Placement disclosure in ad auctions: Evidence from a policy change

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Abstract

Ad exchanges, i.e., platforms where real-time auctions for ad impressions take place, have
developed sophisticated technology and data ecosystems to allow advertisers to target users,
yet advertisers often do not know which sites their ads appear on. In practice, ad exchanges
can easily grant ad placement information to advertisers, allowing advertisers to bid on ads at
specific sites. However, ad exchanges are reluctant to disclose placement information due to fears
that advertisers will start buying ads only on the most desirable sites leaving inventory on other
sites unsold and lowering average revenue. The theoretical literature on information disclosure
in auctions suggests that auction revenue is a concave function of information provided and
prices will fall when too much or too little information is provided about impressions. This paper
explores the empirical effect of ad placement disclosure using a unique data set describing auction
outcomes on a major European ad exchange. We find that average revenue per impression rises
when ad placement information is provided suggesting that ad context information is important
to advertisers. The exception to this are sites which had a low number of buyers prior to the
policy change; consistent with theory, these sites with thin markets see prices go down. Our
analysis adds evidence that publishers and ad exchanges with thick markets should provide
advertisers with site placement information, which can be done at almost no cost.

Keywords: Online display advertising, Real-time bidding, Advertising auctions, Information
disclosure, Conflation, Bundling
1 Introduction

Digital display is a rapidly-growing advertising medium and of major interest to many researchers since it enables user-level targeting and tracking (Goldfarb and Tucker 2011a,b, Reiley et al. 2012, Lambrecht and Tucker 2013, Budak et al. 2014, Johnson et al. 2017, Choi and Mela 2018, Rafieian and Yoganarasimhan 2018). It is also of growing importance to advertisers due to new targeting possibilities based on user demographics and their online behavior as well as lower transaction costs enabled by the emergence of real-time bidding (RTB) platforms. US programmatic digital display ad spending (including RTB and programmatic direct deals\(^1\)) is projected to reach $45.72 billion representing 83.60% of total digital display ad spending in 2019 (AppNexus 2017).

Figure 1 depicts the basic structure of an RTB market. When a user requests a page from a site, an opportunity to advertise to that user becomes available. If the site publisher wants to sell this impression on the exchange, they can submit a bid request to the ad exchange, which includes a cookie ID identifying the user. The ad exchange subsequently broadcasts the bid request to potential advertisers typically through intermediaries including demand side platforms (DSPs.) In response, advertisers submit bids for the impression and the exchange sells the impression typically in a second-price auction. Finally, the winning advertiser pays the bid offered by the second-highest bidder plus 1 cent and their ad is displayed to the user. This entire process typically occurs within 400ms so that the ad loads almost instantaneously for the user. Since advertisers receive the cookie ID for the impression in the bid request, they are able to place independent bids for each impression to a specific user. Data describing the characteristics of each cookie are often purchased from third-party data aggregators, a practice which raises privacy concerns (for example see Goldfarb and Tucker 2011b, Johnson 2013, Goldberg et al. 2019).

\[\text{Figure 1 here}\]

RTB has fundamentally changed the landscape of digital display advertising because it allows advertisers to target impressions to individual users as those users visit many different sites, enabling advertising practices like retargeting, where ads are targeted to consumers who have previously shown interest in a brand. Initially, many RTB platforms did not provide advertisers with

\(^{1}\)Programmatic direct deals are a way to automate direct ad buys and do not involve an auction. These deals use technological infrastructure similar to RTB, but, as opposed to RTB, ad buys are guaranteed.
information about which site their ads will appear on. According to a survey conducted among US media buyers in 2015 (eMarketer 2016), uncertainty regarding which sites ads appear on is a major concern to more than six in ten advertisers (61.4%), and only 31% of advertisers feel that this issue is being sufficiently addressed by the digital advertising industry. Placement information may be important to advertisers because the site where an ad is placed may have an effect on the consumer’s response to the ad. For example, an ad promoting a food product displayed to a particular user may increase purchase intent for that user more when displayed on a site that provides recipes (i.e., when the ad is contextually targeted) because the user is more open to information about food when they are browsing that site. Previous research has reported effects of site placement on ad effectiveness (Goldfarb and Tucker 2011a, Shamdasani et al. 2001, Bleier and Eisenbeiss 2015, Lambrecht and Tucker 2013).

Certainly, brand safety issues can be considered the most extreme consequence of not having access to context information. Brand safety, i.e., avoiding ad placements near content that is inappropriate for the advertised brand, is one of the top challenges that the industry has to tackle (eMarketer 2019). More than two-thirds of US marketers report having experienced a brand safety issue at least once (eMarketer 2018), which has led to a decline in the share of programmatic purchases made via RTB (eMarketer 2017). Especially after YouTube’s ad controversy concerning ad placements near extremist content and hate speech (Heine 2017), major brands such as AT&T, Verizon, Pepsi, and Johnson & Johnson decided to pull all advertising budgets from Google’s display advertising platforms asking for more control over where their ads appear.

In practice, the market becomes more transparent if the ad exchange provides the URL of the site that the ad will be displayed on in the bid request to the advertiser (for example see Figure 2). As a consequence, advertisers are able to place ads at individual sites, which were previously only offered as part of a bundle2. However, our discussions with industry professionals involved in managing RTB platforms revealed that ad exchanges are often reluctant to provide advertisers with more information about ad placements due to concerns about potential negative effects on revenue for certain publishers. In line with practitioners’ concerns, some of the theoretical and empirical

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2 On the exchange we study, advertisers previously could set up their online advertising campaigns to run on the unrestricted inventory of the ad exchange known as “run of network” (RoN) or on a bundle of sites called “run of channel” (RoC). The channels that are offered to advertisers by the platform bundle together sites related to a theme that is desirable to advertisers (e.g., “automotive” or “finance”).
literature argues that more information about a good offered in an auction will not always generate higher selling prices (Levin and Milgrom 2010). For example, the counterfactual simulations done by Rafieian and Yoganarasimhan (2018) suggest that providing detailed behavioral information about users to buyers may reduce platform revenues by thinning out the market. However, providing ad buyers with site placement information allows advertisers to put a more precise valuation on each impression that they bid on. If the sites are horizontally differentiated, meaning different advertisers prefer different sites, then when advertisers bid their valuations for individual sites rather than the average valuation of the bundle, auction prices rise (Tadelis and Zettelmeyer 2015, Hummel and McAfee 2016).

While the literature primarily reports the results of counterfactual simulations of information disclosure policies from structural models, there is little direct empirical evidence on the effect of context information on ad auctions. This paper, thus, investigates a change in the ad placement disclosure policy at a major European ad exchange. In April 2016, one buyer that uses a specific demand side platform (DSP) to setup bidding rules was provided with ad placement information in the bid request allowing them to specify the specific URLs to include in their campaign. Figure 2 shows how the user of this DSP was able to include the site URL in their targeting criteria. Starting in May 2016, all bidders were able to set up campaigns for specific URLs. The ad exchange was motivated to make this change in order to be recognized as a brand safe platform. Prior to the change, the platform had provided buyers with a list of sites where ads may appear, but had not provided the URL in the bid request for each impression. The platform hoped that this change toward greater transparency would assuage advertisers’ concerns about brand safety. However, the ad exchange had lengthy debates internally about the change. While some at the company were confident that revenue would rise for most or all publishers, others were concerned that cherry-picking of the most desirable sites would lead to lower overall revenue for the platform and some dissatisfied publishers.

[Figure 2 here]

With this empirical study, we are able to shed light on the question of what happens when placement information is granted to advertisers. The data we analyze was provided by the ad exchange and records the number of impressions that each advertiser won on each day at each site
along with the average price paid by that advertiser for those impressions. Our analysis shows that the context information provided is important to advertisers, over and above the information they already had about users. Specifically, sites that had a higher number of bidders prior to the policy change achieved higher revenue per impression after the policy change, while sites with fewer bidders prior to the policy change experienced a slight revenue loss per impression. During the period when one buyer was provided with ad placement information, there was no significant change in prices, but that buyer won more impressions, suggesting that the buyer with context information was bidding higher on preferred sites. These findings show that advertisers value site placement information, that the sites are horizontally differentiated across advertisers, and that providing this information moves the market to a higher point on the revenue curve for the platform and for most sites.

This paper proceeds as follows: In the next section, we review findings on information disclosure from the theoretical literature, which suggests that prices may go up or down when more information is provided to all bidders, depending on market thickness and bidders’ valuations. We extend these results in a simulation study, to show that a bidder who obtains exclusive placement information will win more auctions, but prices paid by this bidder will not rise. In the following section, we describe the institutional setting and policy change in more detail. We then analyze the empirical effect of information disclosure on all bidders using a difference-in-difference analysis, which shows theoretically-predicted heterogeneity in treatment effects among sites. A mechanism check then shows that the right tail of the distribution of winning bids increased. Following that, we show the empirical effects of partial information disclosure by comparing auction outcomes for the bidder who received site placement information early to a synthetic control and find that the auction outcomes under partial disclosure are similar to those predicted by our simulation. We conclude with a summary of our findings and a discussion of our study’s implications.

2 Theory

There is an ongoing interest in the theoretical and empirical literature on auctions about how information disclosure will affect auction outcomes (Hummel and McAfee 2016, Tadelis and Zettelmeyer
2015, Johnson 2013, Rafieian and Yoganarasimhan 2018). However, the findings in this literature are mixed, with some theoretical researchers arguing that ad prices achieved in the auction should go up when more information is available about each impression while others argue they should go down. These predictions depend on 1) the valuations of advertisers for sites and 2) the number of bidders for each site after the information is disclosed (Levin and Milgrom 2010). If advertisers all value the same sites (i.e., sites are vertically differentiated), then prices will rise for the desirable sites and fall for the others. However, as illustrated by Hummel and McAfee (2016), prices can actually rise for all sites if each advertiser prefers different sites (i.e., sites are horizontally differentiated). The conclusion of this literature is that the relationship between auction outcomes and information disclosed is concave with an intermediate amount of information (or equivalently bundling) producing the highest revenue (Rafieian and Yoganarasimhan 2018).

For example, consider an ad exchange where there are two sites. Each bidder $i \in \{1, 2, ..., N\}$ has independently distributed valuations ($v^i_1$ and $v^i_2$) for the two sites which are each drawn from a Gaussian distribution with the following parameters:

$$v^i_1 \sim \mathcal{N}(\mu, \sigma^2) \quad v^i_2 \sim \mathcal{N}(\mu + \delta, \sigma^2)$$

(1)

When information is disclosed to all bidders, they each bid their valuation for each site ($v^i_1$ and $v^i_2$). Without information disclosure, bidders do not know which site is which and are forced to bid their average valuation, ($v^i_1 + v^i_2)/2$ for both sites. Here $\sigma$ represents the heterogeneity in bidders’ valuations for the same site and $\delta$ represents the difference in average preferences between the two sites. When $\sigma$ is large and $\delta$ small, we have what Tadelis and Zettelmeyer (2015) refer to as “horizontally differentiated” or “heterogeneous” buyers. When there are a sufficient number ($N$) of heterogeneous bidders, then disclosure will increase auction prices for both sites because bidders bid more for the sites they uniquely prefer (Palfrey 1983, Chakraborty 1999, Hummel and McAfee 2016, Chen et al. 2018). Figure 3 left panel illustrates this scenario: The “No Bidders” scenario shows the distribution of winning bids when bidders bid their average valuation for the two sites and the “All Bidders” scenario shows the same outcomes when bidders bid their individual valuations.

\[\text{Information disclosure is related to the literature on bundling in consumer marketing, cf. Stremersch and Tellis (2002), Bakos and Brynjolfsson (1999), Elberse (2010), however we focus on the more closely-related literature on auctions.}\]
bids. Under this scenario with \( N = 10 \) heterogeneous bidders, average prices rise, which has been shown analytically by Hummel and McAfee (2016). (In their analysis valuations are independently and identically distributed across bidders, similar to the simulation we show here.)

[Figure 3 here]

Even in the case where there are horizontally differentiated buyers (\( \sigma \) large and \( \delta \) small), if there are an insufficient number of bidders, prices may fall. This is illustrated in the middle panel in Figure 3 where average prices fall for both sites under information disclosure when there are \( N = 2 \) bidders. Levin and Milgrom (2010) refer to this as an “orphaned category” and argue that ad platforms should conflate markets so that “similar but distinct products are treated as identical in order to make markets thick or reduce cherry-picking.”

However, if \( \delta \) is large and \( \sigma \) is small, meaning buyers uniformly prefer one site to the other, then prices will rise for the preferred site and fall for the other (Figure 3, right panel). This outcome may be revenue-neutral for the auction platform (depending on the mix of sites it represents), but it does have a substantial effect on revenue for individual publishers and may make publishers of less-preferred sites dissatisfied. The potential for this scenario was of concern to the platform operator.

Research on information disclosure and bundling has focused on the cases like those illustrated in Figure 3 where all bidders have access to the same information and product offerings (Milgrom and Weber 1982, Eaton 2005, Tadelis and Zettelmeyer 2015, Hummel and McAfee 2016). However, in the policy change we study, the auction platform initially provided site information to one bidder. The literature on ad auctions does not address what happens when a single bidders obtains exclusive information in a second-price auction. To understand the expected effect of partial disclosure, we simulated auction outcomes to show the effect of disclosure to a single bidder.

Specifically, we assume that the first bidder has the site information and will bid their valuations \( (v_1^1 \text{ and } v_2^1) \), while the other buyers bid their average valuation for both sites \( ((v_1^i + v_2^i)/2), i \in \{2, ..., N\} \). Figure 4 shows simulated winning prices under no, partial and full information disclosure with the auctions won by the first bidder colored red. When information is disclosed to just one bidder, that buyer’s bids are more dispersed than the others, resulting in the treated bidder winning more often. This can be seen by the larger proportion of red in the “One Bidder” case in Figure 4.
However, the distribution of revenue per item does not rise substantially under partial information disclosure; the other bidders have not changed their bids and so the second-price is unchanged. Thus, in this example where there is a large number of bidders who are heterogeneous in their valuations, partial disclosure will result in the treated bidder winning more, but no substantial increase in prices. Under full disclosure (see “All Bidders” Figure 4), the relative advantage of this bidder disappears and the winning rate for the first bidder is similar to that in the no information case.

[Figure 4 here]

Our analysis contributes to the growing body of empirical work investigating what happens when information disclosure policies are changed in advertising auctions. Most of this literature estimates structural models to bid-level data on auction outcomes and then reports counterfactual predictions for policy changes. Johnson (2013) estimates a structural model from US-based ad auction data and uses this model to predict that both advertisers and publishers are worse off when the platform introduces stricter privacy policies, which limit access to user data and thereby reduce advertisers’ ability to target individual users. Lu and Yang (2019) use a structural model to predict that by optimizing the level of information provided about users, an ad platform may improve its revenue. Rafieian and Yoganarasimhan (2018) fit a structural model to data from an Asian ad exchange and use counterfactuals to predict the effect of limiting both user and context information on advertisers’ surplus as well as platform’s revenue. They find that context information affects revenue, but user information has a greater effect. All these studies rely on structural assumptions of the model, whereas we investigate an actual change in policy in the field at a major ad exchange.

Specifically, the theoretical and structural literature on auctions relies on the assumption that bidders will maximize their expected value. However, research on managerial decision making shows that managers are often risk-averse (Amihud and Lev 1981) relying merely on historical performance patterns (Busenitz and Barney 1997, Little 1970), such that they do not change their investment decisions when receiving better information (Lambert et al. 2007). Given the many potential targeting options available to online advertisers, they or their agencies may not have the time or incentive to focus on specific site placements. Consequently, it is unclear whether advertisers will put placement information to use at all.
While we are not aware of a paper that studies a real-world policy change in an ad auction, there are a number of empirical papers on other types of auctions. Eaton (2005) find that providing additional positive information about guitars in eBay auctions increases prices, while negative information decreases prices. Tadelis and Zettelmeyer (2015) report on a field experiment where additional information on quality was provided to bidders in a used-car auction, resulting in an increase in prices. They argue that the bidders are horizontally differentiated in their preferences for quality and that the information produces a better match between buyers and cars.

To summarize, it is difficult to predict whether site placement information will affect outcomes for three reasons: 1) if site placement is not valued by advertisers then the change will have no effect, 2) even if advertisers value the site placement, they may not change their bidding strategy due to the complexity of the advertising environment, and 3) even when advertisers are behaving optimally, the effect of information disclosure on auction outcomes is a complex function of advertiser valuations and market thickness, and prices may fall or rise for particular sites or overall. Thus, it remains an empirical question how site placement information will affect auction outcomes.

3 Institutional setting

The data we analyze comes from a leading European ad exchange who made a policy change in 2016. The ad exchange is a private marketplace and sells about 170M impressions per week to roughly 720 individual advertisers via real-time bidding auctions. Publishers participating in the ad exchange exclusively sell all their inventory via this platform, either through programmatic direct or RTB. Most of the publishers are widely-recognized media outlets in Europe; there are few if any publishers who would be characterized as providing low-quality ad impressions, i.e., “clickbait”. The full list of sites where the impressions may appear is available to advertisers via the ad exchange’s site.

Before the policy change, advertisers were able to bid on individual impressions based on cookie information, without knowing which specific site their ads would be displayed on. After the policy change, advertisers were given information about where each ad would be displayed for each impression. The ad exchange conducted a “test” in April 2016 where they provided information about

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4The majority of bidders in our data are advertisers, but some bidders are agencies bidding on behalf of several advertisers.
ad placements to one bidder who used a specific DSP. The ad platform chose this DSP because it is one of the leading DSPs worldwide. In May 2016, after observing an aggregate rise in revenue, the exchange made placement information available to all advertisers. As this feature was made available, advertisers were notified by the ad exchange, often through personal phone calls from representatives of the ad platform.

Our goal is to use data before and after the policy change to determine how this change affected auction outcomes. The data consist of the number of impressions purchased and average selling price for each bidder-publisher pair in each week. The primary data set spans a period of five months in 2016 that covers four weeks before the change (March 2016), four weeks where some advertisers had access to placement information (April 2016), and twelve weeks where all advertisers received placement information (May, June and July 2016). Similar data for the same months in the previous year is also available.

The publishers in our data vary greatly in the amount of inventory they produce and include major general interest sites (similar to yahoo.com in the US), forums (similar to quora.com in the US), sports sites (similar to espn.com in the US) as well as special interest sites featuring health (similar to webmd.com in the US) or various niche content (similar to allrecipes.com or zillow.com in the US). Table 1 shows summary statistics on the supply and average revenue per impression for each publisher before the policy change. Across all sites, the mean revenue per thousand impressions (CPM) was €0.77 in the first week of March 2016. In addition, the average revenue per thousand impressions varies substantially across publishers, with some sites as low as €0.20 and as high as €2.09. Prior to the policy change, advertisers did not know which site the ad would be placed on when the impression was sold, so the variation in revenues across publishers is due to differences in how advertisers value the users that visit each site. Table 1 also shows that on average each site put 4,043,631 impressions into the auction and sells 3,942,774, leaving about 100K impressions unsold for each site in each week. The relatively high prices and low unsold inventory reflect the generally high quality of the publishers that participate in this exchange.

Table 1 here

Apart from differences in size, our publishers also differ in how competitive their respective auctions are. Since we do not have information about individual bids, we assess market competi-
tiveness using a proxy: the average number of daily unique winning advertisers for each publisher. As can be seen in Figure 5, most publishers have anywhere from 5 to 20 daily unique winning advertisers. However, there are a large number of sites with fewer than 5 winning bidders each day, and the policy change could exacerbate this, leading to thin markets.

![Figure 5 here](image)

Because this is a non-randomized policy change, we leverage two strategies to identify the effect of the policy change on auction outcomes. Our first analysis uses a difference-in-difference strategy to compare the average revenue per impression for each site in the months after the policy change to the revenue the year prior. To further gauge heterogeneity in treatment effects, we analyze the effect of the policy change for sites that are thick and thin in competition in the period prior to the policy change. Consistent with theory, we find that sites with thick markets had increases in revenue, while prices fell for those with fewer bidders prior to the change.

In our second analysis, we investigate the partial disclosure effect by looking at the period in April 2016 where only one advertiser using a particular DSP was granted placement information. This analysis allows us to make a contemporaneous comparison between the bidder who received placement information in April and a synthetic control advertiser. Analyzing both the revenue per impression sold and the total amount purchased, we find that the bidder with placement information purchased more, but did not pay higher prices, which is consistent with our simulation results (see “One Bidder” scenario in Figure 4).

4 Full disclosure of site information increases auction revenue for thick markets

In this section, we investigate the effect of granting ad placement information on the average revenue per impression for each publisher. Specifically, we divide the total weekly revenue for each publisher by the weekly total impressions that the publisher submitted to the RTB platform (including sold and unsold impressions) and compare this average revenue per impression before and after the policy change for each publisher. The ad exchange typically receives a fixed percentage of the revenue, so that average revenue per impression reflects income for publishers and the ad exchange.
We observe a few advertisers purchasing a small number of impressions for an unusually high price (e.g. €200 CPM). These sales are likely advertisers buying retargeted ads that are atypical for this platform. Therefore, we filtered out any observations where an advertiser bought less than 500 impressions from a publisher on a given day. The removed impressions make up 3.75% of impressions sold. We further excluded sites that were not regularly participating in the auction over the periods we analyze (i.e., those that only sold impressions on <4 days out of any week). This avoids situations where no price is observed for a particular site in a particular week. After excluding these publishers, which only sell about 0.96% of impressions, we are left with 48 moderate-to-high volume sites to analyze.

4.1 Model-free evidence

We begin by providing model-free evidence of the effect that the policy change had on average revenue per impression. Figure 6a and 6b shows the percentage change in average revenue per impression for each publisher. Revenue increases for most publishers when ad placement information is provided to some advertisers (average around 12.0%), and later to all advertisers (around 29.1%). However, the policy change coincided with a substantially lower supply of impressions as shown in Figure 7, requiring further analyses in order to make causal claims. This drop in supply is consistent with seasonal patterns in web traffic, which tend to fall in the spring and summer. Another potential explanation for the observed supply drop is that bidders have moved inventory out of the RTB market and into programmatic direct deals in response to the policy change. In Figure 8 we visualize the number of impressions sold through these two selling mechanisms from March to July 2016. The lack of an obvious shift from RTB to programmatic direct suggests that publishers did not react in that way, making seasonal patterns the more likely explanation for the supply drop.

[Figure 6a and 6b here]
[Figure 7 here]
[Figure 8 here]

The publishers on this exchange are contractually obligated to sell all their impressions at this exchange either through the RTB market or through programmatic direct (which we observe).
All in all, this model-free evidence suggests that the ad exchange’s revenue increased after the policy change. However, we have not yet ruled out the possibility that the revenue increase was due to the seasonal supply shortage. In order to address this concern and provide a better understanding of the effect that the policy change had, we turn to a diff-in-diff analysis where we use the prior year as a control for seasonality in ad prices.

4.2 Year-over-year results

Recall that our data consist of the daily number of impressions purchased and price paid for each bidder-publisher pair. We summarize this up to the weekly level so that our observations are the average revenue per impression for each site in each week; this avoids having periods where a site did not sell any impressions. We investigate the impact of the policy change utilizing a regression where we use the data from 2015 as a control. Figure 7 shows that 2015 is a reasonable counterfactual for year 2016 as both years follow typical seasonal patterns in available inventory. In addition to using 2015 as a control, we include the average supply and average number of unique winning bidders as additional controls. We also factor in site fixed effects. The regression also allows us to look at how the effect of the policy developed over time as more advertisers began to utilize the information provided in the bidding process.

While the display advertising market can change quickly, this market was particularly stable, which allows us to use 2015 as a control for the seasonality in inventory. The sites in our data set are all well-established publishers with stable traffic and inventory. Furthermore, we can see from Figure 7 that the supply drop in 2015 was slightly more pronounced in March and April of 2016 making the change in average revenue per impression in year 2016 relative to year 2015 a conservative estimate of the causal effect of the policy change.

Table 2, columns (2)-(4) show the estimated coefficients for several alternative regression specifications specifically excluding site fixed effects and control variables. We focus on interpreting model results in column (4), which includes fixed effects and both controls. The interaction terms April x Year16, May x Year16, June x Year16 and July x Year16 are the key coefficients of interest, which gauge whether ad placement information increases or decreases average revenue per impression relative to the year prior. Note that the regression weights the observations for each publisher in each week by the number of impressions, so that these estimates represent the average
change in price across all impressions.

[Table 2 here]

For the period where information was provided to one bidder, there is a small change of 7.9 EUR cents in average revenue per impression (see April x Year16). However, there is a substantial increase in average revenue per impression beginning in May 2016 when all advertisers have site information. Average revenue per impression increases by 15-20 EUR cents (see May x Year16, June x Year16 and July x Year16 in column 4), which is quite substantial. These results are consistent directionally with the theoretical predictions in Section 2 for thick markets with horizontally differentiated bidders. All control variables show the expected signs: increasing supply decreases average revenue per impression and increasing the number of bidders (unique winning advertisers) increases average revenue per impression.

4.3 Heterogeneous treatment effects for sites with thin versus thick markets

The model reported in column (4) indicates that information on ad placements increased the average revenue per impression. However, the change in revenue might vary with the thickness of the market (see Figure 3): site placement information may cause prices to fall if there are an insufficient number of bidders interested in a particular site. Therefore, we further investigate heterogeneous treatment effects for sites with regard to competition. To do so, we create a dummy variable for sites with thin markets based on the average number of unique winning advertisers per day prior to the policy change. We set the cutoff point at the first quartile, which is 2.2 advertisers. This variable captures market thinness before the policy change, and we assume that advertisers with thin markets before the policy change were likely to have thin markets after the change. Figure 5 indicates that this is a reasonable assumption since market competitiveness remained rather stable post treatment. This pre-treatment covariate is also not contaminated by the treatment.

The model reported in column (5) in Table 2 shows the moderating effect of competition on average revenue per impression. First, note that the constant increases substantially in model (5) because it now represents the sites with thicker markets, which also generally sell for higher prices. The effect of the policy change for these thick-market publishers is shown in the first four rows (e.g., April x Year16) and the subsequent four rows (e.g., April x Year16 x Thin sites) show the
incremental effect for sites that are thin in competition. Based on our simulation and the literature on auctions, we expect thick (thin) markets to experience an increase (decrease) in average revenue per impression. Our results indicate that disclosure increases average revenue per impression if markets are thick (e.g., 23.9 EUR cents increase in May 2016.) However, revenue per impression for sites that are thin in competition falls slightly when placement information is provided to all advertisers (e.g., the total effect for May is $0.239 - 0.325 = -0.086$). Both these findings are consistent with the literature on auctions and the simulations in Section 2.

While Table 2 captures the average treatment effect of the policy change, we additionally explore the variance in the average revenue per impression as another mechanism check. Figure 9 shows that the average revenue per impression gets more dispersed when advertisers are provided with site placement information. After site information is available, the right tail of the distribution for sites with thick markets becomes substantially heavier suggesting that site placement information increases some advertisers’ valuation for impressions. This finding is consistent with auction theory – bids should spread out when buyers have additional information and this results in a thicker right tail of winning bids.

[Figure 9 here]

5 Partial information disclosure does not increase revenue, but advantages the bidder with information

Next, we investigate the effect of the policy change for the period where only the buyer who used a particular DSP was provided with ad placement information (i.e., April 2016). Theoretically, when information is disclosed to only one bidder, their bids become more dispersed than those of the bidders who were not provided with information (see Figure 4). This results in the treated bidder winning more often, but paying more or less the same price. The other bidders do not change their bids and so the second-price remains the same. The unique nature of the policy change we observe allows us to test whether this is what happens when information is disclosed to only one bidder.
5.1 Construction of synthetic control

To provide a better understanding of the policy change, we analyze the behavior of the bidder who obtained exclusive access to site placement information in April 2016 relative to other bidders. This bidder was an agency bidding on behalf of several advertisers. We focus on two dependent variables: average winning price paid and number of impressions won. Prior to the policy change, the bidding behavior of the treated advertiser differs from most other advertisers. As can be seen in the first column of Table 4, the treated bidder bought fewer impressions and also paid higher prices than the average of all other advertisers shown in column 4. To construct a counterfactual for what would have happened if this buyer had not gotten placement information, we use a synthetic control (Abadie and Gardeazabal 2003, Abadie et al. 2010).

The synthetic control method constructs a synthetic (or counterfactual) buyer that resembles the treated buyer during the pre-intervention period, by creating a convex combination of untreated buyers that matches on several pre-treatment covariates known as “predictors” in the synthetic control literature. The weights that define the control buyer are chosen such that the counterfactual buyer’s behavior approximates the treated buyer during the period prior to the policy change. Then, the constructed synthetic buyer is used to estimate the causal counterfactual for how the treated buyer would have behaved if not provided with placement information. Since our theoretical prediction is that the treated bidder will be winning more often, but paying more or less the same, we look at both winning price and impressions won as dependent variables and construct separate synthetic controls for each (respectively labelled Synthetic 1 and Synthetic 2 in Table 4). Technically, the impressions won and prices paid by buyers who did not have access to this information may have been affected somewhat since they are participating in an auction with the treated bidder. However, since our treated buyer represents less than 2% of impressions sold, the control buyers would have only been affected by a small amount.

In order to create the synthetic control bidder, we use the following pre-treatment covariates: (1) number of impressions won in each genre per week, (2) average of winning price in each genre per week, (3) total number of impressions won in each week and (4) average winning price in each week. Genres were utilized to create the covariates, since advertisers were able to target channels or users based on behavioral information prior to the policy change. The covariates are created
based on the five available months in 2015 (same time frame as in 2016), as well as March 2016. The core identifying assumption is that these pre-treatment covariates represent the key ways in which the treated buyer is different than the untreated.

The synthetic control is created to match the behavior of the treated bidder prior to the policy change (March-July 2015 and March 2016). This is done separately for the two independent variables in this analysis: average winning price (i.e., average price paid per impression) and number of impressions won. Table 4 reports the summary of the covariates used in the construction of the synthetic buyer and compares them to the treated buyer, which are by construction largely similar. Furthermore, buyers in the control group that are picked by the algorithm are mainly the same for both independent variables and the highest weights are assigned to agencies bidding on behalf of advertisers (similar to the treated buyer).

5.2 Synthetic control results

We first examine the effect of placement information on average winning price comparing the treated buyer with the synthetic buyer in each week. Figure 10a shows that the trajectory of the synthetic buyer’s average winning price closely follows the treated buyer’s price, which suggests that the synthetic buyer nicely mimics the treated buyer prior to policy change. Consistent with the simulation results from Section 2, the additional placement information does not affect the average winning price for the treated bidder, as can be seen by comparing the treated bidder to the synthetic control in Figure 10a after the policy change. Even if treated advertisers were bidding higher after being provided with ad placement information, prices did not rise because the bids from other buyers, which result in the second-price, were not affected.

However, the simulation in Section 2 suggested that the number of impressions won by the treated bidder should be higher when provided with placement information, so we compare the number of impressions won for the treated and synthetic control bidders in Figure 10b. To the left
of the vertical line, the number of impressions won is similar for the treated and synthetic control bidder suggesting that the algorithm was able to find a comparable synthetic buyer. After the policy change, we see a swift rise in the gap between treated and synthetic buyer in the number of impressions won. While impressions won by treated advertisers increased substantially after the policy change, they remained flat for the synthetic control. As predicted by the simulation results (see “One Bidder” in Figure 4), we do not observe a rise in average winning price, but the information disclosure clearly resulted in a higher number of impressions won for the treated advertiser.

To assess statistical significance, we conduct a series of placebo tests by applying the synthetic control method to the advertisers who were not provided with placement information.\textsuperscript{7} By doing so, we produce a distribution of weekly estimated gaps between each advertiser and its optimal synthetic control (see Figure 11). The quality of fit of the synthetic control can be assessed by using the mean squared prediction error (MSPE) prior to the policy change. Following Abadie and Gardeazabal (2003), Abadie et al. (2010) and Tirunillai and Tellis (2017), Figure 11 visualizes the placebo buyers having a pre-intervention MSPE of less than 5 times the MSPE of the treated buyer which results in 62 control buyers in Figure 11a and 70 control buyers in Figure 11b. As denoted by the thick black lines in Figure 11a and 11b, the synthetic control method provides a very good fit for the treated buyers. The estimated number of impressions won has a p-value of 0.032,\textsuperscript{8}, suggesting the theoretically-predicted, significant increase in impressions won for the treated bidder. Also consistent with theory, we do not observe a significant effect on average winning price in the same period (p-value = 0.942).

[Figures 11a and 11b here]

6 Discussion and implications

This paper uses auction data provided by a major European ad exchange to investigate a policy change where ad placement information was provided to advertisers in the bidding process. Our

\textsuperscript{7}This is the standard method of assessing significance for synthetic controls (cf. Tirunillai and Tellis 2017).

\textsuperscript{8}p-values are calculated by means of the ratio of post - pre intervention MSPE. If an advertiser were randomly treated, the probability of obtaining a post - pre intervention MSPE ratio as large as the one for the treated buyer would be 2 (number of advertisers exceeding the treated advertiser’s MSPE ratio) over 62 (number of advertisers).
analysis shows that average revenue per impression rose after the policy change relative to the previous year. The increase in prices was most pronounced for the sites with a large number unique winning bidders prior to the policy change. Sites with fewer bidders (thin markets) experienced a slight drop in prices. As we illustrate with a simulation reported in Figure 3, these heterogeneous treatment effects are consistent with a scenario where advertisers prefer different sites. Such horizontally differentiated preferences lead to an increase in prices with site disclosure (Tadelis and Zettelmeyer 2015), so long as the market does not become thin (Levin and Milgrom 2010, Hummel and McAfee 2016). Under this scenario, advertisers bid higher for the sites they prefer after the policy change, which shifts the distribution of winning bids to the right. The mechanism check in Figure 9 confirms that this happened on the ad exchange we study.

A unique feature of the policy change we observe is that the site information was made available to one advertiser one month earlier than the other advertisers. Since this partial disclosure situation is not covered in the existing literature on auctions, we use a simulation to predict auction outcomes under partial disclosure. When preferences for sites are heterogeneous across bidders and markets are thick, information disclosure to one bidder results in that bidder winning more auctions, but not paying higher prices. While we do not directly observe the auction bids in our data, we can empirically test these two predictions about aggregate auction outcomes. A contemporaneous comparison of the bidder who was given early access to the site placement information and a synthetic control that had similar pre-treatment purchase patterns shows that the treated bidder won more auctions than they had previously (thus was bidding higher), but did not pay higher prices, consistent with the simulation. While this is not a randomized treatment, the contemporaneous comparison between advertisers who did and did not have site placement information, adds evidence that the policy change had a causal effect on auction outcomes that is consistent with auction theory.

In sum, we provide empirical evidence that 1) advertisers value site information, 2) different advertisers value different sites (horizontally differentiated preferences), and 3) when markets are thick, this results in higher selling prices when site information is disclosed. To outline the economic relevance of our findings, we estimate the amount of additionally generated revenue resulting from the policy change. The average weekly supply of a site in our sample is roughly 4M impressions (see Table 1), sold for an average CPM of 77.0 EUR cents. According to our analysis, average
CPM rises by about 20 EUR cents when all advertisers are provided with placement information (see Table 2, column 4, July x Year16). Therefore, on average each site generates an additional yearly revenue of \((4\text{M}/1000) \times 20\text{ EUR cents} \times 52\text{ weeks} = €41,600\). Hence, the overall revenue across all publishers increases by about \(€41,600 \times 48 = €1,996,800\) per year. Since ad exchanges typically receive a revenue share from the publishers in their portfolio (in our case about 2.5%), the additional yearly revenue for our ad exchange is roughly \(€1,996,800 \times 2.5% = €49,920\). Note that this calculation depends on the figures obtained from our sample and is highly dependent on the scale of the ad exchange, yet these rough calculations show that the policy change is associated with a substantial increase in revenue for publishers and the ad exchange.

Finally, our findings suggest that site placement information provides advertisers with additional information about the value of an impression, above-and-beyond what they already know (e.g., information about the cookie). While this suggests that site information is at least partially complementary to user-level data, we don’t observe whether advertisers were also using the site information as a substitute for user data purchased from data brokers. We are unaware of any empirical studies of policy changes that have reduced access to user information, however Johnson (2013) and Rafieian and Yoganarasimhan (2018) both report counterfactual predictions from structural models that suggest that access to user data improves outcomes for advertisers. In addition, Marotta et al. (2019) show that when the user’s cookie is available, publisher’s revenue increases, but the increase is just about 4% corresponding to an average increase of $0.00008 per advertisement. The authors argue that organizational measures that ensure the compliance with privacy regulations come at a cost and sometimes a prohibitive one, making it unattractive for publishers to enable cookie tracking. Instead providing advertisers with the URL of the site the ad is placed on is nearly cost free; we provide convergent evidence that doing so results in a substantial revenue increase. We look forward to more empirical studies on changes to policies around user data as regulations like GDPR limit the amount of user-level targeting that is possible (for example see the working paper of Goldberg et al. (2019)).

As with any empirical work, there are a number of limitations to our study. First, the publishers that participate in the exchange we study were well-established media platforms in Europe. There may be a higher risk of deconflation in other markets when site placement information is disclosed. In particular, we expect publishers that produce extreme content might see prices fall
and become “orphaned”, as evidenced by the recent drop in demand for advertising at the alt-right site Breitbart.com in the US (Bhattarai 2017).

Second, although we demonstrate the impact of information disclosure on average revenue per impression utilizing a data set that consists of winning auction outcomes, we would be able to gain more insight into advertiser’s valuations by investigating data on individual advertisers’ bids for specific impressions. Instead, we only have data on the selling prices for the winning bids, which makes it difficult to determine precisely how the ad placement information affected bidders’ valuations. In addition, if we had data on individual bids, we could better assess market competitiveness by counting the number of advertisers bidding for each impression.

Despite these limitations, our study represents an important step in understanding the information disclosure effect in advertising auctions following an empirical setting. Moreover, our results have important implications for different market players in digital marketing.

*Implications for ad exchanges* Ad exchanges are often reluctant to provide advertisers with more information about ad placements, due to concerns that advertisers may start cherry-picking specific publishers leaving some ad inventory unsold. Yet, our study presents first empirical evidence that disclosure of ad placement information increases revenue per impression on average. Disclosing ad placement information will therefore not only improve advertisers’ trust that sites on the platform are brand safe, but also presents an opportunity for the platform to increase their revenue.

*Implications for publishers* Our study shows that information disclosure leads to a decrease in revenue only for sites that do not have a large number of buyers. This is good news for sites with thick markets who should prefer to have site information disclosed to buyers.

*Implications for advertisers* Another market player that benefits from provided ad placement information is advertisers since information disclosure allows them to whitelist/blacklist specific publishers. In that case, advertisers cannot only match their ads to specific sites, potentially increasing ad effectiveness (Goldfarb and Tucker 2011a, Bleier and Eisenbeiss 2015, Goldfarb and Tucker 2011c), but they also rest assured that these sites are generally brand safe. This increased control does come at a cost, however, in the complexity of setting up bidding rules.

*Implications for consumers* While this is somewhat speculative and beyond our data, consumers may also benefit from better content and superior user experience provided by publishers as they may be incentivized to improve their sites in order to benefit more from the policy change.
Implications for industry organizations and regulators As brand safety discussions are becoming prevalent, regulators as well as industry organizations such as the Interactive Advertising Bureau (IAB), which develops industry standards, conducts research, and provides legal support for the online advertising industry, should create incentives for ad exchanges to disclose ad placement information since all parties (i.e., ad exchanges, publishers as well as advertisers) benefit from such disclosure.
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Table 1: Summary statistics on sites during the first week of March 2016 (prior to the policy change).

| Statistic                          | Mean       | St. Dev.    | Min       | Median     | Max        |
|-----------------------------------|------------|-------------|-----------|------------|------------|
| Supply of impressions             | 4,043,631  | 16,345,905  | 1,227     | 240,129    | 103,309,076|
| Impressions sold                  | 3,942,774  | 16,267,049  | 1,197     | 121,779    | 103,290,072|
| Revenue per impression (CPM)      | 0.77       | 0.41        | 0.20      | 0.72       | 2.09       |
| Number of winning bidders         | 9.30       | 10.14       | 1.00      | 5.14       | 47.43      |
Table 2: Year-over-year analysis of the change in average revenue per thousand impressions due to the policy change.

|                          | (1)       | (2)       | (3)       | (4)       | (5)       |
|--------------------------|-----------|-----------|-----------|-----------|-----------|
| Constant                 | 0.482***  | 0.257***  | 0.303***  | 0.315***  | 1.504***  |
|                          | (0.014)   | (0.050)   | (0.048)   | (0.057)   | (0.112)   |
| April x Year16 (Partial disclosure) | 0.099***  | 0.089**   | 0.081**   | 0.079**   | 0.079**   |
|                          | (0.034)   | (0.035)   | (0.040)   | (0.039)   | (0.039)   |
| May x Year16 (Full disclosure) | 0.173***  | 0.216***  | 0.242***  | 0.238***  | 0.239***  |
|                          | (0.042)   | (0.038)   | (0.039)   | (0.039)   | (0.039)   |
| June x Year16 (Full disclosure) | −0.021    | 0.057     | 0.147**   | 0.139**   | 0.139**   |
|                          | (0.058)   | (0.053)   | (0.059)   | (0.069)   | (0.069)   |
| July x Year16 (Full disclosure) | 0.005     | 0.105*    | 0.202***  | 0.196***  | 0.196***  |
|                          | (0.060)   | (0.059)   | (0.064)   | (0.067)   | (0.067)   |
| April x Year16 x Thin sites (Partial disclosure) | −0.022    |           |           |           |           |
|                          |           |           |           |           |           |
| May x Year16 x Thin sites (Full disclosure) | −0.325*** |           |           |           |           |
|                          |           |           |           |           |           |
| June x Year16 x Thin sites (Full disclosure) | −0.182    |           |           |           |           |
|                          |           |           |           |           |           |
| July x Year16 x Thin sites (Full disclosure) | −0.122    |           |           |           |           |
|                          |           |           |           |           |           |
| Supply in millions        | −0.002*** | −0.002*** | −0.002*** |           |           |
|                          | (0.0004)  | (0.0004)  | (0.0004)  |           |           |
| Number of unique winning bidders | 0.001     | 0.001     |           |           |           |
|                          | (0.003)   | (0.003)   |           |           |           |

Notes: Standard errors, in parentheses, are clustered at the week level. Baseline is March 2015 for columns (1)-(4) and sites that are thick in competition in March 2015 for column (5). ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.
Table 3: Year-over-year analysis of the change in average revenue per thousand impressions due to the policy change (continued).

|            | (1)   | (2)   | (3)   | (4)   | (5)   |
|------------|-------|-------|-------|-------|-------|
| April      | −0.017| 0.006 | 0.005 | 0.006 | 0.006 |
| (Partial disclosure) | (0.018) | (0.010) | (0.019) | (0.019) | (0.019) |
| May        | 0.117***| 0.111***| 0.066***| 0.064***| 0.064***|
| (Full disclosure) | (0.038) | (0.031) | (0.024) | (0.024) | (0.024) |
| June       | 0.312***| 0.277***| 0.181***| 0.183***| 0.183***|
| (Full disclosure) | (0.032) | (0.019) | (0.026) | (0.029) | (0.029) |
| July       | 0.307***| 0.258***| 0.171***| 0.169***| 0.169***|
| (Full disclosure) | (0.026) | (0.030) | (0.040) | (0.040) | (0.040) |
| Thin       | −0.819***| | | | |
| (0.195)     | | | | | |
| April x Thin sites | | | | | |
| (Partial disclosure) | | | | | |
| May x Thin sites | | | | | |
| (Full disclosure) | | | | | |
| June x Thin sites | | | | | |
| (Full disclosure) | | | | | |
| July x Thin sites | | | | | |
| (Full disclosure) | | | | | |
| Year16     | 0.236***| 0.230***| 0.184***| 0.171***| 0.172***|
| (Year16 x Thin sites) | (0.033) | (0.033) | (0.037) | (0.059) | (0.059) |
| Site FE    | | | | | |
| No         | 5,357.4| 3,653.1| 3,568.7| 3,569.5| 3,584.7|
| Yes        | 1,696  | 1,696  | 1,696  | 1,696  | 1,696  |
| R²         | 0.409  | 0.795  | 0.805  | 0.806  | 0.806  |
| Adjusted R²| 0.406  | 0.788  | 0.799  | 0.799  | 0.798  |

Notes: Standard errors, in parentheses, are clustered at the week level. Baseline is March 2015 for columns (1)-(4) and sites that are thick in competition in March 2015 for column (5). ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.
Table 4: Descriptive statistics for pre-treatment behaviors used to construct the synthetic control (predictor means).

|                          | Treated       | Synthetic 1 | Synthetic 2 | All Others |
|--------------------------|---------------|-------------|-------------|------------|
| Impressions              | 1,018,449     | 1,148,543   | 1,558,314   | 1,913,844  |
| Impressions (Community & Forums) | 40,410       | 28,499      | 24,364      | 34,450     |
| Impressions (General interest) | 924,816      | 1,063,601   | 1,467,518   | 1,770,087  |
| Impressions (Health)     | 3,363         | 3,483       | 3,755       | 7,400      |
| Impressions (Special interest) | 3,620         | 3,301       | 3,624       | 11,144     |
| Impressions (Sports)     | 46,240        | 49,659      | 59,053      | 90,763     |
| Price                    | 3.54          | 3.53        | 3.32        | 0.97       |
| Price (Community & Forums) | 4.33          | 4.36        | 4.43        | 0.78       |
| Price (General interest) | 3.50          | 3.64        | 4.85        | 0.96       |
| Price (Health)           | 2.23          | 1.75        | 1.99        | 0.30       |
| Price (Special interest) | 1.09          | 1.07        | 1.06        | 0.31       |
| Price (Sports)           | 3.77          | 3.11        | 3.52        | 0.70       |

Note: Data is given on weekly buyer level prior to the policy change.
Figure 1: Real Time Bidding (RTB) markets match advertisers with opportunities to advertise in real time.
Figure 2: Example of a demand side platform (DSP) interface where users can enter the URLs of the sites where they want their ads to appear. This feature only became available after the policy change. Advertisers were notified of the change via a phone call.
Figure 3: Effect of information disclosure on auction prices. Each dot represents the outcome of a simulated auction where valuations are defined as in (1). Average price is shown with horizontal lines. Auctions won by bidder 1 are shown in red. With a large number of heterogeneous bidders, average price rises (left). When there are only two bidders, prices fall slightly (middle). When bidders homogeneously prefer site 2, prices fall for site 1 and rise for site 2.
Figure 4: Effect of partial information disclosure on auction prices. Each dot represents the outcome of a simulated auction and is colored red if the treated buyer wins. Average price is shown with horizontal lines.
Figure 5: Competitiveness of the auction for each publisher as measured by the number of average unique daily winning advertisers in 2016.

Note: Sites are sorted in order of weekly supply of impressions in the auction (highest to lowest).
Figure 6: Percentage change in average revenue per impression for each site in 2016 compared to the period before the policy change.

(a) Partial information disclosure (April 2016)  (b) Full information disclosure (May - July 2016)
Figure 7: Weekly supply of impressions from March to July for 2015 and 2016 shows a decline in supply in spring.

Note: Red lines represent the first week of each month.
Figure 8: Number of impressions transacted via programmatic direct and RTB before and after the policy change in 2016 (including unsold inventory).
Figure 9: Density plots of average revenue per impression per thin vs thick sites.

(a) Thin sites

(b) Thick sites
Figure 10: Synthetic control results for average winning price and number of impressions won.

(a) Average winning prices over time

(b) Number of impressions won over time

Note: Weeks prior to the vertical line representing March 2016 correspond to the weeks over March - July 2015.
Figure 11: Distribution of weekly estimated gaps for treated and control advertisers.

(a) Average winning price gaps for treated advertiser (thick black line) and placebo gaps for advertisers in control group (grey lines)

(b) Number of impressions won gaps for treated advertiser (thick black line) and placebo gaps for advertisers in control group (grey lines)

Note: Weeks prior to the vertical line representing March 2016 correspond to the weeks over March - July 2015.