Reserve Prices in Internet Advertising Auctions: A Field Experiment

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We present the results of a large field experiment on setting reserve prices in auctions for online advertisements, guided by the theory of optimal auction design suitably adapted to the sponsored search setting. Consistent with the theory, revenues increased substantially after the new reserve prices were introduced.

I. Introduction

Auctions are used to sell a wide variety of objects, ranging from flowers, paintings, and used cars to electromagnetic spectrum and Internet advertisements. One of the most natural questions about the design of an auction is revenue maximization: How should an auction be designed to generate the highest expected payoff to the seller? This question was answered by Myerson (1981) and Riley and Samuelson (1981) for the setting with one object for sale and independently distributed private bidder

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values. For the case with symmetric bidders, the answer is particularly elegant: the optimal mechanism can be implemented by a first- or second-price auction with an appropriately chosen reserve price.

This theoretical work has been extended in many directions: for example, Cremer and McLean (1988) and McAfee, McMillan, and Reny (1989) construct optimal auctions in settings with correlated and common bidder values; Maskin and Riley (1984) derive optimal mechanisms in settings with risk-averse bidders; and Maskin and Riley (1989), Armstrong (2000), and Avery and Hendershott (2000) study optimal design in settings with multiple objects.

Economists have also obtained empirical estimates of (and bounds on) optimal reserve prices for a variety of auctions (McAfee and Vincent 1992; Paarsch 1997; Athey, Cramton, and Ingraham 2002; McAfee, Quan, and Vincent 2002; Bajari and Hortaçsu 2003; Haile and Tamer 2003; Tang 2011). Notably, taken together, the results of these papers present a puzzle: these papers typically find that reserve prices actually observed in real-world auctions are substantially lower than the theoretically optimal ones. This raises the possibility that reserve prices are not a particularly important part of auction design, and sellers cannot use them to substantially raise revenues. Moreover, if participation in the auction is costly for bidders, increasing the reserve price may make the auction less attractive to them, and fewer will bid, leading to lower revenues. Indeed, Bulow and Klemperer (1996) find that in symmetric single-object auctions, adding just one more bidder (and setting a zero reserve price) is always preferable to setting the optimal reserve price. So perhaps reserve prices are not important in practice?

In this paper, we address this question directly, by presenting the results of a large-scale field experiment on reserve prices in a particular setting: "sponsored search" auctions conducted by Yahoo! to sell advertisements. Reserve prices in the randomly selected treatment group were set based on the guidance provided by the theory of optimal auctions, while in the control group, they were left at the old level of 10¢ per click.[1] We find that, overall, the revenues in the treatment group have increased substantially relative to the control group. In addition, we find that the impact of reserve prices varies in important ways by keyword characteristics. First, the impact of reserve prices is particularly strong for keywords that are often searched by the users (see sec. IV.A for a discussion of theoretical reasons behind this fact). Second, as we discuss in section IV.B, policy considerations have led the company to deviate from using the optimal reserve prices generated by the model, with the deviations being more significant for keywords with low optimal reserve prices. As a result, the

[1] Prior to the experiment, reserve prices were constant across keywords and bidders, at 10¢ per click.

experimental impact of reserve prices is positive for keywords with high reserve prices, for which these deviations are relatively less important, but is negative for keywords with low reserve prices. Finally, we consider one of the classic predictions of auction theory, that the impact of reserve prices is higher when the number of bidders is lower. Our results are directionally consistent with the theory. Overall, our results show that reserve prices in auctions can have a substantial impact on revenues and that economic theory provides a useful guide for setting them and interpreting the results.

Two prior studies have analyzed the results of controlled experiments on setting reserve prices in auctions. Reiley (2006) reports the results of a field experiment on reserve prices in a first-price online auction for trading cards for a popular collectible card game. His findings confirm several predictions of auction theory, such as the reduction in the probability of a sale when reserve prices are present and, more subtly, the increase in bids when they are present (which is a consequence of equilibrium behavior in first-price auctions). Brown and Morgan (2009) report the results of field experiments on auctions for collectible coins conducted on Yahoo! and eBay. The primary focus of the study is the competition between platforms and market tipping, but the authors also consider the effects of reserve prices. They find that positive reserve prices, set at the level of 70% of the purchase price of the coins from the dealer, lead to significantly higher revenues and lower numbers of bidders, relative to zero reserve prices.

Our paper makes several contributions relative to these studies. First, it analyzes a much larger and economically important setting, with hundreds of thousands of keywords in a multibillion dollar marketplace. Consequently, many of the bidders in this setting spend considerable time and resources on optimizing their advertising campaigns. Second, the reserve prices in the experiment are guided by theory, based on the estimated distributions of bidder values. To the best of our knowledge, ours is the first paper describing a successful practical application of the seminal results of Myerson (1981) and Riley and Samuelson (1981).[2] Third, unlike the previous randomized experiments, the benchmark in our analysis is not a zero reserve price but the existing reserve price set by the company after a long period of experimentation.[3] Finally, our paper emphasizes the fact that the potential impact of reserve prices is much higher in multiunit auctions than in single-unit ones (in some cases, by orders of magnitude). This observation applies not just to sponsored search auctions but to any multiunit, simultaneous, or sequential auctions in which substitutable

[2] Walsh et al. (2008) describe the results of a small live test of an automated reserve pricing system for a reseller of returned goods over a 2-month period, after which the system was turned off.

[3] The initial reserve price set in 1998 was 1¢ per click. The reserve price was subsequently raised to 5¢ per click in 2001 and then to 10¢ in 2003.

goods are sold to bidders who have limited demands, ranging from timber auctions to procurement auctions.

The paper is organized as follows. Section II provides an overview of the sponsored search setting. Section III extends theoretical results on optimal auction design (Myerson 1981; Riley and Samuelson 1981) to the current setting and discusses simulations of revenue impact of reserve prices. Section IV describes the design of the experiment. Section V presents the experimental results. Section VI concludes.

II. Sponsored Search Auctions

We start with a brief description of the sponsored search setting; for a detailed description, see Edelman, Ostrovsky, and Schwarz (2007). When an Internet user enters a search term ("query") into a search engine, he gets back a page with results containing both the links most relevant to the query and the sponsored links, that is, paid advertisements. The ads are clearly distinguishable from the actual search results, and different searches yield different sponsored links: advertisers target their ads based on search keywords. For instance, if a travel agent buys the word "Hawaii," then each time a user performs a search on this word, a link to the travel agent will appear on the search results page. When a user clicks on the sponsored link, he is sent to the advertiser's Web page. The advertiser then pays the search engine for sending the user to its Web page. Different positions of an ad on the search results page have different desirability for advertisers: an ad shown at the top of a page is more likely to be clicked than an ad shown at the bottom.

To allocate positions to advertisers, most search engines use variations of the generalized second-price (GSP) auction. In the simplest GSP auction, for a specific keyword, advertisers submit bids stating their maximum willingness to pay for a click. An advertiser's bid remains active until he changes or disables it. When a user enters a keyword, she receives search results along with sponsored links, the latter shown in decreasing order of bids. In particular, the ad with the highest bid is displayed at the top, the ad with the next-highest bid is displayed in the second position, and so on. If a user clicks on an ad in position i, that advertiser is charged by the search engine the amount equal to the next-highest bid, that is, the bid of the advertiser in position $(i + 1)$.

If a search engine offered only one ad position per result page, this mechanism would be equivalent to the standard second-price auction, coinciding with the Vickrey-Clarke-Groves (VCG) mechanism (Clarke 1971; Vickrey 1961; Groves 1973). With multiple ad positions, GSP generalizes the second-price auction (hence the name). Here, each advertiser pays the next-highest advertiser's bid. Aggarwal, Goel, and Motvani (2006), Edelman, Ostrovsky, and Schwarz (2007), and Varian (2007) show that with multiple positions, the GSP auction is no longer equivalent to the VCG auction. In particular, unlike the VCG mechanism, GSP generally does not have an equilibrium in dominant strategies, and truth-telling is not an equilibrium of GSP. Nevertheless, GSP has a natural equilibrium, with advertisers in general bidding less than their true values, in which the payoffs of advertisers and the search engine are the same as under VCG for every realization of bidder values.

III. Theory

A. Derivation

The ideas of Myerson (1981) can be combined with the analysis of Edelman, Ostrovsky, and Schwarz (2007) and Varian (2007) to derive the optimal mechanism for the sponsored search setting and to show how it can be implemented with minimal changes to the existing GSP auction. Below is a sketch of the derivation, using the notation of Edelman, Ostrovsky, and Schwarz (2007).[4] Suppose in an auction for a particular keyword there are K bidders and N positions on the screen. The (expected) number of clicks per period received by the advertiser whose ad was placed in position i is α_i. The value per click to advertiser k is s_k. These values are private information of the advertisers, drawn from distribution $F_k(\cdot)$ on $[0, \bar{s}_k]$. Values are independently distributed, so the distribution over vectors of values s is $F(s) = F_1(s_1) \times \cdots \times F_K(s_K)$ over $S = [0, \bar{s}_1] \times \cdots \times [0, \bar{s}_K]$. Advertisers are risk-neutral, and advertiser k's payoff from being in position i is equal to $\alpha_i s_k$ minus his payments to the search engine. Without loss of generality, positions are labeled in descending order ($\alpha_1 > \alpha_2 > \ldots$).

Now consider an incentive-compatible direct revelation mechanism. Let $t_k(s_k)$ be the expected payment of bidder k with value s_k, let $x_k(s_k)$ be the expected number of clicks received by bidder k with expected value s_k, and, slightly abusing notation, let $x_k(s)$ be the expected number of clicks received by bidder k when the vector of bidder values is s. Then, using the same arguments as in the case of single-object optimal auctions (for an exposition, see, e.g., Krishna 2009), except that the probability of receiving the object in the single-object case is replaced by the expected number of clicks in our case, we have the following equality for the expected payment of each bidder:

$$t_k(s_k) = t_k(0) + x_k(s_k)s_k - \int_0^{s_k} x_k(u_k)\,du_k.$$

[4] Similar derivations are contained in Iyengar and Kumar (2006), Roughgarden and Sundararajan (2007), and Edelman and Schwarz (2010).

This, following the standard argument, in turn implies that the expected payoff of the search engine is equal to

$$\sum_{1\leq k\leq K} t_k(0) + \int_S \left(\sum_{1\leq k\leq K} \psi_k(s_k) x_k(s) \right) f(s)\, ds,$$

where $\psi_k(s_k) = s_k - ([1 - F_k(s_k)]/f_k(s_k))$ is the virtual valuation of advertiser k with value s_k.

We now make two additional assumptions. First, assume that the virtual valuation is an increasing function.[5] Second, assume that bidders are symmetric, that is, have identical distributions of values (and thus identical virtual valuation functions $\psi_k(\cdot) = \psi(\cdot)$). Then the revenues of the search engine are maximized when $t_k(0) = 0$ for any k and when $(\Sigma_{1\leq k\leq K} \psi(s_k) x_k(s))$ is maximized pointwise, for every s, which happens when (1) only bidders with positive virtual valuations are allocated clicks and (2) among them, bidders with higher virtual valuations (and thus, by assumption, with higher actual valuations) are allocated as many clicks as possible. Since each advertiser can have only one position on the screen, this simply means that the bidder with the highest value receives the top position, the bidder with the second-highest value receives the second position, and so on.

Now consider an indirect mechanism: the generalized second-price auction with reserve price r^* such that $\psi(r^*) = 0$. By the argument analogous to that in Edelman, Ostrovsky, and Schwarz (2007), in the bidder-optimal envy-free equilibrium of this auction (or, equivalently, in the unique equilibrium of the corresponding generalized English auction with reserve price r^*), bidders with values less than r^* (i.e., bidders with negative virtual valuations) will receive no clicks; among the bidders with values greater than r^* (i.e., with positive virtual valuations), the ones with higher values will receive higher positions; and finally, bidders with value zero receive (and make) payments of zero. Hence, the allocations and expected payoffs in this mechanism are the same as those in the optimal direct mechanism, and thus GSP with reserve price r^* is a revenue-maximizing mechanism.

B. *The Impact of Reserve Prices on Revenues*

The optimal reserve price r^* depends neither on the number of bidders nor on the number of available positions. The impact of reserve prices

[5] As described later in the paper, reserve prices in the experiment were computed under the assumption that bidders' values are distributed lognormally. Through simulations, it was determined that for lognormal distributions with parameter values relevant for the experiment, virtual valuations are increasing. A recent paper by Ewerhart (2013) establishes sufficient conditions under which virtual valuations for lognormal distributions are monotonically increasing.

TABLE 1
Impact of Reserve Prices, Uniform Distribution

Bidders	$r = 0$	$r = .5$	Impact (%)
Single-object second-price auction:			
$n = 2$	.3333	.4167	25
$n = 6$	.7143	.7165	.31
GSP with a decay factor of .7:			
$n = 2$	.1	.475	375
$n = 6$	.8123	1.1764	44.82

on revenues, however, depends critically on these parameters. In fact, in single-object auctions, reserve prices only play an important role if the number of bidders is small. To give a simple example (table 1), suppose bidder values are distributed uniformly on [0, 1], with the corresponding optimal reserve price $r^* = 0.5$. Then with just two bidders, the effect of setting the optimal reserve price rather than no reserve price is substantial: it raises the expected revenues by 25%, from 0.33 to 0.42.[6] With six bidders, however, the effect is small: moving from no reserve price to the optimal reserve price changes the expected revenues by less than one-third of 1%. The intuition for this decline is straightforward: reserve price r has a positive impact only when one bidder's realized value is above r and the other bidders' values are all below r, and the probability of this event becomes small as the number of bidders increases.

Of course, the same effect holds for multiunit auctions, like the sponsored search ones, if the number of slots is fixed but the number of bidders increases. However, reserve prices retain their power for much higher numbers of bidders and are, in general, much more important. To see this, consider a generalized second-price auction with the decay factor of 0.7 (i.e., the top position expects to receive one click, the second position expects to receive 0.7 clicks, the third position expect to receive 0.49 clicks, etc.: $\alpha_{i+1} = 0.7\alpha_i$).[7] With two bidders and no reserve price, the expected revenue of the auctioneer is only 0.1: in essence, both bidders get 0.7 clicks for free and only compete for the remaining 0.3 clicks, thus generating the revenue of $0.3 \times 0.33 = 0.1$.[8] Note, however, that it would be feasible for the search engine to shut down all positions below the top one, not allocating them to anyone, and so the revenue in the optimal auction has to be at least as high as in the optimal single-object one, that is, 0.42. As we know from the theoretical analysis, the optimal

[6] The expected revenue without a reserve price is equal to $E[\min\{s_1, s_2\}] = 0.33$. The expected revenue with $r^* = 0.5$ is equal to $0.25 \times E[\min\{s_1, s_2\} | s_1 > 0.5, s_2 > 0.5] + 0.5 \times 0.5 = 0.42$.

[7] The average decay factor of 0.7 is typical in the sponsored search setting, and so we use it throughout our examples and simulations.

[8] The amount 0.33 is the expectation of the minimum of the two bidders' per-click values.

auction does not in fact involve shutting down any positions: the auctioneer simply sets the reserve price equal to 0.5. The resulting expected revenue turns out to be 0.475, that is, an improvement of 375% relative to the case of no reserve price.

Even with six bidders, reserve prices remain very important: the optimal reserve price improves the revenues by almost 45%. To see why the difference relative to the single-object case is so dramatic, consider what would have happened if the decay factor in the sponsored search auction was equal to 1 rather than 0.7 (i.e., all positions received the same number of clicks) and there were as many available positions as bidders. Without a reserve price, there would be no competition for positions and the auctioneer's revenue would be equal to zero. With the optimal reserve price $r^* = 0.5$, each bidder would have a 50% chance of having the per-click value above the reserve price, and thus the revenue would be equal to the number of bidders times 0.25—an infinite improvement. Of course, with the decay factor of 0.7, the positions are no longer perfect substitutes, and the importance of reserve prices is not as dramatic, but the intuition is essentially the same. Note that in many other settings, multiple substitutable objects are also auctioned off, either simultaneously or sequentially, and if bidders in these auctions have limited demands or each is restricted to one or only a small number of objects, then for the same reason, the analysis based on an individual single-object auction may severely understate the importance of reserve prices.

In order to estimate optimal reserve prices for the experiment, it was assumed that bidders' values are drawn from lognormal distributions. Table 2 shows the impact of various levels of reserve prices on revenues in GSP under this assumption, with the parameters of the distribution chosen in such a way that its mean is equal to 0.5 and its standard deviation is also equal to 0.5.[9] The corresponding optimal reserve price is equal to 0.37. These parameters were chosen to give an illustration of a representative keyword; for instance, as we describe below, the optimal reserve price of 37¢ corresponds to the 75th percentile of estimated optimal reserve prices for the analyzed sample and is close to the average estimated optimal reserve price. The table presents the expected revenues for four levels of reserve prices: 0, 0.10 (corresponding to the old reserve price at Yahoo!, 10¢), 0.235 (corresponding to the midpoint between the old reserve price and the theoretically optimal reserve price), and 0.37 (the theoretically optimal reserve price). Similar to the example with the uniform distribution of values, the impact of optimal reserve prices on revenues in the GSP auction is substantial: with six bidders, setting the reserve price at

[9] Here and below, when we talk about the mean and/or the standard deviation of a lognormal distribution, we refer to the moments of the distribution itself, rather than those of the underlying normal distribution.

TABLE 2
Impact of Reserve Prices, Lognormal Distribution

Bidders	$r = 0$	$r = .10$	$r = .235$	$r = .37$
$n = 2$	.08	.22	.32	.34
	(24%)	(63%)	(93%)	(100%)
$n = 6$	.68	.78	.87	.91
	(75%)	(86%)	(96%)	(100%)
$n = 10$	1.24	1.28	1.33	1.36
	(91%)	(94%)	(98%)	(100%)

zero instead of the optimal level results in the loss of 25% of revenues; and even with 10 bidders, the loss is noticeable: 9%.

Table 3 presents the results of analogous impact calculations for four actual keywords taken from our sample. The first example has a lognormal distribution with mean 0.31, standard deviation 0.26, and $n = 6$ bidders; these values are close to the median ones in our sample. The corresponding optimal reserve price is $r^* = 0.22$. The second example has parameters (mean = 0.78, standard deviation = 0.11, $n = 6$, $r^* = 0.63$), with the same number of bidders but a higher optimal reserve price due to a higher mean and lower standard deviation of the underlying distribution of values. The third example has parameters (mean = 0.22, standard deviation = 0.13, $n = 5$, $r^* = 0.15$), with a lower optimal reserve price due to a lower mean. The fourth example, with parameters (mean = 2.18, standard deviation = 0.99, $n = 9$, $r^* = 1.50$) demonstrates that even with as many as nine bidders, the reserve price still has substantial impact.

Table 3 presents the expected revenues for each example under four different policies: zero reserve price, the status quo reserve price (prior to our experiment) of 10¢, the optimal reserve price r^* given our estimated distribution of values, and a point midway between 10¢ and r^*. The results in the table lead to several important observations.

TABLE 3
Impact of Reserve Prices, Sample Keywords

Keyword Parameters (Mean, SD, n)	r^*	$r = 0$	$r = .10$	$r = (.10 + r^*)/2$	$r = r^*$
(.31, .26, 6)	.22	.446	.541	.578	.591
		(76%)	(92%)	(98%)	(100%)
(.78, .11, 6)	.63	1.446	1.547	1.812	2.037
		(71%)	(76%)	(89%)	(100%)
(.22, .13, 5)	.15	.272	.381	.396	.401
		(68%)	(95%)	(99%)	(100%)
(2.18, .99, 9)	1.50	5.500	5.550	5.908	6.130
		(90%)	(91%)	(96%)	(100%)

First, it is clear from the table that while for most of these keywords, the reserve price of 10¢ produces higher revenues than the reserve price of zero, it still falls far short of the optimal revenue. By contrast, moving to the midpoint between 10¢ and the optimal reserve price allows the search engine to capture most of the upside from optimal reserve prices. This is not surprising because at the optimal reserve price level, the derivative of expected revenues with respect to reserve price is zero. Consequently, the cost of small deviations is also small. As we discuss in section IV.B.2 below, this observation played an important role in the implementation of reserve price levels in the field experiment.

Second, the impact of moving from the reserve price of 10¢ to the optimal reserve price (and to the midpoint between 10¢ and the optimal reserve price) strongly depends on the optimal level of the reserve price (e.g., for the third example, which has the optimal reserve price of 15¢, the impact of moving from 10¢ to the midpoint is approximately 4%; for the first example, which has an optimal reserve price of 22¢, the impact is 7%; and for the second example, which has an optimal reserve price of 63¢, the impact is 17%). This is not surprising—if 10¢ is already close to the optimal reserve price level r^*, there is relatively little upside to moving closer to r^* (to take an extreme example—if the optimal reserve price level happens to be 10¢, then there is zero upside from moving closer). However, this observation makes it important to consider how the impact of reserve prices differs for keywords with high prices and those with low ones. In particular, as we discuss in section IV.B.1, details of the practical implementation of the intervention deviate somewhat from the stylized model above. These deviations can potentially reduce revenues, with the relative impact being more important for keywords with low optimal reserve prices than for those with high prices. As we discuss in section V.C, this concern turns out to be valid—while the empirical results of our experiment for keywords with high optimal reserve prices are strongly positive, the results go in the opposite direction for keywords with low optimal reserve prices.

Third, just as in tables 1 and 2 (and in standard auction theory, more generally), the impact of reserve prices depends on the number of bidders: ceteris paribus, the more bidders the auction has, the lower is the impact of reserve prices on expected revenue. This is clearly visible by comparing the fourth example keyword (which has nine bidders) to the other three (which have five or six bidders). Moving from no reserve price to the optimal reserve price improves revenues in the fourth example by only 11%, while for the other three, such a move improves revenues by 33%–47%. This observation motivates our analysis in section V.D, in which we compare the impact of reserve prices on revenue for keywords with a large number of bidders versus those with a small number of bidders. While the comparison turns out not to be statistically significant, it is directionally consistent with the above prediction.

IV. Experiment

In practice, sponsored search auctions have a number of complicating features that make the model of section III only a stylized representation of reality. Nevertheless, the model was viewed as a useful approximation and was used as the basis for the experiment. In this section, we outline the implementation of the experiment and discuss several of the complicating features. Broadly speaking, the implementation of the experiment involved two steps: estimating the distributions of bidder values and setting reserve prices.

A. *Estimating the Distributions of Bidder Values*

The company picked a set of criteria for choosing keywords suitable for the experiment. One important criterion was to only include keywords that had a sufficient number of searches. There were several reasons for this requirement. First, for keywords with a small number of searches, there was concern about an insufficient amount of data and thus the inability to reliably estimate distributions of bidder values. Second, rarely searched keywords are relatively less important for advertisers, who are therefore less likely to adjust their bids in response to changes in reserve prices. Since in GSP auctions, most of the impact of reserve prices on revenue is due to advertisers adjusting their bids (sec. II.A of Edelman and Schwarz 2010), there was concern about modifying reserve prices on the low-volume keywords. As we discuss in section V.B, our experimental results corroborate these concerns.

The resulting sample consisted of 461,648 keywords. The company also selected a time interval of several weeks during which the data for estimation were collected. For each keyword in the sample, the following moments were computed: the average number of advertisers bidding on this keyword, the average bid, and the average standard deviation of bids, where the standard deviation was taken across bids within a single search and the average was taken across searches for the same keyword. The bid of the highest bidder in every auction was excluded from the statistics, because the theory does not allow us to pin it down (just like in a single-object second-price auction, under GSP, every bid of the highest bidder above a certain value results in the same vector of payoffs).

Next, it was assumed that bidders' values were drawn from a lognormal distribution with a mean and a standard deviation to be estimated. The number of potential bidders needed to be estimated as well: during the period when data were collected, Yahoo!'s sponsored search auctions had a uniform reserve price of 10¢, and so bidders with per-click values of less than 10¢ were not observed in the data (the reserve price was implemented as a "minimum bid"—i.e., it was impossible for advertisers to enter a bid below 10¢ into the system).

The next step was to simulate the three moments (observed number of bidders, average bid in positions 2 and below, and the standard deviation of the bids in positions 2 and below) for various true values of the number of potential bidders and the mean and the standard deviation of the lognormal distribution of values. To do that, for each combination of true values of the variables of interest, several hundred draws of the vectors of bidder values were drawn. For each draw, equilibrium bids were computed, taking into account the 10¢ reserve price and assuming that the bidders were playing the bidder-optimal locally envy-free equilibrium of the generalized second-price auction.[10] The moments of interest were then computed and averaged over all draws of vectors of bidder values.

For each keyword, the number of bidders and the parameters of the distribution of bidder values were then estimated by matching the observed moments to the simulated ones. Note that the number of bidders is irrelevant for setting the optimal reserve price, but it needs to be estimated in order to get an accurate estimate of the mean and the standard deviation of the distribution of values. Finally, for each keyword, the theoretically optimal reserve price was computed using the formula in section III.

Figure 1 shows the histogram of the distribution of estimated optimal reserve prices for the sample, and table 4 lists several key percentiles. The median optimal reserve price is 20¢, the 10th percentile is 9¢, and the 90th percentile is 72¢. Note that just like in the previous empirical studies estimating optimal reserve prices in auctions, we find that for most of the sample (almost 90%), the estimated optimal reserve price exceeds the actual reserve price used in the auction (10¢), and for much of the sample, the difference is substantial. Unlike in those studies, however, here we can directly measure the importance of this difference by conducting a controlled experiment.

Several details of the estimation procedure deserve additional attention. First, as a simplification, in the simulation procedure, it was assumed that each ad's probability of being clicked (conditional on where it is shown) is the same and that the ads are ranked solely based on bids. This is an approximation: in practice, ads' likelihoods of being clicked may differ, and auctions rank ads based not only on the bids but also on the estimates of these likelihoods.

Second, in the simulations, the same decay curve was used for all keywords. The decay curve is a function that estimates the ratios of the numbers of clicks the same ad would receive in different positions on

[10] This equilibrium also corresponds to the unique perfect Bayesian equilibrium of the corresponding generalized English auction; see Edelman, Ostrovsky, and Schwarz (2007) for details.

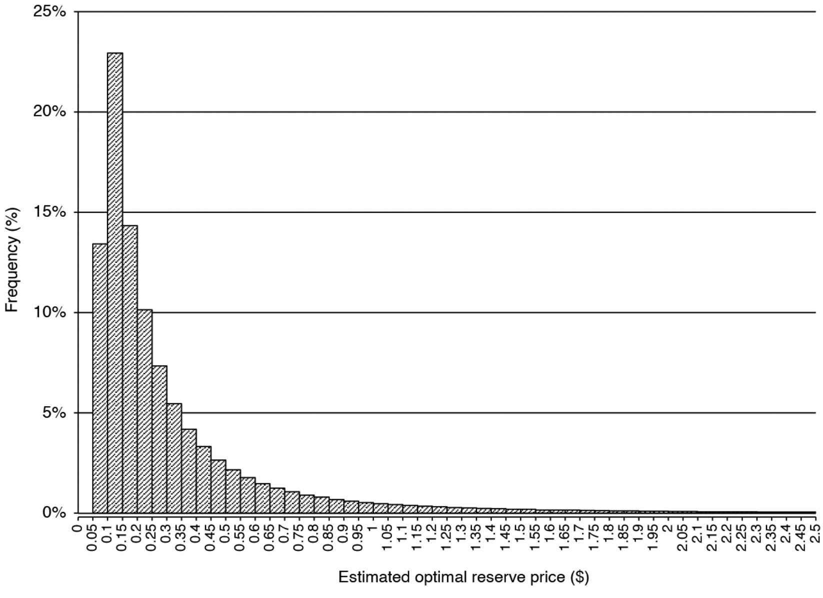

FIG. 1.—Distribution of estimated keyword-specific optimal reserve prices (histogram).

the screen. The decay curve used in simulations was calibrated to the average estimated decay curve for a number of auctions. Note also that this assumption implicitly rules out the possibility that the number of clicks that an ad receives, conditional on its position, is influenced by what other ads are shown on the screen (Jeziorskiy and Segal 2015).

Third, it was assumed that the values that advertisers assigned to clicks did not depend on where on the screen the ads were shown or on which or how many other ads appeared on the screen. Athey and Ellison (2011) present an alternative model of sponsored search auctions that allows for this possibility by endogenizing advertiser values and discuss how the derivation of optimal reserve prices in that setting differs from the current one.

Fourth, in sponsored search auctions on the Yahoo! platform, advertisers could allow the platform to "advanced match" their ads, by showing them not only for the keyword on which the advertiser submitted

TABLE 4
DISTRIBUTION OF ESTIMATED KEYWORD-SPECIFIC OPTIMAL RESERVE PRICES (Percentiles)

Percentile	10%	25%	Median	75%	90%
Estimated r^* ($)	.09	.12	.20	.37	.72

a bid but also for other closely related keywords (e.g., an ad for the keyword "car insurance" might also be shown to a user searching for "auto insurance"). For the purposes of the experiment, this possibility was ignored.

Next, the "theoretical optimality" of the computed reserve prices ignores the dynamic aspects of the real-world sponsored search environment: if bidders know that their bids will be used to set reserve prices in the future, they will change their bids. This problem can, in principle, be circumvented by setting each advertiser's reserve price based only on the bids of other advertisers. However, the company's view was that all advertisers for a given keyword should face the same quality-score-adjusted reserve price (more on that below). In addition, with sufficiently many bidders, this dynamic effect becomes small. Hence, it was ignored.

Finally, note that while the estimation procedure is based in spirit on the method of simulated moments, we cannot make any claims about its consistency, because that would require a large number of independent observations for each keyword, whereas in our setting, observations are of course serially correlated (e.g., for a given keyword, the profile of bids at time t is not independent of the profile of bids at time $t + 1$). Nevertheless, based on a number of simulations, this procedure was viewed as providing sufficiently accurate estimates to be used in practice.

B. Setting Reserve Prices

1. Quality Scores

The theoretically optimal reserve prices were computed under the assumption that all bidders were ranked solely on the basis of their bids, which is a simplification that essentially assumes that all ads have the same quality. In practice, the ranking also incorporated each ad's quality score, based primarily on the probability of the ad being clicked conditional on being shown. The ads were ranked based on the product of their quality scores and bids, and the amount each advertiser paid was lower when his ad's quality score was higher. Thus, in order to keep the implementation of reserve prices consistent with the company's ranking and pricing philosophy, the theoretical reserve prices were converted into advertiser-specific reserve prices that reflected the quality scores of the ads: ads with higher quality scores faced lower per-click reserve prices, and vice versa. Note that this is a deviation from the theoretically optimal auction design with asymmetric bidders, which generally suggests favoring weaker bidders (see, e.g., the theoretical and empirical analysis of asymmetric auctions by Athey, Coey, and Levin [2013], largely motivated by a "well-known insight of Myerson [1981] . . . that appropriately handicapping strong bidders can increase revenue relative to a standard open or sealed bid auction" [2–3]).

This deviation is not innocuous and can in fact lead to a reduction in expected revenue, especially for keywords whose level of optimal reserve prices is close to the original 10¢ (which was constant across bidders and did not depend on their quality scores). To see this, consider a simple example of a single-slot auction with two bidders whose per-click values are distributed uniformly from 0 to 20¢. Bidder A receives two clicks per hour (and has a quality score of 2), while bidder B receives zero clicks per hour (and has a quality score of 0).[11] With a common reserve price of 10¢ per click, the expected revenue in the auction is 10¢ per hour (if bidder A's value is above 10¢, he wins the auction regardless of the value of bidder B and pays 20¢ for the two clicks that he receives; otherwise, the revenue is zero).

With personalized reserve prices, bidder A faces a reserve price of 5¢, while bidder B faces an infinite reserve price. (The average quality score of bidders in the auction is 1, and a hypothetical average bidder with that quality score would face the reserve price of 10¢. The reserve prices to the actual bidders are set so that the product of the personalized reserve price and quality score is the same for all bidders.) The expected revenue in such an auction is 7.5¢ per hour (the .75 probability of bidder A's value exceeding the reserve price, times the reserve price of 5¢, times the two clicks per hour). This is a 25% reduction in revenue relative to the flat reserve price of 10¢.

Note that, by contrast, for keywords with a high average per-click value, the benefits of moving to a higher reserve price outweigh the costs of giving advantage to stronger bidders. For example, if in the same single-slot auction example we assume that the bidders' per-click values are distributed uniformly from 0 to 100¢, then the expected revenue in the preintervention auction (where every bidder faces the same reserve price of 10¢) is 18¢ per hour (the .9 probability of bidder A's value exceeding the reserve price, times the reserve price of 10¢, times the two clicks per hour), while the expected revenue in the postintervention auction, in which bidder A faces the reserve price of 25¢, is 37.5¢ per hour ($.75 \times 25 \times 2$)—a very large increase.

Despite this issue, the company nevertheless decided to proceed with the reserve prices based on the product of an advertiser's bid and quality score, for consistency with the auction's ranking rules and the company's policy of emphasizing ad relevance. At the same time, this deviation from theoretically optimal design made it especially important to monitor the impact of the changes for different reserve price levels. As we discuss in

[11] This is, of course, an extreme assumption, but it makes our calculations for this example particularly simple and transparent. If we consider a somewhat more realistic example in which bidder B receives, say, 1 click per hour rather than 0, the calculations become more cumbersome, but the substantive takeaway remains the same.

section V.C below, this concern turned out to be valid—while the impact of the change was positive for keywords with high reserve prices, it was the opposite for those with low ones.

2. Experimental Price Setting

The company allocated 95% of the keywords to the treatment group and 5% to the control group.[12] In the control group, reserve prices remained unchanged. In the treatment group, each keyword was randomly assigned an adjustment factor, with values .4, .5, or .6 for most keywords, and the keyword-specific reserve price was set equal to (optimal reserve price) × (adjustment factor) + 10¢ × (1 − adjustment factor)—a number between the old reserve price of 10¢ and the theoretically optimal reserve price.[13] Simulations like the ones presented in tables 2 and 3 suggest that this conservatism need not be very costly, since most of the upside from the reserve prices is already obtained once the price is set at the midpoint between 10¢ and the optimal reserve price. Moreover, overshooting by the same amount may be considerably more costly, and therefore the seller facing uncertainty about the optimal reserve price will prefer to be conservative.[14] This may, in fact, be a part of the explanation of the reserve price puzzle that we discussed in the introduction. The flatness of the revenue function around the optimal reserve price level also makes distinguishing between different adjustment factors statistically hard. Indeed, our experiment did not find any statistically significant differences between different adjustment factors. Hence, when discussing the results, we put all of the treatment keywords in the same group.

V. Experimental Results

In this section, we report the results of the experiment. We start with comparing the changes in revenues in the treatment and the control groups, normalized by group size. Average revenue per keyword in the treatment group increased relative to that in the control group by 12.85% of the average preintervention per-keyword revenue. However, this estimate is not robust: for instance, by excluding a single keyword from the control sample, this number can be reduced to around 8%. The reason why this estimate is not robust is that average revenues per keyword are affected not

[12] The reason for the small size of the control group was that both theoretical considerations and a smaller pilot experiment were strongly suggestive that new reserve prices would substantially increase revenues, and so allocating more keywords to the control group would be costly for the company.

[13] As discussed in sec. IV.B.1, these keyword-specific reserve prices were then further adjusted with quality scores.

[14] See Kim (2013) for a detailed discussion of this asymmetry.

only by the bids of the advertisers but also by the number of searches per keyword, and the number of searches per keyword turns out to be highly skewed and, for some keywords, highly volatile. To address this issue, we exclude from our sample the top 0.1% of keywords by search volume, which reduces the difference to 3.8% (see sec. V.B for details).[15]

Summary statistics and the test of treatment-control balance are presented in table 5. The unit of observation in the experiment is a keyword—that is, a separate auction market for each keyword (one auction market for keyword "car insurance," another auction market for keyword "cheap laptop," etc.), and the sample contains 438,198 keywords in the treatment group and 22,989 keywords in the control group. The data in table 5 come from a 30-day period before the introduction of reserve prices, in May and June of 2008. We normalized to 1 both the average revenue per keyword over that period and the average revenue per search.[16] The other statistics are reported without renormalization. The average keyword in our sample was searched by users 232 times over the 30-day period and had, on average, 5.9 advertisers active in the auction (depth). The average estimated optimal reserve price was approximately 35¢. Comparing the summary statistics for the treatment group and the control group, for only one variable (depth) is the difference statistically significant, and the absolute value of that difference is small.

A. Outcome Measures

To measure the effect of new reserve prices on various quantities of interest, we consider difference-in-differences estimates: we compare the preintervention to postintervention change in the average quantity of interest in the treatment group to that change in the control group.[17] We look at the effects of new reserve prices on three outcome variables. First, we look at the effect on "depth"—the average number of advertisers whose bids exceed the reserve price and whose ads are thus shown to search engine users. Second, we look at the effect on the average monthly revenue

[15] For completeness, in table A.1 (tables A.1 and A.2 are available online) we also report the results for the uncensored sample.

[16] This normalization was needed to keep revenue per search confidential. The formulas for the normalization procedures are as follows. Suppose each keyword i (in the sample of n keywords) was searched s_i times over the 30-day period and generated the total revenue of R_i (and its revenue per search is therefore $RPS_i = R_i/s_i$). That keyword's normalized revenue is then equal to $\hat{R}_i = R_i(n/\Sigma_{j=1}^{n} R_j)$, and its normalized revenue per search is equal to $\widehat{RPS}_i = RPS_i(n/\Sigma_{j=1}^{n} RPS_j)$.

[17] The preintervention data come from a 30-day period before the introduction of reserve prices, in May and June of 2008; then several weeks of data are skipped, because new reserve prices were phased in gradually and advertisers had grace periods before the new reserve prices became binding; and then the postintervention data come from a 30-day period after all reserve prices were phased in and all grace periods ended, in August of 2008.

TABLE 5
SUMMARY STATISTICS AND TEST OF TREATMENT–CONTROL BALANCE

Variable	All	Treatment	Control	Difference	p-Value
Revenue[a]	1	.9984	1.0305	−.0321	.6518
	(10.4636)	(10.4614)	(10.5060)	(.0711)	
Revenue per search[a]	1	.9996	1.0085	−.0089	.5313
	(2.0807)	(2.0793)	(2.1078)	(.0143)	
Number of searches	231.94	231.93	232.15	−.22	.9700
	(855.19)	(854.62)	(865.86)	(5.8548)	
Depth	5.9173	5.9159	5.9427	−.0268	.0397**
	(1.9176)	(1.9172)	(1.9258)	(.0130)	
Estimated optimal reserve price	.3515	.3514	.3525	−.0011	.7594
	(.5129)	(.5129)	(.5124)	(.0035)	
Sample size	461,187	438,198	22,989		

[a] Revenue and revenue per search are renormalized, to the average value of 1 across the overall sample. Numbers in parentheses give the standard deviations for the statistics in the first three columns and the standard errors for the differences in the fourth.
** Significant at the 5% level.

per keyword. As mentioned in section V above, while this outcome measure is very natural, estimates based on the average revenue per keyword are not robust, because they are affected not only by the bids of the advertisers but also by the number of searches for each keyword. Our experimental intervention has no effect on the number of searches, yet that variable is highly skewed and highly volatile. So the last outcome variable that we consider is "revenue-per-search": for each keyword, we compute the average revenue generated by the search engine every time a user searches for this keyword and then look at averages of these revenue-per-search estimates across keywords for various subsamples. This measure is not affected by the highly skewed and volatile number of searches and is not disproportionately affected by outliers.[18]

B. *Results*

The results for the overall sample are reported in the first column of table 6. Each observation is a separate keyword: 438,198 keywords in the treatment group and 22,989 keywords in the control group. The introduction of new reserve prices has a strong negative effect on the number of advertisements shown on the page when a user searches for a keyword: on average, new reserve prices reduce this number by 0.91; that is, almost one fewer ad per page is shown as a result of these reserve prices. This number is highly statistically significant. This effect should not be surprising: as table 4 shows, most reserve prices were raised substantially,

[18] For each subsample that we analyze, for both revenue and revenue-per-search outcome variables, we report the results in percentage terms relative to the preintervention averages of those variables in the subsample.

TABLE 6
RESULTS: FULL SAMPLE, SPLIT BY SEARCH VOLUME

	Full Sample	<10 Searches per Day	≥10 Searches per Day
Δ-in-Δ depth:	−.91***	−.90***	−.97***
t-statistic	[−80.4]	[−75.5]	[−27.8]
p-value	(< .0001)	(< .0001)	(< .0001)
Δ-in-Δ revenue (%):	3.80	10.34	2.06
t-statistic	[.94]	[1.19]	[.45]
p-value	(.347)	(.235)	(.653)
Δ-in-Δ revenue per search (%):	−1.45	−2.53**	3.90**
t-statistic	[−1.55]	[−2.36]	[2.31]
p-value	(.121)	(.018)	(.021)
Observations in treatment group	438,198	382,860	55,338
Observations in control group	22,989	20,133	2,856
Fraction of total revenue(%)	100	24.9	75.1

NOTE.—Changes in revenue and revenue per search are reported relative to the average revenue and average revenue per search in the corresponding subsample before the experiment.
** Significant at the 5% level.
*** Significant at the 1% level.

thus pricing out many advertisers whose ads were previously shown. Next, we consider the effect on the average revenue per keyword. The new reserve prices raised revenues by 3.8%, although the estimate is not statistically significant. Finally, looking at revenue-per-search estimates, the new reserve prices reduced revenue per search for the average keyword by 1.45% (although this estimate is also not statistically significant). This contrast between the signs of the effects of new reserve prices on the average revenue and on the average revenue-per-search may at first appear puzzling. The reason for the difference becomes clear when we recall the concerns discussed in section IV.A about the impact of reserve prices on rarely searched keywords and investigate to what extent these issues manifested themselves in our experiment by splitting the overall sample into two subsamples by search volume: the rarely searched keywords (those that are on average searched less than 10 times per day) and the frequently searched ones (those that are on average searched at least 10 times per day). The frequently searched sample contains only 12.6% of keywords but receives 66.9% of searches and generates 75.1% of revenue; conversely, the rarely searched sample contains the vast majority (long tail) of keywords but is only responsible for around a quarter of overall revenue. The impact of new reserve prices on the average revenue-per-search in the rarely searched subsample is negative, reducing it by 2.5%, while the effect in the frequently searched subsample is positive, at 3.9%.[19] Both effects are highly

[19] As discussed in sec. IV.A, one likely reason why the effect of reserve prices on revenues for rarely searched keywords is negative is that advertisers simply do not spend much time

statistically significant. When one computes the average impact on revenue-per-search for the overall sample, the rarely searched subsample dominates (since it contains the majority of the keywords), while when one computes the average impact on revenue, the frequently searched subsample dominates (since it is responsible for the majority of revenue), resulting in the net positive impact on overall auction revenue.

Given the size of the sponsored search advertising market, each percentage point of positive impact translates into potential improvements to search engine profits and revenues on the order of hundreds of millions of dollars per year. Moreover, by identifying the segments of keywords where new reserve prices perform relatively poorly and modifying them accordingly, the impact can be further improved. The analysis above, motivated by the concerns about the impact of reserve prices on rarely searched keywords (sec. IV.A), provides one such example. Our simulations of revenue impact under various parameters (sec. III.B), and the concerns about this impact for keywords with relatively low optimal reserve prices (sec. IV.B.1) motivate two additional analyses: comparing the effects of the experiment on keywords with relatively high and relatively low optimal reserve prices and comparing the effects on keywords with a relatively large and a relatively small number of bidders. We present the results of these analyses in the next two sections.[20]

C. *Experimental Results by Reserve Price Level*

Keywords differ substantially in their estimated theoretically optimal reserve prices, varying from 9¢ for the 10th percentile of keywords to 72¢ for the 90th percentile (sec. IV.A; table 4). As we discuss in section III.B, since the original reserve price for all keywords was equal to 10¢, the shift from the old reserve prices to the new ones, set midway between the old and the theoretically optimal ones, is much more important for the keywords with high optimal reserve prices than for the keywords with optimal reserve prices close to 10¢. Moreover, as we discuss in section IV.B.1, setting personalized reserve prices that favor higher-quality bidders may

optimizing bids on these keywords. They may set bids less carefully or update them less frequently, thus making the theory less applicable. Another related possibility is that low search volumes result in less accurate estimates of bidder values, which in turn leads our methodology to set less accurate reserve prices for these keywords.

The effect on average revenue (rather than revenue per search) appears to be large and positive, at 10.34%, but this number is driven by outliers and is not robust. For example, removing just two keywords from the treatment group reduces this number to 0.19%.

[20] The additional cuts of data are presented for the subsamples on which the new reserve prices have a statistically significant positive effect on revenue per search (frequently searched keywords for table 7 and frequently searched keywords with high optimal reserve prices for table 8). For completeness, in table A.2, we present the results for these cuts of data applied to the overall sample.

have a negative impact, potentially strongly affecting keywords whose theoretically optimal reserve price is close to 10¢.

To investigate these issues, in table 7 we present the results for two subsamples of keywords: those with the optimal reserve price lower than 20¢ and those with the optimal reserve price greater than or equal to 20¢ (following the analysis in the previous section, we restrict attention to the sample of frequently searched keywords). These two subsamples are of comparable sizes; however, the revenue generated by the subsample with the lower optimal reserve prices is an order of magnitude smaller than the revenue generated by the subsample with the higher reserve prices, because the keywords in the latter subsample, on average, have much higher revenues per search than those in the former. The average keyword in the high-price subsample receives approximately 34% more searches and 8.2 times as much revenue per search as the average keyword in the low-price subsample.

For keywords with high theoretically optimal reserve prices, the intervention is very successful: the impact of new reserve prices on revenue-per-search is equal to 4.9% and is highly statistically significant. However, for the group of keywords with theoretically optimal reserve prices closer to the old level of 10¢, the concerns discussed in section IV.B.1 turned out to be valid: the intervention reduced revenues per search by 8.7%. For keywords in this group, the positive effect from a small change in reserve prices was outweighed by a negative effect from deviating from the principles of optimal design for asymmetric auctions and giving advantage to stronger bidders.

TABLE 7
RESULTS: KEYWORDS WITH AT LEAST 10 SEARCHES PER DAY, SPLIT BY THE LEVEL OF ESTIMATED OPTIMAL RESERVE PRICE

	Full Subsample	$r^* < 20$¢	$r^* \geq 20$¢
Δ-in-Δ depth:	−.97***	−1.00***	−.94***
t-statistic	[−27.8]	[−21.2]	[−19.9]
p-value	(< .0001)	(< .0001)	(< .0001)
Δ-in-Δ revenue (%):	2.06	−13.64*	3.06
t-statistic	[.45]	[−1.66]	[.64]
p-value	(.653)	(.097)	(.525)
Δ-in-Δ revenue per search (%):	3.90**	−8.73**	4.88***
t-statistic	[2.31]	[−2.04]	[2.75]
p-value	(.021)	(.042)	(.006)
Observations in treatment group	55,338	21,760	33,578
Observations in control group	2,856	1,122	1,734
Fraction of total revenue (%)	75.1	4.6	70.5

NOTE.—Changes in revenue and revenue per search are reported relative to the average revenue and average revenue per search in the corresponding subsample before the experiment.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

D. *Results by the Number of Advertisers*

Our last analysis is motivated by the classic observation in auction theory, discussed in section III.B: the more bidders there are, the lower is the impact of reserve prices on expected auction revenue. To investigate this prediction, we further split the sample of frequently searched, high-price keywords into subsamples by depth: the average number of bidders placing ads on the keyword (preintervention). Theory predicts that reserve prices should be particularly effective for relatively "shallow" keywords that have relatively few advertisers and less effective for "deeper" keywords. Table 8 presents the results for the two subsamples of keywords: those with an average depth of less than 5.5 and those with an average depth of a least 5.5 (where 5.5 is the median depth in the full sample of keywords). The results are consistent with the theory: the average impact on revenue-per-search in the shallow subsample is 7.8%, higher than the average impact in the deep subsample (4.5%). However, the first of these estimates is not statistically significant, so we view this evidence as merely suggestive rather than conclusive.

VI. Conclusion

The results of the experiment described in this paper show that setting appropriate reserve prices can lead to substantial increases in auction revenues. These results also show (to the best of our knowledge, for the first time) that the theory of optimal auction design is directly applicable

TABLE 8
RESULTS: KEYWORDS WITH AT LEAST 10 SEARCHES PER DAY AND ESTIMATED OPTIMAL RESERVE PRICE OF AT LEAST 20¢, SPLIT BY AVERAGE NUMBER OF ADVERTISERS

	Full Subsample	Depth < 5.5	Depth ≥ 5.5
Δ-in-Δ depth:	−.94***	−.98***	−.92***
t-statistic	[−19.9]	[−18.2]	[−15.6]
p-value	(< .0001)	(< .0001)	(< .0001)
Δ-in-Δ revenue (%):	3.06	8.63	2.48
t-statistic	[.64]	[1.08]	[.47]
p-value	(.525)	(.280)	(.639)
Δ-in-Δ revenue per search (%):	4.88***	7.83	4.51**
t-statistic	[2.75]	[1.22]	[2.48]
p-value	(.006)	(.223)	(.013)
Observations in treatment group	33,578	11,378	22,200
Observations in control group	1,734	590	1,144
Fraction of total revenue (%)	70.5	7.1	63.4

NOTE.—Changes in revenue and revenue per search are reported relative to the average revenue and average revenue per search in the corresponding subsample before the experiment.
** Significant at the 5% level.
*** Significant at the 1% level.

in practice. Following the experiment, Yahoo! continued using and further fine-tuning this methodology for setting reserve prices. An executive described the overall impact of improved reserve prices on company revenues as follows:

> "On the [revenue per search] front I mentioned we grew 11% year-over-year in the quarter . . ., so that's north of a 20% gap search growth rate in the US and that is a factor of, attributed to rolling out a number of the product upgrades we've been doing. [Market reserve pricing] was probably the most significant in terms of its impact in the quarter. We had a full quarter impact of that in Q3, but we still have the benefit of rolling that around the world." Sue Decker, president, "Yahoo! Inc. Q3 2008 Earnings Call"[21]

Following the circulation of a working paper version of our results, other researchers and companies have also experimented with using and extending our approach to setting reserve prices in sponsored search auctions. On Microsoft's Bing search platform, reserve prices are now set using a similar methodology, which, as a starting point, uses the same approach of finding keyword-specific reserve prices at which virtual valuations given estimated value distributions are equal to zero. Sun, Zhou, and Deng (2014) report promising simulation results using data from the largest Chinese search engine, Baidu (although the paper does not present any experimental results). Topinsky (2014) presents the results of a controlled experiment conducted at the largest Russian search engine, Yandex, using a methodology similar to ours. Dimitrellos (2022) reports the results of an analogous experiment on the Tripadvisor search engine, also building on our methodology. The results of these experiments confirm our findings: the introduction of theory-based reserve prices has led to a substantial increase in auction revenues.

Data Availability

The data and code used to generate reserve prices in the production environment are proprietary. A synthetic dataset and MATLAB code that can be used to generate the tables corresponding to the ones in this paper can be found in Ostrovsky and Schwarz (2023) in the Harvard Dataverse, https://doi.org/10.7910/DVN/I9HGT6.

[21] http://seekingalpha.com/article/101002-yahoo-inc-q3-2008-earnings-call-transcript. The experiment described in this paper was one of several experiments comprising the market reserve pricing project.

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