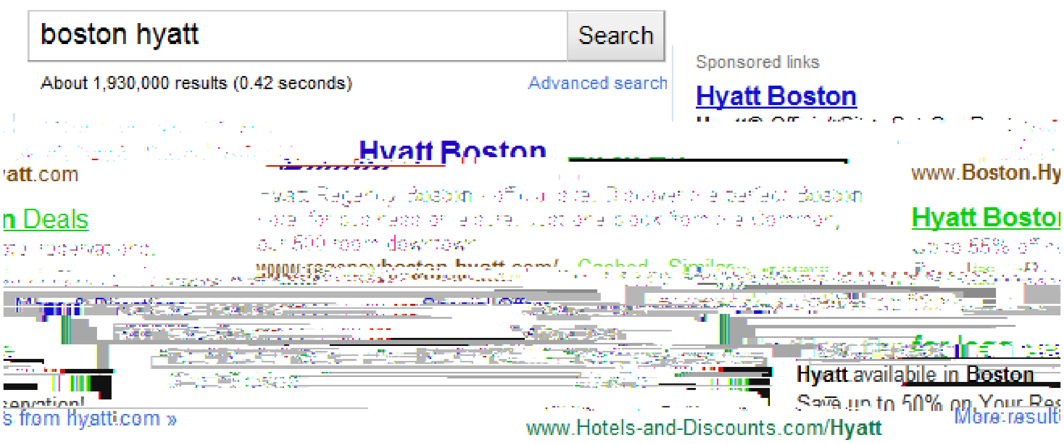
The interdependency between paid ads and non-paid links in search results is not a new finding: Yang and Ghose (2010) find a positive interdependence between whether a paid ad is present for a particular retailer and whether someone clicks through the retailer's non-paid listing, Chiou and Tucker (2010a) show that the extent of interdependence varies with whether the search term is a brand name. What is novel about our study is the finding of spillover effects to the non-paid search result from *other retailers'* ads if these ads highlight the trademark. Such spillover effects are analogous to Anderson et al. (2010)'s finding that when a catalog company shares its mailing list with a rival firm, sales actually increase for some of the firm's own products.

2 Policy Change

On May 14, 2009, Google announced that they would begin allowing advertisers to use a trademark within the text of their ads without the trademark holder's permission as long as the trademark is referred to in `a descriptive or generic way,' and the advertiser either resells or offers information about the trademark holder's products. This was a major shift from



(a) No Trademarks



(b) Trademarks

Figure 1: How the appearance of search results changed

brand name (Bechtold, 2011).[1] Empirically, such instances of competitive `piggy-backing' have found to be rare (Rosso and Jansen, 2010).

Several legal cases have also focused on the use of trademarks in the ad copy. For example, in *Edina Realty Inc. v. TheMLSonline.com* (2006), the Court objected that the ad by TheMLSonline.com used the Edina Realty trademark as their headline. Similarly, the recent European Court of Justice decision relating to *Hotels Meridien v. Google France* (2004) and *Accor v. Overture* suggests that trademarks in ad content could be problematic.[3]

3 Conceptual Framework

This discussion shows that, in general, the legal policy literature has assumed that if third-of trademarks could increase advertising clutter in two ways. First, when all advertisers focus their ad around the same trademark, consumers may experience each ad as being less distinct. Paid ads will offer a less compelling reason for the consumer to divert from the main non-paid listing. Second, if advertisers are encouraged to start advertising because they can now use trademarks, then the number of similar ads will increase, again contributing to clutter.

The theory predicts that the number of paid clicks for the trademark holder will decrease as its ad is made less distinct relative to its competitors. However, the effect on non-paid clicks for the trademark holder is ambiguous, and if the effects of advertising clutter are strong enough, non-paid clicks for the trademark holder may even increase.

4 Field Studies

4.1 Data

We use data on consumer search and navigation behavior from comScore. ComScore tracks the online activity of a panel of more than two million users in order to provide commercial data products. ComScore is not open about its recruitment methods, but it does claim that the panel is representative.

We had access to a database named comScore Marketer. The database records the total aggregate number of paid and non-paid clicks that various websites received after a search for a specified search term at major search engines for the past two years.[4] We extracted aggregate data on searches that contained the trademarked name for major hotel brands in the US. We focus on the hotel industry for two reasons. First, since comScore data records only whether someone visited a website and not their subsequent activity at a website, we wanted to study a sector where a visit to a company's website is meaningful

[4] The aggregate nature of this commercial dataset contrasts with the individual nature of the comScore data for 100,000 panelists used by researchers such as Park and Fader (2004). However, this individual-level data has only been released to researchers for 2002 and 2004, and so it cannot be used for this study.

in itself. Hotel brand websites currently account for 69% of all online hotel bookings in the US (PhoCusWright, 2009). Second, the hotel industry has been the setting for major litigation over trademarks and search advertising. Owners of hotel brands do not have to pay commission if they sell their rooms directly, so they have an incentive to direct internet business to their site (Vinhas and Anderson, 2005).[5].

To determine our sample of hotel brands, we started with the top 300 hotel brands as reported by Hotels Magazine in its July 2007 edition.[6] Of these, we identi ed brands that were based primarily in the US and where comScore panel members conducted more than one search in April 2009. Our sample contains 53 such some of the clicks their website receives. On average, our data suggests that hotel trademark holder's pay for 18% of the clicks they receive.[9] A high correlation exists between the total number of clicks and the number of rooms that a hotel chain controls (0.74). This provides some face validity to the data. The correlation is weakest for economy motel chains such as Econolodge, which presumably rely more heavily on `walk-in'customers than on customers who book ahead online.

Table 1: Data summary

	Mean	Std. Dev.
Search Term Level		
Monthly Average Paid Clicks for Search Term	25472.0	39378.5
Monthly Average Non-Paid Clicks for Search Term	109799.6	197655.6
Observation: Search Engine-Search Term-Website-Month		
Paid Clicks	865.1	5675.8
Non-Paid Clicks	3729.0	24858.5
Google Search Engine	0.50	0.50
Trademark Holder Website	0.10	0.30
Number of Paid Ads associated with Search Term	4.11	4.58
Number of Third-Party Ads associated with Search Term	2.67	3.71

Notes: 6,360 Observations. Summary statistics from April 2009-September 2009.

In addition to the trademark holder's website, people also visited 66 distinct third-party websites in sufficient numbers for comScore to report data. The sites were either online travel agencies (e.g., Expedia.com, Hotels.com) or websites that direct customers to online travel agencies (e.g., Tripadvisor).

Since comScore provides data on a monthly basis, we collected this data for April-October 2009. In our main analysis, we compare April and May 2009 with July and August 2009. We use the September and October data in our analysis of long-run effects in Section 4.5. We omit data from June 2009 from our empirical analysis, as the date of the policy change

[9] Table A-1 in the appendix records the total number of clicks by search term and the proportion of these

(June 15) fell exactly in the middle of that month, making inference difficult. We use data for the Yahoo! and Google search engines. On June 3 2009, Microsoft rebranded its live search engine as `Bing,' making it a problematic candidate for a control group.

An observation occurs at the Search Engine-Search Term-Website-Month level. For example, we observe the number of paid and non-paid clicks that Hilton.com receives in a month from people who use the search term `Hilton' on Yahoo!. There are 795 observed website and search-term combinations for each search engine in each month. The bottom panel of Table 1 describes our data at this level.

4.2 Univariate Analysis

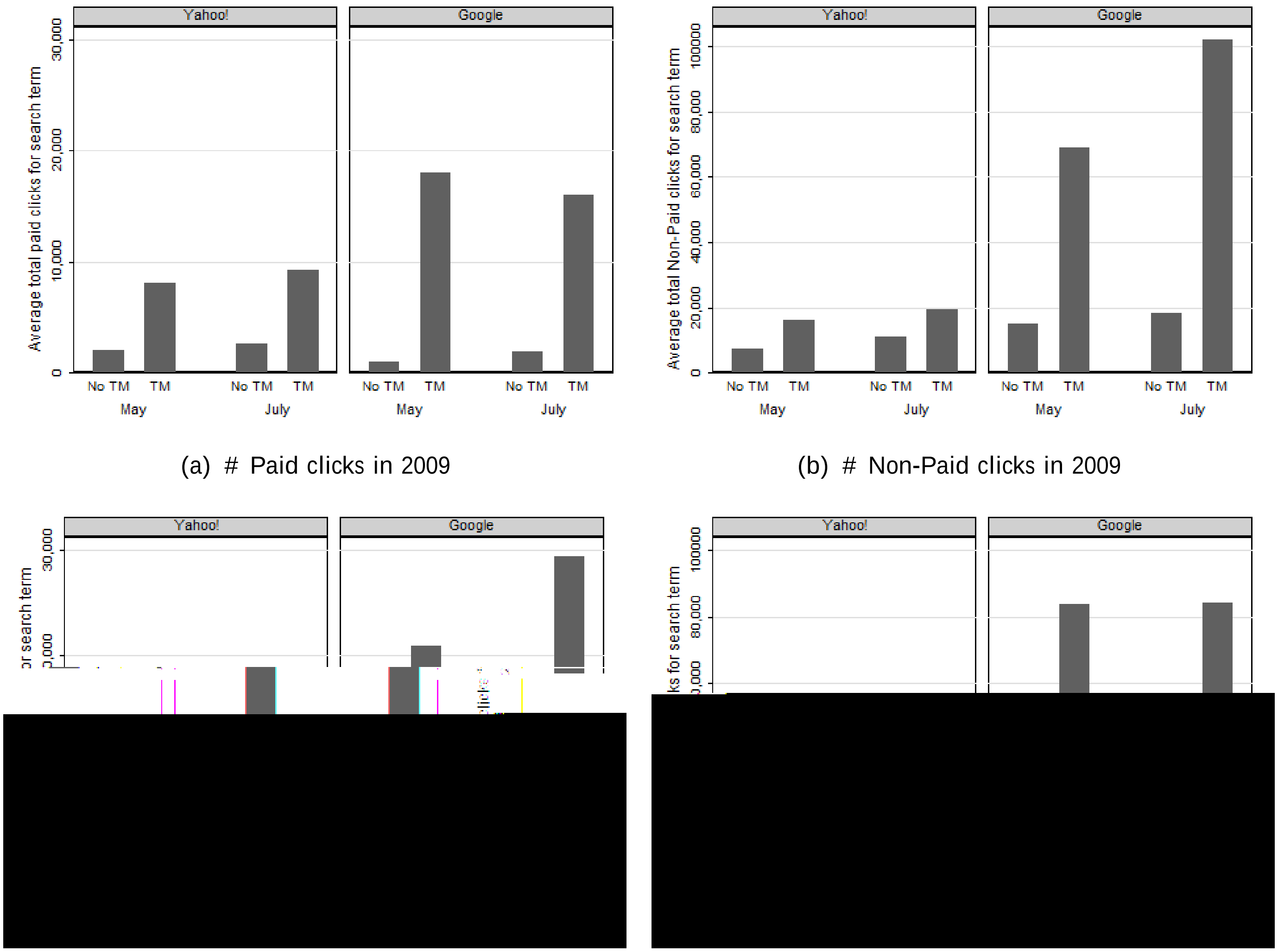
Figures 2(a) and 2(b) compare the paid and non-paid clicks for each search term before and after the policy change (May and July) on Yahoo! and Google.[10] Two patterns are apparent. First, paid clicks fell for trademark holders on Google after the policy change relative to Yahoo!, much as hoteliers feared. However, a large increase occurred in non-paid clicks for trademark holders at the same time. The small gains in paid clicks for the non-trademark holder sites do not appear significantly different from the patterns on Yahoo!.

To check that the variation was not simply seasonal, we collected similar data for 2008. Figures 2(c) and 2(d) shows the results. Reassuringly, there was no upward shift in `non-paid' clicks or downward shift in `paid' clicks on Google for trademark holders for similar months in a previous year. Instead, the general trend in `paid' clicks appeared to be upward (perhaps owing to a larger number of summer bookings) on both Yahoo! and Google with little change in non-paid clicks.

4.3 Empirical Analysis

We formalize the insights of Figure 2 in an econometric framework. For each website i, that is potentially reached by consumers who search trademarked brand name j on search engine

[10] For simplicity, we look only at May and July, the months surrounding the policy change. For completeness, we report the full monthly analysis in Figure A-1.



(a) # Paid clicks in 2009

(b) # Non-Paid clicks in 2009

(c) # Paid clicks in 2008 (No Policy Change)

(d) # Non-Paid clicks in 2008 (No Policy Change)

Figure 2: How the number of clicks an average website received changed on Google and Yahoo!.

k in month t, we model the number of clicks as:

$$clicks_{ijkt} = \quad + \quad {}_{1} TMHolder_{ij} \quad PostChange_{t} \quad Google$$

Table 2: Trademark holders lose paid clicks but gain non-paid clicks after the policy change

	(1) Non-Paid Clicks	(2) Paid Clicks	(3) Total Clicks
PostChange Google TMHolder	13431.6	-3269.0	10162.7
	(3635.5)	(1744.1)	(2997.9)
PostChange Google	-3.908	18.56	14.65
	(78.91)	(44.08)	(92.36)
PostChange TMHolder	-454.4	73.99	-380.4
	(893.9)	(671.5)	(1078.8)
PostChange	148.7	14.48	163.2
	(94.53)	(46.44)	(110.7)
May Indicator	6.184	-34.46	-28.28
	(159.2)	(68.68)	(186.8)
Search Engine-Search Term-Website Controls	Yes	Yes	Yes
Observations	6360	6360	6360
R-Squared	0.176	0.154	0.179

Notes: Ordinary Least Squares estimates. An observation is the number of clicks for a website in a month for searches using a speci c trademarked term on a speci c search engine. April, May, July, August 2009 data. *Google TMHolder, Google, TMHolder* are dropped due to their collinearity with the Search Engine-Search Term-Website xed e ects. Standard errors clustered at search-term level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in policy on Google (relative to Yahoo!). This supports the theory that growing indistinctness of paid ads encourage users to navigate simply to the main non-paid listing.

In Column (2) we display results for the change in number of clicks on paid links. The (marginally) signi cant coe cient estimate for $TMHolder_{ij}$ $PostChange_t$ $Google_k$ suggests that after the policy change, trademark holder websites experienced a decrease of around 3,269 paid clicks on Google as compared to Yahoo!. The result is as expected and follows conventional legal wisdom about the negative e ects of permitting trademark dilution on an advertising message. When other paid ads could use the trademark, the trademark holder's ad was less distinctive and attracted fewer clicks. However, a comparison of Columns (1) and (2) suggests that the decrease in paid clicks was outweighed four-fold by the increase in non-paid clicks. Column (3) evaluates the e ect of the policy change on total clicks to the website. The policy change was associated with a net increase of 10,163 in the number of monthly visits to the direct channel website. The lower-order interactions are insignificant in all three columns.

We then re-estimate the model using a semi-log (log-linear) specification. We use a semi-log specification because it can be interpreted in terms of percentage changes, addressing the concern that our results might be driven by the difference in the absolute level of clicks between Google and Yahoo! (as observed in Figures 2(a) and 2(b)) or by extreme values. We estimate the semi-log specification using the generalized estimating equation (GEE) framework (Mullahy, 1999; Manning and Mullahy, 2001). The logarithmic transformation inherent in this specification means that the results can be interpreted as a percentage change. These results suggest that the number of non-paid clicks increased by 42% after the change in policy for trademark holders on Google and that total clicks increase by 26% relatively. The

Table 3: Log speci cation: Trademark holders lose paid clicks but gain non-paid clicks after the policy change

4.4.1 Control Group Checks

To be a valid control group, Yahoo! users must behave similarly to Google users in the absence of a policy change. We control for static differences between Yahoo! and Google, but a concern may be that the composition of users may be changing in a way that could distort our results - this process is sometimes referred to as maturation (Cook and Campbell, 1979). This would be particularly problematic if the composition of Google users shifted towards groups of people who were more likely to simply use search engines as a navigation tool and not click on ads relative to Yahoo!. To investigate this, we collected data from Experian Hitwise on the demographic profile of Google Search and Yahoo! Search users in the period we study. Table A-2 in the appendix indicates that the income and age distribution of Google and Yahoo! users appears relatively similar, and remains similar over the period we study.[13] Yahoo! has slightly more female users than Google, but this pattern did not change over the period we study. Table A-3 in the appendix also shows that no other interface or operational changes occurred on either Yahoo! or Google.

4.4.2 Falsification Checks

We have already shown that there was no similar trend in 2008 for Google relative to Yahoo! (Figures 2(c) and 2(d)). However, there is still the possibility of time-varying unobserved factors, or history (Cook and Campbell, 1979), that were specific to 2009. For instance, perhaps Google did not publicly report a change in the search engine's algorithm, which led to hotel websites being highlighted more within the main results. To check for such possibilities, we conducted two 'falsification checks.'

In the first falsification check, we looked at a set of trademark holder clicks that were not affected by Google's policy change, and we examine whether they exhibited a similar pattern to that displayed in Table 2. We looked specifically at searches where consumers navigated

[13] We also checked that our results held if we only looked at searches that only used the trademarks, which helps us rule out time-varying heterogeneity in the nature of search terms used.

to a trademark holder's website after searching on a competitor's trademark. Such searches were not affected by the policy change because Google only permitted advertisers who sold the specific brand to use the trademark in their ad copy. For example, Hilton could not use `Marriott' in its ad copy. If our results capture a general increase in consumer clicks to trademark holders' non-paid link in the summer of 2009 on Google relative to Yahoo!, shocks and impulses. We collected this kind of search data for the top 10 most populous metropolitan statistical areas in the US.[14] Since these are generic searches and city names are not subject to trademark restrictions, these types of searches were not affected by the policy change.

We then analyzed whether the trademark searches enjoyed a similar increase in clicks relative to these non-trademark searches. If there was no difference, this might suggest that our result simply reflects a shift in preferences of Google users seeking travel information towards clicking on the top main search result rather than paid search results in the period we study. Table 4 displays our results for this new data sample. In this specification, the new indicator variable $TrademarkSearch_j$ is 1 when the search was conducted using a trademark and is 0 if the searcher used a geographical term. Even with using only variation among searchers on Google seeking hotel information, the positive coefficient for $PostChange_t \times TMHolder_{ij} \times TrademarkSearch_j$ suggests a sizable increase in the number of non-paid clicks for branded website in the main results for the trademark searches relative to non-trademark searches associated with the timing of the policy change. Since the regression uses a different dataset, the absolute numbers cannot be directly compared to Table 4.[15]

4.5 Magnitude of the Spillover Effects

The coefficient size suggested by these log-results is large with an overall effect size of 26%. In this section, we investigate how long an effect of this size persisted and how the size of the effect varied across websites.

[14] New York, Chicago, Los Angeles, Dallas, Houston, Miami, Atlanta, Washington D.C., Philadelphia, and Boston.

[15] The log estimates reported in the online technical appendix to the paper suggest a slightly larger positive effect proportionally for non-paid clicks and a larger negative effect proportionally for non-paid clicks when we analyze only within-Google variation after the policy change.

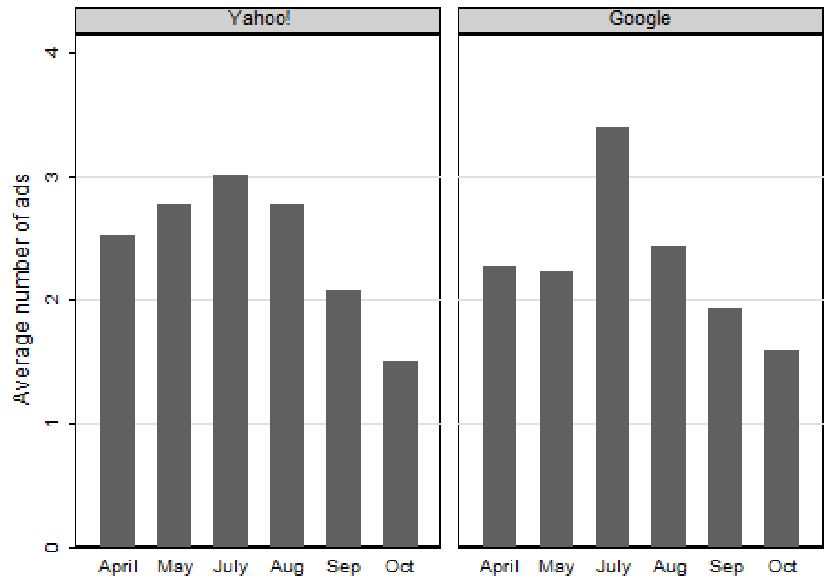


Figure 3: How the average number of ads for each search term changed on Google and Yahoo! across multiple months

automated systems that allocate their expenditures to advertising campaigns that attract the most click-throughs, since search engines' pricing algorithms penalize advertisers who do not attract su cient clicks. Therefore, advertisers tend not to continue to run ads that do not attract signi cant clicks.

Therefore, large gains in non-paid clicks to trademark holders may not have been sustained if third parties pulled the ine cient ads. To examine this, Table 5 repeats the analysis of Table 2 but includes data from September and October 2009. It compares the e ect for July and August 2009 (captured by `PostChange') with the incremental shift in the e ect in September and October (labeled as `long-term'). The new long-term interaction is captured by an indicator variable $LongTerm$, which is equal to 1 if it was September or October. $PostChange$ continues to indicate whether the month occurs after the policy change. The coe cient for $LongTerm$ $Google$ $TMHolder$ is negative for non-paid clicks, though only marginally signi cant in the linear speci cation and insigni cant in the log speci cation.

Table 5: The spillover e ects decreased in the long run

	(1) Non-Paid Clicks	(2) Paid Clicks	(3) Total Clicks
PostChange Google TMHolder	15917.6	-1203.1	14714.4
	(4120.9)	(1573.6)	(4139.3)
Long-Term Google TMHolder	-4340.8	-2196.4	-6537.1
	(2345.6)	(1239.3)	(2893.6)
PostChange	343.1	56.56	399.7
	(85.05)	(25.57)	(89.20)
PostChange Google	-188.7	14.97	-173.8
	(142.3)	(35.77)	(147.5)
PostChange TMHolder	1900.2	1298.9	3199.1
	(890.5)	(602.9)	(1261.2)
Long-Term	-317.1	-73.84	-391.0
	(76.36)	(34.79)	(85.60)
Long-Term Google	56.24	37.75	93.98
	(142.3)	(32.18)	(147.2)
Long-Term TMHolder	-2582.0	-1128.3	-3710.2
	(966.5)	(612.7)	(1138.0)
May Indicator	-298.5	-45.95	-344.5
	(124.1)	(66.67)	(148.0)
Search Engine-Search Term-Website Controls	Yes	Yes	Yes
Observations	11130	11130	11130
R-Squared	0.0744	0.173	0.0871

Notes: Ordinary Least Squares estimates. An observation is the number of clicks for a website in a month for searches using a speci c trademarked term on a speci c search engine. April, May, July, August, September, October 2009 data. Pre-policy months are April and May 2009. Long-term e ect captures the incremental change in *PostChange* in September and October 2009. *Google TMHolder, Google, TMHolder* are dropped due to their collinearity with the Search Engine-Search Term-Website xed e ects. Standard errors clustered at search-term level.* p < 0:10, ** p < 0:05, *** p < 0:01

4.5.2 Search Engine Motivation

A remaining question is why Google would allow the use of trademarks in paid search ads if it encouraged non-paid clicks. Since we cannot obtain pricing data, we cannot calculate

Table 6: Changes in paid search and non-paid search by number of competitors' ads

	(1)	(2)	(3)
	Non-Paid Clicks	Paid Clicks	Total Clicks
PostChange Google TMHolder # Comp Using TM	5719.9	-1961.3	3758.6
	(560.1)	(225.9)	(577.5)
PostChange Google TMHolder	6256.7	-891.5	5365.3
	(1412.7)	(569.8)	(1456.6)
PostChange Google # Comp. Using TM	-29.66	16.50	-13.16
	(173.4)	(69.93)	(178.8)
# Comp. Using TM	-52.46	7.081	-45.37
	(164.0)	(66.16)	(169.1)
PostChange # Comp. Using TM	40.53	0.133	40.67
	(117.8)	(47.53)	(121.5)
Google # Comp Using TM	34.55	-8.828	25.72
	(216.5)	(87.31)	(223.2)
TMHolder # Comp Using TM	972.8	-464.0	508.8
	(623.1)	(251.3)	(642.5)
PostChange TMHolder # Comp Using TM	253.7	34.16	287.9
	(382.9)	(154.4)	(394.8)
Google TMHolder # Comp Using TM	-1484.5	1747.9	263.5
	(836.5)	(337.4)	(862.5)
PostChange	62.29	8.865	71.15
	(397.7)	(160.4)	(410.1)
PostChange Google	69.22	-9.286	59.94
	(506.3)	(204.2)	(522.0)
PostChange TMHolder	-1153.0	128.4	-1024.6
	(1044.7)	(421.4)	(1077.2)
May Indicator	6.431	-39.50	-33.08
	(236.6)	(95.44)	(244.0)
Search Engine-Search Term-Website Controls	Yes	Yes	Yes
Observations	6360	6360	6360
R-Squared	0.291	0.0160	0.287

Notes: Ordinary Least Squares estimates. An observation is the number of clicks for a website in a month for searches using a speci c trademarked term on a speci c search engine. April, May, July, August 2009 data. *Google TMHolder, Google,* and *TMHolder* are dropped due to their collinearity with the Search Engine-Search Term-Website xed e ects. Standard errors clustered at search-term level.* $p < 0{:}10$, ** $p < 0{:}05$, *** $p < 0{:}01$

4.6.1 The Spillover E ects Increase in the Quantity of Advertising Clutter

A greater the number of ads increase the perception of advertising clutter (Danaher et al., 2008; Pieters et al., 2007). Therefore, we would expect the e ect of exposure to increase with the number of ads displayed by third-party sellers after the policy change.

Table 6 displays a speci cation that allows the e ect of the policy change to vary with the number of ads displayed by third-party sellers. This should pick up the variation in the number of third-party seller ads observed in Figure 3. The key effect is captured by the four-way interaction $PostChange_t \quad Google_k \quad TMHolder_i j \quad No{:}Comp{:}UsingTM_{ijtk}$. The positive coefficient for $PostChange_t \quad Google_k \quad TMHolder_i j \quad No{:}Comp{:}UsingTM_{ijtk}$ for non-paid clicks suggests that as expected the positive incremental effect of the policy change increased in the number of third-party reseller ads. Similarly, the negative coefficient for $PostChange_t \quad Google_k \quad TMHolder \quad No{:}Comp{:}UsingTM_{ijtk}$ for paid clicks suggests that the negative effect of the policy change for paid clicks indeed increased in the number of third-party reseller ads.[16]

Table 6 suggests that the effect of the policy change for trademark holders was indeed moderated by the number of non-trademark holder ads that appeared after the policy change on Google.

4.6.2 Negative Spillovers for Third Parties with the Most Distinct Message Pre-policy

We then turned to see whether the negative effects of this policy were felt hardest by websites that potentially could have put forward the most distinctive advertising message. To explore this, we identified websites that had a very salient `low-price' brand message. If these websites changed the text of their ads to reflect the trademarks, they may have lost

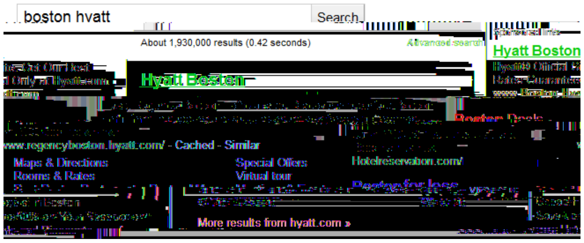
Table 7: Websites that focused on offering discounted prices received fewer paid clicks after the policy change

	(1) Non-Paid Clicks	(2) Paid Clicks	(3) Total Clicks
PostChange × Google × TMHolder	13425.4	-3318.3	10107.2
	(3636.3)	(1744.5)	(2998.8)
PostChange × Google × Bargain Site	-43.91	-351.9	-395.8
	(104.8)	(149.0)	(183.1)
PostChange × Google	2.242	67.85	70.09
	(91.30)	(45.52)	(104.5)
PostChange × TMHolder	-478.1	117.7	-360.4
	(894.5)	(671.5)	(1079.3)
PostChange	172.4	-29.21	143.2
	(98.92)	(44.00)	(113.6)
PostChange × Bargain Site	-169.2	311.9	142.7
	(55.59)	(143.2)	(153.2)
May Indicator	6.184	-34.46	-28.28
	(159.2)	(68.69)	(186.8)
Search Engine-Search Term-Website Controls	Yes	Yes	Yes
Observations	6360	6360	6360
R-Squared	0.176	0.152	0.179

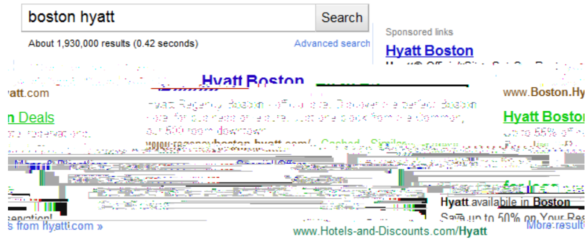
Notes: Ordinary Least Squares estimates. An observation is the number of clicks for a website in a month for searches using a specific trademarked term on a specific search engine. April, May, July, August 2009 data. *Google × TMHolder, Google × Bargain Site, Google, TMHolder, Bargain Site* are dropped due to their collinearity with the Search Engine-Search Term-Website fixed effects. Standard errors clustered at search-term level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is represented by the new indicator variable $BargainSite$ which is equal to 1 if the URL contains one of these words, and 0 otherwise. No trademark holders' websites were classified as bargain sites. This allows us to distinguish third-party sellers that are price-focused. As shown in Table 7, the negative coefficient for $PostChange_t \times Google_k \times BargainSite_i$ for paid search clicks suggests that these paid clicks decreased for these 'bargain' websites relative to third-party websites on Google after the policy change.[17] This occurs despite the fact that the coefficient on $PostChange_t \times BargainSite_i$ is positive, which suggests a time trend, as one might expect, for more clicks on such sites during the summer months.

[17] There were very few non-paid clicks for these bargain websites, making precision difficult in a regression with non-paid clicks as a dependent variable.



(a) Baseline: No Trademark



(b) Baseline Trademark

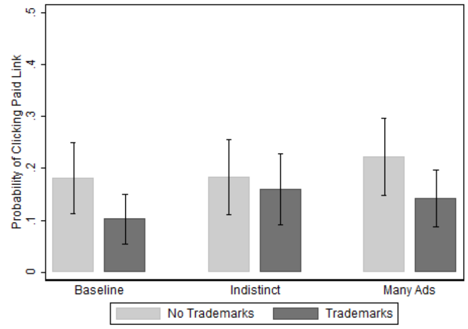
information.

Figure 5(a) presents the outcomes of the experiment for whether the respondents would use the trademark holder's non-paid link to book their hotel in each of the conditions. In the Baseline scenario, a higher proportion of respondents said they would book a hotel using the main non-paid link if trademarks were present (51% vs 69%, t=2.07, p-value=0.04). In the Indistinct scenario, as predicted, there was no change in the proportion of people who were prepared to use a third-party's link to book their website (71% vs 78%, t=.74, p-value>0.1). In the Multiple Ads scenario, a higher proportion of respondents said they would book a hotel using the main non-paid link (31% vs 67%, t=4.18, p-value<0.01) when trademarks are present. The difference is larger and more significant than in the Baseline scenario where there were fewer listings.

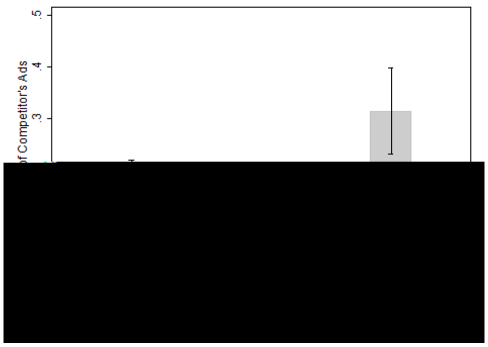
We then examined the effects of the change on the likelihood of a respondent using the


[redacted]

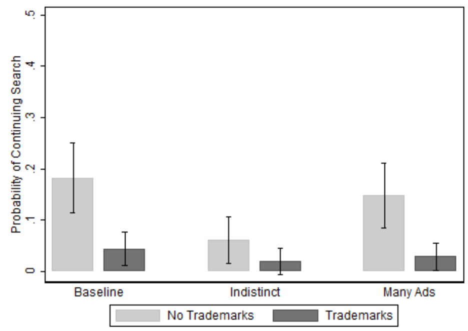
(a) Comparison of Likelihood of Using Trademark Holders' Non-Paid Link



(b) Lab Experiment: Comparison of Likelihood of Using Trademark Holders' Paid Link


[redacted]

(c) Lab Experiment: Comparison of Likelihood of Using Non-Trademark Holders' paid link



(d) Lab Experiment: Comparison of Likelihood of continuing search

Figure 5: Lab Experiment

to continue to search for other deals was smaller in the presence of trademarks (18.1 vs 4.4%, t=2.51, p-value=0.013) and (14% vs 2%, t=2.46, p-value=0.015).

6 Implications

This paper explores how marketing outcomes are affected by the use of trademarks in ads by third-party sellers who compete with a firm's direct channel. We use data from a natural experiment where Google changed its policy to align with that of other major search engines by permitting the use of trademarks in ad copy. Our results suggest that, surprisingly, this policy change benefited trademark holders. While trademark holders lost paid clicks, this decrease was outweighed by a four-fold increase in non-paid clicks. We present evidence that shows when third-party sellers highlight the brand in their ads, they reduce their sellers' ability to convey a message distinct from the other ads, such as offering a lower price. As a result, consumers are less likely to be diverted by paid ads and more likely to click on the main non-paid link.

implication of course rests on the assumption that, as happened in the case we study, an increase in trademark use by competitors in their advertising can lead to increased ad clutter (both in terms of the nature of ads and the number of rivals' ads).

More broadly, our results provide empirical evidence on the policy question of trademarks and search advertising. In the US, the possibility of trademark infringement has been proposed by researchers such as Clemons and Madhani (2010) as a major justification for the regulation of search engines. Many lawsuits have been filed in the US over the use of trademarks in search advertising, and the court decisions have been contradictory. Recently in Europe, two cases related to the hotel industry, *Hotels Meridien v. Google France* (2004) and *Accor v. Overture* (2004), resulted in search engines paying large fines for allowing competitors to advertise next to a trademark. These cases have led to attempts to clarify the law at the European level. The Advocate General of the European Court of Justice, Poiares Maduro, ruled that `Google has not committed a trademark infringement by allowing advertisers to select, in AdWords, search terms corresponding to trademarks.' However, crucially for our study, the decision suggested that this exemption did not apply to the use of trademarks as *content* featured in ads.[22] It is precisely this use of trademarks in the content of ads that we study in this paper.

There are limitations to our findings. First, the policy change we study was confined to changes in the ability of a brand's partners to use the trademark in their ad copy on search engine ads. This makes it harder to draw conclusions about other potential trademark usage restrictions, such as restricting other firms from bidding on a competitor's brand trademark as a search term or the effect of policies offline. Second, we do not have data on the cost of paid search before the policy change. The increase in number of bidders on a particular search term that was occasioned by the policy change may have increased the cost per click for trademark holders in ways we cannot measure, so we cannot measure how this

[22] Advocate General's Opinion in Joined Cases C-236/08, C-237/08 and C-238/08, 22 September 2009.

change a ected search engine revenues. Third, we measure only the number of clicks each website receives | we cannot measure how the policy change a ected reservations. Last, it is not clear how our results extend to other sectors of the economy where direct sales are less crucial to the brand-owner's business model. These limitations notwithstanding, our empirical analysis does highlight an unexpected consequence of trademark usage in the digital age with signi cant implications for rms' online advertising strategies.

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B Further empirical tables and data description

Table A-1: Summary of hotel trademark search terms and the associated number of clicks

No.	Brand	Beds	Total Clicks	Percentage of clicks the advertiser paid for
1	Best Western	315,401	2,243,275	18
2	Hilton	172,605	7,736,176	14
3	Days Inn	151,438	2,142,488	14
4	Hampton Inn	138,481	3,059,937	16
5	Sheraton	135,900	2,466,953	21
6	Super 8	126,175	647,511	21
7	Comfort Inn	110,877	2,661,719	23
8	Ramada Inn	105,986	634,901	17
9	Motel 6	90,243	951,294	34
10	Radisson	90,080	1,039,602	18
11	Crowne Plaza	75,632	655,368	24
12	Quality Inn	72,054	991,570	28
13	Hyatt Regency	69,733	814,748	21
14	La Quinta Inn	61,570	545,764	27
15	Westin	54,200	1,330,296	24

Figure A-1: How the number of clicks changed on Google and Yahoo! monthly analysis

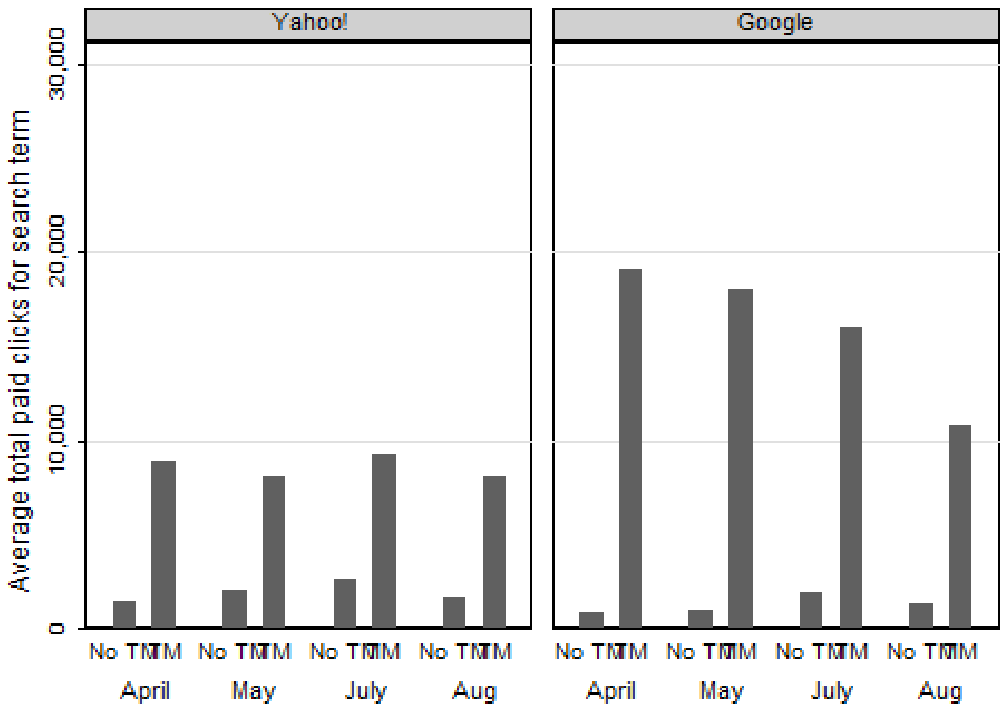

Table A-2: Comparison of demographics of Yahoo! and Google users

	April-May 2009	July-August 2009

Table A-4: Robustness checks using collapsed data

	Linear Speci cation			Log Speci cation		
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Paid Clicks	Paid Clicks	Total Clicks	Non-Paid Clicks	Paid Clicks	Total Clicks
PostChange Google TMHolder	26863.1	-6538.0	20325.3	0.416	-0.678	0.262
	(7272.6)	(3489.1)	(5997.2)	(0.131)	(0.475)	(0.122)
PostChange Google	-7.817	37.12	29.30	-0.108	0.331	-0.0743
	(157.9)	(88.18)	(184.8)	(0.0896)	(0.432)	(0.0927)
PostChange TMHolder	-908.8	148.0	-760.8	-0.265	-0.204	-0.246
	(1788.2)	(1343.4)	(2158.2)	(0.112)	(0.244)	(0.0985)
PostChange	291.2	63.42	354.7	0.234	0.224	0.233
	(95.14)	(60.61)	(112.6)	(0.0696)	(0.208)	(0.0691)
Search Engine-Search Term-Website Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3180	3180	3180	3180	3180	3180
R-Squared	0.176	0.154	0.179	0.184	0.186	0.194

Notes: An observation is the number of clicks for a website in a two-month period for searches using a speci c trademarked term on a speci c search engine. April+May (combined), July+August (combined) 2009 data. Ordinary Least Squares estimates in Columns (1)-(3). Log-linear estimates in Columns (4)-(6) (Generalized Estimating Equation estimates with population-averaged e ects rather than standard xed e ects). *Google* *TMHolder*, *Google*, *TMHolder* are dropped due to their collinearity with the Search Engine-Search Term-Website xed e ects. Standard errors clustered at search-term level.* $p < 0{:}10$, ** $p < 0{:}05$, *** $p < 0{:}01$

Table A-5: Trademark holders' sites reached through competitor trademarks. Such combinations were not a ected by the policy change.

	Linear Speci cation			Log Speci cation		
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Paid Clicks	Paid Clicks	Total Clicks	Non-Paid Clicks	Paid Clicks	Total Clicks
PostChange Google TMHolderSite	-105.4	-96.54	-201.9	0.0225	5.389	1.623
	(196.1)	(177.6)	(299.6)	(28.48)	(1099.3)	(27.47)
PostChange Google	-28.59	26.19	-2.398	-0.117	0.735	-0.0930
	(90.15)	(39.96)	(98.24)	(0.114)	(0.560)	(0.107)
PostChange TMHolderSite	-179.3	-146.0	-325.3	-0.353	-7.713	-2.171
	(54.84)	(73.52)	(91.67)	(28.47)	(1099.3)	(27.46)
PostChange	140.7	60.60				

Table A-6: Results for trademark holders' sites where the trademark holder forbade third-party sellers from using the trademark as a contractual condition.

	Linear Speci cation			Log Speci cation		
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Paid Clicks	Paid Clicks	Total Clicks	Non-Paid Clicks	Paid Clicks	Total Clicks
PostChange Google TMHolder	-2864.9	-2879.0	-5743.8	-0.825	-0.366	-0.611
	(4966.0)	(3504.4)	(7129.0)	(0.933)	(1.557)	(1.034)
PostChange Google	-177.7	54.89	-122.8	0.320	-0.0488	0.334
	(193.1)	(80.97)	(212.2)	(0.378)	(0.173)	(0.414)
PostChange TMHolder	-3670.8	-1042.1	-4713.0	0.750	-0.495	0.386
	(2679.7)	(1047.6)	(3336.8)	(0.860)	(1.423)	(0.955)
PostChange	-122.5	-9.316	-131.8	-0.350	0.0475	-0.243
	(285.4)	(128.9)	(248.4)	(0.266)	(0.102)	(0.281)
May Indicator	-164.1	-42.80	-206.9	0.156	-0.140	0.134
	(553.0)	(257.1)	(475.8)	(0.255)	(0.119)	(0.253)
Search Engine-Search Term-Website Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	496	496	496	496	496	496
R-Squared	0.414	0.390	0.446	0.218	0.648	0.496

// Notes:

Sample consists of trademark searches for brands that appeared successful at preventing their third-party sellers from advertising (Intercontinental, Courtyard by Marriott, Ritz Carlton, Springhill Suites, Towne Place Suites.) that were excluded from the original sample in Table 2 as the policy change did not apply. Ordinary Least Squares estimates in Columns (1)-(3). Log-linear estimates in Columns (4)-(6). An observation is the number of clicks for a website in a month for searches using a speci c trademarked term on a speci c search engine. April, May, July, August 2009 data. *Google TMHolder, Google, TMHolder* are dropped due to their collinearity with the Search Engine-Search Term-Website xed e ects. Standard errors clustered at search-term level.* $p < 0{:}10$, ** $p < 0{:}05$, *** $p < 0{:}01$