Design of Search Engine Services:  
Channel Interdependence in Search Engine Results  

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January 18, 2016  

Abstract  
The authors examine prominent placement of search engines’ own services and effects on users’ choices. Evaluating a natural experiment in which different results were shown to users who performed similar searches, they find that Google’s prominent placement of its Flight Search service increased the clicks on paid advertising listings by more than half while decreasing the clicks on organic search listings by about the same quantity. This effect appears to result from interactions between the design of search results and users’ decisions about where and how to focus their attention: Users who decide what to click based on listings’ relevance became more likely to select paid listings, while users who are influenced by listings’ visual presentation and page position became more likely to click on Google’s own Flight Search listing. The authors consider implications of these findings for competition policy and for online marketing strategies.  

Keywords: search engines, organic search, sponsored search advertising, user interface, channel substitution  

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The authors are grateful to Susan Athey, Andrei Hagiu, Ian Larkin, Greg Lewis, Michael Luca, Al Roth, and six anonymous referees for helpful comments and discussions, as well as seminar and conference participants at HBS-NOM and CAEC-MIT. We thank ComScore for providing data. Although Edelman advises Microsoft on subjects unrelated to this article and Lai was previously an intern at Microsoft Research, this article was not prepared at the request of, nor funded by any third party. All views expressed here, as well as any errors, are the authors’ own.
Far from their roots providing solely unformatted links to web sites operated by independent publishers, search engines now operate platforms that include their own content within search results (Sullivan, 2012). For example, Google search results include the company’s specialized search services for flights, hotels, images, maps, shopping, videos, and more.¹ Thus, a user searching for a celebrity musician might see not only links to that musician’s web site, fan pages, and media coverage, but also image thumbnails directly within search results, as well as previews of videos available at a single click.

As of 2015, search engines present results drawn from three distinct channels. Search engines are typically best known for organic results which select destinations via crawler-based examination of, in principle, the entire web. Second, paid advertising results link to advertisers that pay to show their offers to users running a given search. Finally, search engine services highlight other offerings from the company that provides the search engine.

As search engine designs change, it is important to understand how these changes influence user interactions. Web sites make significant channel-based investments to obtain both paid advertising and organic search traffic from search engines. For one, search engine optimization adjusts site design and code in hopes of obtaining additional organic traffic from search engines’ algorithms. (See, for example, Berman and Katona, 2013.) In parallel, search engine marketing entails submitting and updating bids in paid advertising auctions. (See, for example, Edelman, Ostrovsky, and Schwarz, 2007.) The market is large: In the US alone, advertisers spent $18.4 billion on search engine optimization and marketing in 2013 (Internet Advertising Bureau, 2014), and reasonable estimates suggest that organic traffic, though unpriced, is at least as valuable. This paper examines users’ online search behavior by exploring how the design of search results influences sorting of search engine users into different channels. This paper also considers implications for the online marketing industry, including for the effectiveness of common practitioner strategies.

Relying on a natural experiment, we consider how the prominent placement of search engine

¹For a partial list of Google’s specialized search services, see: http://www.google.com/about/products. Other search engines, such as Bing and Yahoo, also incorporate their own specialized services into search results.
services affects users’ tendency to click on organic search listings and paid advertising listings. Specifically, we examine a natural experiment in Google’s display of its Flight Search service (henceforth GFS): for a time, Google systematically displayed GFS above the top organic listing in response to certain search queries but not others, based on minor differences in how users expressed their search intent. For example, GFS was reliably displayed in search query results for “flights to Orlando” but not for “flights to Orlando fl” because the former phrasing was identified by Google’s algorithm as associated with a GFS-supported destination whereas the latter was not. We exploit the variation in timing of users’ search queries around the introduction of GFS to conduct a differences-in-differences estimation of its effects, focusing on clicks to the airlines and online travel agents (OTAs) that are the most natural results for the keywords at issue.

This difference-in-differences estimation mitigates a key endogeneity concern—that the display of a search engine’s service is a function not only of the search engine’s exogenous design choices but also of users’ intent and search behavior. We limit possible endogenous variation in users’ intent and search behavior by restricting our analysis to a narrowly-specified set of searches involving unbranded search queries for flights to US destinations. (We ignore branded search queries because GFS did not appear for queries that include keywords specifying a company name within the search phrase, such as “expedia flight to new york.”) In this sample of searches, Google’s assignment of GFS relies on idiosyncratic variation in users’ input of search phrases and is exogenous to factors correlated with users’ propensity to click differentially between paid and organic listings. This approach allows us to infer the causal effect of search engine services on user demand for paid advertising listings and organic search listings that are simultaneously displayed on the search results page. By relying on searches within four months before and after the introduction of GFS, we abstract away from long-run effects that may confound our measurement, such as whether a search engine can influence how users specify search phrases or whether search engine services ultimately affect the brand awareness of OTAs.²

²Over time, reduced prominence may lower clicks for organic and paid listings (Baye, Santos, and Wildenbeest, 2013; Yao and Mela, 2011). During the period of our study, GFS has limited effect on long-run brand awareness of already-popular OTAs.
Our results indicate a shift in user clicks from organic listings to paid listings on Google. Our regression estimates show that the display of GFS results increased the volume of paid clicks by about 65% and decreased the volume of organic clicks by about 55%. Based on cost data from Google Keyword Planner, this shift in incoming site traffic would increase OTAs’ marketing expenditures by about a dollar per click on average. We show that our results are not driven by differential trends in seasonal travel searches using additional data on search volumes, and also that our results are robust to key alternative explanations of our findings.

The literature on search engine marketing suggests several explanations for users’ substitution patterns as a result of design changes. Under an ordered user search process, prominent search engine listings are substitutes for less prominent listings (Armstrong et al., 2009; Athey and Ellison, 2007; Chen and He, 2011). At the same time, the inclusion of an additional listing channel may increase total user demand and clicks on search results (Yang and Ghose, 2010). These cross-channel relationships in user demand are mediated by search engines’ efforts to manage users’ perceptions of each listing channel. For example, Berman and Katona (2013) present a model where, in equilibrium, users expect the organic search channel to offer a higher probability of finding a high quality result in equilibrium, and hence users first examine organic search listings before (perhaps) proceeding to paid advertising listings. Changes to advertisers’ bids can also affect the search engine’s positioning of ads and volume of user clicks (Ghose and Yang, 2009).

We study the underlying mechanisms for observed patterns of interdependence in user demand between search engine services, organic search, and paid listing channels. Using data on the set of advertisers and their respective advertising intensity, we rule out advertising-side explanations by showing that Google’s search algorithm did not systematically alter the ordering and selection of advertisers based on the display of GFS. However, additional analysis shows differences in magnitude of observed GFS effects across OTAs, which suggests that users’ search preferences interact with the display of GFS. In particular, GFS led users to substitute from organic to paid listings in a way that most affected the OTAs which previously presented listings most rel-
evant to users’ queries. In a follow-up experiment on Amazon Mechanical Turk, we confirmed this finding. We find that salience searchers, who prefer to click attention-grabbing listings, were more likely to click on the GFS result when it appeared, whereas relevance searchers, who prefer to click a listing based on its relevance to the query, were more likely to select paid listings when GFS results pushed organic results downwards. In light of these mechanisms, we discuss implications for antitrust policy debate and for internet marketing strategies across a range of industries which rely on traffic from Google and other search engines.

Our results extend a literature examining how users perceive different channels of search results. For example, Hotchkiss, Alston, and Edwards (2005) find that over 75% of participants trust the ordering of organic listings to be an unbiased indicator of quality. In contrast, Jansen (2007) finds that paid advertising listings are often more relevant than organic search listings for e-commerce search queries. We also join a broader line of papers that explore how users interact with search engine results. Blake, Nosko, and Tadelis (forthcoming) measure the response of eBay users to changes in that company’s search engine advertising. Rutz and Bucklin (2012) estimate the effect of spillover between non-branded and branded search on conversion rates, while Jeziorski and Segal (2012) quantify the effect of ad substitutability on the click-through rates of competing ad listings. We add to this literature by examining a search engine’s impact on organic search and paid advertising traffic when it assigns prominent placement to its own services. Finally, our results complement the literature that studies interactions between organic search and paid advertising (Taylor, 2013; White, 2013).

Closest to our paper is Luca et al. (2015) which also tests the effect of Google’s changing search results on traffic to publisher web sites and on user welfare. Where we use a natural experiment, they use something closer to a laboratory experiment: They create screenshots of alternative search results and show these images to users at the UsabilityHub online testing portal. The approaches have varying strengths and weaknesses: Their controlled experiment makes randomization particularly clear-cut, but we are able to assess the actual behavior of real users, which could differ from users in a lab.
Search engine results have evolved from providing paid and organic links to displaying multi-channel offerings that include a search engine’s own services and content. For example, a search engine may display a result that immediately answers a user’s question, such as reporting the time of sunset at a user’s location (left screenshot of Figure 1). Some search engines may also respond to search queries by recommending their own services, such as hotels (right screenshot of Figure 1), image search, maps, restaurants, shopping, videos, and—the focus of this paper—air travel.

**FIGURE 1**
SPECIAL DISPLAY OF SEARCH RESULTS

When a search engine’s own services appear within search results, they typically receive both prominent placement and differentiated visual format. This placement (above the top organic search listing in Figure 1) is usually reserved exclusively for the search engine’s own service. Historically, organic and paid search listings took the format of plain text links. In contrast to those simple “blue links,” search engine services often include unusual layout, color, images and even interactivity. These features attract user attention, allow for greater user engagement, and create an additional channel which search engines may utilize to influence users’ online search behavior.

*Google’s Flight Search Service*

Shortly after acquiring ITA Software, Google launched Google Flight Search (GFS). Initially,
GFS results were available at [http://www.google.com/flights](http://www.google.com/flights). Later in 2011, Google started to show special GFS listings within Google search results. Displayed above organic search listings, GFS listings present air carriers, their respective flight itineraries and price quotes in the format of interactive tables that allow users to check fares on alternative dates and apply custom sorting and filtering. (The left screenshot of Figure 2 shows search results before the change, and the right screenshot of Figure 2 shows search results after the change.) In contrast, organic search and paid advertising listings to other travel services usually appear in the traditional format of one header line and a brief summary, without notable colors or images.

**FIGURE 2**

GOOGLE RESULTS WITH AND WITHOUT GFS

Within Google search results, GFS listings include interactive features that allow users to adjust search criteria (including dates and nonstop versus connecting itineraries), as well as links that point users to landing pages showing the full GFS tool (URLs that begin with “google.com/flights/...”). Once in the GFS tool, a user can invoke additional GFS features such as selecting a specific flight option and clicking a “Book” button to proceed to a chosen travel provider (left screenshot of Figure 3). By clicking the “Book” button, a user avoids reentering flight preferences and instead reaches the travel provider’s site with the desired origin, destination, dates, and flights all pre-
selected. In contrast, organic search and paid advertising listings do not allow interactivity, in this period, and linked to a website’s home page where a user had to reenter travel details (right screenshot of Figure 3).

Google indicates that GFS displays flights based on Google’s assessment of a user’s requirements, and that GFS rates a flight equally whether or not the airline pays to participate in GFS (Gharachorloo, 2011). Instead, it seems that the appearance of the “Book” button is contingent on an airline’s participation in GFS: If an airline participates, the button turns red and works as expected; if not, the button is grey and nonfunctional. Notably, an airline’s participation in GFS is understood to require paying fees, though there may be some exceptions (particularly immediately upon launch).  

At launch, Google indicated that GFS would link the “Book” button only to airlines’ own sites (and not to OTAs).  

FIGURE 3
GFS LANDING PAGE VS. OTA HOME PAGE

Google’s Algorithm for Display of GFS Listings

When Google added GFS listings to search results, it said that GFS listings would appear for flight-related searches specifying origins and destinations that were supported by GFS (Connolly, 2011). To implement this approach, Google’s search algorithms must parse search phrases for a combination of flight-related intent and valid representations of pre-approved origin and destina-

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3Google has not publicly discussed the terms on which airlines participate in GFS. But Google labels GFS as “sponsored,” suggesting that money changes hands. Multiple airlines have told us that they pay to activate their “Book” links or that they were asked to pay.

4Throughout the period we study, GFS “Book” buttons linked to airline sites only. Outside the period we study, Google briefly tested links to some OTAs.
tion keywords.

In practice, users can express their flight intent and location requirements through many idiosyncratic forms, and some but not all random user-generated perturbations of these search phrases will allow the automated algorithm to trigger the display of a GFS listing. (Web Appendix B provides sample search phrases that, in our testing, did and did not trigger GFS.) Google indicates that it utilizes users’ searches to improve its algorithms, although its exact algorithms and methods of parsing search phrases are trade secrets.

Over time, we observed that Google displayed GFS listings for an increasing number of flight-related search queries. For example, Google initially limited the display of GFS listings to search queries with US-based origins and destinations, but added international locations in February 2012. Even for domestic destinations, GFS display conditions broadened; for example, Google initially treated “orlando” but not “orlando fl” as a valid destination for GFS display, but later broadened GFS display conditions to capture both searches. Our sense is that Google started with a relatively narrow “whitelist” of exact matches of exact cities where Google knew GFS could provide flight results. Only later did Google broaden the display conditions to allow perturbations such as the addition of state names and state abbreviations. This focus on exact match to a whitelist is consistent with prior targeting observed for Google’s display of specialized services (Edelman, 2010). One might think of Google’s initial GFS display conditions as needlessly narrow, compared to GFS’s ultimate capabilities and Google’s ultimate implementation. Google’s arbitrarily-imposed initial display conditions appear to be random, at least in the sense that they are uncorrelated with user characteristics and hence, we will argue, facilitate a natural experiment.

METHODOLOGY AND DATA

In this section, we measure whether Google’s display of its GFS listings affected users’ tendency to click on organic search listings and paid advertising listings. Specifically, we examine how the display of GFS listings impacted the volume of clicks to OTAs across different listing
channels.

Research Design

An ideal experiment would rely on random assignment of displaying GFS results across a sample of internet searches. If search results sometimes randomly listed GFS and sometimes randomly did not, we could determine the effect that the design of GFS has on user demand by simply comparing behavior in the two randomly-assigned conditions. With random assignment, we would not worry that a search engine chose the display of its search engine service based on result relevance. Unfortunately, we do not have the ability to run such a randomized experiment on actual search engines. (Some experimenters perform such experiments thanks to their affiliation with search engines (e.g. Reiley, Li, and Lewis (2010)), and search engines often use this method for internal testing. In both cases, this method is limited to answering questions that a search engine wants to study.)

Instead, we rely on a quasi-experiment resulting from Google’s introduction of GFS listings into its search results. Google’s algorithm decides whether to display GFS listings based on the specific phrasing of the users’ search request, and for a time immediately after the introduction of GFS, the algorithm checked for only a portion of the phrases users reasonably chose to express a particular search. For example, a Google search for “flights to orlando” displayed GFS, but a Google search for “flights to orlando fl” did not because the former phrase was identified by Google’s algorithm to be associated with a GFS-supported destination whereas the latter was not. We used multiple user profiles, computers, and locations to verify these patterns at multiple occasions throughout the relevant time period, and Google’s algorithm to display GFS listings appeared to remain constant for the patterns of search terms we examined. In particular, user profile, computer type, and user’s location did not affect whether GFS appeared, but even a small change to the word choice of the search query could make GFS appear or disappear. These differences were systematic and persisted through at least the first four months of 2012.

Within the set of possible flight-related search queries specifying GFS-supported origins and destinations, our analysis relies on the identifying assumption that Google’s classification of
GFS-eligible versus GFS-ineligible search queries is orthogonal to users’ decisions about which site and type of listing to click. Our quasi-experiment helps rule out alternative explanations for users’ clicks. Consider two users who searched for “flights to orlando” and “flights to orlando, fl” respectively. The appendage of “, fl” is effectively random—the sort of addition that some users type almost instinctively. There is little reason to think that users who search for the former term differ systematically from those who search for the latter. If they systematically click different links, we will argue that the difference should be ascribed to the impact of GFS, which in the relevant period appeared for only the former search term and not the latter.

Our quasi-experiment also relies on additional assumptions about advertiser behavior and Google’s approach. First, we assume that OTAs did not change advertising spending after the introduction of GFS. We discuss this assumption later using data on paid advertising exposures.

Next, we assume that advertisers seek to display ads only based on the quality of the match between the advertiser’s content and the user’s intent, i.e. the likely click-through rate and conversion rate. We similarly assume that Google’s incentive to display GFS is only based on attempting a high-quality match with user intent. This rules out both Google and advertisers idiosyncratically seeking to reach users who are more likely to click on ads, but whose search terms otherwise reflect identical search intent. These assumptions are supported by the institutional details surrounding GFS: First, Google does not select GFS results based on whether sites pay to obtain click links in GFS. Second, Google only allowed airlines and not OTAs to place booking links into GFS landing pages during the time period we study, which ruled out OTAs making strategic shifts in marketing budgets and thereby influencing users’ click decisions.

With data on which listings users clicked, we perform a before-and-after comparison of clicks to travel sites across groups of similar searches with idiosyncratic differences in user expression of search queries.

Data

Our primary dataset comes from ComScore Search Planner, a commercial database tracking the online behavior of a panel of internet users. ComScore observes users’ search activities and
tracks both searches and destinations. The panel is understood to be nationally representative and includes adjustments based on panel and census-based weights. ComScore tracks both algorithmic clicks and paid advertising clicks from Google. Our dataset contains clicks on organic listings and on paid listings in a search results page, but does not contain clicks on links within the GFS listing or on links leading out of GFS landing pages.\(^5\) This data includes users’ searches for flights to US destinations during the four months prior to the launch of GFS, from May to August 2011, as well as four months after the launch of GFS, from January to April 2012.\(^6\) The sample of searches included search queries matching Google’s criteria for displaying GFS as well as similar search queries that express the same user intent but did not trigger the display of GFS due to minor variations in search phrase.

We exclude clicks arising from three types of searches in our data sample. First, we omit searches for non-US destinations because GFS added international support significantly later. Second, we omit the four months immediately surrounding the launch of GFS. During this transition period, Google used a variety of GFS result formats and triggering conditions. For example, Google sometimes displayed the GFS result in a sidebar (linked to google.com/flights) while displaying various flight schedule information within the main body of search results (sometimes, but not always, with links to airlines’ sites). These many variations prevent us from assessing whether a GFS result appeared for a given search in this period, removing the exogenous variation that underpins our research design. Third, we only analyze searches involving unbranded search queries for identified travel destinations. Thus, we ignore searches which do not specify a flight destination (e.g. “cheap flights”) or directly specify a desired site (e.g. “Orbitz,” “Jetblue”). We take this approach because generic and branded search queries never prompted the display of GFS during the time period we consider. This exclusion allows us to focus on search queries that state a flight destination; these queries tend to have higher conversion rates (clicks yielding

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\(^5\)When a user clicks on a GFS listing, ComScore records that click using a destination URL that starts with google.com/flights. We omit these GFS clicks and only study traffic flowing from Google to external web properties from links not associated with GFS. During this period, ComScore did not collect (or our ComScore dataset does not provide) reliable data on users’ clicks on paid listings leading out of GFS or embedded inside GFS landing pages.

\(^6\)We did not collect data on searches and clicks during the intermediate period, in which GFS display was in flux.
actual purchases) and hence are particularly valuable to travel sites. Web Appendix A provides instructions for replicating our data construction.

Because a user can enter any search query, there are idiosyncratic variations in phrasing that require us to aggregate over searches. To allow some expression of heterogeneous user intent, we group searches on two dimensions. First, we subdivide searches by the flight destination specified in the search query. As described in Web Appendix A, we divide flight destinations into six geographic regions within the US. Due to data constraints, we are unable to test more granular levels of geographic aggregation. Nevertheless, our grouping of searches allows us to control for some region-specific differences in flight search behavior, such as differences in the online search behavior of business travelers to the northeast versus snowbird vacationers to the southeastern states. We also tested perturbations of these definitions of geographic aggregation, and results were robust to changes.

Second, we classify clicks as being associated with either “GFS-eligible” or “GFS-ineligible” search queries based on the exact wording of the user’s search phrase. To infer Google’s criteria for displaying GFS, we conduct search queries at google.com, both manually and using automation. We tag Google searches as belonging to the GFS-eligible category if a Google search query would trigger the display of a GFS listing after December 2011. Thus, the “treatment effect” of displaying GFS differentially affects groups of searches in our data.

Our dataset consists of the reported traffic volumes for each site for each time period and classification of GFS-eligibility. Of the more than 6 million clicks on organic search results within our sample, 68% of clicks were associated with a GFS-eligible search query. Clicks were roughly evenly distributed across two-month time periods within our sample. Table 1 describes the detailed composition of traffic volumes. Clicks on paid listings constituted slightly more than half of our sample, consistent with the high commercial value of these searches. 93% of clicks led to an OTA, while the rest of clicks led to an airline site. We limit our analysis to 17 popular OTAs which account for about 91% of all clicks. Other OTAs in our sample each received less than 25,000 clicks from search queries matching the patterns we specify.
We augment our primary dataset on click traffic with a secondary dataset containing Google search volumes for each group of search phrases during the time periods of our study. We constructed this dataset from two data sources. First, we used Google Trends to obtain normalized historical search volume patterns for each search phrase in our primary dataset. Next, we used recent search traffic estimates from Google Keyword Planner to match the tail end of each search phrase’s historical trend and to obtain re-scaled estimates of historical search volumes during the time periods of our study. With this common scaling, we aggregate search volume patterns across groups of search phrases. Figure 4 presents trends in total Google search volume for GFS-eligible and GFS-ineligible search queries. We observe that search volumes associated with GFS-eligible and GFS-ineligible search queries follow similar seasonal patterns. There is no apparent differential trend in the volume of searches between groups, nor is there a noticeable change in searches for GFS-eligible queries.

**FIGURE 4**

**GOOGLE SEARCH VOLUME TRENDS**

![Graph showing Google search volume trends for GFS-eligible and GFS-ineligible searches. The graph indicates similar seasonal patterns without a noticeable differential trend or change in search volumes between groups.]

**GFS-eligible vs. GFS-ineligible Search Queries**

In this section, we check Google’s classification of search phrases for apparent differences be-
between groups of GFS-eligible versus GFS-ineligible search queries. This provides support for our empirical strategy, which requires groups of search queries to be comparable except for phrasing differences exogenous to user intent.

Table 2 reports the average query length for GFS-eligible and GFS-ineligible search queries. While imperfect, we use query length as a proxy for the amount of detail conveyed by the search phrase. We infer that searchers in our sample are relatively close to purchase because the dataset consists only of specific queries which are fairly descriptive (average query length of about six words). Average query length is similar for GFS-eligible and GFS-ineligible searches. (The difference is less than a single word and less than one standard deviation.) A comparison of keywords also suggests that both groups of queries entail similar user intent. In both groups, about 40 percent of search phrases express user intent for competitive pricing by including “cheap” or “deal,” and about 1 percent of search phrases express desire for “non stop.”

Table 3 provides examples of GFS-eligible and GFS-ineligible search queries. Although the phrasing differs, manual examination of search phrases shows that search intent is virtually identical. For example, as the first row suggests, the display of GFS results are triggered when a user queries “flights from <US city name> to <US city name>” but not for “flights from <US state name> to <US city name>.” One concern is that GFS-ineligible search queries may not contain exact destinations in the search phrase and hence reflect searchers with less intention to purchase. Table 4 reports the number of search phrases for each region in our traffic sample. About 70% of GFS-ineligible queries include search phrases with exact destinations. This suggests that GFS-eligible queries are not selected on the basis of search phrase specificity. To showcase the lack of apparent systematic difference between GFS-eligible and GFS-ineligible queries, Table 5 presents example search phrases that were used in queries for flights to Tampa Bay, Florida.

We next check whether queries classified as GFS-eligible are comparable to queries classified as GFS-ineligible based on differences in what users click. Table 6 reports a logistic regression of the probability that the search query entered during the pre-GFS period (May to August 2011) was eventually classified as being GFS-eligible. Although GFS-eligible queries account for about
twice as many clicks and searches as GFS-ineligible queries (since Google’s algorithm correctly identifies user intent for the majority of flight-related search queries), we see in Column 1 that GFS-eligible and GFS-ineligible queries are not statistically different in their pre-GFS probabilities of users clicking on paid listings. Column 2 adds a supplementary dataset of ad exposures for each group of searches. With this addition, we check whether Google classified GFS-eligible and GFS-ineligible queries according to whether they were likely to lead to sites for which users were exposed to a high volume of paid advertising at search engines. GFS-eligible and GFS-ineligible queries are not statistically significantly different in their probability of a user visiting a site within the top half of advertising exposures, either via an organic search or paid advertising listing. Column 3 shows that this result holds when controlling for the flight destination stated in the search query.

To examine if the selection of GFS-eligible groups is orthogonal to users’ click-through behavior in our sample, we analyze whether treatment and control groups have similar click-through rates (CTR) prior to the GFS period. We divide the organic and paid clicks from our primary dataset by the search volume from our secondary dataset to calculate organic and paid CTR for each group of search queries. Table 7 shows that the GFS-ineligible and GFS-eligible groups of searches have similar organic and paid CTR in periods before GFS launch. (Figure 5 shows that differences between treatment and control groups are within bounds of 2 standard errors.) While our dataset is restricted to specific search queries of similar intent, overall findings are consistent with Google’s display of GFS results being exogenous to factors related to users’ click decisions.

RESULTS

The click dataset illustrates how the display of GFS results impacted relative traffic volumes to individual sites from organic and paid listings. Figure 6 provides a visual representation. The panels present total clicks to OTAs within our ComScore sample, with and without the display of GFS results. The dark bars denote traffic from paid listings, while the light bars denote traf-

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7We also compare CTRs using a t-test and find that differences are statistically insignificant across GFS-ineligible and GFS-eligible groups.
fic from organic listings. Searches with GFS results (in the period when GFS appeared, for keywords that trigger GFS) are associated with a higher proportion of web traffic from paid listings. For example, Orbitz received about 225,000 clicks from organic listings and 10,000 clicks from paid listings when GFS results were not displayed, a ratio of about 22:1. When GFS results were displayed, Orbitz received about 70,000 clicks from organic listings, compared to 35,000 clicks from paid listings, making the ratio approximately 2:1. In short, the introduction of GFS greatly skewed the composition of incoming traffic from an unpaid channel to a paid channel.

The change in users’ propensity for clicking across paid and organic listing channels is particularly apparent in Figure 7. The shaded region indicates the period during which GFS was gradually introduced. We normalize clicks to individual OTAs, dividing by the total clicks generated by each group of search queries. The dashed line presents the average difference in clicks between GFS-eligible and GFS-ineligible queries for the OTAs in our sample. This difference becomes negative (More organic clicks from GFS-ineligible searches than organic clicks from GFS-eligible searches) after Google began to display GFS results. Meanwhile, paid listings show the opposite pattern. The solid line shows an increase in clicks for paid listings on GFS-eligible
searches, relative to ineligible searches. The comparison of trends across the dashed and solid line indicates that introducing GFS led to user substitution from organic to paid listings.

**Regression Analysis**

With data on traffic volumes to OTAs over time, we use a difference-in-difference approach to estimate the causal effect of displaying GFS on users’ choices of which listings to click. We regress the number of clicks to OTA listings on Google’s display of GFS results. To control for cross-sectional heterogeneity, we include fixed effects for each group of searches (partitioned along the dimensions of website $i$, flight destination region $j$, and GFS-eligibility $k$). These fixed effects allow for a consistent estimate of GFS impact when the differences in expected group-level errors remain correlated with unobserved components of user intent. We include dummy variables for each two-month period $t$ in our sample, which controls for time-varying factors such as seasonal differences in search advertising expenditures and users’ purpose for traveling, both of which may be correlated with users’ search intent.
Identification relies on Google’s differential treatment across similar searches in its GFS display criteria and on the discrete change when GFS was introduced in search results. In the following specification, we interpret the interaction $\beta$ as measuring the causal effect of GFS results on clicks to OTAs’ organic search and paid advertising listings:

$$\log(\text{Clicks}_{ijk}) = \beta(\text{GSeligible}_k) \times (\text{GFSintroduced}_t) + \text{FE}_{ijk} + \text{Time}_t + \epsilon_{ijk}$$

Column 1 of Table 8 report our estimates of $\beta$ in regressions of the logarithm of the number of paid clicks. On average, the display of GFS results increased the number of paid clicks to OTAs by 70%. Column 2 reports the same regression on paid CTR (calculated using number of searches in each group from Google Trends and Keyword Planner data). The display of GFS results increased paid CTR by about 64%, showing that a large portion of our result is not driven by a post-introduction increase in search volume for GFS-eligible search phrases.

Column 3 of Table 8 report estimates of $\beta$ from a similar difference-in-difference regression of the logarithm of the number of organic clicks. The display of GFS results decreased the num-
ber of organic clicks to OTAs by 46%. In column 4, a similar regression reports that GFS results decreased organic CTR by about 66%. Clustering standard errors at the level of site and destination region, all estimates are statistically significant at the 5% level or less. Overall, Table 8 indicates that the net impact of displaying GFS results was to encourage user substitution from organic search clicks to paid advertising clicks, shifting the resulting composition of traffic to OTAs.

**Robustness checks**

Our identifying assumption requires us to consider unobserved factors that may explain why users prefer to click paid listings and that are also correlated with Google’s display of GFS results. One possibility is that Google modified its search algorithm to complement GFS results with the simultaneous display of paid listings, promoting OTAs that were systematically trending up in paid traffic over time. Another possibility is that Google distinctively displayed GFS results on searches for flight destinations that were expected to be in high seasonal demand, and that holiday travelers who searched for flights to these destinations were more likely to be attracted to click on paid listings. A third concern is that the GFS effect on clicks was driven by differential seasonal trends in online searches or in online advertising between GFS-eligible and GFS-ineligible search phrases. We check the robustness of our results by expanding our regression specification to include interactions of time-period dummy variables by website and by flight destination:

\[
\log(\text{Clicks}_{ijkt}) = \beta(GFSelelgible_k) \times (GFSinroduced_t) \\
+ FE_{ijk} + \text{Site}_i \times \text{Time}_t + \text{Region}_j \times \text{Time}_t + \epsilon_{ijkt}
\]

Columns 1 and 3 of Table 9 report our estimates of \(\beta\) using this expanded specification. When we add controls to account for destination and site-specific, time-varying unobservables, the effect of displaying GFS results remains statistically significant. The magnitude of the GFS effect

\[8\text{We also tried clustering standard errors by pre and post periods to allow for potential advertising strategy changes due to GFS. Estimates remain statistically significant at the 5\% level or less.}\]
also increases, showing that our earlier estimates were conservative: Clicks increase by 76% on paid listings and decrease by 62% on organic listings, compared to earlier estimates of 70% and 46% from Table 8.

Next, we use our supplementary dataset of ad exposures to control for the total number of paid listings viewed by users across each time period and group of search queries. This addresses the possibility that Google may have endogenously affected the number of paid listings, for example by choosing whether to display paid ads across different search queries. Columns 2 and 4 of Table 9 show that the effects of GFS remain robust when we consider differences in the number of ads displayed in search results.⁹

Finally, we check if our results arise due to corresponding seasonal patterns either in the volume of travel-related searches or in the volume of Google advertising purchased by OTAs. Although search and advertising volumes may vary seasonally for travel-related queries, we examine whether the assumption of parallel trends is violated between GFS-eligible and GFS-ineligible queries. We focus on differential changes in advertising spending across queries because any post-GFS aggregate change is indistinguishable from seasonal patterns in travel advertising.¹⁰ We test this hypothesis by running regressions using the same difference-in-difference setup on Google search volumes and on OTA’s ad exposures across groups of GFS-eligible and GFS-ineligible queries during the time periods before and after the introduction of GFS:

\[
\log(\text{Searches}_{jkt}) = \beta(GF\text{Seligible}_k) \times (GF\text{Sintroduced}_t) + FE_{jk} + Time_t + \varepsilon_{jkt}
\]

\[
\log(\text{AdExposures}_{ijkt}) = \beta(GF\text{Seligible}_k) \times (GF\text{Sintroduced}_t) + FE_{ijk} + Time_t + \varepsilon_{ijk}
\]

Column 1 of Table 10 reports our estimate of \( \beta \) in a regression of the logarithm of the number of Google searches. If seasonal trends in searches on GFS-eligible search phrases drive the GFS effect on clicks, we would expect to observe a positive significant coefficient on \( \beta \). The lack of a significant coefficient indicates that seasonal trends do not cause the GFS effects we analyze.

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⁹In Table 9, regressions on paid and organic CTR remain similarly robust.

¹⁰Unfortunately we lack data to examine post-GFS changes in SEO activity.
Likewise, column 2 of Table 10 reports our estimate of \( \beta \) in a regression of the logarithm of the number of ad exposures by each OTA. The lack of a significant coefficient indicates that seasonal trends in online advertising do not drive the GFS effect on clicks and CTR. In summary, these checks are consistent with our interpretation of the GFS effect as evidence of a shift in user clicks from an organic listing channel to a paid listing channel.

**HOW SEARCH RESULT DESIGN AFFECTS SEARCH ENGINE TRAFFIC**

Having established the observed shift in user clicks from organic to paid listings, we now investigate mechanisms that might explain this effect. In a model of sequential user search, we expect the volume of organic clicks to decrease because Google’s display of GFS results pushes organic listings downwards, below other prominent listings that users would likely consider first. For paid listings, the volume of paid clicks can increase or decrease depending on advertising changes and advertiser participation as well as user preferences and substitution patterns between listing channels. To assess these possibilities, we first examine evidence for synchronous changes to keyword auctions and bids from advertising-side channels. Next, we consider how the display of GFS results influences the search behavior of different segments of users and how this may correlate with heterogeneous effects observed across OTA brands.

**Advertising-Side Channels**

We first explore whether Google’s introduction of GFS in search results was accompanied by changes to the selection and ordering of paid listings shown. For example, Google could have changed its search algorithm to show a different set of advertisers whenever GFS was displayed. Advertisers could also have responded to the display of GFS by re-assembling their portfolio of sponsored keywords or by re-allocating bids and advertising budgets within their keyword portfolio.

The top two panels of Figure 8 lists the ten top OTAs by their share of paid listing exposures after the introduction of GFS (January to April 2012). From our supplementary dataset of ad exposures for these queries, we calculate these shares by normalizing each OTA’s ad exposures
against the total volume of ad exposures across all OTAs.\textsuperscript{11} Nine out of the top ten advertisers remain the same across GFS-eligible and GFS-ineligible queries, and the relative frequency of having a paid listing shown is ordered in a similar fashion across the two sets of advertisers. The bottom two panels of Figure 8 reveal that the relative frequency of showing a paid listing is also ordered in a similar fashion before and after the introduction of GFS. These comparisons indicate that Google’s search algorithm did not systematically differ in its display of paid listings across treatment and control groups. As seen from the insignificant coefficient in Column 2 of Table 10, OTA brands did not respond to GFS either by increasing advertising levels to substitute paid clicks for organic clicks, or by decreasing advertising levels on queries facing competition from GFS. These advertising patterns are consistent with an interpretation that rules out changes in paid listing results as the primary reason for the increase in paid clicks.

\textbf{FIGURE 8}
\textit{COMPARISON OF ADVERTISERS ACROSS QUERIES}

\textsuperscript{11}These ad exposures refer to paid links shown anywhere on the page (excluding sponsored links within GFS). We cannot adjust for the position of these ad exposures because we do not have data on rankings.
User Search Behavior and Preferences for OTA Brands

We now use our research design to explore whether different user search preferences are associated differentially with the GFS effects we reported above. If advertising-side channels remain fixed, our quasi-experiment introduces two sources of exogenous variation into Google search results. First, users now have the added option to click on GFS listings. Second, users’ click decisions are affected by the decreased prominence of organic listings. Linking user search preferences with their responses to these display changes allows us to better understand the mechanisms causing the observed user substitution patterns.

Several mechanisms could cause the display of GFS results to yield a lower volume of clicks on both organic and paid listings. For example, GFS results may take clicks from competing listings using differentiated visual features that capture users’ attention. Users may also infer that GFS is of a higher quality than other travel sites based on the lowered position of organic listings on the search results page. If user preferences for this position-implied quality is high, the display of GFS results may lead to a lower volume of clicks on OTAs’ organic listings and, by brand association, their paid listings as well.

Alternatively, the display of GFS could cause an increase in volume of OTA paid clicks if users infer the quality of travel sites based on the relevance of listing destination to query intent. An example of this occurs if organic and paid listings contain similar content, i.e. promoting the same sites, making them close substitutes for each other. When the display of GFS results makes an OTA’s organic listing less prominent by pushing it down the page, users with a strong preference for that listing (and its relevance-implied quality) would substitute to the OTA’s paid listing. The OTA’s volume of paid clicks would increase if the net substitution effect to paid listings is stronger than the substitution effect to the GFS result.

In addition, a search preference for relevance-implied quality would suggest that the volume of paid clicks will increase most at brands which primarily attract users by offering the listings

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12The experiment in Blake, Nosko, and Tadelis (forthcoming) suggests that paid and organic listings to the same site can be close substitutes. In removing paid listings on searches containing the phrase “eBay,” users substituted almost completely to clicking eBay’s organic listings.
that are most relevant to users’ queries. Conversely, this hypothesis would predict the smallest effect on OTAs which focus on attracting users through prominent paid listings. We examine this hypothesis by dividing OTAs in the treatment group according to three categories:

- **Organic**: Airfarewatchdog, Cheapflights, Cheaptickets, Expedia, Farecompare, Tripadvisor
- **Balanced**: Cheapoair, Kayak, Orbitz, Priceline, Travelocity
- **Paid**: Bookingbuddy, Farespotter, Lowfares, Onetravel, Travelzoo, Tripmama

Within our sample of search queries, we classify OTAs using a proxy for their relevance-implied quality based on their ratio of organic to total clicks received during the months before the introduction of GFS. On travel-related queries, Google search results displayed both organic and paid listings for the seventeen popular OTAs in our sample, and OTAs that received a higher ratio of organic to total clicks were positioned more prominently in Google’s organic listings relative to the OTA’s total exposure in search results. Category assignments are also consistent with the heterogeneity in observed GFS effects across brands as shown in Figure 6.

Table 11 present results from the regressions in columns 1 and 3 of Table 8, expanded to separate out the treatment effect by our classification of organic, balanced, and paid OTAs. Consistent with our hypothesis, the effect of displaying GFS results is strongest for organic OTAs: These sites lost about 75% of organic clicks while increasing paid clicks by more than 200% (although having a smaller base of paid clicks by definition). Only the effect on paid clicks was statistically significant for balanced OTAs, while effects on both organic and paid clicks were statistically insignificant for paid OTAs. Although some of the coefficients are statistically insignificant (largely due to fewer observations), we observe that the magnitude of coefficients on the GFS effect is ordered similarly to our proxy for relevance-implied quality. These estimates indicate that the display of GFS affects user substitution patterns primarily through users who are less influenced by listings’ visual presentation and position in search rankings, but who evaluate the sites displayed on the relevance of the search result listing to their query.

*User Substitution Patterns: An Experiment on Amazon Mechanical Turk*

To collect additional data on the mechanism behind the observed user substitution effect,
we construct a controlled environment that allows us to link users’ preferred method of parsing search results with their decisions about which link to click. We conduct our experiment on Amazon Mechanical Turk (MTurk), an online labor platform. (See Goldstein et al. (2014) for another example of use of MTurk in research on online advertising.) Notably, our experiment mimics the layout of the GFS natural experiment. (See screenshots in Figure 9.)

**FIGURE 9**
SEARCH RESULT LAYOUT IN EXPERIMENTS

The experiment begins with a screenshot of search results for a flight search. We ask the user to envision needing to buy a plane ticket for the specified destination, and we ask the user to click the listing that he/she would select in that circumstance. Half of the participants saw a treatment with GFS results, while the other half saw no GFS results. The algorithmic and paid results were identical. We then ask participants to answer questions to explain their search preferences and prior search experience. Our analysis includes a total of 300 MTurk participants. We restricted the task to US-based participants. Web Appendix C presents additional details about the experimental setup.

Notably, one question provides participants with a list of statements containing possible reasons for their choice, asking them to assess whether each statement correctly captures their reas-
soning. Statements include:

(A) I clicked this because it captured my attention the most
(B) I clicked this because it was the most useful link to get me where I want to go

Based on participants’ stated search preferences, we divide respondents into two groups. We identify 45 respondents who assign a strictly higher score to (A) over (B); these are salience searchers who are more likely to be affected by visually prominent search listing features. We also identify 175 respondents who assign a strictly higher score to (B) over (A); these are relevance searchers who are more likely to make click decisions based on the relevance of search result listings to their query.  

Table 12 reports the fraction and number of respondents contained within each bucket of our experiment. For salience searchers, the display of GFS results reduced the probability of choosing a paid listing from 59.1% to 17.4% (statistically significant at the 1% level). Salience searchers were likely to substitute to the GFS channel and we find, from the subsequent survey, that salience searchers who clicked on GFS results were more likely to indicate that GFS is a paid rather than organic link. For relevance searchers, the display of GFS reduced the probability of choosing an organic listing from 95.7% to 63.4% (also significant at 1%). Relevance searchers were about half as likely as salience searchers to substitute to GFS (29.3% for relevance searchers versus 56.5% for salience searchers) and although statistically insignificant, we observe a small increase in the probability of choosing a paid listing (from 4.3% to 7.3%). This substitution pattern for relevance searchers was similar in direction to the GFS effect observed in our quasi-experiment.

Table 13 reports additional results on these substitution patterns across searcher types based on participants’ prior experience purchasing plane tickets on OTA sites. We classify participants

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13We drop 77 respondents who assigned equal scores to (A) and (B) and three respondents who skipped this question.
14We evaluate statistical significance using a logistic model with a dependent variable of respondents’ choice of listing, regressed on whether GFS was displayed.
15Participants would be more familiar with GFS by the time of our experiment (three years after GFS introduction). This may have led to more clicks on the GFS result.
as “experienced” users if they indicated that they previously bought plane tickets at an OTA site displayed in our experiment, and as “inexperienced” users if they did not.\textsuperscript{16} Substitution patterns are similar across our sample of experienced and inexperienced users both for salience and relevance searchers. Salience searchers who saw GFS results became less likely to click paid listings whether they were experienced (from 50.0\% to 18.2\%) or inexperienced (from 62.5\% to 16.7\%). Relevance searchers who saw GFS results became more likely to click paid listings whether they were experienced (from 3.5\% to 6.8\%) or inexperienced (from 5.6\% to 7.9\%). This suggests that the GFS effect is likely to persist over time, and will not drop as user experience increases, so long as participants’ search preferences do not change. Overall, our online experiment indicates that GFS most increases the paid clicks of users who consider search result relevance when deciding which listings to click.

\textbf{IMPLICATIONS AND CONCLUSION}

Based on actual behavior from a large panel of internet users, we document patterns of interdependent traffic flows across search engine services, organic search, and paid listing channels. Our analysis of substitution patterns indicates that users’ preferences for method of search are correlated with users’ responses to the display of search engine services within search results. We reach three broad conclusions about the effects of search result design on web traffic flows and about the users who favor each listing channel.

First, search engines have significant influence over salience searchers, as the layout and format of search results significantly influence the destinations these users visit. Control over search result page layout and format thus allows a search engine to influence whether salience searchers discover competing sites, and this power could be used to impede competitors’ access to users. Among the proposed requirements recently proposed in European Commission investigation of Google for possible competition violations, the EC proposed to require that Google more clearly label its own services as paid offerings (European Commission, 2013). But our results

\textsuperscript{16}We cannot classify participants based on their prior experience with GFS because we did not request that information from participants.
suggest that this approach may be ineffective. For one, most salience searchers who select GFS already view them as paid offerings rather than organic search, suggesting that the label would not change the information available to them and thus would not change their click patterns. Furthermore, for these salience searchers, the prominence of a search result plays the strongest role in decisions about which listing to click, regardless of whether searchers have past experience visiting and purchasing at less prominently displayed options. Notably, these effects hold even for established firms with known brands.

Second, understanding users’ substitution patterns can help explain seemingly-surprising outcomes. At first glance, it might seem odd for the insertion of GFS to cause a large increase in paid clicks; after all, GFS appears in the portion of the page where algorithmic links previously appeared, and the paid advertising section remains unchanged when GFS is added. But our analysis and AMT experiment reveal relevance searchers who examine search results by assessing a listing’s relevance to the searcher’s query. The substitution patterns of these relevance searchers explain why the addition of GFS causes an increase in clicks on paid listings: These users found the paid links more relevant than GFS, and moved their clicks accordingly. More generally, this divergence in user behavior suggests that heterogeneity in user search behavior should be considered in models that optimize the selection, ordering, and pricing of search results. (See, for example, Katona and Sarvary (2012).) Also, our analysis suggests that labeling search engine services more clearly as paid offerings may not lead relevance searchers back to the organic search channel; rather, it may divert more traffic to paid listings. While available data offers limited insight into the full welfare effects of such a labeling requirement, our results make clear that obscuring, reducing, or otherwise deemphasizing organic search listings brings direct cost increases to commercial sites, which must then pay for traffic they previously received from organic links without charge. These industry-wide cost increases may be passed back to users through higher prices when firms jointly optimize their price-setting and advertising expenditures (Dorfman and Steiner, 1954), and could also deter entry (Katz, 2011; Stoppelman, 2011).17 While our analy-

17In Senate testimony, Yelp CEO Jeremy Stoppelman and Nextag CEO Jeffrey Katz indicated that their companies would not have launched if Google was using these practices to display its own search engine services at the time
sis operates in the context of flight search, the same reasoning applies in the myriad other sectors that receive traffic from search engines, including all manner of e-commerce sites.

Third, our findings should shape online marketing strategy for sites that rely on search engine traffic. Historically, many online marketers relied both on search engine optimization as well as keyword advertising. As search engines shift traffic towards their own services, online marketers must re-optimize their efforts and consider the changing selection of search engine users who click on organic search and paid listings. Our research suggests that search engine services are well-positioned to capture a disproportionate share of salience searchers, and that independent sites will mostly reach relevance searchers but, even then, primarily on a paid basis. Online marketers may want to change their ad targeting strategies, adjust the content of their landing pages to serve a differing mix of users, and revise their valuations of clicks from each listing channel. Online marketers may also develop new strategies to engage salience searchers, particularly in industries where both sites and users have access to new search engine listing channels. Our measurement establishes that the introduction of Flight Search into Google search results led to sizeable traffic volume changes for US-based OTAs, and we expect these effects to have an even larger impact on OTA marketing strategies in Europe, where travelers rely more heavily on Google and less on OTAs in their online search for flight tickets.\(^\text{18}\)

Further research should build deeper understanding of these implications. Our empirical work is limited in part by our lack of clickstream-level user data. With full observation of such a panel, researchers could identify more specific user-level search strategies, allowing additional analysis of the effect of search result design on search and welfare. Meanwhile, our MTurk experiment suggests possible extensions, including showing users alternative result pages in an experimental context. Through both passive monitoring panels and active experiments, future research could usefully assess the extent to which search result design influences users, and investigate if and how users’ search preferences adapt over time.

\(^{18}\text{PhoCusWright (2011) report that European travelers are less familiar with OTAs and that over half of travelers in France, Germany and the UK visit general search sites when shopping for flights. The report also notes that Google’s market share in Europe is significantly higher than in the US.}^{18}\)
References


# Tables

### TABLE 1
COMPOSITION OF GOOGLE SEARCHES

<table>
<thead>
<tr>
<th>Sample of Google Searches</th>
<th>All Searches</th>
<th>GFS-eligible</th>
<th>GFS-ineligible</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Clicks:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>total</td>
<td>6,789,299</td>
<td>4,648,012</td>
<td>2,141,287</td>
</tr>
<tr>
<td>Paid Clicks Only:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>total</td>
<td>3,127,869</td>
<td>2,302,005</td>
<td>825,864</td>
</tr>
<tr>
<td>by time period</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1/2012-2/2012</td>
<td>949,633</td>
<td>740,309</td>
<td>209,324</td>
</tr>
<tr>
<td>3/2012-4/2012</td>
<td>865,329</td>
<td>720,700</td>
<td>144,629</td>
</tr>
<tr>
<td>Organic Clicks Only:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>total</td>
<td>3,661,430</td>
<td>2,346,007</td>
<td>1,315,423</td>
</tr>
<tr>
<td>by time period</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1/2012-2/2012</td>
<td>722,104</td>
<td>386,473</td>
<td>335,631</td>
</tr>
<tr>
<td>3/2012-4/2012</td>
<td>745,541</td>
<td>416,875</td>
<td>328,666</td>
</tr>
<tr>
<td>By Destination:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>“popular” OTAs</td>
<td>6,165,021</td>
<td>4,152,925</td>
<td>2,012,096</td>
</tr>
<tr>
<td>other OTAs</td>
<td>182,063</td>
<td>126,187</td>
<td>55,876</td>
</tr>
<tr>
<td>airline sites</td>
<td>442,215</td>
<td>368,900</td>
<td>73,315</td>
</tr>
</tbody>
</table>

### TABLE 2
QUERY CHARACTERISTICS

<table>
<thead>
<tr>
<th></th>
<th>GFS-eligible</th>
<th>GFS-eligible</th>
<th>GFS-eligible</th>
<th>GFS-eligible</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>sd</td>
<td>mean</td>
<td>sd</td>
</tr>
<tr>
<td>All Search Queries:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. of words in search query</td>
<td>5.46</td>
<td>(1.38)</td>
<td>6.02</td>
<td>(1.88)</td>
</tr>
<tr>
<td>Including “cheap”, “deal”:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. of words in search query</td>
<td>5.76</td>
<td>(1.35)</td>
<td>5.88</td>
<td>(1.77)</td>
</tr>
<tr>
<td>share of search queries</td>
<td>.418</td>
<td>.399</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Including “non stop”:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>no. of words in search query</td>
<td>6.55</td>
<td>(1.43)</td>
<td>5.94</td>
<td>(1.78)</td>
</tr>
<tr>
<td>share of search queries</td>
<td>.011</td>
<td>.014</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### TABLE 3
EXAMPLES OF GFS-ELIGIBLE VS. GFS-INELIGIBLE QUERIES

<table>
<thead>
<tr>
<th>GFS-eligible queries</th>
<th>GFS-ineligible queries</th>
</tr>
</thead>
<tbody>
<tr>
<td>flights from atl to dallas tx</td>
<td>flights from nj to houston tx</td>
</tr>
<tr>
<td>plane ticket to vegas</td>
<td>plane ticket to vegas discount</td>
</tr>
<tr>
<td>austin to nyc flights</td>
<td>nebraska to new york flight</td>
</tr>
<tr>
<td>flights to green bay from miami</td>
<td>flights to kansas from sf</td>
</tr>
<tr>
<td>direct flight from portland, maine to orlando</td>
<td>direct flights to miami from michigan</td>
</tr>
<tr>
<td>cheap flights from sfo to san</td>
<td>cheaper flights from sfo to san</td>
</tr>
<tr>
<td>cheap airline tickets from omaha ne to los angeles</td>
<td>cheap tickets from salt lake intl to philadelphia intl</td>
</tr>
<tr>
<td>cheap tickets to washington dc</td>
<td>cheap airline tickets to california</td>
</tr>
<tr>
<td>cheap flights to phoenix from baltimore</td>
<td>cheap flights to massachusetts</td>
</tr>
<tr>
<td>fly from detroit to new orleans</td>
<td>dirt cheap flights from chicago to atlanta</td>
</tr>
</tbody>
</table>

*As of January 2013. Search queries are not case-sensitive.*

### TABLE 4
SEARCH PHRASE SAMPLE STATISTICS

<table>
<thead>
<tr>
<th>Region</th>
<th>GFS-eligible queries</th>
<th>GFS-ineligible queries</th>
<th>(% exact destinations)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All search phrases</td>
<td>All search phrases</td>
<td>Only exact destinations</td>
</tr>
<tr>
<td>Midwest</td>
<td>257</td>
<td>189</td>
<td>142</td>
</tr>
<tr>
<td>Mountain West</td>
<td>399</td>
<td>268</td>
<td>213</td>
</tr>
<tr>
<td>Northeast</td>
<td>479</td>
<td>273</td>
<td>188</td>
</tr>
<tr>
<td>Pacific West</td>
<td>429</td>
<td>368</td>
<td>242</td>
</tr>
<tr>
<td>Southeast</td>
<td>661</td>
<td>638</td>
<td>463</td>
</tr>
<tr>
<td>Southwest</td>
<td>241</td>
<td>166</td>
<td>123</td>
</tr>
<tr>
<td>Total</td>
<td>2466</td>
<td>1902</td>
<td>1371</td>
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<tr>
<td>GFS-eligible queries</td>
<td>GFS-ineligible queries</td>
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<tr>
<td>-----------------------------------------------</td>
<td>-------------------------------------------------</td>
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<td>cheap flight to tampa</td>
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<td></td>
<td></td>
</tr>
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<td>cheap flights to tampa</td>
<td>cheap flights to tampa, fl</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cheap flights to tampa bay</td>
<td>cheap one way flights to tampa</td>
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<td></td>
</tr>
<tr>
<td>cheap flights to tampa florida</td>
<td>cheap airline tickets to tampa fl</td>
<td></td>
<td></td>
</tr>
<tr>
<td>cheap tickets to tampa florida</td>
<td>cost of tickets to fly to tampa bay</td>
<td></td>
<td></td>
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<tr>
<td>flights from chicago to tampa, florida</td>
<td>flights from chicago to tampa, fl</td>
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<td></td>
</tr>
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<td>flights from newark to tampa</td>
<td>flights to tampa</td>
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<td></td>
</tr>
<tr>
<td>flights to tampa</td>
<td>flights to tampa, fl</td>
<td></td>
<td></td>
</tr>
<tr>
<td>nyc to tampa flights</td>
<td>flights to tampa bay fl</td>
<td></td>
<td></td>
</tr>
<tr>
<td>flights to tampa florida from dfw</td>
<td>flights tampa fl from shreveport, la</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

As of January 2013. Search queries are not case-sensitive.

<table>
<thead>
<tr>
<th>Probability Query is GFS-eligible</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Search led to click on paid listing</td>
<td>.683</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.44)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Search led to click on organic listing to low advertising website</td>
<td>.811</td>
<td>.925</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-.59)</td>
<td>(-.20)</td>
<td></td>
</tr>
<tr>
<td>Search led to click on organic listing to high advertising website</td>
<td>1.650</td>
<td>1.301</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(.74)</td>
<td>(.48)</td>
<td></td>
</tr>
<tr>
<td>Search led to click on paid listing to high advertising website</td>
<td>.412</td>
<td>.520</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.14)</td>
<td>(-.97)</td>
<td></td>
</tr>
<tr>
<td>Region FEs for flight destination</td>
<td>no</td>
<td>no</td>
<td>yes (not significant)</td>
</tr>
</tbody>
</table>

Note: An observation is a Google search during May to August 2011, in the period before GFS was introduced. Reported values are odds ratios from a logistic regression on probability that the search query used was later classified by Google as GFS-eligible. T-statistics in parenthesis are calculated from robust (White) standard errors, clustered at level of website and one of six US geographic regions for flight destination. Asterisks indicate * p<.10, ** p<.05, *** p<.01.
### TABLE 7
DESCRIPTIVE STATISTICS OF PRE-PERIOD CLICK-THROUGH RATES

<table>
<thead>
<tr>
<th></th>
<th>Organic CTR</th>
<th>Paid CTR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GFS-ineligible</td>
<td>GFS-eligible</td>
</tr>
<tr>
<td>mean</td>
<td>.079</td>
<td>.054</td>
</tr>
<tr>
<td>s.d.</td>
<td>.128</td>
<td>.093</td>
</tr>
<tr>
<td>mean</td>
<td>.058</td>
<td>.054</td>
</tr>
<tr>
<td>s.d.</td>
<td>.098</td>
<td>.087</td>
</tr>
</tbody>
</table>

### TABLE 8
CLICK TRAFFIC TO ONLINE TRAVEL AGENTS

<table>
<thead>
<tr>
<th>Dependent variable (in logs):</th>
<th>Paid clicks</th>
<th>Paid CTR</th>
<th>Organic clicks</th>
<th>Organic CTR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>GFS result displayed</td>
<td>.700**</td>
<td>.644**</td>
<td>-.459**</td>
<td>-.655***</td>
</tr>
<tr>
<td></td>
<td>(.315)</td>
<td>(.294)</td>
<td>(.221)</td>
<td>(.219)</td>
</tr>
<tr>
<td>Dummy Variables: Time</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>July to August</td>
<td>.304</td>
<td>.355</td>
<td>.088</td>
<td>.060</td>
</tr>
<tr>
<td></td>
<td>(.238)</td>
<td>(.226)</td>
<td>(.161)</td>
<td>(.163)</td>
</tr>
<tr>
<td>January to February</td>
<td>.139</td>
<td>.069</td>
<td>.169</td>
<td>.181</td>
</tr>
<tr>
<td></td>
<td>(.329)</td>
<td>(.334)</td>
<td>(.188)</td>
<td>(.192)</td>
</tr>
<tr>
<td>March to April</td>
<td>.393</td>
<td>.324</td>
<td>.197</td>
<td>.187</td>
</tr>
<tr>
<td></td>
<td>(.338)</td>
<td>(.353)</td>
<td>(.193)</td>
<td>(.189)</td>
</tr>
<tr>
<td>FE: destination X site X eligible</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>No. of observations</td>
<td>324</td>
<td>324</td>
<td>435</td>
<td>435</td>
</tr>
</tbody>
</table>

Note: An observation is a group of searches which terminate with the user clicking on either a paid or organic Google listing to either one of seventeen OTAs. Robust (White) standard errors are reported in parenthesis, clustered at the level of website and one of six US geographic regions specified for flight destination. Asterisks indicate * p<.10, ** p<.05, *** p<.01.
TABLE 9
ROBUSTNESS TO ADDITIONAL CONTROLS

<table>
<thead>
<tr>
<th>Dependent variable (in logs):</th>
<th>Paid clicks</th>
<th>Organic clicks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>GFS result displayed</td>
<td>.762**</td>
<td>.786*</td>
</tr>
<tr>
<td></td>
<td>(.373)</td>
<td>(.424)</td>
</tr>
<tr>
<td>Google Trends Data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(no. of searches)</td>
<td>1.378***</td>
<td>1.527***</td>
</tr>
<tr>
<td></td>
<td>(.456)</td>
<td>(.525)</td>
</tr>
<tr>
<td>log(no. of ad exposures)</td>
<td>-.141</td>
<td>.339*</td>
</tr>
<tr>
<td></td>
<td>(.210)</td>
<td>(.184)</td>
</tr>
</tbody>
</table>

FE: destination X site X eligible yes yes yes yes
time X destination yes yes yes yes
time X site yes yes yes yes
No. of observations 324 287 435 218

Note: Asterisks indicate * p < .10, ** p < .05, *** p < .01.

TABLE 10
SEASONAL TRENDS IN SEARCHES AND AD EXPENDITURE

<table>
<thead>
<tr>
<th>Dependent variable (in logs):</th>
<th>No. of searches</th>
<th>No. of ad exposures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GFS result displayed</td>
<td>.288</td>
<td>.196</td>
</tr>
<tr>
<td></td>
<td>(.294)</td>
<td>(.149)</td>
</tr>
<tr>
<td>Dummy Variables: Time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>July to August</td>
<td>.097</td>
<td>.359***</td>
</tr>
<tr>
<td></td>
<td>(.161)</td>
<td>(.088)</td>
</tr>
<tr>
<td>January to February</td>
<td>-.077</td>
<td>.166*</td>
</tr>
<tr>
<td></td>
<td>(.139)</td>
<td>(.088)</td>
</tr>
<tr>
<td>March to April</td>
<td>.079</td>
<td>.152</td>
</tr>
<tr>
<td></td>
<td>(.158)</td>
<td>(.111)</td>
</tr>
</tbody>
</table>

Fixed effects destination X eligible destination X site X eligible
No. of observations 48 508

Note: In the first column, an observation is a group of queries for a flight destination. In the second column, an observation is either one of seventeen online travel agencies advertising on Google for a group of queries. Robust (White) standard errors are reported in parenthesis, clustered at the level of the fixed effects used. Asterisks indicate * p < .10, ** p < .05, *** p < .01.
### TABLE 11
DIFFERENTIAL GFS EFFECTS ACROSS OTAS

<table>
<thead>
<tr>
<th>Dependent variable (in logs):</th>
<th>Paid clicks</th>
<th>Organic clicks</th>
</tr>
</thead>
<tbody>
<tr>
<td>GFS displayed X Organic OTA</td>
<td>2.287***</td>
<td>-.773***</td>
</tr>
<tr>
<td></td>
<td>(.325)</td>
<td>(.229)</td>
</tr>
<tr>
<td>GFS displayed X Balanced OTA</td>
<td>1.126**</td>
<td>-.356</td>
</tr>
<tr>
<td></td>
<td>(.559)</td>
<td>(.360)</td>
</tr>
<tr>
<td>GFS displayed X Paid OTA</td>
<td>.303</td>
<td>-.140</td>
</tr>
<tr>
<td></td>
<td>(.316)</td>
<td>(.665)</td>
</tr>
<tr>
<td>Google Trends Data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(no. of searches)</td>
<td>1.170***</td>
<td>.595***</td>
</tr>
<tr>
<td></td>
<td>(.326)</td>
<td>(.204)</td>
</tr>
<tr>
<td>Dummy Variables: Time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>July to August</td>
<td>.355</td>
<td>.066</td>
</tr>
<tr>
<td></td>
<td>(.230)</td>
<td>(.160)</td>
</tr>
<tr>
<td>January to February</td>
<td>.055</td>
<td>.173</td>
</tr>
<tr>
<td></td>
<td>(.346)</td>
<td>(.192)</td>
</tr>
<tr>
<td>March to April</td>
<td>.301</td>
<td>.188</td>
</tr>
<tr>
<td></td>
<td>(.363)</td>
<td>(.190)</td>
</tr>
</tbody>
</table>

FE: destination X site X eligible | yes | yes |
No. of observations             | 324 | 435 |

Note: Asterisks indicate * p<.10, ** p<.05, *** p<.01.
### TABLE 12
GFS EFFECT IN ONLINE EXPERIMENT

<table>
<thead>
<tr>
<th></th>
<th>Salience Searchers</th>
<th>Relevance Searchers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No GFS</td>
<td>With GFS</td>
</tr>
<tr>
<td>Clicked Organic</td>
<td>40.9% (9 of 22)</td>
<td>26.1% (6 of 23)</td>
</tr>
<tr>
<td>Clicked Paid</td>
<td>59.1% (13 of 22)</td>
<td>17.4% (4 of 23)</td>
</tr>
<tr>
<td>Clicked GFS</td>
<td>56.5% (13 of 23)</td>
<td></td>
</tr>
<tr>
<td>Clicked GFS believing</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GFS is organic link</td>
<td>13.0% (3 of 13)</td>
<td>15.9% (13 of 24)</td>
</tr>
<tr>
<td>GFS is paid link</td>
<td>26.1% (6 of 13)</td>
<td>7.3% (9 of 24)</td>
</tr>
<tr>
<td>don’t know</td>
<td>17.4% (4 of 13)</td>
<td>6.1% (5 of 24)</td>
</tr>
</tbody>
</table>

|                      | Total              | 100.0% (22 of 22)   | 100.0% (23 of 23)  | 100.0% (93 of 93)  | 100.0% (82 of 82) |

### TABLE 13
GFS EFFECT BY USER EXPERIENCE IN ONLINE EXPERIMENT

<table>
<thead>
<tr>
<th></th>
<th>Salience Searchers</th>
<th>Relevance Searchers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No GFS</td>
<td>With GFS</td>
</tr>
<tr>
<td><strong>Experienced Users</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clicked Organic</td>
<td>50.0% (3 of 6)</td>
<td>45.4% (5 of 11)</td>
</tr>
<tr>
<td>Clicked Paid</td>
<td>50.0% (3 of 6)</td>
<td>18.2% (2 of 11)</td>
</tr>
<tr>
<td>Clicked GFS</td>
<td>36.4% (4 of 11)</td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>100.0% (6 of 6)</td>
<td>100.0% (11 of 11)</td>
</tr>
<tr>
<td><strong>Inexperienced Users</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Clicked Organic</td>
<td>37.5% (6 of 16)</td>
<td>8.3% (1 of 12)</td>
</tr>
<tr>
<td>Clicked Paid</td>
<td>62.5% (10 of 16)</td>
<td>16.7% (2 of 12)</td>
</tr>
<tr>
<td>Clicked GFS</td>
<td>75.0% (9 of 12)</td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>100.0% (16 of 16)</td>
<td>100.0% (12 of 12)</td>
</tr>
</tbody>
</table>
Web Appendix A: Description of ComScore Dataset

Our primary dataset originates from ComScore Search Planner, a commercial service tracking online behavior of a panel of internet users. More information on the dataset is available at: http://www.comscore.com/Products/Audience_Analytics/Search_Planner. ComScore Search Planner provides the destination URL and corresponding internet traffic volumes of outgoing US search engine users, grouped by their exact search queries.

We compile our dataset using the following steps:

IDENTIFY SEARCH PHRASES

First, we identify the search query terms that led to outgoing search engine traffic to 17 popular online travel agencies (OTAs). We limit our analysis to 17 popular OTAs which account for about 91% of all clicks. Other OTAs in our sample each receive less than 25,000 clicks from search queries matching the patterns we specify. These 17 OTAs are:

1. www.airfarewatchdog.com
2. www.bookingbuddy.com
3. www.cheapflights.com
4. www.cheapoair.com
5. www.cheaptickets.com
6. www.expedia.com
7. www.farecompare.com
8. www.farespotter.com
9. www.kayak.com
10. www.lowfares.com
11. www.onetravel.com
12. www.orbitz.com
13. www.priceline.com
14. www.travelocity.com
15. www.travelzoo.com
16. www.tripadvisor.com
17. www.tripmama.com
We identify these search query terms for four bi-monthly time periods: May to June 2011, July to August 2011, January to February 2012, and March to April 2012. We intentionally omit the four months immediately surrounding the launch of GFS because the appearance of GFS links was unpredictable during this period. In the main text, we provide further explanation about why we omitted this period.

To collect the exact wording of all search queries that led to these sites in each of the bi-monthly time periods, we used the “Site Profile” tab in Comscore Search Planner. Because Google began to offer its international flight search tool significantly later, on March 15, 2012, we retain only search queries that mention a US destination, and we delete references to international destinations. We also delete all search queries that mention a phrase that disqualifies search intent for flights (for example, “flight attendant school”) or that directly specify a desired site (for example, “Orbitz” or “Jetblue”).

**CLASSIFICATION OF SEARCH PHRASES**

Next, we classify these search queries into 12 groups. First, we classify each search query as being either “GFS-eligible” or “GFS-ineligible,” based on whether the exact wording of the search query specified would trigger the display of GFS results in a Google search after December 2011. To verify the classification of these query patterns, we used multiple user profiles and computers at different US locations to conduct searches at http://www.google.com, both manually and by using automation. We conduct this verification exercise three times, in June 2012, November 2012, and January 2013. Across these occasions, we checked that Google’s eligibility criteria for display of GFS results did not depend on user profile, computer or location, but that it depended only on the exact word choice of the search query. Our checks also reveal that Google’s eligibility classification was persistent: search queries classified as “GFS-eligible” maintained their classification during checks at subsequent dates.

Second, each search query expresses an intended flight destination, which we use to classify the search queries into six groups by geographic region. We divide the 50 US states into the fol-
following six geographic regions:

1. **Midwest Region.** Includes Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin.

2. **Mountain West Region.** Includes Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming.


4. **Pacific West Region.** Includes Alaska, California, Hawaii, Oregon, Washington.

5. **Southeast Region.** Includes Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, West Virginia (plus Puerto Rico).

6. **Southwest Region.** Includes Arkansas, Louisiana, Oklahoma, Texas.

We tested perturbations to our definitions of geographical aggregation, and results were robust to changes.

*OBTAINING GOOGLE TRAFFIC*

For each classified group of search queries, we obtain the outgoing organic traffic volumes and paid advertising traffic volumes to each destination URL. We use the Search Planner interface to require that traffic originate from searches that correspond with an “exact” match of the specified search queries rather than a “broad” match, and that traffic occur during one of our specified bi-monthly time periods. Search Planner reports outgoing Google traffic volume separately for user clicks on organic search listings and on paid advertising listings.

Table 1 (in the paper) describes the composition of searches in our sample.
Web Appendix B: Sample List of Search Phrases

From Search Planner data, we obtain several thousand different versions of exact wording of queries entered by users searching for flights. We note that GFS-eligible and GFS-ineligible queries are similar in user intent. Below, we provide a sample list of 500 search phrases.

SEARCH PHRASES CLASSIFIED AS GFS-ELIGIBLE

- air flights to las vegas
- airfare to las vegas
- airfare to orlando
- airfare to seattle
- airline tickets to las vegas
- cheap air tickets to chicago
- cheap airline tickets to chicago
- cheap flight to las vegas
- cheap flight to new york
- cheap flight to vegas
- cheap flights from las vegas to chicago
- cheap flights to atlanta
- cheap flights to boston
- cheap flights to charlotte
- cheap flights to chicago
- cheap flights to chicago il
- cheap flights to cleveland ohio
- cheap flights to dallas
- cheap flights to dayton ohio
- cheap flights to dc
- cheap flights to denver
- cheap flights to detroit
- cheap flights to flint
- cheap flights to fort lauderdale
- cheap flights to houston
- cheap flights to kansas
- cheap flights to kansas city mo
- cheap flights to la
- cheap flights to las vegas
- cheap flights to lax
- cheap flights to los angeles
- cheap flights to miami
- cheap flights to michigan detroit
- cheap flights to msp
- cheap flights to new orleans
- cheap flights to new york
- cheap flights to ny
- cheap flights to nyc
- cheap flights to orlando
- cheap flights to philadelphia
- cheap flights to phoenix
- cheap flights to san diego
- cheap flights to san francisco
- cheap flights to seattle
- cheap flights to sfo
- cheap flights to tampa
- cheap flights to vegas
- cheap flights to washington dc
- cheap tickets to atlanta ga
- cheap tickets to boston ma
- cheap tickets to boston massachusetts
- cheap tickets to charlotte nc
- cheap tickets to chicago
- cheap tickets to detroit
- cheap tickets to las vegas
- cheap tickets to miami
- cheap tickets to new york
- cheap tickets to nyc
- cheap tickets to orlando
- cheap tickets to orlando fl
- cheap tickets to orlando florida
- cheap tickets to orlando, fl
- cheap tickets to philadelphia
- cheap tickets to phoenix
- cheap tickets to portland or
- cheap tickets to portland oregon
- cheap tickets to reno from new york
- cheap tickets to sacramento ca
- cheap tickets to sacramento
- cheap tickets to salt lake city utah
- cheap tickets to san diego
- cheap tickets to san francisco
- cheap tickets to tampa florida
- cheap tickets to tampa from new york
- cheap tickets to tulsa
- cheap tickets to utah salt lake city
- cheap tickets to vegas
- cheap tickets to vegas from portland
- cheap tickets to virginia beach
- cheap tickets to washington dc
- cheap tickets to washington state
- cheapest flights to allentown pa
- cheapest flights to atlanta
- cheapest flights to baltimore
- cheapest flights to chicago
- cheapest flights to fresno
- cheapest flights to las vegas
cheapest flights to savannah ga
cheapest flights to vegas
flight to atlanta
flight to baltimore
flight to charlotte
flight to las vegas
flight to los angeles
flight to miami
flight to nashville
flight to new orleans
flight to new york
flight to newark
flight to ny
flight to orlando
flight to san diego
flight to seattle
flight to sfo
flight to Vegas
flights austin to chicago
flights from boston to chicago
flights from portland oregon to lawton oklahoma
flights from portland oregon to phoenix
flights from providence to dc
flights from raleigh to atl
flights from rochester ny to baltimore md
flights from rochester to flint
flights from sacramento ca to seattle wa
flights from sacramento to philadelphia
flights from san antonio tx to nashville tn
flights from san antonio, tx to chicago o’hare
flights from san diego to cleveland
flights from san diego to miami
flights from san diego to missoula mt
flights from tampa to chicago
flights to anchorage
flights to atl
flights to atlanta
flights to atlanta ga
flights to baltimore
flights to bloomington il
flights to boise
flights to boston
flights to charleston sc
flights to charlotte
flights to charlotte nc
flights to chicago
flights to cleveland
flights to colorado springs
flights to dallas
flights to dallas tx
flights to daytona
flights to dc
flights to denver
flights to denver colorado
flights to detroit michigan
flights to fort lauderdale
flights to fort myers
flights to ft lauderdale
flights to grand rapids michigan
flights to honolulu
flights to kansas city
flights to key west
flights to las vegas
flights to las vegas cheap
flights to lexington ky
flights to los angeles
flights to los angeles cheap
flights to memphis
flights to miami
flights to miami fl
flights to milwaukee
flights to new orleans
flights to new york
flights to new york cheap
flights to new york new york
flights to ny
flights to nyc
flights to orlando
flights to orlando cheap
flights to orlando florida
flights to portland oregon
flights to rapid city sd
flights to reno
flights to rochester
flights to sacramento
flights to salt lake city
flights to san diego
flights to san francisco
flights to san jose
flights to sarasota
flights to seattle
flights to seattle cheap
flights to sfo
flights to st louis mo
flights to tampa
flights to vegas
flights to vegas cheap
fly to las vegas
fly to vegas
las vegas to new york
lowest air fare from msp to boston
lowest air fare to new york la guardia
lowest airfare from syracuse to sarasota
lowest airfare san diego to san francisco
lowest airfare to atlanta
lowest airfares from msp to memphis
lowest fare from iah to sna
new york to chicago flight
non stop flight phoenix to colorado springs
non stop flight to panama city florida
non stop flights form milwaukee, wisconsin to orlando
non stop flights from baltimore to memphis
non stop flights from hartford ct to augusta georgia
non stop flights from knoxville to nashville
non stop flights from new orleans to orlando
non stop flights from san diego to las vegas
non stop flights ny to san francisco
non stop flights to myrtle beach
non stop flights to new york city
non stop flights to philadelphia
non stop flights to san antonio tx
non stop las to fl
non stop los angeles to philadelphia
non stop new orleans to orlando fl
non stop oklahoma city to charlotte
non-stop flight atlanta to gunnison colorado
nonstop flights to chicago
plane tickets chattanooga to joplin mo
plane tickets chicago to los angeles
plane tickets dallas to jackson ms
plane tickets from boston mass to sacramento ca
plane tickets from buffalo to vegas
plane tickets from charleston to d.c.
plane tickets from charlotte to miami
plane tickets from charlotte to new york
plane tickets from charlotte to orlando
plane tickets from chattanooga to miami
plane tickets from el paso, tx to los angeles, ca
plane tickets from halifax to portland oregon
plane tickets from houston to new york
plane tickets from los angeles to san francisco
plane tickets from montgomery to newyork
plane tickets from orlando to augusta ga
plane tickets from pullman to san francisco
plane tickets from salt lake city neto portland mai
plane tickets from san antonio texas to fresno ca
plane tickets from san antonio to phoenix
plane tickets from san francisco to boston massachusetts
plane tickets from seattle wa to sacramento ca
plane tickets from spokane to springfield mo
plane tickets from syracuse ny to nyc
plane tickets greensboro nc to rochester ny
plane tickets greensboro nc to rochester ny
plane tickets greensboro nc to rochester ny
plane tickets greensboro nc to rochester ny
tallahassee to ft myers flights
tallahassee to miami flights
ticket from fort walton to new york
ticket from seattle to san antonio
tickets ny to vegas
washington dc to detroit flights
washington dc to las vegas cheap flight

air fare prices to las vegas
air fare to grands rapids north dakota
air fares from philadelphia to florida
air to las vegas
airline tickets to daytona fla
airline tickets to florida
airline tickets to texas
cheap airline tickets to philadelphia to las vegas
cheap airline tickets to philadelphia to los vegas
cheap airline tickets to texas
cheap airlines to chicago
cheap airlines to vegas
cheap flight to jacksonville fl
cheap flight to orlando fl from san diego
cheap flights for dallas from newport news
cheap flights from springfield, il to phl az
cheap flights from stockton ca to dallas
cheap flights from syracuse
cheap flights from tampa
cheap flights from tampa to nicholasville ky
cheap flights from tucson
cheap flights from virginia to atlanta
cheap flights milwaukee to oklahoma
cheap flights to atlantic city from greenville, sc
cheap flights to baltimore bwi
cheap flights to dallas fort worth texas
cheap flights to florida
cheap flights to ft lauderdale fl
cheap flights to iowa
cheap flights to jacksonville fl
cheap flights to kennewick washington
cheap flights to kentucky from atlanta
cheap flights to killeen texas
cheap flights to las vegas from stockton
cheap flights to mn st.paul
cheap flights to orlando fl
cheap flights to palm beach florida from nc
cheap flights to stockton california
cheap flights to tacoma washington
cheap flights to take into columbia, sc
cheap flights to tampa fl
cheap flights to walnut ridge
cheap flights to washington state
cheap flights washington dc
cheap flightsd
cheap last minute flights to atlanta
cheap last minute flights to denver
cheap last minute flights to houston
cheap last minute flights to la
cheap last minute flights to miami
cheap last minute flights to seattle
cheap miami new york tickets
cheap nonstop flights from fl to iah
cheap nonstop flights nyc to tpa
cheap nonstop flights to orlando
cheap round trip tickets to killeen tx
cheap round trip tickets to las vegas
cheap ticket to fort lauderdale fl from san francisco
cheap tickets for atlanta georgia
cheap tickets from boston to kc
cheap tickets from salt lake intl to philadelphia intl
cheap tickets from sfo to san diego
cheap tickets to florida
cheap tickets to georgia atlanta one way
cheap tickets to kansas
cheap tickets to kansas on any flight
cheap tickets to new york without tax
cheap tickets to north co
cheap tickets to nyc in july
cheap tickets to oklahoma
cheap tickets to pr from ct
cheap tickets to puerto rico
cheap tickets to rdu to atl
cheap tickets to reno from las vegas
cheap tickets to sa
cheap tickets to san francisco to seattle wa
cheap tickets to sanfrancisco,ca
cheap tickets to texas
cheapest airline tickets to orlando fl
cheapest airline to las vegas
cheapest airlines tickets sfo to charlotte
cheapest airlines tickets to houston
cheapest airlines tickets to las vegas
cheapest airplanes tickets to houston
cheapest flight from melbourne fl to atlanta ga
cheapest flight from nc to chicago
cheapest flight from pa to dallas
cheapest flights from gulf shores al to missouri
cheapest flights from sfo or oakland to albuquerque
cheapest flights to killeen texas
cheapest flights to seattle washington from philadelphia
cheapest route from new york to nashville
cheapest route from ny to los angeles
flight sarasota,fl. to portland,me
flight to california
flight to colorado
flight to florida
flight to fort hood texs
flight to jacksonville fl
flight to kansas
flight to puerto rico
flight to west memphis arkansas
flight to wisconsin
flights from akron canton to tampa florida
flights from ft.myers,fl to portland,me
flights from grand junctions to durango
flights from greenville to atlantic city
flights from melbourne fl to key west
flights from memphi to colorado springs
flights from memphis tn to arizona
flights tickets from charlotte to west palm beach
flights to alaska
flights to aneheim ca
flights to anehiem ca
flights to arizona
flights to arizona from seattle
flights to atlantic city from buffalo
flights to beaumont tx from phoenix
flights to california
flights to charleston sc from tampa fl
flights to colorado
flights to corona del mar,ca.
flights to dallas tx from sanford fl
flights to dc from montego bay
flights to destin fl
flights to duck key, fl
flights to florida
flights to forks, wa
flights to ft lauderdale fl from lax
flights to go to greensboro nc
flights to jacksonville fl
flights to kansas from sf
flights to kentucky
flights to laguna niguel california
flights to lake havasu city
flights to lake orion michigan
flights to landover maryland
flights to larenburg nc
flights to las vegas from michigan
flights to laurinburg
flights to massachusetts
flights to menominee mi
flights to methow valley from seattle
flights to miami fl from cedar rapids
flights to miami fl one way cheap
flights to miami florida airlines
flights to michigan
flights to nebraska
flights to new jersey from dfw
flights to new york city new york
flights to new york from puerto rico
flights to newport oregon
flights to newport ri
flights to oregon
flights to orlando fl
flights to pensacola fl
flights to providence ri
flights to puerto rico
flights to seattle from ms]
flights to seattle washington
flights to seattle washington from phl
flights to sierra vista az
flights to tampa bay fl
flights to tampa fl
flights to texas
flights to topeka, ks
flights from new orleans to jackson, tn
flint michigan airfare prices from philadelphia
fly from atlanta to orleans
fly to hartford wi
fly to santa ana, ca for cheap
last minute airfare from charlotte to vegas
last minute airfare to orlando
lowest airline prices from atlanta ga to oklahoma
lowest fare from orlando to norfolk virginia
lowest fare to new york
lowest fares from sfo to chicago
lowest flight from dc to la
lowest flight rates from atlanta to los angeles

lowest price flights from charleston wv
nashville to newark flights deals
nashville, tn flights to sarasota, fl
niagara falls flights to nyc
non stop flight to arizona
non stop flight to chattanooga,ga
non stop flights from anchorage
non stop flights from charleston sc
non stop flights from chicago
non stop flights from denver
non stop flights from killeen tx to fort lauderdale
non stop flights to puerto rico from virginia
non stop to myrtle beach, sc
non stops flights to puerto rico from virginia
nonstop stl bangor me
nonstop to san diego to oakland ca
one way flight from raleigh, nc to fort lauderdale, fl
one way flight tampa to lexington
one way flights from knoxville tn to detroit mi
one way flights from pax to phl
one way flights from raleigh, nc to fort lauderdale, fl
one way flights to houston
one way flights to las vegas
one way flights to san francisco
one way from miami to washington dc flights
one way plane from philadelphia to hollywood fl
one way ticket from san antonio to st louis
one way ticket from savannah to syracuse
plane from philadelphia to hollywood fl
plane ticket to dallas texas from fort walton beach fl
plane tickets from austin to orlando florida round trip
plane tickets from maine to pittsburgh
plane tickets from new braunfels tx to chicago il
plane tickets from new jersey to detroit
plane tickets to atlanta georgia for cheap
plane tickets to orlando cheap
plane tickets to puerto rico
plane tickets to san diego from charlotte round trip
plane tickets to seattle washington
plane tickets to vegas cheap
really cheap flights to vegas from chicago
really cheap tickets to chicago
round trip from seattle to louisville
round trip from stockton to long beach
round trip modesto los angeles
round trip plane tickets denver to maryland
round trip plane tickets from boston to pittsburgh pa
round trip tickets to lexington ky
roundtrip airfare nashville to augusta ga
roundtrip airfare to san antonio
salt lake city to chicago cheap flight ticket
seattle to san jose cheep airline ticats
stockton to vegas flight
the cheapest flight from san antonio to st louis
the cheapest flight to new york
the cheapest flights from seattle to san antonio texas
ticket to bakersfield ca
tickets from boise to cleveland
tickets from boston to washington
tickets from chicago to portland
tickets from dc to providence
tickets from houston to fresno california
tickets from la to seattle
tickets from milwaukee to ft lauderdale
tickets to atlantic city
tickets to boston
tickets to miami
tickets to miami from ny
tickets to tacoma washington
tickket price from dallas to new york
Web Appendix C: Description of Online Experiment

We conduct an online experiment to link users’ preferred method of considering search results with their decisions of which link to click. Our experimental subjects were 300 participants recruited on Amazon Mechanical Turk. The task was restricted to US-based participants with Amazon Masters qualification. We paid each participant $.50.

The experiment began by showing each participant a screenshot of search results. Half of participants saw a treatment with GFS results while the other half saw no GFS results. The remaining algorithmic and paid results were identical. Participants received the following instructions:

When searching online to buy a plane ticket, you run a search engine query for (GFS condition: “flights from boston to orlando”; non-GFS condition: “flights from boston to orlando fl”) and the following links appear in your browser. In this situation, which would you choose?

- Please click on one of the results you see below as if you were facing this situation for real.
- Then answer the questions that follow.

Participants assigned to the treatment group then saw sample search results that included GFS:
while participants who were assigned to the control group saw sample search results without GFS:

We recorded each participant’s choice of search result. Next, we asked participants brief questions about their click decisions:

1. Please indicate the extent to which each of the following reasons influenced your choice of why you may have clicked the link labeled *(insert participants' choice of link here)*.

   - I clicked this because it captured my attention the most
     *(1: strongly disagree, 2: disagree, 3: slightly disagree, 4: neither agree or disagree, 5: slightly agree, 6: agree, 7: strongly agree)*
   - I clicked this because it captured my attention the most and would get me to where I want to go
     *(1: strongly disagree, 2: disagree, 3: slightly disagree, 4: neither agree or disagree, 5: slightly agree, 6: agree, 7: strongly agree)*
   - I clicked this link because moving my link to click on a link in another position would have been a little more effort
     *(1: strongly disagree, 2: disagree, 3: slightly disagree, 4: neither agree or disagree, 5: slightly agree, 6: agree, 7: strongly agree)*
   - I clicked this because it was the most useful link to get me where I want to go
     *(1: strongly disagree, 2: disagree, 3: slightly disagree, 4: neither agree or disagree, 5: slightly agree, 6: agree, 7: strongly agree)*
   - I clicked this because I trust the destination site
     *(1: strongly disagree, 2: disagree, 3: slightly disagree, 4: neither agree or disagree, 5: slightly agree, 6: agree, 7: strongly agree)*
   - I know that the link is not a paid ad
     *(1: strongly disagree, 2: disagree, 3: slightly disagree, 4: neither agree or disagree, 5: slightly agree, 6: agree, 7: strongly agree)*

2. Do you know the difference between a paid ad and an organic link in search engine results? *(yes/no)*

3. Classify the links below as either paid ads or organic links *(participants were again shown the search results they had previously seen and asked to select one of three options next to each link: Organic, Paid, Not Sure)*
4. Which of the following statements best describes your attitude towards paid ads and organic links in the search engine results page (participants had to select one of the following options)

- I only click on organic links on the search engine results page
- I usually click on organic links but sometimes also click on paid ads in search engine results
- I usually click on paid ads but sometimes click on organic links in search engine results
- I only click on paid ads on the search engine results page
- I do not care about which link I click, as long as I believe that the link will take me to the website I want to visit

5. Which internet search engines have you ever used to search for plane tickets? (participants had to select one of the following options)

- I have used Google to search for plane tickets
- I have never used Google to search for plane tickets, but I have used other search engines (such as Bing, Yahoo, AOL and Ask.com) to search for plane tickets
- I have searched for plane tickets online, but never used search engines (such as Bing, Yahoo, AOL and Ask.com) to search for plane tickets
- I have not previously searched for plane tickets online

6. How familiar are you with each of the following websites? (For each website, participants had to select one of the following options: Never heard of / Heard of, not visited / Visited, not bought / Visited, bought at)

- Cheapoair
- Expedia
- Jetblue
- Kayak
- Onetravel
- Orbitz
- Travelzoo

We used participants’ answers to question 1 to classify each participant as either a salience searcher or a relevance searcher. Respondents who assigned a strictly higher score to the first option (compared to the fourth option) were classified as salience searchers, while respondents who assigned a strictly higher score to the fourth option were classified as relevance searchers.

We also used participants’ answers to question 6 to classify them as either experienced users or inexperienced users. During the experiment, organic and paid listings to seven sites (listed in question 6) were displayed to participants. Respondents were classified as experienced with using online travel agencies if they selected the option “Visited, bought at” for at least one of the six online travel agencies in the displayed list of sites (all sites excluding Jetblue).