

Targeting and Privacy in Mobile Advertising

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Abstract

Mobile in-app advertising is now the dominant form of digital advertising. While these ads have excellent user-tracking properties, they have raised concerns among privacy advocates. This has resulted in an ongoing debate on the value of different types of targeting information, the incentives of ad-networks to engage in behavioral targeting, and the role of regulation. To answer these questions, we propose a unified modeling framework that consists of two components – a machine learning framework for targeting and an analytical auction model for examining market outcomes under counterfactual targeting regimes. We apply our framework to large-scale data from the leading in-app ad-network of an Asian country. We find that an efficient targeting policy based on our machine learning framework improves the average click-through rate by 66.80% over the current system. These gains mainly stem from behavioral information compared to contextual information. Theoretical and empirical counterfactuals show that while total surplus grows with more granular targeting, ad-network’s revenues are non-monotonic, i.e., the most efficient targeting does not maximize ad-network revenues. Rather, it is maximized when the ad-network does not allow advertisers to engage in behavioral targeting. Our results suggest that ad-networks may have economic incentives to preserve users’ privacy without external regulation.

Keywords: advertising, mobile, machine learning, targeting, behavioral targeting, privacy, auctions, regulation, public policy

1 Introduction

1.1 Mobile Advertising and Targeting

Mobile advertising now constitutes the largest share of total digital ad spend (eMarketer, 2019). The popularity of mobile advertising stems from an ad format unique to the mobile environment: in-app ads or ads shown inside apps. These ads have excellent user-tracking properties, and allow ad-networks to stitch together user data across sessions, apps, and advertisers.¹ Thus one of the main attractions of in-app advertising is its ability to facilitate behavioral targeting (Edwards, 2012).

While the advertising industry has lauded the trackability of in-app ads, consumers and privacy advocates have derided them, citing privacy concerns. Advertisers argue that tracking allows consumers to enjoy free apps and content, and see relevant ads, whereas users demand higher privacy and limits on behavioral tracking and targeting (Edwards-Levy and Liebelson, 2017). Responding to consumer concerns, regulatory bodies have started taking action. For example, the European Union’s General Data Protection Regulation agreement requires users to opt into, rather than opt out of, behavioral targeting (Kint, 2017).

Even as consumers, businesses, and regulators are trying to find the right balance between consumer protection and business interests, we do not have a good understanding of the key issues at the core of targeting and privacy. For example, to what extent does targeting improve the efficiency of the advertising ecosystem, what is the value of different types of targeting information, and what are the incentives of different players in the advertising industry to engage in user-tracking and behavioral targeting? The lack of a cohesive framework to analyze these issues hampers our ability to have an informed discussion and to form policy on them.

1.2 Research Agenda and Challenges

In this paper, we seek to address this gap by providing a unifying framework to answer the following sets of questions related to targeting and privacy in the advertising ecosystem.

The first set of questions relates to targeting and efficiency. How can ad-networks use the data available to them to develop targeting policies? How can we evaluate the performance of these policies in both factual and counterfactual settings? In particular, what are the gains in CTR from adopting an efficient (CTR-maximizing) targeting policy? The second set of questions relates to the value of targeting information. We are particularly interested in the relative value of contextual vs. behavioral information. The former captures the context (when and where) of an impression, and

¹Advertisers and ad-networks have access to a unique device ID associated with the mobile device referred to as IDFA (ID For Advertisers) in iOS devices, and AAID (Android Advertiser ID) in Android devices. This device ID is highly persistent and remains the same unless actively re-set by the user.

the latter summarizes an individual user’s past app usage, ad exposure, and ad response. Contextual information is privacy-preserving, whereas behavioral information is based on user-tracking and therefore impinges on users’ privacy. Third, we are interested in quantifying the revenue-efficiency trade-off and ad-network’s incentives to enable different forms of targeting. What is the empirical relationship between efficiency and ad-network revenues? What is the optimal level of targeting from the perspective of different players in the market? Finally, to what extent are the ad-network’s and advertisers’ incentives aligned?

There are three main challenges that we need to overcome to satisfactorily answer these questions. First, to develop efficient targeting policies, we need to obtain accurate estimates of CTR for all ads that could have been shown in an impression (i.e., counterfactual ads), and not just the ad that was actually shown in that impression. Thus, we need exogenous variation in the ad allocation mechanism to evaluate counterfactual targeting policies. Second, to quantify the value of different pieces of targeting information, we need a model that can accurately predict whether a targeted impression will lead to a click or not. Models with poor predictive ability will lead to downward bias in the estimates of the value of information. Third, we need an underlying model of strategic interactions that can quantify market outcomes (e.g., ad-network and advertiser revenues) under different targeting regimes. Without an economic model that puts some structure on the ad-network’s and advertisers’ utilities, we cannot make any statements on their incentives to target and/or the extent to these incentives are aligned.

1.3 Our Approach

We present a unified and scalable framework that coherently combines predictive machine learning models with prescriptive economic models to overcome the challenges listed above. Our framework consists of two main components. The first, a machine learning framework for targeting, addresses the first two challenges of obtaining counterfactual CTR estimates and achieving high predictive accuracy in this task. The second is an analytical model that incorporates competition and characterizes the ad-network’s and advertisers’ profits under different targeting regimes. This addresses the third challenge of linking targeting regimes to ad-network and advertiser revenues.

The main goal of the first component is to estimate the match value between an impression and an ad, where match value can be interpreted as the CTR of an impression-ad combination. Once we have match values for all impression-ad combinations, we can use them to define and evaluate any counterfactual targeting strategy. Match values are thus the key primitives of interest here, and we infer them by combining ideas from causal inference with predictive machine learning models. Our approach consists of three parts – (a) a filtering procedure, (b) a feature generation framework, and (c) a learning algorithm. The goal of the filtering procedure is to identify the set of ads for which

we can generate accurate counterfactual estimates of CTR for each impression. If the platform uses a deterministic ad allocation mechanism (as is the common practice in the industry), then this set is null, by definition. However, in our setting, there is exogenous variation in the ad allocation process, which gives us a non-empty set of counterfactual ads for each impression. Our filtering procedure determines this set by identifying the ads which have a non-zero propensity of being shown in a given impression. Next, our feature generation framework relies on a set of functions to generate a large number of features that capture the contextual and behavioral information associated with an impression. Using these functions, we generate a total of 160 features that serve as input variables into a CTR prediction model. Finally, we use XGBoost, proposed by Chen and Guestrin (2016), a fast and scalable version of boosted regression trees, as our learning algorithm.

In the second component, we focus on the ad-network’s incentives to allow targeting. In an influential paper, Levin and Milgrom (2010) conjecture that while high levels of targeting can increase efficiency in the market, it can reduce the ad-network’s revenue by softening the competition between advertisers. We propose a theoretical framework that allows us characterize this revenue-efficiency trade-off under counterfactual targeting regimes. To take this framework to data, we need an estimate of each advertisers’ valuation for a given impression. This valuation can be decomposed into two sets of primitives: (a) match valuations or CTRs for all impression-ad combinations, and (b) advertisers’ click valuations for each impression. While match valuations are already available from the machine learning targeting framework, we need to infer click valuations by inverting advertisers’ observed equilibrium bids (Guerre et al., 2000). The product of these two entities gives us each advertiser’s value of a given impression, which allows us to quantify the ad-network’s revenue, advertisers’ surplus, and total surplus under different targeting regimes.

We apply our framework to one month of data from the leading mobile ad-network from a large Asian country. The scale and scope of the data are large enough to provide realistic substantive and counterfactual results. For our analysis, we sample over 27 million impressions for training, validation, and testing, and use another 146 million impressions for feature generation. A notable feature of our setting is the use of a quasi-proportional auction allocates impressions to ads using a probabilistic rule: an advertiser’s probability of winning an impression is proportional to her bid. This induces randomization or exogenous variation in ad allocation, which in turn, allows us to estimate match valuations for counterfactual ad-impression combinations. At the same time, the auction mechanism preserves the strategic linkage between bids and advertisers’ click valuations, which allows us to estimate click valuations from the bid data. Our setting thus facilitates the separate identification of both match and click valuations.

1.4 Findings and Contribution

We first discuss the results from the machine learning model for targeting. We present both factual and counterfactual evaluations of our model. In the factual evaluation, we use goodness-of-fit measures to evaluate how well our model can predict the observed outcome. We find that our model predicts the outcome on a hold-out test set with substantial accuracy: it achieves a Relative Information Gain (*RIG*) of 17.95% over a baseline model that simply predicts the average CTR for all impressions. Next, we find that behavioral information contributes more to the predictive accuracy of the model compared to contextual information. In the second part of our evaluation, we consider the efficient targeting policy, wherein each impression is allocated to the ad with the highest estimated CTR in that impression. We show that this efficient targeting policy can increase the average CTR in the ad-network by 66.80% over the current system.

Next, we link advertisers’ targeting strategies to ad-network’s incentives and revenues. First, we theoretically prove that in an efficient auction mechanism (e.g., second-price auction) – (a) the total surplus in the system monotonically increases as the extent of targeting increases, but (b) the ad-network’s revenues are not monotonic; it may or may not increase with more granular targeting. So we take our theoretical framework to data and perform empirical counterfactuals to compare ad-network revenues under different targeting regimes.

In particular, we consider four targeting regimes that relate to our research agenda – full (impression-level targeting), behavioral (user-level targeting), contextual (app-time-level targeting), and no targeting. We find that the ad-network’s revenue is maximized when it restricts targeting to the contextual level even though doing so lowers total surplus, i.e., allowing behavioral targeting thins out the market, which in turn reduces ad-network revenues. Therefore, the ad-network has economic incentives to adopt a privacy-preserving targeting regime, especially if it cannot extract additional surplus from advertisers through other mechanisms. On the advertisers’ side, we find that although a majority of them prefer a regime where the ad-network allows behavioral targeting, not all do. An important implication of our findings is that it may not be necessary for an external entity such as EU/FCC to impose privacy regulations, in light of ad-networks’ economic incentives.

Our paper makes several contributions to the literature. First, from a methodological perspective, we propose a novel machine learning framework for targeting that is compatible with counterfactual analysis in a competitive environment. A key contribution of our targeting framework is in combining existing ideas from causal inference literature with recent machine learning literature to generate counterfactual estimates of user behavior under alternative targeting regimes. Further, we present an efficient auction framework with targeting that characterizes advertisers’ utility function under any targeting regime and provides a direct link to the estimation of market outcome such

as efficiency and revenue. Second, from a substantive perspective, we provide a comprehensive comparison of contextual and behavioral targeting, with and without the presence of competition. To our knowledge, this is the first study to compare the role of behavioral and contextual targeting on market outcomes. Third, from a managerial perspective, our results demonstrate a non-monotonic relationship between targeting granularity and revenues. While our findings may depend on the context of our study, our framework is generalizable and can be applied to most standard advertising platforms that use deterministic auctions as long as the platform randomizes ad allocation over a small portion of the traffic (which would satisfy the unconfoundedness assumption). Finally, from a policy perspective, we identify the misalignment of the ad-network’s and advertisers’ incentives regarding behavioral and contextual targeting and information disclosure. We expect our findings to be of relevance to policy-makers interested in regulating user-tracking and behavioral targeting in the advertising space.

The rest of this paper is organized as follows. In §2, we discuss the related literature. We introduce the setting and data in §3. In §4, we present our machine learning framework for targeting, and in §5 we presents a series of results on efficiency gains from targeting. Next, in §6, we develop a theoretical framework for analyzing the revenue-efficiency trade-off and a corresponding empirical analysis of auctions with targeting. In §7, we present the results on market outcomes under counterfactuals targeting regimes. Finally, in §8, we conclude with a discussion on the generalizability of our framework and our main contributions.

2 Related literature

First, our paper relates to the computer science literature on CTR prediction (McMahan et al., 2013; He et al., 2014; Chapelle et al., 2015). These papers make prescriptive suggestions on feature generation, model selection, learning rates, and scalability. Our work differs from these papers in two main ways. First, we develop a filtering procedure that allows us to obtain accurate CTR estimates for both the ad shown during an impression as well as counterfactual ads not shown in the impression. Thus, unlike the previous papers, our framework can be used to develop and evaluate different targeting policies. Second, we quantify the value of different types of information in the targeting of mobile ads, whereas the previous papers were mainly concerned with click prediction.

Our paper also relates to the literature on ad-network’s incentives to allow targeting. Levin and Milgrom (2010) were one of the first to conjecture the trade-off between value creation and market thickness. They argue that too much targeting can thin out markets, which in turn can soften competition and make the ad-network worse off. This is particularly the case when there is significant heterogeneity in the distribution of advertisers’ valuation of impressions (Celis et al., 2014). Building on this insight, a growing stream of analytical papers show that there is a non-

monotonic pattern between the extent of targeting and ad-network revenues (Bergemann and Bonatti, 2011; Amaldoss et al., 2015; Hummel and McAfee, 2016; De Corniere and De Nijs, 2016; Sayedi, 2018). A key difference between these papers and ours is that we do not make any distributional assumptions on the match values in our analytical model.

In spite of the increasing interest from the theoretical side, there has been limited empirical work on this topic with mixed findings. In an early paper, Yao and Mela (2011) present a structural model to estimate advertisers’ valuations and show that targeting benefits both advertisers and the ad-network. In a similar context, however, Athey and Nekipelov (2010) present a case study of two keywords and show that coarsening CTR predictions (worse targeting) can help a search advertising ad-network generate more revenue. However, unlike our paper, neither of these papers can effectively design or evaluate counterfactual targeting regimes because their data come from highly targeted eco-systems without any randomization in ad-allocation. More broadly, ours is the first empirical paper to view revenue-efficiency trade-off through the lens of privacy and quantify the ad-network’s incentives to preserve users’ privacy.

Next, our work relates to the literature on the interplay between privacy and targeting. Goldfarb and Tucker (2011b) use data from a series of regime changes in advertising regulations and show that restricting targeting reduces response rates and thereby advertisers’ revenues. Similarly, Goldfarb and Tucker (2011a) and Tucker (2014) highlight the perils of excessive targeting as users perceive increased targeting as a threat to their privacy. Please see Goldfarb (2014) for an excellent review of targeting in online advertising and Acquisti et al. (2016) for a detailed discussion of consumer privacy issues. Our paper contributes to this literature by providing the first empirical evidence in support of the possibility of self-regulation in this market.

Finally, our paper adds to the growing literature on applications of machine learning in marketing, which focus on prediction problems; see Toubia et al. (2007) and Dzyabura and Yoganarasimhan (2018) for excellent summaries. Our paper contributes to this stream by demonstrating how a combination of theory-driven frameworks and machine-learning methods can be used to go beyond prediction and help answer important substantive and prescriptive questions.

3 Setting and Data

3.1 Setting

Our data come from the leading mobile in-app advertising network of a large Asian country, which had over 85% market-share in the category in 2015. The ad-network works with over 10,000 apps and 250 advertisers and it serves over 50 million ads per day (about 600 auctions per second). This ad-network specializes in the Android Operating System. At the time of our study, smartphone

penetration was reasonably high in the country with over 60% of the population having access to smartphones. The share of Android OS was over 85% of the market in this country in 2015, which is consistent with its share worldwide (Rosoff, 2015).

3.1.1 Players

There are four key players in this marketplace.

Users: Individuals who use apps. They see the ads shown within the apps that they use and may choose to click on the ads.

Advertisers: Firms that show ads through the ad-network. They design banner ads and specify their bid as the amount they are willing to pay per click, and can include a maximum budget if they want to. Advertisers can target their ads based on the following variables: app category, province, connectivity type, time of the day, mobile operators, and mobile brand of the impression. The ad-network does not support more detailed targeting (e.g., behavioral targeting) at this point in time.

Publishers: App developers who have joined the ad network. They accrue revenues based on the clicks generated within their app. Publishers earn 70% of the cost of each click in their app (paid by the advertiser), and the remaining 30% is the ad-network's commission.

Ad-network or Platform: It functions as the matchmaker between users, advertisers, and publishers. It runs a real-time auction for each impression generated by the participating apps and shows the winning ad during the impression. The platform uses a CPC pricing mechanism, and therefore generates revenues only when clicks occur. ²

3.1.2 Auction Mechanism

The platform uses a *quasi-proportional* auction mechanism (Mirrokni et al., 2010). Unlike other commonly-used auctions (e.g., second price or Vickrey), this auction uses a probabilistic allocation rule:

$$\pi_{ia} = \frac{b_a q_a}{\sum_{j \in \mathcal{A}_i} b_j q_j} \quad (1)$$

where π_{ia} is the probability that advertiser a with bid b_a and quality score q_a wins impression i , and \mathcal{A}_i denotes the set of advertisers participating in the auction for impression i . The quality score is an aggregate measure that reflects the advertiser's potential profitability for the platform. Currently, the platform does not use impression-specific quality scores; rather it uses an advertiser-specific quality score that remained constant during our observation period.

Because of the probabilistic nature of the auction, the ad that generates the highest expected revenue for the platform is not guaranteed to win. Rather, advertiser a 's probability of winning is

²An impression lasts one minute. If a user continues using the app beyond one minute, it is treated as a new impression and the platform runs a new auction to determine the next ad to show the user.

proportional to $b_a q_a$.³ Further, advertisers are only charged when a user clicks on their ad. The cost-per-click for an impression is determined using a next-price mechanism similar to that of Google’s sponsored search auctions. In this case, the amount that the winning ad is charged per click is the minimum amount that guarantees its rank among the set of bidders. For example, suppose that there are three advertisers with bids 1, 2, and 3, and quality scores 0.1, 0.2, and 0.3, bidding on an impression. Then, the product of bid and quality score for the three advertisers are 0.1, 0.4, and 0.9, respectively. In this case, if the second-ranked bidder wins the auction, he only needs to pay $\frac{1 \times 0.1}{0.2} = 0.5$, since it is the minimum bid amount that guarantees that he will be ranked higher than the third-ranked bidder. Formally, we can write the cost-per-click for ad a in impression i as:

$$CPC_{ia} = \inf \left\{ b' \mid \sum_{j \in \mathcal{A}_i, j \neq a} \mathbb{1}(b' q_a \leq b_j q_j) = \sum_{j \in \mathcal{A}_i, j \neq a} \mathbb{1}(b_a q_a \leq b_j q_j) \right\}, \quad (2)$$

where $\sum_{j \in \mathcal{A}_i, j \neq a} \mathbb{1}(b_a q_a \leq b_j q_j)$ is essentially the number of ads whose product of bid and quality score is lower than ad a , and the infimum over this set finds the minimum bid (b') that guarantees ad a ’s rank. Finally, note that the platform uses a fixed reserve price, r_0 , for all impressions. It is the minimum bid that is accepted by the platform. So, if an advertiser is not willing to pay at least r_0 per click, he is automatically out of competition.

3.2 Data

We have data on all the impressions and corresponding clicks (if any) in the platform for a 30-day period from 30 September, 2015, to 30 October, 2015. For each impression, we have data on:

- Time and date: The time-stamp of the impression.
- AAID: Android Advertising ID is a user re-settable, unique, device ID that is provided by the Android operating system. It is accessible to advertisers and ad networks for tracking and targeting purposes. We use it as the user-identifier in our main analysis.
- App ID: A unique identifier for apps that advertise through the platform.
- Ad ID: Identifier for ads shown in the platform.
- Bid: The bid that the advertiser has submitted for her ad. Advertisers bids do not change across impressions in our sample.
- Cost-per-Click (CPC): The price that the winning advertiser has to pay, if she wins the impression and a click occurs. This is calculated by the ad-network based on Equation (2).

³From a practical perspective, probabilistic auctions ensure that individual users are not exposed to the same ad repeatedly within the same app-session (which can be irritating). In contrast, in a deterministic auction, the same advertiser would win all the impressions until his budget runs out.

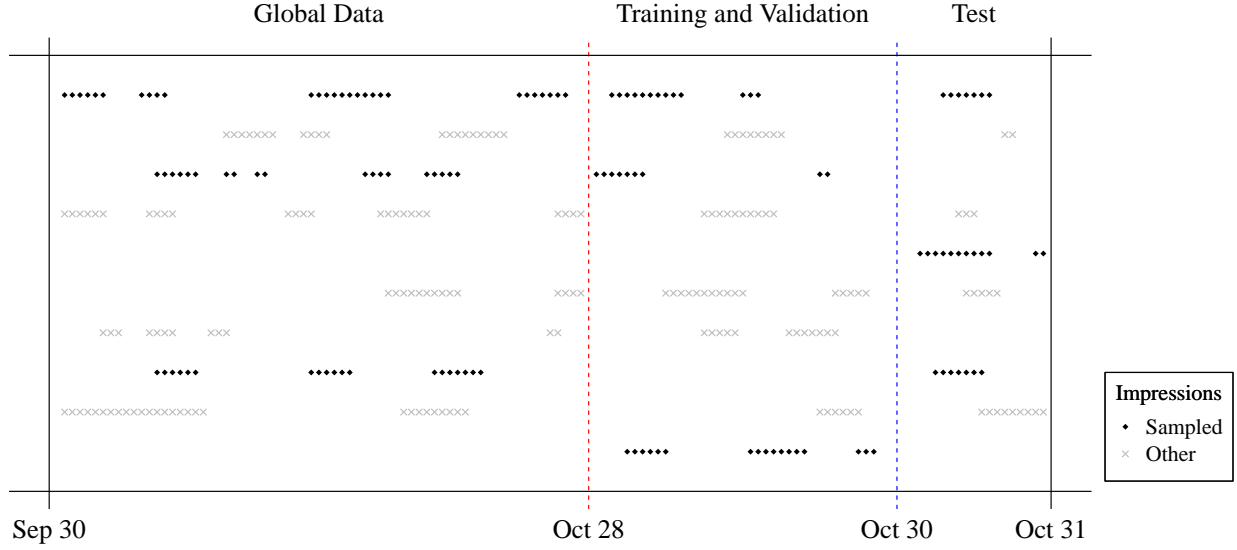


Figure 1: Schema for data generation.

- Location: This includes the province as well as the exact location of a user, based on latitude and longitude.
- Connectivity type: It refers to the user’s type of connectivity (e.g., Wi-Fi or cellular data).
- Smartphone brand: The brand of user’s smartphone (e.g., Samsung, Huawei, etc.).
- MSP: The user’s mobile-phone service provider.
- ISP: The user’s Internet service provider.
- Click indicator: This variable indicates whether the user has clicked on the ad or not.

The total data we see in this one month interval is quite large. Overall, we observe a total of 1,594,831,699 impressions and 14,373,293 clicks in this time-frame, implying a 0.90% CTR.

3.3 Data Splits and Sampling

We use penultimate two days of our sample period (October 28 and 29) for training and validation, and the last day for testing (October 30). We also use the preceding history from September 30 to Oct 27 (referred to as global data) to generate the features associated with these impressions. The splits of data are shown in Figure 1. Note that we do not fit our model on the global data because we do not have sufficient history to generate features for these impressions. Further, constraining all the three data-sets – training, validation, and testing – to a three-day window has advantages because recent research has shown that data freshness plays an important role in CTR prediction, i.e., using older history for prediction can lead to poor predictive performance (He et al., 2014).

We draw a sample of 728,340 unique users (out of around 5 million) seen on October 28, 29,

Variable	Number of categories	Share of top categories			Number of impressions
		1 st	2 nd	3 rd	
App	9709	37.12%	13.56%	3.05%	27,482,444
Ad	263	18.89%	6.71%	6.31%	27,482,444
Hour of the Day	24	7.39%	7.32%	6.90%	27,482,444
Province	31	25.25%	6.65%	6.51%	21,567,898
Smartphone Brand	8	46.94%	32.30%	9.53%	25,270,463
Connectivity Type	2	54.64%	45.36%		27,482,444
ISP	9	68.03%	14.02%	7.09%	10,701,303
MSP	3	48.57%	43.67%	7.76%	26,051,042

Table 1: Summary statistics for the categorical variables.

and 30 to form our training, validation, and test data-sets.⁴ In Web Appendix §E.4, we show that this sample size is sufficient and that larger samples do not significantly improve model performance.

Figure 1 presents a visual depiction of the sampling procedure. Rows represent users. The impressions by users in our sample are shown using black points. There are 17,856,610 impressions in the training and validation data, and 9,625,835 impressions in the test data. We have an additional 146,825,916 impressions by these users in the time preceding October 28, which form global data. These impressions will be solely used for feature generation (and not for model fitting). Note that both our user-based sampling procedure and feature generation approach (see Web Appendix §B) require us to be able to identify and track users. For this purpose, we use the AAID variable as our user identifier.

3.4 Summary Statistics

We now present some summary statistics on our training, validation, and test data, which constitutes a total of 27,482,444 impressions.

Table 1 shows the summary statistics of the categorical variables in the data. For each variable, we present the number of unique values, the share of top three values that the categorical variable can take, and the number of non-missing data. While we always have information on the app, ad, and time-stamp of the impression, the other variables are sometimes missing. The shares are shown after excluding the missing variables in the respective category.

We observe a total of 263 unique ads and 9709 unique apps in the data. The top three sub-categories in each have large shares and there is a long tail of smaller apps and ads. Moreover, as shown in Figure 2, we find that the top 37 ads account for over 80% of the impressions, and

⁴Another approach would be to randomly sample impressions in each split of the data. However, this would not give us the complete user-history for each impression in the training, validation, and test data-sets. This in turn would lead to significant loss of accuracy in user-level features, especially since user history is sparse. In contrast, our user-based sampling approach gives us unbroken user-history.

similarly, the top 50 apps account for 80% of impressions.

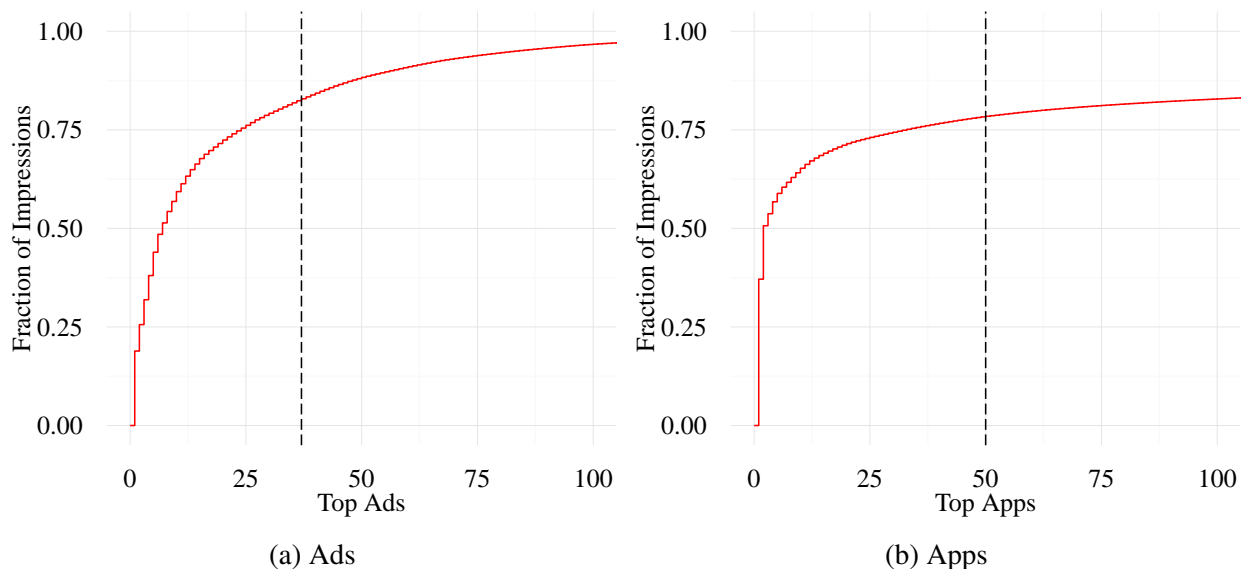


Figure 2: Cumulative fraction of impressions associated with the top 100 ads and top 100 apps.

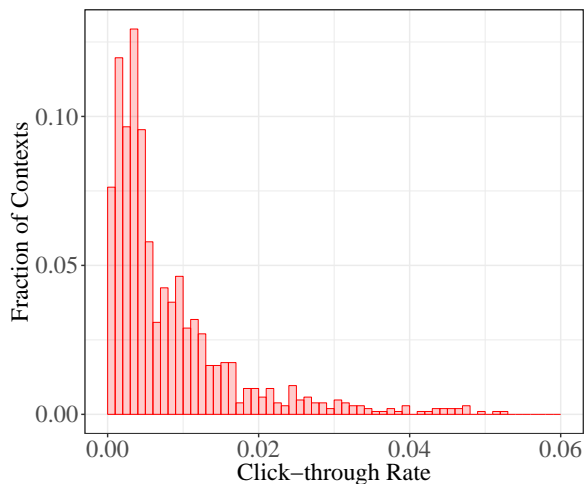


Figure 3: Histogram of click-through rates (CTR) for different contexts. Context is defined as a unique combination of an app and an hour of the day (where and when of an impression)

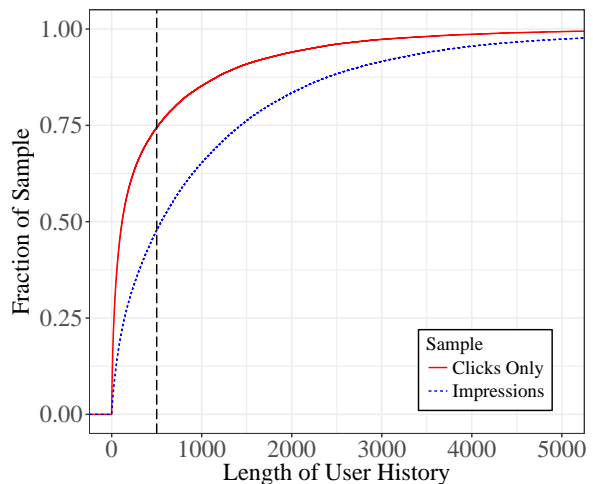


Figure 4: Empirical CDF of the length of user history for impressions and clicks (truncated at 5000). History is defined as the number of previous impressions from September 30 till the current impression.

Next, we present some descriptive analysis that examines the role of contextual and behavioral information in predicting CTR. A context is characterized by the ‘when’ and ‘where’ of an impression. As such, we define a unique context as a combination of an app and a specific hour of the day. Figure 3 shows the histogram of CTR for different contexts. As we can see, there is a significant

amount of variation in CTR across contexts, which suggests that contextual information can be informative for predicting clicks. Next, to understand the role of behavioral information, we focus on the length of history available for a user. Figure 4 shows the CDF of the length of history for all the impressions and clicks. It suggests that users with longer histories are less sensitive to ads. Most of the clicks come from users with shorter histories, while most impressions come from users with longer histories. Thus, user-history or behavioral information also seem helpful in explaining the clicking behavior observed in data.

4 Machine Learning Framework for Targeting

In this module, our goal is to develop a framework that can accurately estimate the gains in efficiency or the CTR for any targeting policy. To do that, we first need to specify and train a machine learning model that accurately predict the match between an impression and an ad, i.e., predict whether an impression will generate a click or not, for both factual and counterfactual ads.

This section is organized as follows. We first define our problem in §4.1. Next, in §4.2, we discuss our empirical strategy. Here, we explain the need for, and the extent of, randomization in our data generating process, and propose a filtering approach that establishes the scope of our framework in estimating both factual and counterfactual targeting policies. In §4.3, we present the details of our feature generation framework. Finally, in §4.4, we discuss our estimation procedure which consists of the learning algorithm, the loss function, and the validation method.

4.1 Problem Definition

Consider a setting with N impressions and A ads. We begin with a formal definition of a targeting policy.

Definition 1. A targeting policy τ is defined as a mapping between impressions to ads such that each impression is allocated one ad. For example, $\tau(i) = a$ means that targeting policy τ selects ad a to be shown in impression i .

In order to evaluate the effectiveness of a targeting policy, we first need an accurate prediction of CTR for each ad for a given impression in our data. That is, for each impression i and ad a , we need to estimate $\Pr(y_{i,a} = 1)$, where $y_{i,a}$ is the indicator that ad a receives a click when it is shown in impression i . This brings us to the formal definition of match value matrix:

Definition 2. Let $m_{i,a} = \Pr(y_{i,a} = 1)$. The $N \times A$ match value matrix M is defined as:

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \dots & m_{1,A} \\ m_{2,1} & m_{2,2} & \dots & m_{2,A} \\ \vdots & \vdots & \ddots & \vdots \\ m_{N,1} & m_{N,2} & \dots & m_{N,A} \end{bmatrix}, \quad (3)$$

where N denotes the total number of impressions in our data and A denotes the total number of ads competing for these impressions. There is a corresponding $N \times A$ matrix of outcomes Y , which consists of elements $y_{i,a}$. Note that we only observe the realized outcome for one element in each row or impression i for Y , which corresponds to the ad $a = a_i$ which was actually shown in that impression in our data. The rest of the elements are treated as potential or unrealized outcomes.

In this section, our goal is to develop a machine learning framework to estimate this match value matrix. We can use our estimated match value matrix, \hat{M} , to perform the following analyses:

1. **Evaluate model performance:** We can evaluate the predictive performance of our model using the observed outcome. Let τ_0 denote the *current targeting policy*, such that:

$$\tau_0(i) = a_i, \quad (4)$$

where a_i is the ad that is actually shown in impression i . Since we observe the actual outcomes for y_{i,a_i} , we can evaluate how well our \hat{m}_{i,a_i} 's estimate these outcomes.

2. **Evaluate the gains from efficient targeting policy:** Using the match value matrix, we can evaluate the expected CTR of any counterfactual targeting policy τ as follows:

$$\hat{m}^\tau = \frac{1}{N} \sum_{i=1}^N \hat{m}_{i,\tau(i)} \quad (5)$$

In particular, we are interested in the *efficient targeting policy*, τ^* , determined by our model that allocates each impression to the ad with the highest CTR for that impression:

$$\tau^*(i) = \operatorname{argmax}_a \hat{m}_{i,a} \quad (6)$$

In §5.2, we quantify the gains in average CTR from efficient targeting over the current system.

4.2 Empirical Strategy

We now present our empirical strategy to estimate matrix M . At a high-level, our goal is to build a model to predict whether an impression i showing ad a will receive a click or not, based on the joint distribution of impressions and clicks in our data. That is, we seek to estimate a function $f(X_{i,a})$ such that:

$$m_{i,a} = Pr(y_{i,a} = 1) = f(X_{i,a}), \quad (7)$$

where $X_{i,a}$ is a set of features that are informative of whether impression i showing ad a will receive a click. Since this problem can be interpreted as function evaluation, we turn to machine learning algorithms that can capture complex relationships between the covariates and the outcome without imposing strong parametric restrictions on $f(\cdot)$.

While machine learning methods can flexibly learn the function f from the data, their prediction power is bounded by the joint distribution of co-variates and outcome (click) in the data. That is, these methods can accurately predict the outcome for an observation only if that observation could have been observed in the data. This requirement gives rise to two main challenges in evaluation of counterfactual targeting policies:

Challenge 1. Function f cannot learn $m_{i,a}$ from the data if ad a could have never been shown in impression i , i.e., ad a has zero propensity of being shown in impression i .

The reason is simple: if ad a could have never been shown in impression i , then the set of features $X_{i,a}$ is not within the joint distribution of the observed data. For example, if the ad for a fashion clothing brand was never shown in a sports app, then it is not possible to recover the fashion ad's click probability in the sports app.

It is worth noting that if the platform runs a deterministic auction (e.g., second price auction), the set of ads that could have won the auction (and hence been shown during an impression) is a singleton. Similarly, the set of ads that can be shown in an impression in highly targeted environments would be very small. Therefore, data-sets generated without any randomization in the ad allocation mechanism will not allow researchers to push the scope of their analysis beyond the set of actual outcomes observed in the data. Randomization in ad allocation is thus necessary if we want to use our framework to evaluate the effectiveness of counterfactual targeting policies. This brings us to our first remark, that addresses Challenge 1.

Remark 1. Any ad participating in the auction for impression i ($\forall a \in \mathcal{A}_i$) has a non-zero propensity of being shown in impression i .

This is a direct result of the quasi-proportional auction run by the platform. As shown in Equation (1), each ad that participates in an auction has a non-zero probability of winning. This

claim is the equivalent of the *positivity* or *overlap* assumption in the causal inference literature (Rosenbaum and Rubin, 1983).

While any kind of randomization can help overcome Challenge 1, we need to know the distribution of randomization to be able to correctly infer the click probability of counterfactual ads in any given impression i , i.e., infer m_{ia} for ads $a \neq a_i$. If ads are randomized according to an unobserved rule, we may run into selection issues and obtain biased estimates of m_{ia} . We can characterize this challenge as follows.

Challenge 2. Function f cannot correctly infer match values (m_{ia} s) for counterfactual ads, if the allocation rule is a function of an unobserved variable that is correlated with the outcome.

The following example helps illustrate this challenge: suppose that ad a_Y is targeted more towards younger users, whereas ad a_O is targeted more towards older users. Now, if younger users have a higher probability of click, failure to account for users' age will lead us to attribute the better performance of ad a_Y to the ad, rather than to users' age. In the causal inference literature, this is usually known as endogeneity or selection on unobservables (Wooldridge, 2010).

In our setting, we can simulate the allocation rule using the observed covariates. This gives us the unconfoundedness assumption, which we characterize in Remark 2.

Remark 2. For any impression i , ad allocation is independent of the set of the potential outcomes for participating ads ($a \in \mathcal{A}_i$), after controlling for the observed covariates:

$$\{y_{i,a}\}_{a \in \mathcal{A}_i} \perp\!\!\!\perp a_i \mid X_{i,a} \quad (8)$$

Again, the allocation rule in Equation (1) directly satisfies the unconfoundedness assumption because everything in the right-hand side of this equation is known. First, for each i , we can infer the set of ads competing (\mathcal{A}_i) from our data because we observe all the targeting variables that can induce variation in \mathcal{A}_i . Second, advertisers do not change their bids and the platform does not customize the quality score for each impression. Hence, $b_a q_a$ remains constant throughout our study and we can easily infer propensity scores π_{ia} from the data, controlling for \mathcal{A}_i .

Together, in light of Remarks 1 and 2, we can estimate the match values $m_{i,a}$, not only for the ad that is shown in impression i , but for any counterfactual ad that could have been shown with non-zero propensity score. Naturally, estimates for small ads with a very small probabilities of winning will be noisy. However, it is possible to overcome this issue by focusing on the top 37 ads that constitute over 80% of our data. In §4.2.1, we discuss our procedure for identifying the set of all participating ads in each impression that have non-zero propensity scores. Next, in §4.2.2, we discuss how we estimate these propensity scores and assess covariate balance.

4.2.1 Filtering Procedure

As discussed earlier, if ad a could have never been shown in impressions i , we cannot accurately estimate the match value for that impression-ad combination $m_{i,a}$. As such, we need to identify the set of participating ads in each impression and filter those that have zero propensity of being shown. In general, two factors influence whether an ad is available to participate in an auction for an impression.

- **Targeting:** Targeting by advertisers is the main reason why some ads are unavailable to compete for certain impressions, and therefore have zero probability of being shown in them. For example, if an ad chooses to target only mornings, then it is not considered in the auctions for impressions in evenings. In that case, we should filter out this ad for all impressions in the evening. While limited, targeting is nevertheless present in our setting, and mainly happens on province, time, and app categories. Hence, for each impression i , we filter out all ads that were excluded from the auction for i because of targeting.
- **Campaign availability:** Second, some ads may be unavailable to compete for a given impression because their ad campaigns may not be running in the system when the impression happens. This could happen either because the advertiser’s budget has been exhausted, or because the advertiser has exited the market. Therefore, for each impression i , we filter out ads that were unavailable when it happens. Empirically, we find that campaign availability is not a major factor that leads to ad-filtering since we focus on top ads.⁵

We now construct a filtering matrix $E_{N \times A} = [e_{i,a}]$ that filters out ads for each impression based on the factors discussed above, where each element $e_{i,a}$ takes value 1 if ad a has a non-zero probability of winning impression i , and 0 otherwise. Each row in this matrix shows which ads are competing for an impression.⁶ However, our filtering may not be accurate for observations with missing targeting variables. Therefore, for all the analyses that use filtering, we only focus on the *Filtered Sample*, which consists of the impressions in the test data for which all targeting variables are non-missing. Figure 5 shows the empirical CDF of the number of competing ads for each impression in the Filtered Sample data among top 37 ads per impression. Note that almost all impressions have at least 8 top ads competing for it, and the median impression has 13 top ad competitors.

⁵Only six ads experience budget exhaustion (at least once) in the training data, four of which are completely out for auctions in the test data.

⁶Note that this information is not directly observed but inferred from advertisers’ targeting decisions and campaign availability.

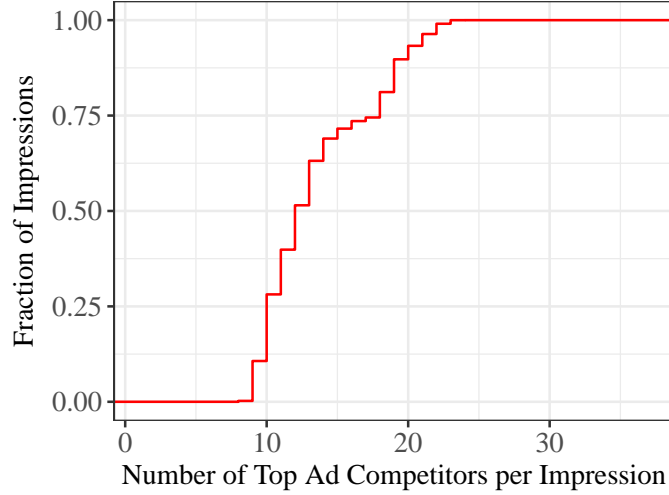


Figure 5: Empirical CDF of the number of competitors (of the top 37 advertisers) per impression for the Filtered Sample.

4.2.2 Propensity Score Estimation and Covariate Balance

As discussed earlier, the accuracy of our counterfactual match value estimates is predicated on the independence of assignment to ads and potential outcomes, given the observed covariates. While we know that this is theoretically true in our setting because of the allocation rule (Remark 2), we nevertheless need to empirically demonstrate the validity of this remark in our setting.

The standard practice in these cases is to assess and show covariate balance, since it is a necessary condition for unconfoundedness assumption. In simple settings, where both treatment and control are randomly assigned with a fixed probability to the entire population, we can easily assess balance by comparing the pre-treatment variables across treatment and control groups. Our case is more complicated because of two reasons: (1) assignment to ads is not fully random, but random given the propensity scores, and (2) since we focus on top 37 ads, we have more than two treatment arms. To assess covariate balance, we therefore need to take the following steps:

1. *Step 1 – Propensity Score Estimation:* The first step is to estimate the propensity score π_{ia} for all a and i . Since we have multiple treatments, the dependent variable is a categorical variable with multiple classes. We use a multi-class XGBoost to estimate propensity scores given the success of machine learning methods in propensity score estimation (McCaffrey et al., 2013). Please see Web Appendix §A.1 for more details.
2. *Step 2 – Assessing Covariate Balance:* Once we have the estimates for propensity scores, we can assess the balance for all pre-treatment covariates. In our case, these covariates are the

variables that advertisers can target on: province, app, time of the day, smartphone brand, connectivity type, and MSP. To assess balance, we need to show that the inverse propensity weighted distribution of each pre-treatment variable is the same across all the ads. Following the norm in the literature, we use standardized difference of the weighted mean of a covariate when assigned to ad a and the population mean of covariate and rule for balance if this difference is below 0.2 (McCaffrey et al., 2013). Please see Web Appendix §A.2 for details on our balance measures and results.

4.3 Feature Generation Framework

As discussed in §4.2, our goal is to build a model, $m_{ia} = Pr(y_{ia} = 1) = f(X_{ia})$ to accurately predict whether an impression i will receive a click or not. As such, we first need a vector of features $X_{i,a}$ that captures the factors that affect whether the user generating impression i will click on ad a .

It is important to generate an exhaustive and informative set of features since the predictive accuracy of our model will largely depend on the quality of features we use. Given our research agenda, our features should also be able to capture the contextual and behavioral information associated with an impression over different lengths of history preceding the impression (long-term, short-term, and session-level). To achieve these objectives, we adopt the main ideas from the functional feature generation framework proposed by Yoganarasimhan (2020). There are three advantages of doing so. First, her function-based approach allows us to generate a large and varied set of features using a parsimonious set of functions. Second, it allows for a natural mapping between feature inputs and feature classification. Third, the general class of features she suggests have been shown to have good predictive power in this class of problems.

We now present a short overview of our feature functions and feature categorization below, and refer interested readers to Web Appendix §B for a more detailed description.

4.3.1 Inputs for Feature Functions

To generate a set of features for each impression, we use feature functions that take some inputs at the impression level and output a corresponding feature for that impression. Our feature functions typically need two types of inputs:

- *Impression-specific information:* Each impression in our data can be uniquely characterized by three types of information – (1) contextual information that captures the context (where and when) of the impression, i.e., which app serves this impression and at what time (hour of day) is the impression being shown, (2) behavioral information that denotes the identity of the user generating this impression, and (3) ad-related information, that denotes the identity of the ad which was shown during this impression.

- *History*: This input characterizes the history over which we aggregate to calculate the output of our functions. We define three different levels that capture the long-term (approximately one month), short-term (3 days), and ongoing session-level history. Besides, we characterize the history in such a way that we can update the features in real-time.

To reduce the dimensionality of our feature sets and boost the speed of our feature generation framework, we group the smaller apps (below top 50) into one app-category and all the smaller ads (below top 37) into one ad-category. Thus, our features do not distinguish the context of smaller apps (ads) as separate from each other, though they are able to distinguish them from the top apps (ads). Please see Web Appendix §B.1 for a complete formal definition of the inputs for feature functions.

4.3.2 Feature Functions

One challenge we face is that most of the information characterizing an impression-ad combination is categorical in nature, e.g., the app showing the ad, the user seeing the ad. As a result, approaches that include all these categorical raw inputs and their interactions as covariates are prone to the curse of dimensionality. So we define functions that take these raw inputs as well as their interactions and map them onto a parsimonious set of features that reflect the outcome of interest – CTR.

We present an overview of our feature functions in Table 2 along with their functionality (see Appendix §B.2 for a detailed description of the feature functions). These functions take different inputs based on the focal impression and return outputs that are integers or real numbers. These inputs are basically interactions of different raw inputs. The following examples give a high-level overview of what these functions do. Let p_i , t_i , u_i , and a_i denote the app, hour, user, and ad associated with impression i . If the function *Impressions* is given p_i , u_i , and a_i and long-term history as inputs, it simply returns the number of times user u_i has seen ad a_i inside app p_i from the start of the data till the time at which impression i occurred. However, if it is only given u_i and short-term history, it returns number of impressions user u_i has seen across all apps and ads over the last three days. Using this logic, we give different sets of inputs to these functions and generate 98 features for each impression i . In addition, we include a few standalone features such as dummies for each of the top ads, the user’s mobile and Internet service providers, latitude, longitude, and connectivity type. Overall, we have a total of 160 features for each impression-ad (ia) combination. Together, these features capture the interactive effects of advertising that are documented in the literature such as carryover effects (Sahni, 2015), spillover effects (Li and Kannan, 2014), and effects of ad variety (Rafieian and Yoganarasimhan, 2020). Please see Web Appendix §B.3 for the full list of features.

Function	Functionality
<i>Impressions</i>	Number of impressions for a given set of inputs over a pre-specified history
<i>Clicks</i>	Number of clicks for a given set of inputs over a pre-specified history
<i>CTR</i>	Click-through rate for a given set of inputs over a pre-specified history
<i>AdCount</i>	Number of distinct ads shown for a given set of inputs over a pre-specified history
<i>Entropy</i>	Dispersion of ads shown for a given set of inputs over a pre-specified history
<i>AppCount</i>	Number of distinct apps used by a given set of inputs over a pre-specified history
<i>TimeVariability</i>	Variance in the user’s CTR at different hours of the day over a pre-specified history
<i>AppVariability</i>	Variance in the user’s CTR across different apps over a pre-specified history

Table 2: Feature functions.

4.3.3 Feature Categorization

All our features capture one or more type of information – contextual, behavioral, and ad-specific. To aid our analysis, we therefore classify features based on the type of information used to generate them and group them into the following (partially overlapping) categories:

- *Contextual* features (F_C): These are features that contain information on the context of the impression – app and/or hour of the day.
- *Behavioral* features (F_B): These are features that contain information on the behavior of the user who generated the impression.
- *Ad-specific* features (F_A): These are features that contain information on the ad shown during the impression.

The three feature sets form our full set of features $F_F = F_B \cup F_C \cup F_A$. We now present a few examples of features generated using the *Clicks* function to elucidate this classification. The total clicks made by user u_i across all apps, ads, and hours of the day in the past month is a purely behavioral feature since it only contains information on the behavior of the user who generated impression i . On the other hand, the total clicks made by user u_i in the app p_i over the last month is both a behavioral and contextual feature since it contains information on both the behavior of u_i as well as the context (app p_i) in which she made these clicks. Finally, the total clicks received by ad a_i over the last one month across all users, apps, and times is a purely ad-specific feature since it only reveals information about the ad’s propensity to receive clicks. Thus a feature can contain any combination of behavioral, contextual, or ad-specific information depending on the inputs used to generate it. Please see Table A1 in the Web Appendix for a mapping between each feature and the categories that it falls under and Figure 6 for a Venn diagram of our classification system.

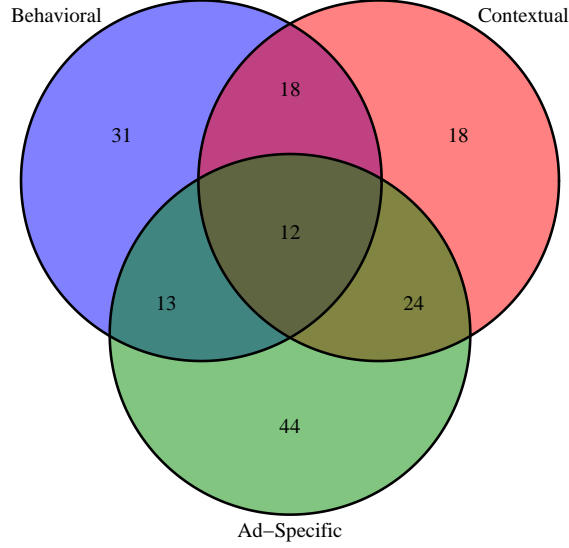


Figure 6: Venn diagram of the three feature sets, with the number of features in each region.

4.4 Learning Algorithm: XGBoost

We now discuss the final step of our machine learning framework – the learning algorithm, which helps us learn the function $f(X_{i,a})$. It provides a mapping between our feature set ($X_{i,a}$) and the match value or click probability, as: $f(X_{i,a}) = m_{i,a} = Pr(y_{i,a} = 1)$. Given that we want to maximize the predictive accuracy of the model, we do not want to impose parametric assumptions $f(\cdot)$. The problem of function evaluation is fundamentally different and harder than the standard approach used in the marketing literature, wherein we simply evaluate parameters after assuming a functional form. In the latter, the researcher only needs to search over the set of parameters given functional form, whereas in the former we have to search over the space of functions. Therefore, we turn to machine learning algorithms that are designed for this task.

Specifically, we employ the XGBoost algorithm proposed by Chen and Guestrin (2016). XGBoost is a variant of the standard boosted regression trees, and is one of the most successful prediction algorithms developed in the last few years. It has been widely adopted in both academia and industry.⁷ At a high level, boosted regression trees can be thought of as performing gradient descent in function space using shallow trees as the underlying weak learners (Breiman, 1998; Friedman, 2001). While boosted trees have been around for over a decade, Chen and Guestrin (2016)’s implementation is superior to earlier implementations from both methodological and

⁷Boosted trees in general, and XGBoost in particular, perform exceptionally well in tasks involving prediction of human behavior. Examples include store sales prediction, customer behavior prediction, product categorization, ad CTR prediction, course dropout rate prediction, etc. Indeed, almost all the KDD cup winners have used XGBoost as their learning algorithm (either as a standalone model or in ensembles) since 2015.

implementation standpoints.⁸ We refer interested readers to Web Appendix §C for a more detailed description of XGBoost and now focus on two key components of our implementation: loss function and validation procedure.

To train any learning model, we need to specify how the model should penalize model fit, i.e., the difference between the observed outcome y_{i,a_i} and model prediction \hat{m}_{i,a_i} (where a_i refers to the ad shown in impression i). This is done using a loss function, which the machine learning algorithm minimizes. Since our outcome variable is binary, we use logarithmic loss (log-loss) as our loss function. It is the most commonly used loss function in the CTR prediction literature (Yi et al., 2013) and has some attractive properties, e.g., a faster convergence rate compared to other loss functions such as squared loss (Rosasco et al., 2004). The log-loss for a model with predictions \hat{M} when the prediction matrix is Y can be written as:

$$\mathcal{L}^{\log \text{ loss}}(\hat{M}, Y) = -\frac{1}{N} \sum_{i=1}^N (y_{i,a_i} \log(\hat{m}_{i,a_i}) + (1 - y_{i,a_i}) \log(1 - \hat{m}_{i,a_i})) \quad (9)$$

Note that while the log-loss function takes as inputs the two matrices \hat{M} and Y , the metric is calculated only over those ad-impression combinations that are actually observed in the data.

Validation is an important part of training any machine learning model. The boosting algorithm is designed to continuously update the prediction rule (or current estimate of $f(\cdot)$) to capture more and more complex relationships between the features $X_{i,a}$, in order to predict $y_{i,a}$. Since we do not impose any assumptions on the parametric form of $f(\cdot)$, this will likely lead to over-fitting, i.e., the model will evolve to fit too closely to the training data and perform poorly out-of-sample. Validation helps us avoid this problem by using parts of the data to validate the model. This ensures that the chosen model, $f(\cdot)$, will have a good out-of-sample performance. Please see Appendix §C.2 for a full description of our validation procedure.

5 Results from the Machine Learning Targeting Models

Recall that the goal of our machine learning framework is to estimate the matrix M defined in Equation (3). As such, our \hat{M} contains CTR estimates for: (1) the ads shown in the data, and (2) counterfactual situations, i.e., ads that could have been shown. In §5.1, we focus on the actual data

⁸First, from a methodological standpoint, XGBoost can be interpreted as performing Newton boosting in the function space (as opposed to gradient descent), and thereby uses information from the Hessian as well. Thus, both the quality of the leaf structure and the leaf weights learned are more accurate in each step. Second, XGBoost uses a trick commonly used in Random Forests – column sub-sampling, which reduces the correlation between subsequent trees. Third, XGBoost employs a sparsity-aware split finding, which makes the algorithm run faster on sparse data. Finally, from an implementation perspective, XGBoost is highly parallelized, which makes it fast and scalable.

and present results on the predictive performance of our framework on the observed sample. We also document the contribution of behavioral vs. contextual information to our framework in this section. Next, in §5.2, we focus on the counterfactual estimates in \hat{M} and evaluate the gains in CTR from an efficiently targeting policy. Finally, in §5.3 we discuss robustness and scalability.

5.1 Predictive Performance of the Machine Learning Model

5.1.1 Evaluation Metric

To evaluate whether a targeting model improves our ability to predict clicks, we first need to define a measure of predictive accuracy or an evaluation metric. In line with our loss function, we use “Relative Information Gain” or *RIG*, which is defined as the percentage improvement in log-loss over the baseline that simply predicts average CTR for all impressions. Formally:

$$RIG(\hat{M}, Y) = \left(1 - \frac{\mathcal{L}^{\log \text{ loss}}(\hat{M}, Y)}{\mathcal{L}^{\log \text{ loss}}(\bar{Y}, Y)} \right) \times 100, \quad (10)$$

where \bar{Y} is a $N \times A$ matrix, each of whose element is equal to $\frac{1}{N} \sum_{i=1}^N y_{i,a_i}$, i.e., the average observed outcome of the sample or the average CTR of the data. Average CTR is the simplest aggregate metric available from any data, and using it as the baseline prediction tells us how well we can do without any model. It is important to control for this baseline because if the average CTR is very high (close to 1) or very low (close to zero, as in most e-commerce settings, including ours), a naive prediction based on the average CTR leads to a pretty good log-loss. Normalizing the log-loss with the average CTR reduces the sensitivity of the metric to the data distribution (He et al., 2014). Nevertheless, we need to be careful when interpreting *RIGs* computed on different datasets because there is no obvious normalization in those cases (Yi et al., 2013).

In Web Appendix §E.1, we present four other commonly used evaluation metrics – (1) Mean Squared Error, (2) AUC, (3) 0/1 Loss, and (4) Confusion Matrix. We discuss the pros/cons of these metrics and demonstrate the performance of our model on them.

5.1.2 Predictive Accuracy of the Full Targeting Model

We now discuss our framework’s ability to predict the actual outcomes in the data. Table 3 shows the gains in prediction for: (1) training and validation data, and (2) test data. The first row depicts the log-loss for the Full model (which uses the set of all features and trains the XGBoost model). The second row depicts the log-loss for the baseline model, which simply predicts the average CTR for the dataset for all impressions. The third row is the *RIG* of the Full model compared to the baseline model.

Evaluation Metric	Training and Validation	Test
LogLoss for Full Model	0.041927	0.044364
LogLoss for Baseline Model	0.051425	0.054070
RIG of Full Model	18.47%	17.95%

Table 3: LogLoss and *RIG* (in percentage) shown for training, validation, and test data.

The *RIG* of the Full model over the baseline is 17.95% on the test data, a substantial improvement in CTR prediction problems. This suggests that the data collected by the ad-network is quite valuable and that our machine learning framework has significant predictive power on whether an impression-ad combination will receive a click.⁹

The *RIG* improvement for training and validation data is 18.47%, which is somewhat higher than 17.95% for the test data. There are two potential reasons for this. First, all statistical models estimated on finite data have higher in-sample fit than out-of-sample fit. Indeed, this is the main reason we use the test data to evaluate model performance. Second, the difference could simply reflect the differences in the underlying data distributions for the two data-sets. As discussed in §5.1.1, we cannot compare *RIG* across data-sets because it is co-determined by the model and data. Thus, the difference between the *RIG* values across the data-sets is not necessarily informative.

5.1.3 Value of Information: Behavioral vs. Contextual Features

We now examine the impact of different types of features on the predictive accuracy of our model. This is important for two reasons. First, data storage and processing costs vary across feature types. For example, some user-specific behavioral features require real-time updating, whereas pure-contextual features tend to be more stable, and can be updated less frequently. In order to decide whether to store and update a feature or not, we need to know its incremental value in improving targeting. Second, the privacy and policy implications of targeting depend on the features used. For example, models that use behavioral features are less privacy-preserving than those that use purely contextual features. Before adopting models that are weaker on privacy, we need objective measures of whether such models actually perform better.

Recall that our features can be categorized into three broad overlapping sets – 1) Behavioral,

⁹One could argue that the significant predictive power of the Full model is due to the weak benchmark, which simply predicts average CTR for all impressions. Therefore, we also evaluate the performance of the Full model against two other baseline models: (1) Ad-specific CTR, and (2) Targeting-area-specific CTR. The first model relates to ad-networks’ quality scoring practice; it predicts the average CTR for each ad as the match-value for impressions showing that ad. The second model resembles the current targeting practice in the platform and predicts the average CTR for each targeting area (defined as the intersection of all targeting variables) as the match value for all impressions within that targeting area. With these benchmark models as the denominator in Equation (10), we find that the Full model has a RIG of 16.86% over the Ad-specific model and 10.06% over the Targeting-area-specific model.

RIG over Baseline	Full Sample	Top Ads and Top Apps	Filtered Sample
Behavioral Model	12.14%	14.82%	14.74%
Contextual Model	5.25%	5.98%	6.77%
Full Model	17.95%	22.85%	22.45%
No. of Impressions	9,625,835	6,108,511	4,454,634
% of Test Data	100%	63.5%	46.28%

Table 4: Comparison of Behavioral and Contextual models for different samples of test data.

denoted by F_B , 2) Contextual, denoted by F_C , and 3) Ad-specific, denoted by F_A . We now use this categorization to define two models:

- **Behavioral model:** This model is trained using behavioral and ad-specific features, without including any contextual features. Formally, the feature set used is $(F_B \cup F_A) \setminus F_C$.
- **Contextual model:** This model is trained using only contextual and ad-specific features, without including any behavioral features. The feature set for this model is $(F_C \cup F_A) \setminus F_B$.

Both models include ad-specific features that are neither behavioral nor contextual, e.g., the total impressions received by the ad shown in the impression in the past month (Feature 2 in Table A1 in the Web Appendix).¹⁰ They also use the same loss function and training algorithm, and only differ on the set of features used. Hence, it is possible for us to directly compare the *RIG* of one model over another within the same data.¹¹

The results from these two models and their comparisons with the Baseline model are presented in Table 4. First, consider the results for the full test data (presented in the second column). The Behavioral model has a 12.27% *RIG* over the baseline, which is considerably higher than 5.12%, the *RIG* of the Contextual model over the baseline. Together, these findings suggest that, from a targeting efficiency perspective, behavioral information is more effective compared to contextual information in mobile in-app advertising.

This difference in the effectiveness of the two models directly relates to the extent of variation in the information used by the two models. The variation in behavioral features is much higher than the variation in contextual features because behavioral features are generated from unique behaviors of over 700,000 users, whereas the total number of unique contexts is limited (to 1200). Hence, the level of granularity of contextual features is much lower and the Contextual model can only learn from aggregate outcome estimates across these limited contexts. Its ability to predict positive labels

¹⁰We can also specify Behavioral and Contextual models that ignore ad-specific information. The qualitative results on the relative value of behavioral and contextual information for that case are similar to those presented here.

¹¹As discussed in §5.1.1, *RIGs* are not directly comparable across different data-sets. Simply put, in Table 4, comparisons within a column are interpretable, but comparisons across a row are not.

(i.e., clicks) is therefore much weaker compared to that of the Behavioral model.

One possible critique of the above analysis is that it does not exploit the full capacity of contextual information since we treat all the non-top ads as one advertiser category and all the non-top apps as one app category during feature generation (see §4.3.1). To address this issue, we consider a sub-sample of the test data which only consists of impressions that were shown in a top app and showed a top ad and re-run all the above comparisons. This accounts for 63.5% of our test data. The performance of our Full model on this subset of the data is even better than that on the full sample because there is no information loss on the ads or apps. The findings on the relative value of behavioral vs. contextual features are even stronger in this data-set, which suggests that our results in the full sample were not driven by the lack of good contextual information.

Finally, in the last column, we show the performance of our model on the Filtered Sample (described in §4.2.1), which is the sample that we use for conducting our counterfactual analysis. Our qualitative findings remain the same for this sample too.

5.2 Counterfactual Analysis: Efficiency Gains from CTR-maximizing Targeting Policy

We now focus on an important counterfactual question from the platform’s perspective – If the platform employs an efficient targeting policy, such that each impression is allocated the ad with the highest predicted CTR in that impression, to what extent can it improve the CTR in the system?

Recall that τ_0 and τ^* denote the current and efficient targeting policy, as defined in Equations (4) and (6), respectively. We can then use the following equation to calculate the gains in average CTR:

$$\rho(\tau^*, \tau_0; N_F) = \frac{\hat{m}^{\tau^*}}{\hat{m}^{\tau_0}} = \frac{\frac{1}{N_F} \sum_{i=1}^{N_F} \hat{m}_{i, \tau^*}(i)}{\frac{1}{N_F} \sum_{i=1}^{N_F} \hat{m}_{i, \tau_0}(i)}, \quad (11)$$

where N_F is the number of impressions in the Filtered sample. It is crucial to conduct this counterfactual on the Filtered Sample (instead of the Full sample) for the reasons discussed in §4.2.1.

We find that an efficient targeting policy based on our machine learning model increases average CTR by 66.80% over the current regime. This is a substantial improvement, and suggests that targeting based on behavioral and contextual features can lead to significant efficiency gains.

Next, we examine how efficiency-gain varies by impression. Specifically, for each impression we calculate the percentage improvement in CTR with efficient targeting as $\left(\frac{\hat{m}_{i, \tau^*}(i)}{\hat{m}_{i, \tau_0}(i)} - 1 \right) \times 100$ and examine the distribution of this metric over impressions. In Figure 7, we show the histogram of this percentage improvement in CTR for the impressions in the Filtered Sample. We document considerable heterogeneity in CTR improvements across impressions: the median improvement in CTR is about 105.35%, implying that efficient targeting policy can make over half the impressions

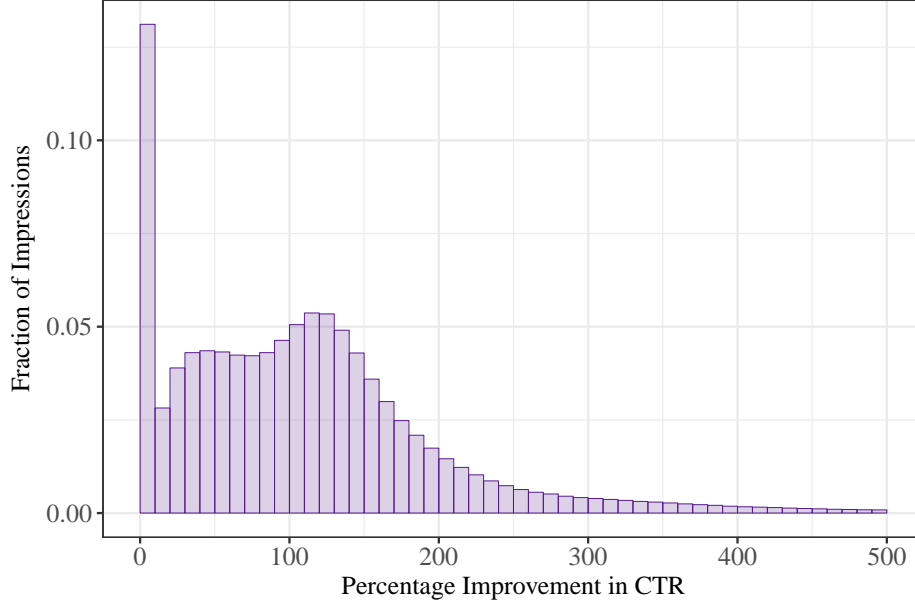


Figure 7: Histogram of percentage improvement in CTR over the current system using the efficient targeting policy.

twice as clickable as the current system. The peak at the left side of the graph (at one) denotes cases where the $\tau_0(i) = \tau^*(i)$, where the platform happened to randomly selected the right ad that maximizes eCTR.

This overlap between our efficient targeting policy and actual data allows us to evaluate the efficient targeting policy by inversely weighting the propensity scores for the actual outcomes in the overlapping area. This is a model-free approach known as *importance sampling*, which is commonly used in the policy evaluation literature (Dudík et al., 2014). We present the details of this approach in Web Appendix §D and show that it establishes 65.53% improvement in average CTR which is similar to our findings based on Equation (11).

In sum, we find that an efficient targeting policy leads to significant gains in clicks for the platform, using both model-based and model-free approaches. Nevertheless, a key question that remains unanswered is whether an efficient targeting policy is also revenue maximizing for the platform. Therefore, in §6, we incorporate competition and examine the relationship between efficiency and revenues.

5.3 Scalability and Robustness

We perform extensive checks on robustness of all aspects of our machine learning approach and its scalability. We discuss these tests briefly here, and refer readers to Web Appendix §E for details.

First, in Web Appendix §E.1, we show that our results are robust even if we use other evaluation metrics (AUC, MSE, 0/1 Loss, and confusion matrix). Second, in Web Appendix §E.2, we confirm that XGBoost is the best learning algorithm for our prediction task by comparing its performance to five other commonly used algorithms (Least Squares, LASSO, Logistic Regression, Classification And Regression Tree, and Random Forests). Third, in Web Appendix §E.3, we run a few robustness checks on the feature generation framework by considering alternative ways of aggregating over history as well as app-specific dummies. Again, we find no improvement in the model’s predictive performance under these different specifications. Fourth, in Web Appendix §E.4, we present some checks to establish that our data sample is sufficient and large enough to produce reliable results. Specifically, we find that the *RIG* gains start stabilizing with the sample of 100,000 users, and that our sample of 728,340 users is more than sufficient for our purposes. Finally, in Web Appendix §E.5, we show that our results are not sensitive to the validation procedure used to pick the tuning parameters by comparing with other methods, e.g., hold-out validation and k -fold cross validation.

6 Analysis of Revenue-Efficiency Trade-off

In §5, we showed that the ad-network can substantially increase CTR with efficient targeting. However, that analysis was silent on the ad-network’s incentives to target and agnostic to revenues. In this section, we seek to answer two sets of important questions by focusing on competition and incentives. First, to what extent is the ad-network incentivized to allow targeting and is there an optimal level of targeting from its perspective? Second, how does the total surplus accrued by advertisers vary with targeting levels, and is there heterogeneity in advertisers’ preferences on the optimal level of targeting?

Incentives are particularly important in this context because if the platform is incentivized to not allow behaviorally targeted bids, then we may naturally converge to a regime with higher consumer privacy protection. In contrast, if the platform is incentivized to allow behavioral targeting, then an external agency (e.g., government) may have to impose privacy regulations that balance consumers’ need for privacy with the platform’s profitability motives. Similarly, if a substantial portion of advertisers prefer a more restrictive targeting regime, then the mobile ad-industry can self-regulate. So we seek to quantify the platform’s and advertisers’ profits under different levels of targeting.

We now present an analytical framework to quantify the ad-network’s revenue-efficiency trade-off. This section proceeds as follows. In §6.1, we present a simple example to fix ideas and highlight the platform’s efficiency-revenue trade-off. In §6.2, we present a stylized analytical model that characterizes the total surplus and platform revenues under different targeting strategies. In §6.3, we take this analytical model to data and present an empirical analysis of auctions with targeting.

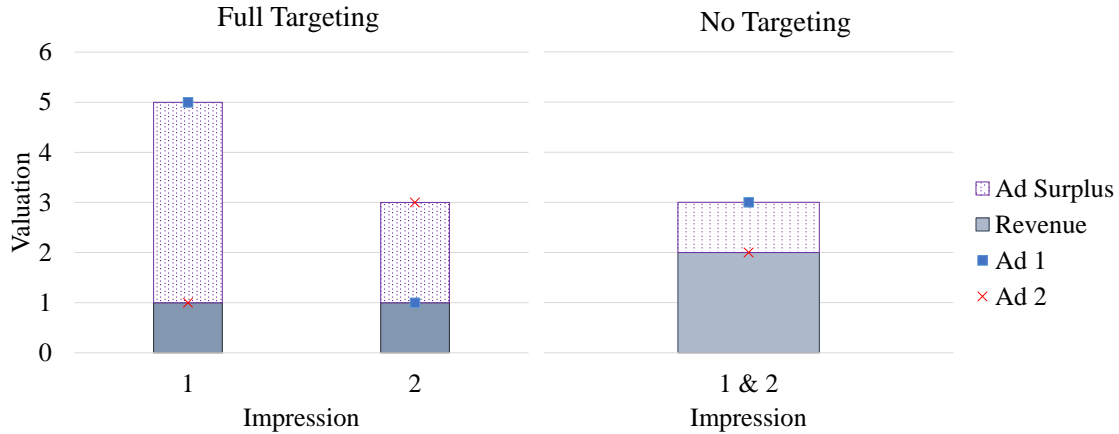


Figure 8: Market outcomes under full vs. no targeting. The platform sells two impressions. Ad 1 and Ad 2 have valuations 5 and 1 for impression 1, and valuation 1 and 3 for impression 2, respectively. When bundled together, advertisers cannot distinguish between ads, giving an aggregate value of 3 and 2 to Ad 1 and 2, respectively. The entire shaded area in each case shows the total surplus generated. The area on the top is the share of advertisers and that in the bottom goes to the platform. See Web Appendix §F for a detailed analyses of this example.

6.1 A Simple Example

In an important paper, Levin and Milgrom (2010) argue that micro-level targeting can thin auction markets, which in turn can soften competition and make the platform worse off. In Figure 8, we present a simple example to illustrate this idea. In this example, we consider a platform with two impressions and two advertisers whose valuations for these impressions do not align: advertiser 1 has much higher valuation for impression 1 compared to impression 2, whereas the opposite is true for advertiser 2. Assume that the platform uses second price auctions with Cost per Impression (CPI) pricing, where the highest bidder wins the impression and pays the bid of the second-highest bidder. We consider two regimes. In the Full Targeting regime, the platform allows advertisers to submit targeted bids for each impression. In the No Targeting case, advertisers cannot distinguish between the two impressions, and therefore have to submit the same bid for both the impressions (i.e., no targeted bidding). As shown in Figure 8, the platform cannot extract sufficient revenue if advertisers can distinguish between impressions (full targeting). However, the platform is able to extract more revenue by not revealing the identity of these impressions since advertisers are forced to rely on their aggregate valuation for both impressions together in this case. This example thus illustrates the platform's trade-off between value creation and value appropriation, and highlights the platform's incentives to limit advertisers' ability to target.

6.2 Analytical Model of Auction with Targeting

We now develop a simple analytical model that captures the trade-offs discussed above. To reflect the idea of narrow targeting and thin markets as envisioned by Levin and Milgrom (2010), we make two modeling choices. First, the idea of revenue loss in thin markets is due to the use of efficient auctions that guarantee that the highest valuation bidder will win (Krishna, 2009). While efficiency is satisfied in many auction mechanisms, we focus on second-price auctions since it is the most commonly used auction in online advertising. Moreover, it has the truth-telling property that makes our analysis more tractable. Second, the idea of narrow targeting by advertisers requires the pricing mechanism to be per-impression. In a cost-per-click mechanism, advertisers do not care about the match value of impressions since they are charged per click. For these reasons, we consider a setting where the platform uses a second-price auction mechanism with CPI pricing. Nevertheless, it is worth noting that neither of these two assumptions are essential to our analysis. Later in this section, we discuss how our results can be extended to other efficient auction mechanisms and/or cost-per-click pricing.

As before, we consider a platform that receives N impressions and serves A advertisers. Let v_{ia} denote ad a 's private valuation from impression i , and let V denote the value matrix:

$$V = \begin{bmatrix} v_{1,1} & v_{1,2} & \dots & v_{1,A} \\ v_{2,1} & v_{2,2} & \dots & v_{2,A} \\ \vdots & \vdots & \ddots & \vdots \\ v_{N,1} & v_{N,2} & \dots & v_{N,A} \end{bmatrix} \quad (12)$$

If an advertiser a can distinguish between all the impressions, s/he will submit targeted bids for each impression i . In a second-price auction, that is equivalent to a 's valuation for impression i , $v_{i,a}$.

However, the extent to which advertisers can target depends on the level of targeting allowed by the platform. If certain information is not disclosed, advertisers may not be able to distinguish two impressions i and j . In such cases, a risk-neutral bidder's valuation for both impressions is the same and is equal to the expected value from the bundle of i and j (Sayedi, 2018). For example, if the platform does not allow targeting at the app level, then advertisers cannot distinguish between impressions in two different apps, and their optimal strategy would be to submit the same bids for the impressions in both apps. Formally:

Definition 3. Let I_l denote the set of impressions in bundle l . A targeting regime $\mathcal{I} = \{I_1, I_2, \dots, I_L\}$ denotes the platform's decision to bundle N impressions into L bundles such that advertisers can only bid for bundles and not impressions within the bundle. As such, impressions are only distin-

guishable across bundles, but not within a single bundle. That is, for bundle I_j , the advertiser a has the valuation $\frac{1}{|I_j|} \sum_{k \in I_j} v_{ka}$.

This definition characterizes all targeting regimes from impression-level targeting to no targeting. Impression-level targeting occurs when each impression is a bundle ($L = N$), i.e., an advertiser can distinguish between all impressions and place targeted bids for each impression. In contrast, no targeting denotes the case where the platform bundles all impressions into one group ($L = 1$) implying that an advertiser can only have one valuation aggregated over all impressions ($\frac{1}{N} \sum_{i=1}^N v_{ia}$ for any a). Any intermediate strategy where $1 < L < N$ can be interpreted as partial targeting. An example of partial targeting is app-level targeting, where each bundle is an app and impressions are distinguishable across apps but not within apps.

We can characterize the relative granularity of two targeting regimes as follows:

Definition 4. Let $\mathcal{I}^{(1)}$ and $\mathcal{I}^{(2)}$ denote two targeting regimes such that $\mathcal{I}^{(1)} = \{I_1^{(1)}, \dots, I_{L_1}^{(1)}\}$ and $\mathcal{I}^{(2)} = \{I_1^{(2)}, \dots, I_{L_2}^{(2)}\}$. Targeting regime $\mathcal{I}^{(1)}$ is at least as granular as $\mathcal{I}^{(2)}$ if for any $I_j^{(1)} \in \mathcal{I}^{(1)}$, there exists a $I_k^{(2)} \in \mathcal{I}^{(2)}$ such that $I_j^{(1)} \subseteq I_k^{(2)}$. In words, if two impressions i and j are distinguishable in $\mathcal{I}^{(2)}$, then they will be distinguishable in $\mathcal{I}^{(1)}$.

We can use this definition to compare the granularity of two targeting regimes. For example, app-user level targeting is more granular than app level targeting. Now, the main question that the platform faces is at what level of granularity they should disclose information and allow targeting. Since we focus on the second-price auction, the highest-bidding ad in any impression wins that impression, and pays second-highest bid. This auction also guarantees truth-telling property, i.e., for each bundle, advertisers submit their aggregate valuation for that bundle as derived in Definition 3. The following proposition determines the relationship between the granularity level of targeting and market outcomes such as surplus and revenue:

Proposition 1. Consider two targeting regimes $\mathcal{I}^{(1)}$ and $\mathcal{I}^{(2)}$ such that $\mathcal{I}^{(1)}$ is at least as granular as $\mathcal{I}^{(2)}$. Let $S^{(j)}$ and $R^{(j)}$ denote the total surplus and platform's revenue under targeting regime $j \in \{1, 2\}$. Then, for any distribution of valuations: $S^{(1)} \geq S^{(2)}$, but there is no fixed relationship between $R^{(1)}$ and $R^{(2)}$.

Proof. See Web Appendix §G.1. □

As the granularity of targeting increases, the total surplus generated increases, but the platform's revenue can go in either direction (unless we impose strong distributional assumptions on match values). Thus, while the matches are more efficient with more granular targeting, the platform may not be able to appropriate these efficiency gains. It is worth emphasizing that our analysis of

revenue and surplus holds for any efficient auction because of the Revenue Equivalence Theorem (Myerson, 1981; Riley and Samuelson, 1981). Further in Web Appendix §H, we show that the same qualitative findings hold for a cost-per-click pricing mechanism. Finally, note that this proposition is not applicable to a quasi-proportional auction since this is not an efficient mechanism.

6.3 Empirical Analysis of Auctions with Targeting

We now take this analytical model to data and examine market outcomes under different targeting regimes. Since the examination of revenue-efficiency trade-off requires an efficient auction, our analytical model focuses on a second-price auction with a pay-per-impression payment scheme. However, we must notice that the mechanism in our data is a quasi-proportional auction with a pay-per-click payment scheme. Thus, our empirical analysis involves counterfactual evaluation of settings different from the one in our data.

As illustrated in our analytical model, the primary estimand that we require for our empirical analysis of auctions with different levels of targeting is matrix V defined in Equation (12). We can characterize each element in matrix V as follows:

$$v_{i,a} = v_a^{(c)} m_{i,a}, \quad (13)$$

where $v_a^{(c)}$ is the private valuation ad a gets from a click and $m_{i,a}$ is the match valuations or expected CTR of ad a if shown in impression i .

In §6.3.1, we discuss how we can identify $v_{i,a}$ from our observed data. We then present our approach to obtain advertisers' click valuations in §6.3.2. Next, in §6.3.3, we explain how we can use our estimated match value matrix, \hat{M} from §4, to derive advertisers' match values under different targeting regimes. Finally, in §6.3.4, we discuss our empirical strategy to estimate the expected surplus, platform revenues, and advertisers' surplus.

6.3.1 Identification Strategy and Counterfactual Validity

To perform counterfactuals, we need to identify the elements of matrix V . While we cannot directly identify $v_{i,a}$ from the data, we can separately identify both elements in the right-hand side of Equation (13) – the click valuation of ad a ($v_a^{(c)}$) and the match valuation of ad a when shown in impression i ($m_{i,a}$). To the extent that these two elements are policy invariant primitives, our counterfactual analysis is valid. We now describe the basis on which these two estimands are identified and the conditions under which these are policy invariant primitives:

- *Click valuations* are identified given advertisers' strategic bidding behavior in the current auction environment. The main assumption required is that advertisers select the bid that maximizes

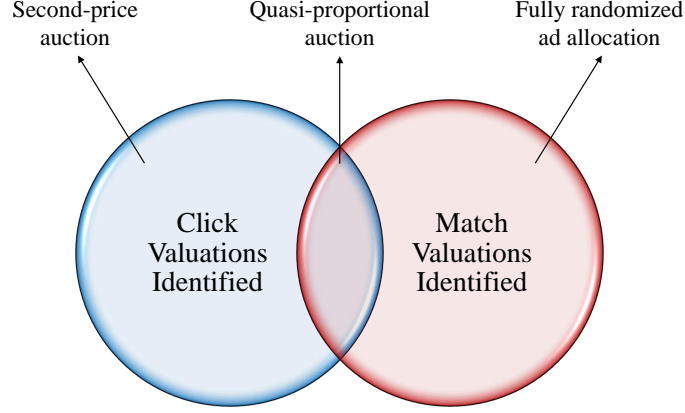


Figure 9: Venn diagram depicting settings where click valuations and match valuations are identified.

their utility. We can then specify advertisers' utility functions under the current auction observed in the data and use a first-order-condition to invert their observed bids to obtain consistent estimates of their click valuations. This is the standard identification strategy employed in the auctions literature (Guerre et al., 2000; Athey and Haile, 2007). It is worth noting that click valuations are policy invariant, although advertisers' bidding strategy can change under different auction mechanisms.

- *Match valuations* are identified given the unconfoundedness assumption: controlling for observed covariates, ad allocation is random. Please see §4.2 for a detailed discussion. Intuitively, match value estimates are policy invariant as long as users' underlying utility model for clicking on ads does not change under a different policy or auction.¹²

In sum, the identification of both click and match valuations is possible in settings that satisfy the unconfoundedness assumption while preserving the linkage between bids and click valuations. Figure 9 presents a Venn diagram of settings where each component is identified. It also highlights how common settings such as a second-price auction or a fully randomized ad allocation fail in this dual identification task. In standard auction mechanisms (e.g., second-price auctions) the identification problem stems from the deterministic allocation rule, which makes identification of match valuations impossible. In contrast, in a fully randomized experiment, there is no relationship between an advertiser's private click valuation and her observed bid, which makes the identification of click valuations impossible. To our knowledge, our setting (i.e., a quasi-proportional auction) is the *only* one in the literature that allows for the identification of both these components.

¹²While we learn users' utility model flexibly using XGBoost without imposing restrictive functional form on the utility function, we still require the underlying utility model to be policy invariant. This is equivalent to treating potential outcomes as structural parameters in potential outcomes framework (Imbens and Rubin, 2015).

6.3.2 Estimation of Advertisers' Click Valuations

We now discuss the estimation of advertisers' click valuations, $v_a^{(c)}$ s, based on the identification strategy discussed in §6.3.1. The standard approach in the structural auctions literature is to assume that agents (advertisers in this case) are utility-maximizing and derive the click valuations by inverting the equilibrium bidding function (Guerre et al., 2000; Athey and Haile, 2007).

In our empirical setting, we observe that advertisers only submit one bid and do not change it (across impressions). Thus, we model advertiser a 's bidding decision as a single-shot optimization, where he selects a bid b_a to maximize his own expected utility across all the impressions that he bids on. Let \mathcal{G}_a denote advertiser a 's beliefs about the joint distribution of the click valuations and quality scores of other advertisers bidding on the impressions that a is competing for.

Next, we define advertiser a 's cost function as the expected payment that he has to make for each click that he receives, given bid b_a , i.e., $c_a(b_a) = \mathbb{E}_{\mathcal{G}_a}[CPC_{ia}]$. Similarly, let $\pi_a(b_a)$ denote advertiser a 's expected probability of winning an impression given bid b_a , i.e., $\pi_a(b_a) = \mathbb{E}_{\mathcal{G}_a}[\pi_{ia}]$. Since the allocation function is proportional, we assume that $\pi_a(b_a) = \frac{b_a q_a}{b_a q_a + Q_{-a}}$, where Q_{-a} is a constant reflecting the competitors' bids and quality scores.¹³

We can then characterize advertisers' equilibrium bidding strategy in our platform by taking the First Order Condition (FOC) of their expected utility. This FOC can then be inverted to obtain the click valuations as shown in Proposition 2.

Proposition 2. Consider a platform which runs quasi-proportional auctions where the allocation rule and cost-per-click are given in Equations (1) and (2) respectively. Suppose that the cost function $c_a(b_a)$ is twice differentiable, $\{b_a^*\}_{a \in \mathcal{A}}$ is the set of observed bids, and $\frac{b_a^* c_a''(b_a^*)}{c_a'(b_a^*)} + 2 \geq 0$ for all ads. Then, we can write the click valuation as:

$$v_a^{(c)} = c_a(b_a^*) + \frac{b_a^* c_a'(b_a^*)}{1 - \pi_a(b_a^*)}. \quad (14)$$

Proof. See Web Appendix §G.2. □

We can obtain consistent estimates of click valuations from Equation (14) as long as we can observe/infer costs and bids from our data. We make three simplifications that make this task straightforward in our setting: (1) advertisers' probability of winning is close zero, i.e., $\pi_a \approx 0$, (2) advertisers' cost-per-click is approximately their bid, i.e., $c_a(b_a) \approx b_a$, and (3) the first-order

¹³While there is no guarantee that $\pi_a(b_a)$ has the quasi-proportional form, it is easy to show by simulated experiments that it is a very accurate approximation. Further, advertisers know that the platform runs a quasi-proportional auction, so it is reasonable to assume that they rely on this functional form.

condition in Equation (14) is satisfied for all advertisers, including reserve price bidders.¹⁴ These three simplifications are reasonable in our empirical setting. First, as shown in Figure A.1 in the Web Appendix, even top ads that won most impressions have a small probability of winning, justifying the first simplification. Second, on average, we find that an advertiser’s cost-per-click is over 92% of their bid, which provides support for the second simplification, i.e., $c_a(b_a) \approx b_a$. Finally, the third simplification is also reasonable: only 11 out of 37 ads are reserve price bidders.

With the three simplifications outlined above, Equation (14) can be approximated as

$$\hat{v}_a^{(c)} \approx 2b_a^*. \quad (15)$$

All the results presented in the main text are based on click valuations estimated based on Equation (15). However, in Web Appendix §I.1, we present six alternative methods to estimate click valuations that progressively relax the simplifications made to derive Equation (15). Table A7 in Web Appendix §I.1 presents an overview of the simplifications relaxed in each of the alternative methods. In particular, the last alternative method employs Rafieian (2020b)’s recently proposed estimator for quasi-proportional auctions. His method is fully non-parametric and does not make any of the simplifications listed earlier. We find that the main results remain the same (qualitatively) even when we use these more complex estimators. Therefore, we stick with the simpler estimator in the main text and refer interested readers to the Web Appendix for these robustness checks.¹⁵

6.3.3 Recovering Match Values

We now discuss how we can use our estimate of matrix M from our targeting framework to recover match values for any targeting regime. $m_{i,a}$ is ad a ’s match value for any impression i , if all impressions are distinguishable to her and she is competing for that impression. This follows naturally from our arguments on the accuracy of match value estimates in §4.2. However, if two impressions are not distinguishable, the advertiser needs to use the aggregate estimate for that bundle. That is, for any targeting regime $\mathcal{I} = \{I_1, I_2, \dots, I_L\}$, we can write the match value of

¹⁴The equality in Equation (14) may be invalid for reserve bidders because they may have submitted a reserve price bid because the platform did not allow them to submit a lower bid. Thus, in the presence of reserve price bidders, the distribution of bids that we see is truncated at the reserve price. In such a situation, we can only infer the truncated distribution of valuations. In Web Appendix §I.1, we discuss how we can address this issue.

¹⁵The underlying theory behind our findings relates to match valuations, and not click valuations: with more granular targeting, advertisers have more accurate match valuations, which in turn, softens the competition and hurts platform’s revenues. As such, the heterogeneity induced by allowing more granular targeting comes from the heterogeneity in match valuations, and click valuations are invariant to targeting scenarios. Therefore, using an approximate method to quantify the distribution of click valuations is sufficient for our purpose, and does not change the main findings.

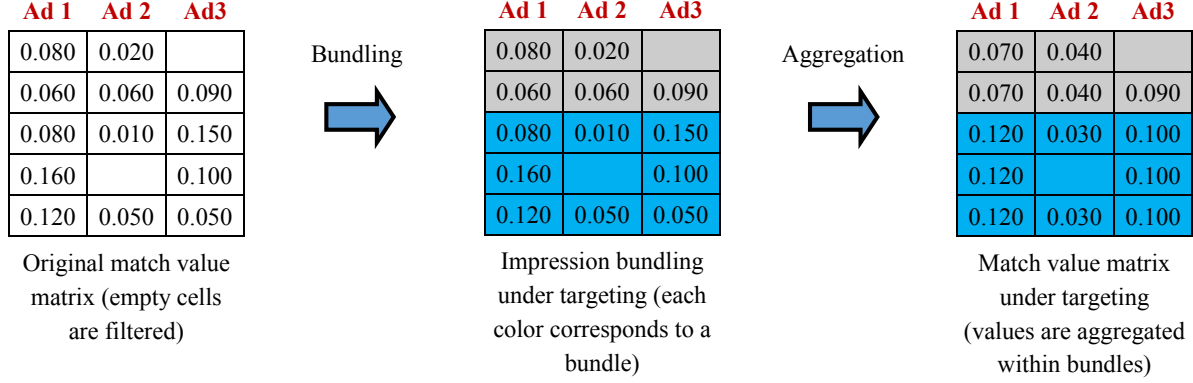


Figure 10: Construction of match value matrix under targeting in a simple example with five impressions and three ads.

advertiser a for impression i in bundle \mathcal{I} , $m_{i,a}^{\mathcal{I}}$, as follows:

$$\hat{m}_{i,a}^{\mathcal{I}} = \sum_{j=1}^L \mathbb{1}(i \in I_j) \frac{\sum_{k \in I_j} \hat{m}_{k,a} e_{k,a}}{\sum_{k \in I_j} e_{k,a}} \quad \forall i \in \mathcal{I}, \quad (16)$$

where $e_{k,a}$ are elements of the filtering matrix that allows us to disregard inaccurate estimates and take the average of the rest. Figure 10 illustrates how the bundling and aggregation are performed on the match value matrix in a simple example with five impressions and three ads.

Here, we assume that for any targeting regime \mathcal{I} , advertisers can infer their private match values for the bundles at that targeting regime $\hat{m}_a^{\mathcal{I}}$. This is reasonable because if the platform allows impression-level targeting, the platform would automatically share the impression-level data of each advertiser a with that advertiser (but not other advertisers). If a has sufficient data, then a can accurately estimate the match value vector $m_{i,a}$ for impression i from their own data. Similarly, if the platform only allows targeting at level \mathcal{I} , then advertisers would automatically have information on which bundle an impression belongs to as well as outcomes (whether impressions in a given bundle received clicks or not), and can therefore accurately infer their match values at the granularity of the bundle. While this assumption always holds from a theoretical standpoint, it may not hold in practice because advertisers need sufficient data to obtain accurate estimates of their match values. Thus, the match value estimates of smaller advertisers and/or new advertisers can be noisy (though they will be consistent). Later, in Web Appendix §I.2, we show that our findings are robust even in situations where advertisers' match value estimates are noisy/imperfect.

Finally, the match value estimates derived from our quasi-proportional auction are assumed to remain the same under a second-price auction. This is reasonable because the match value simply

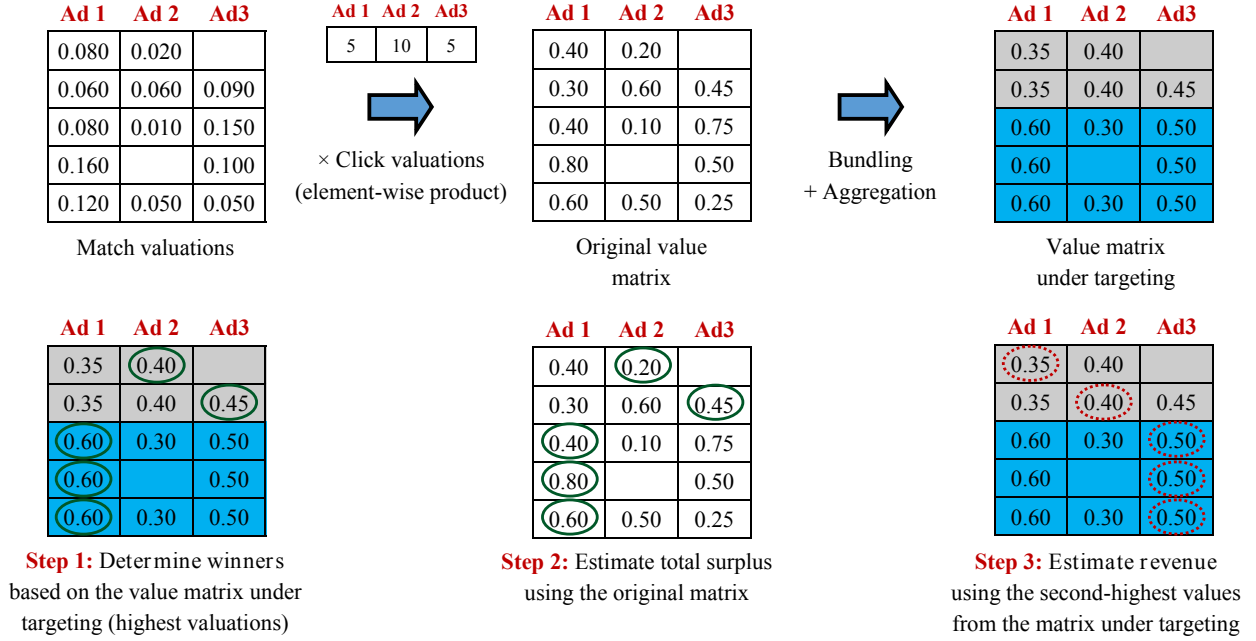


Figure 11: Step-by-step procedure to estimate revenue and surplus in a simple example.

indicates the click probability of a user in a given context for an ad. There is no economic rationale for users' click behavior to be a function of the auction, especially since users often do not know which auction is running at the back-end. Intuitively, click valuations and match valuations are treated as structural parameters.

6.3.4 Estimation of Revenue and Surplus

Given our estimates for click and match valuations, we can obtain estimates of the elements of the valuation matrix V as $\hat{v}_{i,a} = \hat{v}_a^{(c)} \hat{m}_{i,a}$. Further, we can estimate advertisers' expected value of impression i under targeting regime \mathcal{I} as $\hat{v}_{i,a}^{\mathcal{I}} = \hat{v}_a^{(c)} \hat{m}_{i,a}^{\mathcal{I}}$. We now formally discuss our procedure to estimate revenue and surplus for any targeting regime \mathcal{I} .

First, we determine the winners of each impression as follows:

$$\hat{a}_i^*(\mathcal{I}) = \operatorname{argmax}_a \hat{v}_{i,a}^{\mathcal{I}} e_{i,a}, \quad (17)$$

where $\hat{a}_i^*(\mathcal{I})$ is the winner for impression i under targeting regime \mathcal{I} . Note that the multiplication by the element of the filtering matrix $e_{i,a}$ simply ensures that the ad is competing in the auction for impression i and that the counterfactual match value estimates are valid, as discussed in §4.2.1.

While the winner is determined using the advertisers' expected value of impression i under a specific targeting regime, surplus is calculated using the actual valuation matrix because it denotes

the expected value that would be realized in the system if advertiser $\hat{a}_i^*(\mathcal{I})$ is allocated impression i . So we can write the surplus under targeting granularity \mathcal{I} as:

$$\hat{S}^{\mathcal{I}} = \sum_{i=1}^{N^F} \hat{v}_{i, \hat{a}_i^*(\mathcal{I})} \quad (18)$$

To estimate the platform revenues, however, we need to use advertisers' expected values under targeting regime \mathcal{I} , as these values guide their bidding behavior. Further, we need to incorporate the fact that the revenue generated from impression i is the second highest bid (or valuation) for it. Thus, the revenue under \mathcal{I} is:

$$\hat{R}^{\mathcal{I}} = \sum_{i=1}^{N^F} \max_{a \setminus \hat{a}_i^*(\mathcal{I})} \hat{v}_{i,a}^{\mathcal{I}} e_{i,a} \quad (19)$$

Finally, we can estimate advertiser a 's surplus under targeting regime \mathcal{I} as follows:

$$\hat{W}_a^{\mathcal{I}} = \sum_{i=1}^{N^F} \left(\hat{v}_{i, \hat{a}_i^*(\mathcal{I})} - \max_{a \setminus \hat{a}_i^*(\mathcal{I})} \hat{v}_{i,a}^{\mathcal{I}} e_{i,a} \right) \mathbb{1}(\hat{a}_i^*(\mathcal{I}) = a) \quad (20)$$

This estimation is carried out on the Filtered Sample to ensure that our match value estimates are accurate, and hence the averaging in the above equations is done over N_F . Figure 11 presents a step-by-step procedure to estimate revenue and surplus for the example case shown in Figure 10.

7 Counterfactual Results and Privacy Implications

While we can analyze market outcomes for any targeting regime, we focus on the following four targeting regimes that have a one-to-one correspondence with our analysis in §5.1.3:

- No targeting ($\mathcal{I}^{(\mathcal{N})}$) – The platform allows no targeting. As such, there is only one bundle (which constitutes all impressions) and advertisers cannot distinguish between any impressions.
- Contextual targeting ($\mathcal{I}^{(\mathcal{C})}$) – The platform only allows contextual targeting. Here, advertisers can distinguish between impressions in different contexts (app and time). However, impressions from different users in the same context is not distinguishable.
- Behavioral targeting ($\mathcal{I}^{(\mathcal{B})}$) – The platform allows behavioral targeting, thereby allowing advertisers to distinguish between users but not contexts. Here, advertisers can submit bids targeted at the user-level, but cannot distinguish two impressions by the same user in different contexts.
- Full targeting ($\mathcal{I}^{(\mathcal{F})}$) – Platform allows impression-level targeting, i.e., each impression is a bundle and therefore distinguishable. Advertisers can submit targeted bids for each impression. Using Proposition 1, we can show that $S^{(\mathcal{F})} \geq S^{(\mathcal{N})}$, and that $S^{(\mathcal{C})}$ and $S^{(\mathcal{B})}$ lie in between since

Targeting	Total Surplus	Platform Revenue	Advertisers' Surplus
Full	9.45	8.35	1.10
Behavioral	9.18	8.35	0.84
Contextual	8.99	8.44	0.55
No targeting	8.36	8.30	0.06

Table 5: Platform revenues, advertisers' surplus, and total surplus for different levels of targeting. The numbers are reported in terms of the average monetary unit per impression.

both contextual and behavioral targeting can be interpreted as imperfect targeting. However, we cannot theoretically pin down their relative magnitudes because these two types of information are orthogonal (one cannot be interpreted as more granular than the other). So we can only show that: $S^{(\mathcal{F})} \geq S^{(\mathcal{C})}$, $S^{(\mathcal{B})} \geq S^{(\mathcal{N})}$. Further, we have no theoretical guidance on which of these targeting regimes maximizes platform revenues. We therefore use the empirical framework described in §6.3 to derive estimates of platform revenue, advertisers' surplus, and total surplus under the four targeting regimes, and answer the question: “What is the optimal level of targeting that maximizes the platform's revenue?”. The results from this exercise are shown in Table 5.

7.1 Platform's Revenue

Consistent with our theory model, our empirical results suggest that more granular targeting leads to higher efficiency in the market: the total surplus under full targeting is 13.02% higher than the no targeting case. Further, in line with our findings in §5.1.3, we find that the total surplus under behavioral targeting is 2.13% higher than the contextual targeting. However, platform revenues exhibit more of an inverted U-shaped curve. They are maximized when the platform restricts targeting to the contextual level. When the platform allows behavioral targeting, advertisers achieve a greater ability to target. While this increases the total surplus in the system, much of this surplus is appropriated by advertisers and the platform's revenue suffers.¹⁶ Thus, the platform's incentives are not perfectly aligned with that of advertisers. Indeed, the platform's optimal targeting level is privacy preserving and aligned with consumers' preferences. We thus find support for the advertising industry's claim that the industry has natural economic incentives to limit user-tracking/targeting and that self-regulation is feasible.

Our findings give rise to many interesting suggestions/ideas on optimal mechanism design and information revelation from the platform's perspective. Limiting targeting to the contextual-level is an obvious strategy. However, this approach also reduces the total surplus and hence caps the

¹⁶Nevertheless, our findings are weaker than those predicted by theory models, i.e., while revenues reduce with more granular targeting, the drop is not very large. This suggests that the strong distributional assumptions on the match values in earlier theory papers (e.g., Hummel and McAfee (2016)) may not hold in real ad auctions.

To \ From	Full	Behavioral	Contextual	Baseline
Full	NA	23	33	35
Behavioral	14	NA	34	36
Contextual	4	3	NA	33
Baseline	2	1	4	NA

Table 6: Number of advertisers who benefit by moving from one targeting regime (column) to another (row) (out of 37 top advertisers).

platform’s revenues. Thus, the optimal path for the platform may not be to restrict targeting, but instead to consider mechanisms that can do both – increase efficiency and extract the revenue from winning advertisers by shrinking the informational rent. For instance, the platform could allow behavioral targeting, and also adopt the standard theoretical solution proposed for revenue extraction – optimal reserve prices (Myerson, 1981). Ostrovsky and Schwarz (2016) validate these theoretical findings using field experiments for search ads. However, they only consider optimal reserve prices for broad sets of keywords and assume CTRs to be homogeneous across advertisers. In contrast, we have a setting where each impression is a unique product and advertisers’ match values for an impression are heterogeneous. So, in our case, the platform has to develop a system that can set dynamic impression-specific optimal reserve prices.

7.2 Advertisers’ Surplus

We begin by comparing total advertiser surplus across the four targeting regimes. As shown in Table 5, advertiser’s surplus is increasing with more granular targeting. This validates our theoretical prediction that more granular targeting helps advertisers by allowing them to generate more accurate estimates of their match values and place targeted bids. Under full targeting, advertisers’ surplus is 11.69% of the total surplus whereas this share drops to 0.69% when no targeting is allowed. Further, the share of advertisers’ surplus under behavioral targeting is 8.99% which is considerably higher than 6.13%, their share under contextual targeting. Together these findings emphasize the value of behavioral information for advertisers.

Next, we explore whether all advertisers benefit when their ability to target is enhanced. In a competitive environment, greater ability to target does not necessarily translate into higher profits. Instead, it is the ability to target relative to competitors that matters. In Table 6, we show how many advertisers benefit as we move from one targeting regime (column) to another (row).

In general, more advertisers benefit when the platform allows more granular targeting, especially when it allows behavioral targeting. Moving from behavioral, contextual, and no targeting to full targeting benefits 23, 33, and 35 advertisers respectively (first row of Table 6). However, more granular targeting is not uniformly better for all advertisers. The first column of Table 6

depicts situations where advertisers go from the most granular to less granular targeting regimes. Interestingly, it is populated with positive numbers, which suggests that some advertisers actually benefit from less granular targeting. For example, there are 14 advertisers who prefer behavioral targeting to full targeting. Similarly, while the majority of advertisers prefer behavioral targeting, there is a small portion of advertisers (3) who prefer contextual targeting. We present a simple example to highlight the intuition behind this – a nutrition supplement ad that advertises on a fitness app can get all the slots in that app at a low cost because other advertisers would place low bids when only app-level targeting is allowed. However, this ad would be worse off if only behavioral targeting is allowed, because the competition for users in this app becomes more intense and this ad will no longer be able to extract a large informational rent.

In sum, our findings offer some evidence that advertisers are likely to be differentially affected by privacy regulation on user-tracking and behavioral targeting. Further research on the sources of heterogeneity in advertisers’ incentives can help regulators craft the appropriate privacy policies.

7.3 Robustness Checks and Limitations

We run a series of robustness checks on the two main components of our estimation – click valuations and match valuations. First, in Web Appendix §I.1, we consider alternative approaches to estimate click valuations from observed bids and show the robustness of our results. Second, in Web Appendix §I.2, we show that our results are robust to the addition of noise to all the match value estimates (to reflect the cases where advertisers realize a noisy version of match value estimates from our ML framework).

Finally, while we have tried to make our analysis as exhaustive and complete as possible, our results should nevertheless be interpreted as short-run counterfactuals with the necessary caveats. First, we assume that advertisers’ enhanced ability to target is only reflected in their targeted bidding. In reality however, there might be value creation through other decision variables as well. Second, we assume that the set of ads competing for an impression will not change under different targeting regimes. This implies that there is no entry of new ads or exit of existing ads for an impression. While this assumption may not be realistic, it is unlikely to change the qualitative findings of this paper. Third, we consider the case where the platform is a monopolist, which reflects our empirical setting. The question of how upstream competition affects privacy-preserving equilibrium outcomes is an important one, but outside the scope of our empirical setting. Finally, all our analysis is static. However, ad-networks can adopt a forward-looking approach in allocate and sell ads. We refer readers to the recent series of work on adaptive ad sequencing that provides frameworks to maximize user engagement (Rafieian, 2020a) and platform revenues (Rafieian, 2020b).

8 Conclusions

Mobile in-app advertising is now a dominant ad-format in the digital advertising eco-system. In-app ads have unique tracking properties: they allow advertisers and ad-networks to access the device ID of users' mobile devices, and thereby enable high quality behavioral targeting. While this has made them appealing to advertisers, consumers privacy advocates are concerned about their invasiveness. Therefore, marketers and policy-makers are interested in understanding the relative effectiveness of behavioral targeting compared to contextual targeting, the incentives of ad-networks to engage in behavioral targeting, and the role of regulation in preserving privacy.

We propose a unified framework that consists of two components – a machine learning framework for targeting and an analytical framework for targeting counterfactuals when considering the competition in the market. We apply our framework to data from the leading in-app ad-network of an Asian country. Our machine learning model achieves a *RIG* of 17.95% over the baseline when we evaluate it on test data. This translates to a 66.80% increase in the average CTR over the current system if we were to deploy an efficient targeting policy based on our machine learning framework. These gains mainly stem from behavioral information and the value of contextual information is relatively small. Next, we build an analytical model of targeting and theoretically prove that although total surplus grows with more granular targeting between the ad-network and advertisers, the ad-network's revenues are non-monotonic in the granularity of targeting. We then take our analytical model to data and conduct a series of targeting counterfactuals and show that the platform prefers to not allow behavioral targeting. There is also some heterogeneity among advertisers' on their preferred level of targeting. Our findings suggest ad-networks have economic incentives to preserve users' privacy in the mobile advertising domain.

Our paper makes several contributions to the literature. First, from a methodological standpoint, we propose a unified framework for targeting that provides counterfactual estimates of platform revenues and efficiency under various targeting regimes. Our framework is generalizable and can be applied to a wide variety of advertising platforms as long as we are able to recover both match valuations and click valuations. In our setting, this is facilitated by the quasi-proportional auction which induces randomness in the allocation of ads over impressions while preserving the linkage between observed bids and click valuations. However, other ad-networks that employ deterministic auctions can also use our framework as long as they randomize ad allocation for a small portion of their traffic.¹⁷ In such cases – (1) the data from the auctions can be used to recover click valuations,

¹⁷Indeed, this is standard practice in large ad-networks; e.g., Bing always randomizes ads for a small portion of its traffic Ling et al. (2017). More broadly, all prominent ad-networks now run A/B tests on portions of their data, and this portion of the traffic can be used to infer match valuations.

and (2) the data from the randomized traffic would satisfy the unconfoundedness assumption because of the exogenous variation in the allocation of ads, and can be used to recover match valuations using our machine learning framework that combines ideas from causal inference and large-scale prediction tasks. Once these two primitives are available, our framework on revenue-efficiency analysis is directly applicable to evaluate market outcomes under different targeting scenarios.

Next, from a substantive perspective, our paper provides new insights on contextual and behavioral targeting. To our knowledge, this is the first paper to study both revenue and efficiency under these two types of targeting. Finally, from a policy point-of-view, we examine the incentives to target for the two major parties in the advertising eco-system: the platform and advertisers. We expect our model and findings to speak to the debate on privacy regulations in the advertising industry.

References

- A. Acquisti, C. Taylor, and L. Wagman. The Economics of Privacy. *Journal of Economic Literature*, 54(2): 442–92, 2016.
- W. Amaldoss, K. Jerath, and A. Sayedi. Keyword Management Costs and “Broad Match” in Sponsored Search Advertising. *Marketing Science*, 35(2):259–274, 2015.
- S. Athey and P. A. Haile. Nonparametric approaches to auctions. *Handbook of econometrics*, 6:3847–3965, 2007.
- S. Athey and D. Nekipelov. A structural model of sponsored search advertising auctions. In *Sixth Ad Auctions Workshop*, volume 15, 2010.
- D. Bergemann and A. Bonatti. Targeting in Advertising Markets: Implications for Offline Versus Online Media. *The RAND Journal of Economics*, 42(3):417–443, 2011.
- L. Breiman. Arcing Classifier. *The Annals of Statistics*, 26(3):801–849, 1998.
- L. E. Celis, G. Lewis, M. Mobius, and H. Nazerzadeh. Buy-It-Now or Take-a-Chance: Price Discrimination Through Randomized Auctions. *Management Science*, 60(12):2927–2948, 2014.
- O. Chapelle, E. Manavoglu, and R. Rosales. Simple and Scalable Response Prediction for Display Advertising. *ACM Transactions on Intelligent Systems and Technology (TIST)*, 5(4):61, 2015.
- T. Chen and C. Guestrin. Xgboost: A Scalable Tree Boosting System. In *Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 785–794. ACM, 2016.
- A. De Corniere and R. De Nijs. Online Advertising and Privacy. *The RAND Journal of Economics*, 47(1): 48–72, 2016.
- M. Dudík, D. Erhan, J. Langford, L. Li, et al. Doubly robust policy evaluation and optimization. *Statistical Science*, 29(4):485–511, 2014.
- D. Dzyabura and H. Yoganarasimhan. Machine Learning and Marketing. In *Handbook of Marketing Analytics*. Edward Elgar Publishing, 2018.
- J. Edwards. Apple Has Quietly Started Tracking iPhone Users Again, And It’s Tricky To Opt Out, 2012. URL <http://www.businessinsider.com/ifa-apples-iphone-tracking-in-ios-6-2012-10>.
- A. Edwards-Levy and D. Liebelson. Even Trump Voters Hate This Bill He Just Signed, 2017. URL https://www.huffpost.com/entry/trump-online-privacy-poll_n.58e295e7e4b0f4a923b0d94
- eMarketer. Digital Ad Spending 2019, 2019. URL <https://content-na1.emarketer.com/us-digital-ad-sp>
- J. H. Friedman. Greedy Function Approximation: A Gradient Boosting Machine. *Annals of Statistics*, pages 1189–1232, 2001.
- A. Goldfarb. What is Different About Online Advertising? *Review of Industrial Organization*, 44(2):115–129, 2014.
- A. Goldfarb and C. Tucker. Advertising Bans and the Substitutability of Online and Offline Advertising. *Journal of Marketing Research*, 48(2):207–227, 2011a.
- A. Goldfarb and C. Tucker. Online Display Advertising: Targeting and Obtrusiveness. *Marketing Science*, 30(3):389–404, 2011b.
- E. Guerre, I. Perrigne, and Q. Vuong. Optimal nonparametric estimation of first-price auctions. *Econometrica*, 68(3):525–574, 2000.
- X. He, J. Pan, O. Jin, T. Xu, B. Liu, T. Xu, Y. Shi, A. Atallah, R. Herbrich, S. Bowers, et al. Practical Lessons from Predicting Clicks on Ads at Facebook. In *Proceedings of the Eighth International Workshop on Data Mining for Online Advertising*, pages 1–9. ACM, 2014.
- P. Hummel and R. P. McAfee. When Does Improved Targeting Increase Revenue? *ACM Transactions on Economics and Computation (TEAC)*, 5(1):4, 2016.

- G. W. Imbens and D. B. Rubin. *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press, 2015.
- J. Kint. Opinion: Europe’s Strict New Privacy Rules Are Scary but Right, 2017. URL <http://adage.com/article/digitalnext/europe-s-strict-privacy-rules-terrifying-app>
- V. Krishna. *Auction theory*. Academic press, 2009.
- J. Levin and P. Milgrom. Online Advertising: Heterogeneity and Conflation in Market Design. *The American Economic Review*, 100(2):603–607, 2010.
- H. Li and P. Kannan. Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment. *Journal of Marketing Research*, 51(1):40–56, 2014.
- X. Ling, W. Deng, C. Gu, H. Zhou, C. Li, and F. Sun. Model ensemble for click prediction in bing search ads. In *Proceedings of the 26th International Conference on World Wide Web Companion*, pages 689–698, 2017.
- D. F. McCaffrey, B. A. Griffin, D. Almirall, M. E. Slaughter, R. Ramchand, and L. F. Burgette. A tutorial on propensity score estimation for multiple treatments using generalized boosted models. *Statistics in medicine*, 32(19):3388–3414, 2013.
- H. B. McMahan, G. Holt, D. Sculley, M. Young, D. Ebner, J. Grady, L. Nie, T. Phillips, E. Davydov, D. Golovin, et al. Ad Click Prediction: A View from the Trenches. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1222–1230. ACM, 2013.
- V. Mirrokni, S. Muthukrishnan, and U. Nadav. Quasi-Proportional Mechanisms: Prior-Free Revenue Maximization. In *Latin American Symposium on Theoretical Informatics*, pages 565–576. Springer, 2010.
- R. B. Myerson. Optimal Auction Design. *Mathematics of Operations Research*, 6(1):58–73, 1981.
- M. Ostrovsky and M. Schwarz. Reserve Prices in Internet Advertising Auctions: A Field Experiment. Working Paper, 2016.
- O. Rafieian. Optimizing user engagement through adaptive ad sequencing. 2020a.
- O. Rafieian. Revenue-optimal dynamic auctions for adaptive ad sequencing. 2020b.
- O. Rafieian and H. Yoganarasimhan. How does variety of previous ads influence consumer’s ad response? Technical report, Working paper, 2020.
- J. G. Riley and W. F. Samuelson. Optimal Auctions. *The American Economic Review*, 71(3):381–392, 1981.
- L. Rosasco, E. De Vito, A. Caponnetto, M. Piana, and A. Verri. Are loss functions all the same? *Neural Computation*, 16(5):1063–1076, 2004.
- P. R. Rosenbaum and D. B. Rubin. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1):41–55, 1983.
- M. Rosoff. The research firm that once thought Microsoft would beat the iPhone has given up on Windows Phone , 2015. URL <https://www.businessinsider.com/idc-smartphone-os-market-share-2015-12>.
- N. S. Sahni. Effect of temporal spacing between advertising exposures: Evidence from online field experiments. *Quantitative Marketing and Economics*, 13(3):203–247, 2015.
- A. Sayedi. Real-Time Bidding in Online Display Advertising. *Marketing Science*, 2018.
- O. Toubia, T. Evgeniou, and J. Hauser. Optimization-based and Machine-learning Methods for Conjoint Analysis: Estimation and Question Design. In A. Gustafsson, A. Herrmann, and F. Huber, editors, *Conjoint Measurement: Methods and Applications*, pages 231–258. Springer, 4 edition, 2007.
- C. E. Tucker. Social Networks, Personalized Advertising, and Privacy Controls. *Journal of Marketing Research*, 51(5):546–562, 2014.
- J. M. Wooldridge. *Econometric analysis of cross section and panel data*. MIT press, 2010.

- S. Yao and C. F. Mela. A Dynamic Model of Sponsored Search Advertising. *Marketing Science*, 30(3): 447–468, 2011.
- J. Yi, Y. Chen, J. Li, S. Sett, and T. W. Yan. Predictive Model Performance: Offline and Online Evaluations. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1294–1302. ACM, 2013.
- H. Yoganarasimhan. Search personalization using machine learning. *Management Science*, 66(3):1045–1070, 2020.

Appendices

A Propensity Scores and Unconfoundedness Assumption

Our empirical strategy relies on randomization in the allocation of ads, which gives us the unconfoundedness assumption and allows us to perform targeting counterfactuals. As outlined in §4.2.2 in the main text of the paper, one diagnostic test for unconfoundedness assumption is to assess covariate balance. For this, we first need to estimate propensity scores, and then examine whether adjusting for these propensity scores achieves covariate balance. We do the former in §A.1 and the latter in §A.2.

A.1 Estimation of Propensity Scores

We now propose our approach to estimate propensity scores. First, recall the allocation rule presented in Equation (1) in the main text of the paper:

$$\pi_{ia} = \frac{b_a q_a}{\sum_{j \in \mathcal{A}_i} b_j q_j}$$

Our goal is to estimate π_{ia} for all top 37 ads in each impression i . In our filtering procedure, we identify ads with zero propensity of being shown and filter them out of the competition. However, our filtering procedure does not estimate the magnitude of the propensity score for ads with non-zero propensity scores. We therefore discuss our procedure to estimate propensity scores below.

The outcome and covariates for our propensity score model are listed below:

1. *Outcome*: The main outcome of interest is the ad shown. This is a categorical variable that has 38 classes, i.e., $a_i \in A = \{a^{(1)}, a^{(2)}, \dots, a^{(37)}, a^{(s)}\}$, where $a^{(1)}, a^{(2)}, \dots, a^{(37)}$ refer to the identities of the top 37 ads, and all the smaller ads are grouped into one category denoted by $a^{(s)}$.
2. *Covariates*: The set of covariates that we control for are:
 - Filtering indicators for each ad $e_{i,a}$. This controls for whether the ad a is in \mathcal{A}_i .
 - All the targeting variables, including province, app category, hour of the day, smartphone brand, connectivity type, and MSP.
 - Exact location (latitude and longitude), to control for any geographical targeting beyond province-level targeting.
 - Minute-level time of the day, to control for any shocks or changes in the quality scores and bids in the system. Note that we do not expect bids or quality scores to change within

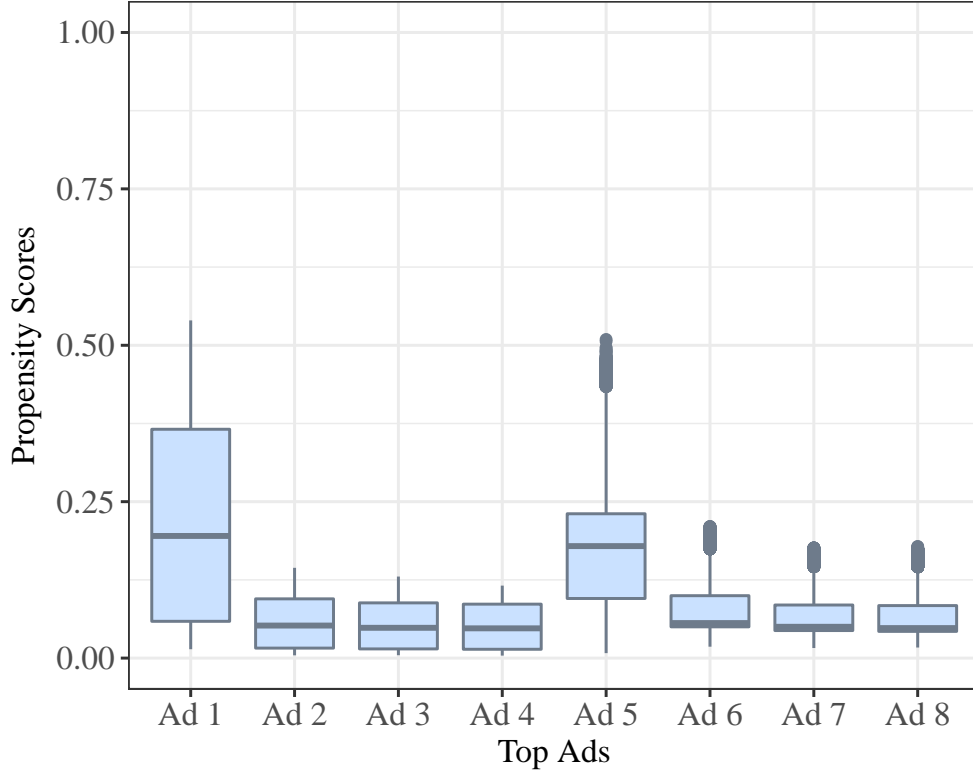


Figure A.1: Distribution of propensity scores for top 8 ads

the observation window. Nevertheless, this control simply ensures that there are no biases even if they did due to system bugs etc.

We use a multi-class XGBoost model to regress our outcome of interest on the set of covariates. We use multi-class logarithmic loss as the evaluation metric, which is defined as follows:

$$\mathcal{L}^{mlog\ loss}(\hat{\pi}, \mathbf{a}) = -\frac{1}{N} \sum_{i=1}^N \sum_{j \in A} \mathbb{1}(a_i = a^{(j)}) \log(\hat{\pi}_{i,j}), \quad (\text{A.1})$$

where the summation over j refers to all the outcome classes that we have. Using a softmax objective, we can then estimate the propensity scores. Figure A.1 shows the distribution of propensity scores for top eight ads, using box plots. As shown in this figure, the average propensity of winning for each ad is below 0.25. Further, there is no disproportionately high propensity of winning: the highest is slightly above 0.50. We also notice that Ad 5 has higher median propensity score than Ad 2, even though the total number of impressions is higher for Ad 2. This is because Ad 5 is targeting more narrowly, and is not available for all the impressions.

A.2 Assessing Covariate Balance Using Inverse Probability Weighting

Now, we use our estimated propensity scores to assess covariate balance across different ads. We begin by describing the balance for a simple case in which we have a fully randomized experiment with one treatment and one control group in §A.2.1. We then extend the same notion to the case where we want to assess balance using propensity scores across multiple treatment arms §A.2.2.

A.2.1 Covariate Balance in a Fully Randomized Experiment with a Binary Treatment

To assess the covariate balance in a fully randomized experiment with two treatment arms, we simply need to show that the distribution of covariate Z is the same across treated and control samples. As such, we rely on standardized bias, which is the absolute mean difference in covariate Z across the treatment and control groups, divided by the standard deviation of the Z in the pooled sample:

$$SB(Z) = \frac{|\bar{Z}_{\text{treated}} - \bar{Z}_{\text{control}}|}{\sigma_Z}, \quad (\text{A.2})$$

where \bar{Z}_{treated} and \bar{Z}_{control} are the mean value of covariate Z for the treated and control groups, and σ_Z is the standard deviation of Z for the pooled sample.

Clearly, the lower the standardized bias is, we have greater balance in covariate Z across treatment and control groups. In practice, different cutoffs are considered acceptable by the researchers. A common cutoff is 0.20 – that is, a standardized bias greater than 0.20 is taken as evidence for imbalance (McCaffrey et al., 2013). In this paper, we follow this norm and set our cutoff to be 0.20.

A.2.2 Covariate Balance Using Inverse Propensity Weights for Multiple Treatments

Our empirical setting is more complicated than a fully randomized experiment with a binary treatment because of two reasons: (1) ad assignment is not fully exogenous, but a function of observed covariates, so covariate balance may not be satisfied for the unweighted distribution of covariates, and (2) unlike a binary treatment, we have multiple treatment arms (ads), so the balance is not simply the difference between two groups. To address the first issue, we need to use our estimated propensity scores to weight our original sample such that an observation with a lower propensity score gets a larger weight to represent what the sample would have been if the platform had run a fully randomized experiment. For the second issue, we follow the approach in McCaffrey et al. (2013) and compare the weighted mean of covariate Z when assigned to ad with the population mean of that covariate and check for the balance by measuring the standardized bias. In principle, if weights are accurate, the weighted mean of covariate Z when assigned to ad a must be the same as the population mean. As such, we define the weight-adjusted standardized bias for covariate Z

when assigned to ad a as follows:

$$SB_a^{\hat{\pi}}(Z) = \frac{|\bar{Z}_a^{\hat{\pi}} - \bar{Z}|}{\sigma_Z}, \quad (\text{A.3})$$

where superscript $\hat{\pi}$ indicates the propensity score estimates used to weight the samples, and $\bar{Z}_a^{\hat{\pi}}$ is defined as follows:

$$\bar{Z}_a^{\hat{\pi}} = \frac{\sum_{i=1}^N \frac{\mathbb{1}(a_i=a)}{\hat{\pi}_{ia}} Z_i}{\sum_{i=1}^N \frac{\mathbb{1}(a_i=a)}{\hat{\pi}_{ia}}}, \quad (\text{A.4})$$

where Z_i is the value of covariate Z in impression i , the term $\mathbb{1}(a_i = a)$ indicates whether ad a is actually shown in that impression, and the weights are simply the inverse propensity scores.

We can then calculate the weight-adjusted standardized bias measure for each ad a and define the standardized bias for variable Z as follows:

$$SB^{\hat{\pi}}(Z) = \max_a SB_a^{\hat{\pi}}(Z), \quad (\text{A.5})$$

where by construction, if $SB^{\hat{\pi}}(Z)$ satisfies the balance criteria, it means that each $SB_a^{\hat{\pi}}(Z)$ satisfies this criteria. To have a baseline of how imbalanced covariates were before adjusting for inverse propensity weights, we define the unweighted measure of standardized bias for covariate Z when assigned to ad a as follows:

$$SB(Z) = \max_a SB_a(Z) = \max_a \frac{|\bar{Z}_a - \bar{Z}|}{\sigma_Z}, \quad (\text{A.6})$$

Comparing $SB(Z)$ (unweighted standardized bias) and $SB^{\hat{\pi}}(Z)$ (weight-adjusted standardized bias) allows us to see how adjusting for inverse propensity scores helped balance covariates.

Now, we focus on all the targeting variables in our sample and calculate both unweighted and weight-adjusted measures of standardized bias. Targeting variables are the main candidates that could potentially fail the balance test because advertisers can target these variables. Since all these variables are categorical, for each targeting variable (Z), we need to assess balance for the dummy variable for each separate category within that targeting variable.

For a given targeting variable (e.g., province), let \mathcal{Z} denote the set of dummy variables corresponding to each sub-category within that targeting variable. We define the standardized bias as the maximum standardized bias across all its sub-categories. As such, for both unweighted and

weight-adjusted methods, we have:

$$SB^{\hat{\pi}}(\mathcal{Z}) = \max_{Z \in \mathcal{Z}} SB^{\hat{\pi}}(Z) = \max_{Z \in \mathcal{Z}} \max_a SB_a^{\hat{\pi}}(Z)$$

$$SB(\mathcal{Z}) = \max_{Z \in \mathcal{Z}} SB(Z) = \max_{Z \in \mathcal{Z}} \max_a SB_a(Z)$$

Figure A.2 shows both unweighted and weight-adjusted measures of standardized bias for all of our targeting variables (on the filtered test data sample, which is used for the counterfactual analysis). Notice that all six targeting variables are initially imbalanced in the actual data. In particular, province, hour of the day, and MSP are the variables with the largest magnitude of imbalance. However, after adjusting for inverse propensity scores, we find that all measures of standardized bias are below the 0.2 cutoff. Thus, we have covariate balance.

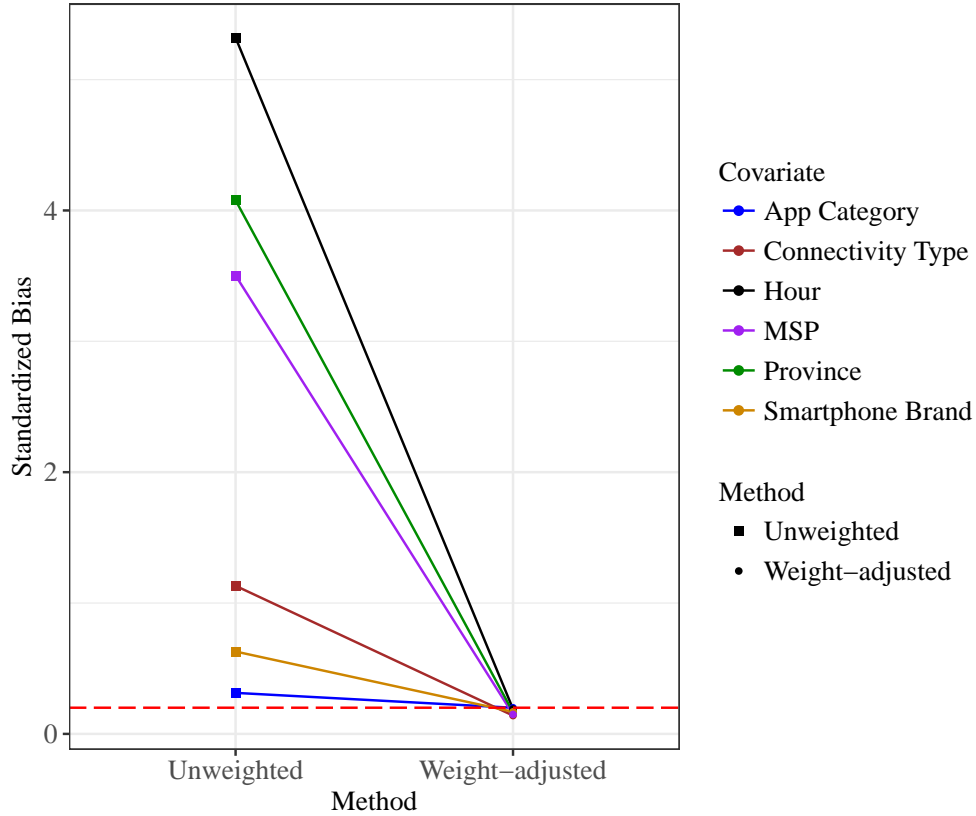


Figure A.2: Weight-adjusted and unweighted measures of standardized bias for all targeting variables (balance plot). The dotted red line shows the 0.2 cut-off.

What is striking about Figure A.2 is the very large measures of unweighted standardized bias for some targeting variables. This is due to the presence of some ads with very low propensity scores and sparse categories within certain targeting variables. For example, there are some provinces in

our data that constitute less than 1% of our observations. Likewise, there are some ads with less than 1% share of observations. As a result, there are very few observations where these ads are shown in these provinces. This may result in substantial imbalance in the original data.

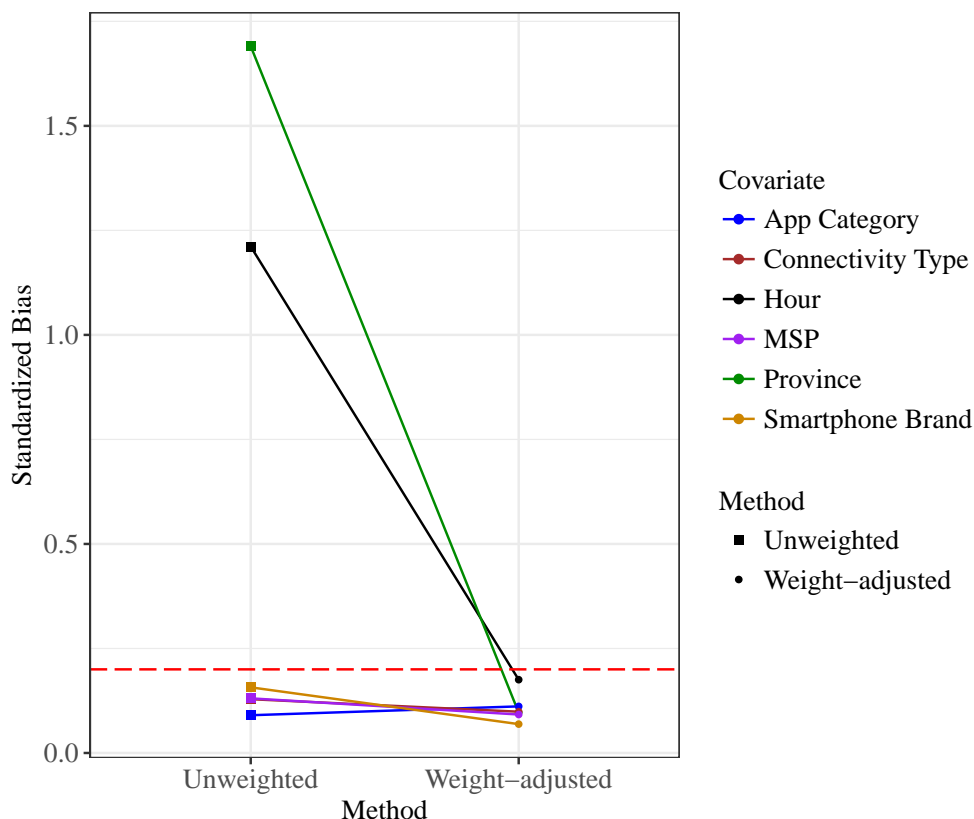


Figure A.3: Weight-adjusted and unweighted measures of standardized bias for all targeting variables, when we only consider ads with over 1% share of total number of observations in the filtered sample in test data (balance plot). The dotted red line shows the 0.2 cut-off.

Next, we focus only on ads that are shown at least in 1% of our sample and make the same balance plot in Figure A.3. In this case, the measures of standardized bias are significantly lower compared to Figure A.2, especially the unweighted measures. Interestingly, we find that four out of six covariates are balanced in the unweighted sample: app category, connectivity type, MSP, and smartphone brand. This is because these variables are not widely used for targeting and their sub-categories have a sufficiently large number of observations. The only two variables that are imbalanced in the original sample are state and hour of the day, most likely because these are the variables are most used for targeting among advertisers. We also find that in both cases, hour of the day has the highest standardized bias (even though we achieve balance at the 0.2 cutoff in both cases). This may also be due to the unavailability of some ads because of reasons other than

targeting such as budget exhaustion.

In sum, the above analysis presents strong empirical evidence for covariate balance in our data after adjusting for propensity scores. This suggests the unconfoundedness assumption is valid in our setting.

B Feature Generation Framework

We need a set of informative features that can help accurately predict the probability of click for a given impression. Given our research agenda, our features should be able to capture the contextual and behavioral information associated with an impression over different lengths of history preceding the impression (long-term, short-term, and session-level). Therefore, we adopt the main ideas from the functional feature generation framework proposed by Yoganarasimhan (2020). In §B.1, we describe the inputs to the feature functions, in §B.2, we describe the functions, and finally in §B.3, we present the full table of features and their classification.

B.1 Inputs for Feature Functions

Each impression i in our training, validation, and test data can be uniquely characterized by the following four variables:

- the ad a_i which was shown in the impression, where $a_i \in A = \{a^{(1)}, a^{(2)}, \dots, a^{(37)}, a^{(s)}\}$. The elements $a^{(1)}, a^{(2)}, \dots, a^{(37)}$ refer to the identities of the top 37 ads, whereas all the smaller ads are grouped into one category, which is denoted by $a^{(s)}$. A denotes the set of all ads.
- the app p_i within which it occurred, where $p_i \in P = \{p^{(1)}, p^{(2)}, \dots, p^{(50)}, p^{(s)}\}$. $p^{(1)}$ through $p^{(50)}$ refer to the top 50 apps, and $p^{(s)}$ refers to the category of all smaller apps (which we do not track individually).
- the hour of the day during which the impression occurred (denoted by t_i). t_i can take 24 possible values ranging from 1 through 24 and the set of these values is: $T = \{1, 2, \dots, 24\}$.
- the user u_i who generated the impression, where $u_i \in U = \{u^{(1)}, \dots, u^{(728,340)}\}$. U is thus the full sample of users in the training, validation, and test data.

We also have an indicator for whether the impression was clicked or not (denoted by y_i). In addition, we have a history of impressions and clicks observed in the system prior to this impression.

To generate a set of features for a given impression i , we use feature functions that take some inputs at the impression level and output a corresponding feature for that impression. Our feature functions are typically of the form $F(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie})$ (though some functions may have fewer inputs). We now define each of these inputs:

1. *Ad related information:* The first input θ_{ia} captures the ad related information for impression

- i*. It can take two possible values: $\theta_{ia} \in \Theta_{ia} = \{\{a_i\}, A\}$. If $\theta_{ia} = \{a_i\}$, then the feature is specific to the ad shown in the impression. Instead, if $\theta_{ia} = A$, then it means that the feature is not ad-specific and is aggregated over all possible ads.
2. *Contextual information*: The second and third inputs θ_{ip} and θ_{it} capture the context (where and when) for impression *i*.
- (a) $\theta_{ip} \in \Theta_{ip} = \{\{p_i\}, P\}$ can take two possible values. If $\theta_{ip} = \{p_i\}$, then the feature is specific to the app where the impression was shown. Instead, if $\theta_{ip} = P$, the feature is aggregated over all apps.
- (b) $\theta_{it} \in \Theta_{it} = \{\{t_i\}, T\}$ characterizes the time-related information for impression *i*. If $\theta_{it} = \{t_i\}$, then the feature is specific to the hour during which the impression occurred. Instead, if $\theta_{it} = T$, the feature is aggregated over all hours of the day.
3. *Behavioral information*: The fourth input, $\theta_{iu} \in \Theta_{iu} = \{\{u_i\}, U\}$, captures the behavioral information for impression *i*. If $\theta_{iu} = \{u_i\}$, the feature is specific to user u_i who generated the impression. Instead, if $\theta_{iu} = U$, the feature is aggregated over all users.
4. *History*: The last two inputs, η_{ib} and η_{ie} , capture the history over which the function is aggregated. η_{ib} denotes the beginning or starting point of the history and η_{ie} denotes the end-point of the history.
- (a) $\eta_{ib} \in \mathcal{H}_{ib} = \{l, s, o_i\}$ can take three possible values which we discuss below:
- $\eta_{ib} = l$ denotes long-term history, i.e., the starting point of the history is September 30, 2015, the date from which data are available.
 - $\eta_{ib} = s$ denotes short-term history, i.e., only data on or after October 25, 2015, are considered.
 - $\eta_{ib} = o_i$ denotes ongoing session-level history, i.e., the history starts from the beginning of the session within which the impression occurs.¹⁸ This history is the most accessible in the user's short-term memory. Note that by definition, $\eta_{ib} = o_i$ implies that the function is calculated at the user level.
- (b) $\eta_{ie} \in \mathcal{H}_{ie} = \{g, r_i\}$ can take two possible values which we define them as follows:

¹⁸A session ends when there is a five-minute interruption in a user's exposure to the ads. So if the time difference between two consecutive impressions shown to a user-app combination is more than five minutes, we assume that the two impressions belong to different sessions.

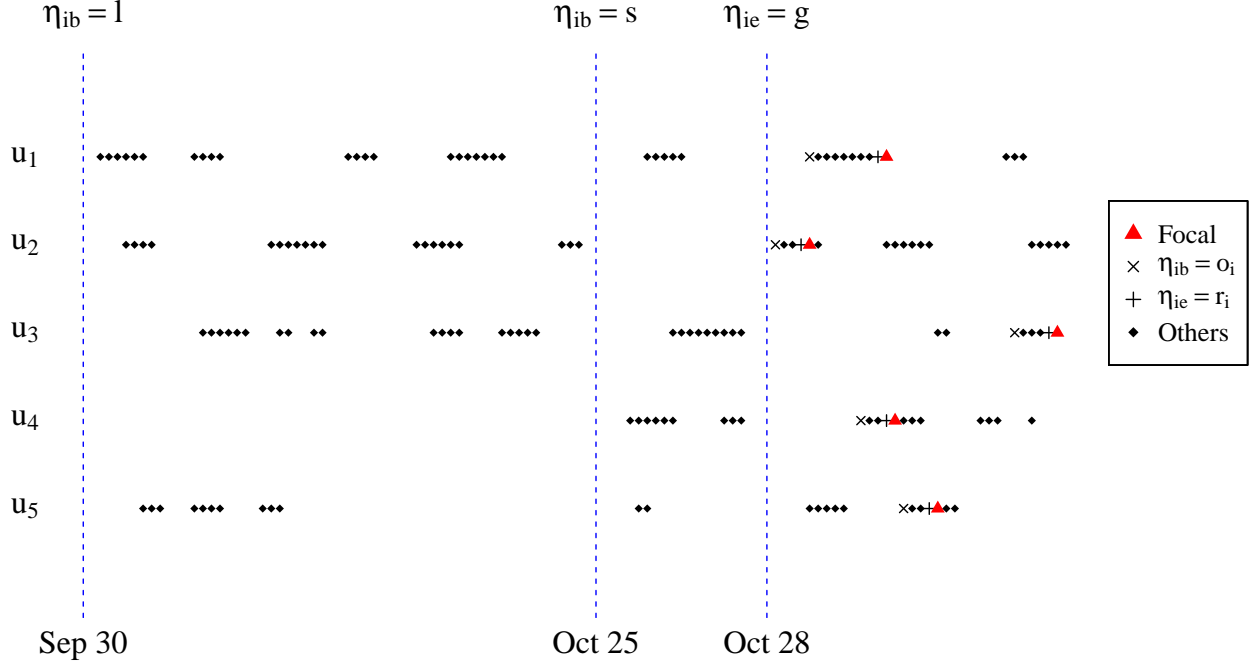


Figure A.4: Depiction of history for five example users. The \blacktriangle refers to the focal impression i for which the features are being generated. $+$ denotes the last impression just before the focal impression, and \times refers to the first impression in the session in which the focal impression occurs.

- $\eta_{ie} = g$ implies that the feature is calculated over the **g**lobal data, i.e., data after October 27, 2015, are not considered. These features are calculated without using any impression from the training, validation and test data-sets.
- $\eta_{ie} = r_i$ refers to **r**ead-time aggregation, i.e., the feature is calculated over all the information up till the focal impression i .

In Figure A.4, we present a picture with five example users to illustrate different types of history.

B.2 Feature Functions

We now use the nomenclature described above to define the following functions.

1. $Impressions(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie})$: This function counts the number of impressions with the characteristics given as inputs over the specified history.

$$Impressions(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie}) = \sum_{j \in [\eta_{ib}, \eta_{ie}]} \mathbb{1}(a_j \in \theta_{ia}) \mathbb{1}(p_j \in \theta_{ip}) \mathbb{1}(t_j \in \theta_{it}) \mathbb{1}(u_j \in \theta_{iu}), \quad (\text{A.7})$$

where j denotes an impression whose time-stamp lies between the starting point of the history η_{ib} and end point of the history η_{ie} .

For example, $Impressions(\{a_i\}, \{p_i\}, \{t_i\}, \{u_i\}; l, r_i)$ returns the number of times ad a_i is shown to user u_i while using app a_i at the hour of day t_i in the time period starting September 30, 2015, and ending with the last impression before i . Instead, if we are interested in the number of times that user u_i has seen ad a_i over all apps and all hours of the days from October 25, 2015, ($\eta_{ib} = s$) till the end of the global data ($\eta_{ie} = g$), then we would have:

$$\begin{aligned} Impressions(\{a_i\}, P, T, \{u_i\}; s, g) &= \sum_{j \in [s, g]} \mathbb{1}(a_j \in \{a_i\}) \mathbb{1}(p_j \in P) \mathbb{1}(t_j \in T) \mathbb{1}(u_j \in \{u_i\}) \\ &= \sum_{j \in [s, g]} \mathbb{1}(a_j \in \{a_i\}) \mathbb{1}(u_j \in \{u_i\}) \end{aligned}$$

Intuitively, the *Impressions* function captures the effects of repeated ad exposure on user behavior, and ad exposure has been shown to yield higher ad effectiveness in the recent literature (Sahni, 2015; Johnson et al., 2016). In some cases, it may also capture some unobserved ad-specific effects, e.g., an advertiser may not have enough impressions simply because he does not have a large budget.

2. $Clicks(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie})$: This function counts the number of clicks with the characteristics given as inputs over the history specified. It is similar to the *Impressions* function, but the difference is that *Clicks* only counts the impressions that led to a click.

$$Clicks(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie}) = \sum_{j \in [\eta_{ib}, \eta_{ie}]} \mathbb{1}(a_j \in \theta_{ia}) \mathbb{1}(p_j \in \theta_{ip}) \mathbb{1}(t_j \in \theta_{it}) \mathbb{1}(u_j \in \theta_{iu}) \mathbb{1}(y_j = 1) \quad (\text{A.8})$$

Clicks is a good indicator of both ad and app performance. Moreover, at the user-level, the number of clicks captures an individual user's propensity to click, as well as her propensity to click within a specific ad and/or app. Thus, this is a very informative metric.

3. $CTR(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie})$: This function calculates the click-through rate (CTR) for a given set of inputs and history, *i.e.*, the ratio of clicks to impressions. If $Impressions(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie}) > 0$, then:

$$CTR(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie}) = \frac{Clicks(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie})}{Impressions(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie})}, \quad (\text{A.9})$$

else if $Impressions(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie}) = 0$, $CTR(\theta_{ia}, \theta_{ip}, \theta_{it}, \theta_{iu}; \eta_{ib}, \eta_{ie}) = 0$. The *CTR*

function is a combination of *Impressions* and *Clicks*. It captures the click-propensity at the user, ad, app, and time-levels as well their interactions.¹⁹

4. $AdCount(\theta_{ip}, \theta_{iu}; \eta_{ib}, \eta_{ie})$: This function returns the number of distinct ads shown for a given set of inputs.

$$AdCount(\theta_{ip}, \theta_{iu}; \eta_{ib}, \eta_{ie}) = \sum_{a \in A^F} \mathbb{1}(Impressions(\{a\}, \theta_{ip}, T, \theta_{iu}; \eta_{ib}, \eta_{ie}) > 0), \quad (A.10)$$

We use the full set of ads seen in our data (denoted by A^F) and not just the top 37 ads in this function.²⁰ This ensures that we are capturing the full extent of variety in ads seen by users. Features derived using this function capture the variety in ads for a given set of inputs. In a recent paper, Rafieian and Yoganarasimhan (2020) show that higher variety of previous ads increases the CTR on the next ad.

An example of a feature based on this function is $AdCount(\{p_i\}, U; l, r_i)$, which counts the number of unique ads that were shown in app p_i across all users in the time period starting September 30 2015 and ending with the last impression before i .

5. $Entropy(\theta_{ip}, \theta_{iu}; \eta_{ib}, \eta_{ie})$: This function captures the entropy or dispersion in the ads seen by a user. We use Simpson (1949)’s measure of diversity as our entropy metric.

$$Entropy(\theta_{ip}, \theta_{iu}; \eta_{ib}, \eta_{ie}) = \frac{1}{\sum_{a \in A^F} Impressions(\{a\}, \theta_{ip}, T, \theta_{iu}; \eta_{ib}, \eta_{ie})^2} \quad (A.11)$$

Entropy contains information over and above just the count of the number of unique ads seen in the past since it captures the extent to which ads were dispersed across impressions. Consider two users who have both seen five impressions in the past, but with the following difference – (a) the first user has seen five distinct ads, or (b) the second has seen same ad five times. Naturally, the dispersion of ads is higher in case (a) than in case (b). The *Entropy* function reflects this dispersion – in case (a) the entropy is $\frac{1}{1^2+1^2+1^2+1^2+1^2} = 0.2$, whereas in case (b) it is $\frac{1}{5^2} = 0.04$. Thus, entropy is higher when ads are more dispersed.

The literature on eye-tracking has shown that individuals’ attention during advertisements

¹⁹In principle, we do not need to *CTR* over and above *Clicks* and *Impressions* if our learning model can automatically generate new features based on non-linear combinations of basic features. Machine learning models like Boosted Trees do this naturally and it is one of their big advantages. However, other methods like OLS and Logistic regressions cannot do automatic feature combination and selection. So we include this feature to help improve the performance of these simpler models. This ensures that we are not handicapping them too much in our model comparisons.

²⁰We observe 263 unique ads in our data. Thus, the range of *AdCount* in our data goes from 0 to 263.

reduces as ad-repetition increases (Pieters et al., 1999). We therefore expect the dispersion of previous ads to influence a user’s attention span in our setting. Since attention is a prerequisite to clicking, we expect entropy-based measures to have explanatory power in our click prediction model.

6. *AppCount*($\theta_{ia}, \theta_{iu}; \eta_{ib}, \eta_{ie}$): This function calculates the number of distinct apps in which a given ad is shown to a specific user. Similar to *AdCount*, it can be defined as follows:

$$AppCount(\theta_{ia}, \theta_{iu}; \eta_{ib}, \eta_{ie}) = \sum_{p \in P} \mathbb{1}(Impressions(\theta_{ia}, \{p\}, T, \theta_{iu}; \eta_{ib}, \eta_{ie}) > 0), \quad (A.12)$$

where P is the set of apps, as defined in §B.1.²¹ Previous studies have documented the spillover effects in multichannel online advertising (Li and Kannan, 2014). We therefore expect click probabilities to vary if a user saw an ad in just one app vs. saw it in many apps. We also expect the click behavior of users to vary based on the number of apps they use. *AppCount*-based features help us capture these differences.

7. *TimeVariability*($\theta_{iu}; \eta_{ib}, \eta_{ie}$): This function measures the variance in a user’s CTR over different hours of the day. We can define this function as follows:

$$TimeVariability(\theta_{iu}; \eta_{ib}, \eta_{ie}) = \text{Var}_t[CTR(A, P, \{t\}, \theta_{iu}; \eta_{ib}, \eta_{ie})] \quad (A.13)$$

Features based on this function capture variations in the temporal patterns in a user’s clicking behavior, and we expect this information to help predict clicks.

8. *AppVariability*($\theta_{iu}; \eta_{ib}, \eta_{ie}$): This function measures the variance in a user’s CTR across different apps and is analogous to *TimeVariability*. This function is defined as follows:

$$AppVariability(\theta_{iu}; \eta_{ib}, \eta_{ie}) = \text{Var}_p[CTR(A, \{p\}, T, \theta_{iu}; \eta_{ib}, \eta_{ie})] \quad (A.14)$$

Note that both *TimeVariability* and *AppVariability* are defined at the user level.

We use the functions defined above to generate 98 features for each impression. In addition, we include a few standalone features such as a dummy for each of the top ads, the mobile and Internet service providers, latitude, longitude, and connectivity type as described below:

²¹ P has 51 elements, the top 1–50 apps and the 51st element being the group of all smaller apps. In principle, we could use all the apps observed in the data and not just the Top 50 apps (like we did in the case of *AdCount*). However, we found that doing so does not really improve model performance. So we stick with this simpler definition.

9. $Bid(a_i)$: The bid submitted for ad a_i shown in impression i .
10. $Latitude(u_i)$: The latitude of user u_i when impression i occurs.
11. $Longitude(u_i)$: The longitude of user u_i when impression i occurs.
12. $WiFi(u_i)$: Denotes whether the user is connected via Wi-Fi or mobile data plan during impression i . It can take two possible values, $\{0, 1\}$.
13. $Brand(u_i)$: Denotes the brand of the smartphone that user u_i is using. We observe eight smartphone brands in our data and therefore capture each brand using a dummy variable. So the range for this function is $\{0, 1\}^8$.
14. $MSP(u_i)$: Denotes the Mobile Service Provider used by user u_i during impression i . We observe four MSPs in our data. So the range for this function is $\{0, 1\}^4$.
15. $ISP(u_i)$: Denotes the Internet service providers (ISP) of user u_i . We observe nine unique ISPs in our data. So the range of this function is $\{0, 1\}^9$.
16. $AdDummy(a_i)$: Generates dummy variables for each of the top ads in the data. Although we expect our main features to capture many of the ad-fixed effects, we include ad dummies to capture any residual ad-fixed effects, e.g., banner design. The range of this function is $\{0, 1\}^{38}$, since there are 37 top ads and a 38th category comprising all the smaller ads.

B.3 Table of Features

In Table A1, we now present our full list of 160 features derived from the feature-functions described above as well as their classification as behavioral, contextual, and/or ad-specific based on the categorization scheme described in §4.3.3 in the main text of the paper.

Table A1: List of Features for impression i .

No.	Feature Name	Feature Classification			Contextual Features	
		Behavioral	Contextual	Ad-specific	App-specific	Time-specific
1	$Impressions(A, P, T, u_i; l, r_i)$	✓				
2	$Impressions(a_i, P, T, U; l, g)$			✓		
3	$Impressions(A, p_i, T, U; l, g)$		✓		✓	
4	$Impressions(A, P, t_i, U; l, g)$		✓			✓
5	$Impressions(a_i, P, T, u_i; l, r_i)$	✓		✓		
Continued on next page						

Table A1 – continued from previous page

No.	Feature Name	Feature Classification			Contextual Features	
		Behavioral	Contextual	Ad-specific	App-specific	Time-specific
6	<i>Impressions</i> ($A, p_i, T, u_i; l, r_i$)	✓	✓		✓	
7	<i>Impressions</i> ($A, P, t_i, u_i; l, r_i$)	✓	✓			✓
8	<i>Impressions</i> ($a_i, p_i, T, U; l, g$)		✓	✓	✓	
9	<i>Impressions</i> ($a_i, P, t_i, U; l, g$)		✓	✓		✓
10	<i>Impressions</i> ($A, p_i, t_i, U; l, g$)		✓		✓	✓
11	<i>Impressions</i> ($a_i, p_i, T, u_i; l, r_i$)	✓	✓	✓	✓	
12	<i>Impressions</i> ($a_i, p_i, t_i, U; l, g$)		✓	✓	✓	✓
13	<i>Impressions</i> ($A, P, T, u_i; s, r_i$)	✓				
14	<i>Impressions</i> ($a_i, P, T, U; s, g$)			✓		
15	<i>Impressions</i> ($A, p_i, T, U; s, g$)		✓		✓	
16	<i>Impressions</i> ($A, P, t_i, U; s, g$)		✓			✓
17	<i>Impressions</i> ($a_i, P, T, u_i; s, r_i$)	✓		✓		
18	<i>Impressions</i> ($A, p_i, T, u_i; s, r_i$)	✓	✓		✓	
19	<i>Impressions</i> ($A, P, t_i, u_i; s, r_i$)	✓	✓			✓
20	<i>Impressions</i> ($a_i, p_i, T, U; s, g$)		✓	✓	✓	
21	<i>Impressions</i> ($a_i, P, t_i, U; s, g$)		✓	✓		✓
22	<i>Impressions</i> ($A, p_i, t_i, U; s, g$)		✓		✓	✓
23	<i>Impressions</i> ($a_i, p_i, T, u_i; s, r_i$)	✓	✓	✓	✓	
24	<i>Impressions</i> ($a_i, p_i, t_i, U; s, g$)		✓	✓	✓	✓
25	<i>Impressions</i> ($A, P, T, u_i; o_i, r_i$)	✓				
26	<i>Impressions</i> ($a_i, P, T, u_i; o_i, r_i$)	✓		✓		
27	<i>Clicks</i> ($A, P, T, u_i; l, r_i$)	✓				
28	<i>Clicks</i> ($a_i, P, T, U; l, g$)			✓		
29	<i>Clicks</i> ($A, p_i, T, U; l, g$)		✓		✓	
30	<i>Clicks</i> ($A, P, t_i, U; l, g$)		✓			✓
31	<i>Clicks</i> ($a_i, P, T, u_i; l, r_i$)	✓		✓		
32	<i>Clicks</i> ($A, p_i, T, u_i; l, r_i$)	✓	✓		✓	
33	<i>Clicks</i> ($A, P, t_i, u_i; l, r_i$)	✓	✓			✓
34	<i>Clicks</i> ($a_i, p_i, T, U; l, g$)		✓	✓	✓	
35	<i>Clicks</i> ($a_i, P, t_i, U; l, g$)		✓	✓		✓
36	<i>Clicks</i> ($A, p_i, t_i, U; l, g$)		✓		✓	✓
37	<i>Clicks</i> ($a_i, p_i, T, u_i; l, r_i$)	✓	✓	✓	✓	
38	<i>Clicks</i> ($a_i, p_i, t_i, U; l, g$)		✓	✓	✓	✓
39	<i>Clicks</i> ($A, P, T, u_i; s, r_i$)	✓				
40	<i>Clicks</i> ($a_i, P, T, U; s, g$)			✓		
41	<i>Clicks</i> ($A, p_i, T, U; s, g$)		✓		✓	
42	<i>Clicks</i> ($A, P, t_i, U; s, g$)		✓			✓

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Table A1 – continued from previous page

No.	Feature Name	Feature Classification			Contextual Features	
		Behavioral	Contextual	Ad-specific	App-specific	Time-specific
43	$Clicks(a_i, P, T, u_i; s, r_i)$	✓		✓		
44	$Clicks(A, p_i, T, u_i; s, r_i)$	✓	✓		✓	
45	$Clicks(A, P, t_i, u_i; s, r_i)$	✓	✓			✓
46	$Clicks(a_i, p_i, T, U; s, g)$		✓	✓	✓	
47	$Clicks(a_i, P, t_i, U; s, g)$		✓	✓		✓
48	$Clicks(A, p_i, t_i, U; s, g)$		✓		✓	✓
49	$Clicks(a_i, p_i, T, u_i; s, r_i)$	✓	✓	✓	✓	
50	$Clicks(a_i, p_i, t_i, U; s, g)$		✓	✓	✓	✓
51	$CTR(A, P, T, u_i; l, r_i)$	✓				
52	$CTR(a_i, P, T, U; l, g)$			✓		
53	$CTR(A, p_i, T, U; l, g)$		✓		✓	
54	$CTR(A, P, t_i, U; l, g)$		✓			✓
55	$CTR(a_i, P, T, u_i; l, r_i)$	✓		✓		
56	$CTR(A, p_i, T, u_i; l, r_i)$	✓	✓		✓	
57	$CTR(A, P, t_i, u_i; l, r_i)$	✓	✓			✓
58	$CTR(a_i, p_i, T, U; l, g)$		✓	✓	✓	
59	$CTR(a_i, P, t_i, U; l, g)$		✓	✓		✓
60	$CTR(A, p_i, t_i, U; l, g)$		✓		✓	✓
61	$CTR(a_i, p_i, T, u_i; l, r_i)$	✓	✓	✓	✓	
62	$CTR(a_i, p_i, t_i, U; l, g)$		✓	✓	✓	✓
63	$CTR(A, P, T, u_i; s, r_i)$	✓				
64	$CTR(a_i, P, T, U; s, g)$			✓		
65	$CTR(A, p_i, T, U; s, g)$		✓		✓	
66	$CTR(A, P, t_i, U; s, g)$		✓			✓
67	$CTR(a_i, P, T, u_i; s, r_i)$	✓		✓		
68	$CTR(A, p_i, T, u_i; s, r_i)$	✓	✓		✓	
69	$CTR(A, P, t_i, u_i; s, r_i)$	✓	✓			✓
70	$CTR(a_i, p_i, T, U; s, g)$		✓	✓	✓	
71	$CTR(a_i, P, t_i, U; s, g)$		✓	✓		✓
72	$CTR(A, p_i, t_i, U; s, g)$		✓		✓	✓
73	$CTR(a_i, p_i, T, u_i; s, r_i)$	✓	✓	✓	✓	
74	$CTR(a_i, p_i, t_i, U; s, g)$		✓	✓	✓	✓
75	$AdCount(A, u_i; l, g)$	✓		✓		
76	$AdCount(p_i, U; l, g)$		✓	✓	✓	
77	$AdCount(p_i, u_i; l, g)$	✓	✓	✓	✓	
78	$AdCount(A, u_i; s, g)$	✓		✓		
79	$AdCount(p_i, U; s, g)$		✓	✓	✓	

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Table A1 – continued from previous page

No.	Feature Name	Feature Classification			Contextual Features	
		Behavioral	Contextual	Ad-specific	App-specific	Time-specific
80	<i>AdCount</i> ($p_i, u_i; s, g$)	✓	✓	✓	✓	
81	<i>AdCount</i> ($A, u_i; o_i, r_i$)	✓		✓		
82	<i>AppCount</i> ($A, u_i; l, g$)	✓	✓		✓	
83	<i>AppCount</i> ($a_i, U; l, g$)		✓	✓	✓	
84	<i>AppCount</i> ($a_i, u_i; l, g$)	✓	✓	✓	✓	
85	<i>AppCount</i> ($A, u_i; s, g$)	✓	✓		✓	
86	<i>AppCount</i> ($a_i, U; s, g$)		✓	✓	✓	
87	<i>AppCount</i> ($a_i, u_i; s, g$)	✓	✓	✓	✓	
88	<i>Entropy</i> ($A, u_i; l, g$)	✓		✓		
89	<i>Entropy</i> ($p_i, U; l, g$)		✓	✓	✓	
90	<i>Entropy</i> ($p_i, u_i; l, g$)	✓	✓	✓	✓	
91	<i>Entropy</i> ($A, u_i; s, g$)	✓		✓		
92	<i>Entropy</i> ($p_i, U; s, g$)		✓	✓	✓	
93	<i>Entropy</i> ($p_i, u_i; s, g$)	✓	✓	✓	✓	
94	<i>Entropy</i> ($A, u_i; o_i, r_i$)	✓		✓		
95	<i>TimeVariability</i> ($u_i; l, g$)	✓	✓			✓
96	<i>TimeVariability</i> ($u_i; s, g$)	✓	✓			✓
97	<i>AppVariability</i> ($u_i; l, g$)	✓	✓		✓	
98	<i>AppVariability</i> ($u_i; s, g$)	✓	✓		✓	
99	<i>Latitude</i> (u_i)	✓				
100	<i>Longitude</i> (u_i)	✓				
101	<i>WiFi</i> (u_i)	✓				
102-109	<i>Brand</i> (u_i)	✓				
110-113	<i>Operator</i> (u_i)	✓				
114-122	<i>ISP</i> (u_i)	✓				
123-160	<i>AdDummy</i> (a_i)			✓		

C XGBoost: Overview and Implementation

C.1 Overview of XGBoost

We start by considering a generic tree ensemble method as follows: let y_i and \mathbf{x}_i denote the click indicator and the vector of features for impression i such that $y_i \in \{0, 1\}$ and $\mathbf{x}_i \in \mathbb{R}^k$, where k is

the number of features. Then, a tree ensemble method is defined as follows:

$$\hat{y}_i = \phi(\mathbf{x}_i) = \sum_{j=1}^J \tau_j(\mathbf{x}_i) = \sum_{j=1}^J w_{q_j(\mathbf{x}_i)}^{(j)}, \quad (\text{A.15})$$

where $q_j : \mathbb{R}^k \rightarrow \{1, 2, \dots, L_j\}$ and $w^{(j)} \in \mathbb{R}^{L_j}$ constitute the j^{th} regression tree τ_j with L_j leaves. Here q_j maps an impression to the leaf index and $w^{(j)}$ represents the weight on leaves. Hence, $w_{q_j(\mathbf{x}_i)}^{(j)}$ indicates the weight on the leaf that \mathbf{x}_i belongs to. The tree ensemble method uses J additive functions to predict the output. In order to estimate the set of functions, Chen and Guestrin (2016) minimize the following regularized objective:

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \gamma \sum_j L_j + \frac{1}{2} \lambda \sum_j \|w^{(j)}\|^2, \quad (\text{A.16})$$

where γ and λ are the regularization parameters to penalize the model complexity, and l is a differentiable convex loss function (in our case, we use log loss as defined in §5.1.1 in the main text of the paper). Here, in contrast to MART, XGBoost penalizes not just tree depth but leaf weights as well.

Since the regularized objective in Equation (A.16) cannot be minimized using traditional optimization methods in Euclidean space, we employ Newton boosting in function space to train the model in an additive manner. Formally, if we define $\hat{y}_i^{(j)}$ as the prediction of the i^{th} impression at the j^{th} iteration, we will add τ_j to minimize the following objective:

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i^{(j-1)} + \tau_j(\mathbf{x}_i), y_i) + \gamma L_j + \frac{1}{2} \lambda \|w^{(j)}\|^2 \quad (\text{A.17})$$

In each iteration, we greedily add the tree that most improves our model according to the objective function in Equation (A.16). Since the model uses a greedy algorithm to find the best split at each iteration, it is impossible to search over all tree structures. Thus, we restrict the set of trees by specifying the maximum depth of a tree. To optimize this objective function, Friedman et al. (2000) propose a second-order approximation:

$$\mathcal{L}(\phi) \simeq \sum_i \left[l(\hat{y}_i^{(j-1)}, y_i) + \mathcal{G}_i \tau_j(\mathbf{x}_i) + \frac{1}{2} \mathcal{H}_i \tau_j^2(\mathbf{x}_i) \right] + \gamma L_j + \frac{1}{2} \lambda \|w^{(j)}\|^2, \quad (\text{A.18})$$

where $\mathcal{G}_i = \partial_{\hat{y}_i^{(j-1)}} l(\hat{y}_i^{(j-1)}, y_i)$ and $\mathcal{H}_i = \partial_{\hat{y}_i^{(j-1)}}^2 l(\hat{y}_i^{(j-1)}, y_i)$ are first and second order gradient statistics on the loss function. This approximation is used to derive the optimal tree at the step.

To implement this optimization routine, the researcher needs to provide a set of hyper-parameters. These include the regularization parameters γ and λ defined in Equation (A.16). Further, XGBoost uses two additional parameters to prevent over-fitting. The first is called shrinkage parameter (ν) introduced by Friedman (2002), which functions like learning rate in stochastic optimization. The second is the column sub-sampling parameter (χ_s), which is used to pick the fraction of features supplied to a tree and ranges from 0 to 1. In addition, we also need to specify parameters that structure the optimization problem and control the exit conditions for the algorithm. The first is d_{max} , the maximum depth of trees. As mentioned earlier, this ensures that the model searches over a finite set of trees. Second, we set the number of maximum number of iterations. Finally, the last parameter defines the early stopping rule, $\kappa \in \mathbb{Z}^+$, which stops the algorithm if the loss does not change in κ consecutive iterations. This parameter also helps prevent over-fitting.

Note all that these parameters cannot be inferred from the training data alone and should be set based on a scientific validation procedure. In the next section of the Web Appendix, §C.2, we provide a step by step explanation and the final values used for these hyper-parameters in our analysis.

C.2 Validation

The goal of validation is to pick the optimal tuning parameters. They cannot be inferred from the training data alone because they are hyper-parameters. The validation procedure uses two separate data-sets – training and validation data (from October 28 and 29, as shown in Figure 1) to pin down the hyper-parameters. It is worth noting that at this stage, the test data is kept separate and is brought out only at the end after the model has been finalized to evaluate the final model performance.

As discussed earlier in §C.1, XGBoost uses five hyper-parameters that need tuning. Let $\mathcal{W} = \{\gamma, \lambda, \nu, d_{max}, \chi_s\}$ denote the set of hyper-parameters, where γ and λ are the regularization parameters, ν is the shrinkage parameter or learning rate, d_{max} is maximum depth of trees, and χ_s is the column sub-sampling parameter, which refers to the percentage of features randomly selected in each round. For each of these parameters, we consider the following sets of values:

- $\gamma \in \{7, 9, 11\}$
- $\lambda \in \{0, 1, 2\}$
- $\nu \in \{0.05, 0.1, 0.5, 1\}$
- $d_{max} \in \{5, 6, 7\}$
- $\chi_s \in \{0.5, 0.75\}$

Overall, \mathcal{W} contains 216 elements. We now describe the validation and testing procedure in detail.

- Step 1: For each element of \mathcal{W} , train the model on the first two-thirds of the training and validation data and evaluate the model’s performance on the remaining one-third. This is the typical hold-out procedure (Hastie et al., 2001). Boosted trees typically over-fit when they are stopped at some point. So when training the model, we use the early stopping rule to avoid this problem (Zhang et al., 2005).
- Step 2: Choose the set of hyper-parameters that gives the best model performance on the validation set (as measured by RIG in our case). Denote this as \mathcal{W}^* .
- Step 3: Using \mathcal{W}^* , train the final model on the full training and validation data, and here too we use the early stopping rule.
- Step 4: Evaluate the final model’s performance on the test data.

Based on the above procedure, we derive the set of optimal hyper-parameters for our empirical setting as $\mathcal{W}^* = \{\gamma = 9, \lambda = 1, \nu = 0.1, d_{\max} = 6, \chi_s = 0.5\}$. Further, when training on the full training and validation data (Step 3), we do not see any improvement in model fit after 276 steps, so at this iteration number (following the early stopping rule).

Note that our validation procedure addresses two potential complications with our data and problem setting. First, our data and features have a time component. Thus, if we are not careful in how we split the validation and training data-sets, we can end up in situations where we use the future to predict the past (e.g., train on data from period t and validate on data from $t - 1$). To avoid this problem, the splits should be chosen based on time. Our validation procedure does this by using the first two-thirds of the validation+training data for training and the latter one-third for validation. However, doing so gives rise to a second problem – by choosing the most recent data for validation (instead of training), we forgo the information in the most recent impressions. In CTR prediction, it is important not to waste the most recent impressions while fitting the model because these impressions are more likely to be predictive of the future (McMahan et al., 2013). To address this, in Step 3, after choosing the optimal hyper-parameters, we train a final model on the full training and validation data. This model is then used as the final model for results and counterfactuals.

D Evaluating Efficient Targeting Policy Using Importance Sampling

As discussed in §5.2, the overlap between our data and the efficient targeting policy provides a unique opportunity to use model-free approaches to evaluate the efficient targeting policy. Intuitively, if we weight the overlapping sample such that it represents the full sample, we can estimate the outcome of interest under the efficient targeting policy. In particular, we use *importance sampling* whereby we weight the impressions in the overlapping area by the inverse propensity score of those

impressions. We can now define the average match value under the efficient targeting as follows:

$$\hat{m}_{IS}^{\tau^*} = \frac{1}{N_F} \sum_{i=1}^{N_F} \sum_{a \in \mathcal{A}_i} \frac{\mathbb{1}(a_i = a) \mathbb{1}(\tau^*(i) = a)}{\hat{\pi}_{ia}} y_{i,a}, \quad (\text{A.19})$$

where $y_{i,a}$ is the click outcome for ad a in impression i , and the indicator functions both take value one only if the efficient targeting policy coincides the actual data. As such, for non-zero elements in the summation above, we actually observe the actual outcome of interest $y_{i,a}$. Now, we can even show that under unconfoundedness assumption, $\hat{m}_{IS}^{\tau^*}$ is a consistent estimator for the match value under the efficient targeting policy, conditional on observed covariates. We can write:

$$\begin{aligned} \mathbb{E} [\hat{m}_{IS}^{\tau^*} | X] &= \mathbb{E} \left[\frac{1}{N_F} \sum_{i=1}^{N_F} \sum_{a \in \mathcal{A}_i} \frac{\mathbb{1}(a_i = a) \mathbb{1}(\tau^*(i) = a)}{\hat{\pi}_{ia}} y_{i,a} | X \right] \\ &= \frac{1}{N_F} \sum_{i=1}^{N_F} \sum_{a \in \mathcal{A}_i} \mathbb{E} \left[\frac{\mathbb{1}(a_i = a) \mathbb{1}(\tau^*(i) = a)}{\hat{\pi}_{ia}} y_{i,a} | X \right] \\ &= \frac{1}{N_F} \sum_{i=1}^{N_F} \sum_{a \in \mathcal{A}_i} \frac{\hat{\pi}_{ia} \mathbb{1}(\tau^*(i) = a)}{\hat{\pi}_{ia}} \mathbb{E} [y_{i,a} | X] \\ &= \frac{1}{N_F} \sum_{i=1}^{N_F} \sum_{a \in \mathcal{A}_i} \mathbb{1}(\tau^*(i) = a) \mathbb{E} [y_{i,a} | X] \\ &= \mathbb{E} \left[\frac{1}{N_F} \sum_{i=1}^{N_F} \sum_{a \in \mathcal{A}_i} \mathbb{1}(\tau^*(i) = a) y_{i,a} | X \right], \end{aligned} \quad (\text{A.20})$$

where the last term is the true match value under the efficient targeting policy. In the first two lines in Equation (A.20), we just use the linearity of the expectation function. In the third line, we use the unconfoundedness assumption. In the last two lines, we again use the linearity of the expectation function.

Now, we use the specification in Equation (A.20) to estimate the match value under the efficient targeting policy. We find that the efficient targeting policy coincides with the ads shown in the Filtered Sample in 67,152 impressions. We use inverse propensity weights to adjust for this fraction of the sample and find that the efficient targeting policy improves the average CTR in the current regime by 65.53%. This is very similar to our original finding using a direct method based on our match value estimates.

E Appendix for Robustness Checks

E.1 Other Evaluation Metrics

We consider three alternative evaluation metrics.

- **Area Under the Curve (AUC):** It calculates the area under the ROC curve, which is a graphical depiction of *true positive rate (TPR)* as a function of *false positive rate (FPR)*. This metric is often used in classification problems, but is less appropriate for prediction tasks such as ours because of two reasons. First, it is insensitive to the transformation of the predicted probabilities that preserve their rank. Thus, a poorly fitted model might have higher AUC than a well-fitted model (Hosmer Jr et al., 2013). Second, it puts the same weight on *false positive rate (FPR)* and *false negative rate (FNR)*. However, in CTR prediction, the penalty of FNR is usually higher than FPR (Yi et al., 2013).
- **0/1 Loss:** This is a simple metric used to evaluate correctness in classification tasks. It is simply the percentage of incorrectly classified impressions. As with AUC, it is not very useful when accuracy of the prediction matters since it is not good at evaluating the predictive accuracy of rare events (e.g., clicks). For example, in our case, the loss is lower than 1% loss even if we blindly predict that none of the impressions will lead to click.
- **Mean Squared Error (MSE):** This is one of the most widely used metrics for measuring the goodness of fit. It is similar to LogLoss, which we use to calculate *RIG*. Both LogLoss and SquareLoss are often used for probability estimation and boosting in the machine learning literature. Let d_i be the Euclidean distance between the predicted value and actual outcome for impression i . This can be interpreted as the misprediction for the corresponding impression. SquareLoss and LogLoss for this impression will then be d_i^2 and $-\log(1 - d_i)$ respectively. Since both functions are convex with respect to d_i , they penalize larger mispredictions more than smaller ones. However, a big difference is that SquareLoss is finite, whereas LogLoss is not. In fact, LogLoss evaluates $d_i = 1$ as infinitely bad. In our problem, this translates to either predicting 1 for non-clicks or predicting 0 for clicks. Therefore, the model optimized by LogLoss will not predict 0 or 1. Given that we do not know how users interact with the app at the moment, it is quite unrealistic to predict 1 for an impression, especially because each impression only lasts a short time. Thus, we choose LogLoss as our main metric, which is also the most common choice in the literature on CTR prediction (Yi et al., 2013).
- **Confusion Matrix:** We also present the Confusion Matrix for our main models. Like AUC and 0/1 Loss, Confusion Matrix is mostly used in classification problems. However, this gives us an intuitive metric to evaluate the performance of our model.

Data	Evaluation Metric	Behavioral	Contextual	Full
Full Sample	AUC	0.7910	0.7014	0.8230
Top Ads/Apps	AUC	0.8082	0.7192	0.8410
Filtered Sample	AUC	0.8073	0.7410	0.8410
Full Sample	0/1 Improvement (%)	0.63%	0.00%	4.74%
Top Ads/Apps	0/1 Improvement (%)	1.07%	0.00%	8.23%
Filtered Sample	0/1 Improvement (%)	1.34%	0.00%	8.47%
Full Sample	MSE Improvement (%)	3.41%	0.55%	8.59%
Top Ads/Apps	MSE Improvement (%)	4.86%	0.67%	13.33%
Filtered Sample	MSE Improvement (%)	4.89%	0.67%	12.93%
Full Sample	True Positives (#)	905	0	5934
Full Sample	True Negatives (#)	9533282	9533605	9531972
Full Sample	False Positives (#)	323	0	1633
Full Sample	False Negatives (#)	91325	92230	86296
Top Ads/Apps	True Positives (#)	757	0	5621
Top Ads/Apps	True Negatives (#)	6057514	6057744	6056235
Top Ads/Apps	False Positives (#)	230	0	1509
Top Ads/Apps	False Negatives (#)	50010	50767	45146
Filtered Sample	True Positives (#)	517	0	2928
Filtered Sample	True Negatives (#)	4424624	4424738	4424343
Filtered Sample	False Positives (#)	114	0	395
Filtered Sample	False Negatives (#)	29379	29896	26968
Full Sample	RIG	12.14%	5.25%	17.95%
Top Ads/Apps	RIG	14.82%	5.98%	22.85%
Filtered Sample	RIG	14.74%	6.77%	22.45%

Table A2: Model performance for the two samples (full and top ads/apps) when evaluated on the alternative metrics.

We now take the optimized models presented in §5 in the main text of the paper and evaluate their performance on these alternative metrics. The results from this exercise are presented in Table A2. Overall, all our substantive results remain the same when we use alternative evaluation metrics.

E.2 Other Learning Methods

We now compare the performance of XGBoost with other five other learning algorithms and present the results in Table A3. Note that XGBoost outperforms all of them.

For each learning model, we describe the hyper-parameters associated with it and our approach to optimizing these hyper-parameters. Note that in all the cases, we use the same high-level validation procedure described in §C.2.

- Least squares does not use any hyper-parameters and hence does not require validation. In this case, we simply train the model on the full training and validation data to infer the model parameters, and report the model’s performance on the test data.
- For LASSO, the validation procedure is straightforward. The only hyper-parameter to set is the

Method	<i>RIG</i> over Baseline
Least Squares	7.72%
LASSO	7.92%
Logistic Regression	11.17%
Regression Tree	15.03%
Random Forest	15.75%
XGBoost	17.95%

Table A3: *RIG* of different learning methods for the test data.

L1 regularization parameter, λ . We search over 100 values of λ and pick the one which gives us the best performance on the validation set ($\lambda = 6.3 \times 10^{-4}$). We then use this parameter and train the model on the entire training and validation set and test the performance on the test set.

- For CART, we use the package *rpart* in R, which implements a single tree proposed by (Breiman et al., 1984). We use recursive partitioning algorithm with a complexity parameter (c_{tree}) as the only hyper-parameter that we need to select through validation. The main role of this parameter is to avoid over-fitting and save computing time by pruning splits that are not worthwhile. As such, any split that does not improve the fit by a factor of complexity parameter is not attempted. We search for the optimal complexity parameter over the grid $c_{tree} \in \{0.1, 0.05, 0.01, 0.005, 0.001, 0.0005, 0.0001, 0.00005, 0.00001\}$, and based on the validation procedure, we derive the optimal complexity parameter as 5^{-5} . That is, the model adds another additional split only when the R-squared increments by at least 5^{-5} .
- For Random Forest, we use the package *sklearn* in Python. There are three hyper-parameters in this case – (1) n_{tree} , the number of trees over which we build our ensemble forest, (2) χ_s , the column sub-sampling parameter, which indicates the percentage of features that should be randomly considered in each round when looking for the best split, and (3) n_{min} , the minimum number of samples required to split an internal node. We search for the optimal set of hyper-parameters over the following grid:
 - $n_{tree} \in \{100, 500, 1000\}$
 - $\chi_s \in \{0.33, 0.5, 0.75\}$
 - $n_{min} \in \{100, 500, 1000\}$

Based on our validation procedure, we find the optimal set of hyper-parameters to be: $\{n_{tree} = 1000, \chi_s = 0.33, n_{min} = 500\}$.

E.3 Robustness Checks on Feature Generation

We also ran the following robustness checks on the feature generation framework.

- We start by considering different ways of aggregating over the history. One possibility is to use $\eta_{ie} = r_i$ for all the features, i.e., update all the features in real-time. We find no difference in terms of the prediction accuracy when we adopt this approach, though it increases the computational costs significantly. Therefore, we stick to our current approach where we use a combination of global and real-time features.
- Next, we examine the model’s performance under an alternative definition of long- and short-term history for features that are updated in real-time. The idea is to fix the length of history, instead of fixing η_{ib} for each impression. In other words, instead of aggregating over $[l, r_i]$ and $[s, r_i]$ where l and s are fixed, we aggregate over $[l_i, r_i]$ and $[s_i, r_i]$ where l_i and s_i are no more fixed, but the length of $[l_i, r_i]$ and $[s_i, r_i]$ are fixed. For example, l_i for impression i on October 28 is the same time on September 30, while l_i for impression i on October 30 is the same time on October 2. Under this new approach, we find a slight decrease in the performance: the *RIG* drops to 17.69% improvement over the baseline.
- We also consider a model with dummy variables for the top apps in our feature set (similar to what we now do for top ads). Again, we find no discernible differences in the results without app dummies: the *RIG* is 17.97% over the baseline. This may be due to the fact that our feature generation framework captures the fixed effects of apps well.

Overall, we find that our feature set works well and any additional features or more complex feature generation mechanisms do not provide any significant benefits in *RIG*.

E.4 Sampling and Data Adequacy

We conduct our analyses using a relatively large sample consisting of 727,354 users in the train, validation, and test data-sets. This corresponds to 17,856,610 impressions in the training and validation data, and 9,625,835 impressions in the test data. We now examine the adequacy the rate the adequacy of our sample by calculating the *RIG* for different (lower) sample sizes. That is, we quantify how much our model gains by using more data, and at what point the marginal value of additional data is minimal.

To calculate the *RIG* for a given sample size of N_u , we do the following: 1) We take ten random samples of N_u users, and generate two data sets – the training data and the test data. 2) For each sample, we train the model using the training data and then test the model’s performance on the test data.²² 3) We then calculate the mean and standard deviation of the *RIG* for each sample. We

²²We use the hyper-parameters obtained from the validation exercise that we performed in the main model for training. This is likely to help the performance of the models trained on smaller samples because if we were to tune the model using smaller data, the estimated hyper-parameters are likely to be worse. Thus, the gains reported here more favorable than what we would obtain if we also validated/tuned the model using the smaller data samples.

User Sample Size (N_u)	\bar{N}_{train}	\bar{N}_{test}	RIG over Baseline CTR	
			Coefficient	Std. error
1,000	24,500	13,274	13.76%	3.17%
5,000	124,521	66,820	14.25%	1.76%
10,000	249,749	139,123	15.26%	1.48%
20,000	486,007	266,497	16.14%	0.40%
50,000	1,220,394	663,569	16.84%	0.28%
100,000	2,436,037	1,332,894	17.27%	0.23%
200,000	4,875,586	2,654,110	17.58%	0.20%
400,000	9,749,402	5,327,471	17.84%	0.18%
600,000	14,699,589	7,928,275	17.91%	0.15%

Table A4: RIG for different sample sizes. \bar{N}_{train} and \bar{N}_{test} are respectively the average size of train and test data after sampling users.

perform this exercise for nine sample sizes starting with $N_u = 1000$ and going up till $N_u = 600,000$. The results from this exercise are shown in Table A4. We also report the average sample size of train and test data respectively as \bar{N}_{train} and \bar{N}_{test} .

In principle, we can perform the above exercise for each sample size with only one sample instead of ten. However, such an approach is likely to be error-prone, especially at smaller sample sizes, since there is heterogeneity among users and each sample is random. So we may randomly find a smaller sample to have a higher *RIG* than a larger sample in one particular instance. To avoid making incorrect inferences due to the particularities of one specific sample and to minimize the noise in our results, we employ the bootstrap procedure described above.

Table A4 suggests that after about 100,000 users, increasing the sample size improves the prediction only slightly. However, increasing sample sizes also increase the training time and computational costs. Given the cost-benefit trade-off, our sample of 727,354 users is more than sufficient for our purposes.

E.5 Other Validation Techniques

The validation procedure outlined in Web Appendix §C.2 is the first-best validation procedure in data-rich situations such as ours. Nevertheless, we examine two other commonly used techniques:

- Hold-out validation – very similar to our current approach, except that at Step 3, instead of training the final model on the combination of training and validation data, we simply use the best model (using the optimal \mathcal{W}^*) trained based on the training data (from Step 2) as the final model. Thus, we do not use the validation data to train the final model. This can lead to some information loss (especially from the recent impressions). We find that the model performance on the test set drops when we use hold-out validation: our *RIG* is 17.21% which is lower than

that of our validation procedure.

- k -fold cross-validation – we find no improvement in the performance of the model selected by 5-fold cross-validation (RIG is 17.33%). Please see Footnote 7 in (Yoganarasimhan, 2020) and (Hastie et al., 2001) for a detailed discussion on the pros and cons of k -fold cross validation.

F Detailed Analysis of the Example Presented in Figure 8

In an important paper, Levin and Milgrom (2010) argue that sharing too much targeting information with advertisers can thin auction markets which in turn would soften competition and make the platform worse. We now present a simple example to highlight this idea. Consider a platform with two advertisers ($a^{(1)}$ and $a^{(2)}$) competing for the impressions of two users ($u^{(1)}$ and $u^{(2)}$). Assume that the platform uses second price auctions with Cost per Impression (CPI) pricing, where the highest bidder wins the impression and pays the bid of the second-highest bidder. These auctions have the useful property of truthful bidding (Vickrey, 1961). Let the advertisers be symmetric in their valuation of a click (normalized to 1 hereafter). Further, let the match values between advertisers and users be as shown in Equation (A.21). Match values can be interpreted as the eCTR of an impression for the advertiser-user pair. Notice that advertiser $a^{(1)}$ has a better match with user $u^{(1)}$ and advertiser $a^{(2)}$ with user $u^{(2)}$.

$$eCTR = \begin{matrix} & u^{(1)} & u^{(2)} & \bar{u} \\ \begin{matrix} a^{(1)} \\ a^{(2)} \end{matrix} & \begin{pmatrix} 0.5 & 0.1 \\ 0.1 & 0.3 \end{pmatrix} & \rightarrow & \begin{pmatrix} 0.3 \\ 0.2 \end{pmatrix} \end{matrix} \quad (A.21)$$

We can formally show that, for a given targeting strategy, both CPI and Cost per Click (CPC) mechanisms generate the same revenues for the platform and advertisers. So we focus on the CPI case throughout the text and refer readers to Appendix H for the CPC example and analysis.

Consider the advertiser's bidding strategy and outcomes under two regimes – 1) No data disclosure by the platform, and 2) Full disclosure of match values by the platform. The results from these two regimes are laid out in Table A5 and discussed below:

- No data disclosure – Here advertisers only know their aggregate match value for both users. So $a^{(1)}$ and $a^{(2)}$'s expected match values for the two users are 0.3 and 0.2. In a second price auction, advertisers bid their expected valuations. So $a^{(1)}$ wins both impressions and pays the next highest bid, $b_1^{(2)} = b_2^{(2)} = 0.2$, for each impression. Therefore, platform's revenue is $R = 0.4$, advertisers' surplus is $W^{(1)} = 0.2$ and $W^{(2)} = 0$, and the total surplus is $S = 0.6$.

No Data Disclosure (or No Targeting)	Full Data Disclosure (or Perfect Targeting)
<p>For both impressions:</p> <p><u>Bids:</u> Advertiser $a^{(1)}$: $b_1^{(1)} = b_2^{(1)} = 0.3$ Advertiser $a^{(2)}$: $b_1^{(2)} = b_2^{(2)} = 0.2$</p> <p><u>Outcome:</u> Advertiser $a^{(1)}$ wins both impressions and pays 0.2 per impression</p> <p>Platform's expected revenue: $R = 2 \times 0.2 = 0.4$</p> <p>Advertiser's expected surplus: $W^{(1)} = 2 \times (0.3 - 0.2) = 0.2$ $W^{(2)} = 0$</p> <p>Total expected surplus: $S = 0.6$</p>	<p>For User $u^{(1)}$'s impression:</p> <p><u>Bids:</u> Advertiser $a^{(1)}$: $b_1^{(1)} = 0.5$, Advertiser $a^{(2)}$: $b_1^{(2)} = 0.1$</p> <p><u>Outcome:</u> Advertiser $a^{(1)}$ wins $u^{(1)}$'s impression and pays 0.1</p> <p>For User $u^{(2)}$'s impression:</p> <p><u>Bids:</u> Advertiser $a^{(1)}$: $b_2^{(1)} = 0.1$, Advertiser $a^{(2)}$: $b_2^{(2)} = 0.3$</p> <p><u>Outcome:</u> Advertiser $a^{(2)}$ wins $u^{(2)}$'s impression and pays 0.1</p> <p>Platform's expected revenue: $R = 0.1 + 0.1 = 0.2$</p> <p>Advertiser's expected surplus: $W^{(1)} = 0.5 - 0.1 = 0.4$ $W^{(2)} = 0.3 - 0.1 = 0.2$</p> <p>Total expected surplus: $S = 0.8$</p>

Table A5: Example depicting two regimes: 1) No data disclosure and 2) Full disclosure.

- Full data disclosure – Since advertisers now have information on their match for each impression, they submit targeted bids that reflect their valuations as shown in Table A5. Therefore, the advertiser who values the impression more wins it. However, because of the asymmetry in advertisers' valuation over impressions, the competition over each impression is softer. This ensures higher advertiser revenues, with $W^{(1)} = 0.4$ and $W^{(2)} = 0.2$. However, the platform's revenue is now lower, at $R = 0.2$. Thus, even though ads are matched more efficiently and the total surplus generated is higher, the platform extracts less revenue.

This example illustrates the platform's trade-off between value creation and value appropriation, and highlights the platform's incentives to withhold targeting information from advertisers.

G Proofs

G.1 Proof of Proposition 1

We first prove the proposition for the general case of two sets of bundles $\mathcal{I}^{(1)}$ and $\mathcal{I}^{(2)}$, where $\mathcal{I}^{(1)}$ is at least as granular as $\mathcal{I}^{(2)}$. Under a given targeting regime, risk-neutral advertisers' valuation for an impression in a bundle is their aggregate valuation for that bundle, as they cannot distinguish

between different impressions within a bundle. Thus, all impressions within a bundle have the same expected valuation for an advertiser. As such, for any $i \in I_j$, incentive compatibility constraint in the second-price auction induce advertiser a to place the bid $b_{ia} = \frac{1}{|I_j|} \sum_{k \in I_j} v_{ka}$.

According to Definition 4, for any $I_k^{(2)} \in \mathcal{I}^{(2)}$, there exist $I_{j_1}^{(1)}, \dots, I_{j_l}^{(1)}$ such that $\bigcup_{s=1}^l I_{j_s}^{(1)} = I_k^{(2)}$. We can write:

$$\max_a \sum_{i \in I_k^{(2)}} v_{ia} \leq \sum_{s=1}^l \max_a \sum_{i \in I_{j_s}^{(1)}} v_{ia} \quad (\text{A.22})$$

where the LHS is the surplus generated from the impressions in bundle $I_k^{(2)}$ for targeting regime $\mathcal{I}^{(2)}$, and RHS is the surplus generated from the same impressions for targeting regime $\mathcal{I}^{(1)}$. Since inequality (A.22) holds for any $I_k^{(2)} \in \mathcal{I}^{(2)}$, we can show that $S^{(1)} \geq S^{(2)}$, *i.e.*, the surplus is increasing with more granular targeting.

However, platform revenues can go either way. If the second-highest valuation is exactly the same as the highest valuation for all impressions, the revenue and surplus are identical, *i.e.*, $R^{(1)} \geq R^{(2)}$. On the other hand, consider a case where, for any given impression, one advertiser has a high valuation and the rest of advertisers have the same (lower) valuation. In this case, the second-highest valuation is the minimum valuation for each impression. Thus, we can write (A.22) with \min function instead of \max and change the sign of inequality. This gives us $R^{(1)} \leq R^{(2)}$. Therefore, the platform revenues can be non-monotonic with more granular targeting.

Finally, it is worth noting that this result can be applied to any efficient auction in light of revenue-equivalence theorem.

G.2 Proof of Proposition 2

To write the FOC, we first need to specify advertisers' expected utility function. If ad a gets a click in impression i , the utility he extracts from this impression is $v_a^{(c)} - CPC_{ia}$. As such, ad a 's utility from impression i is

$$(v_a^{(c)} - CPC_{ia}) \mathbb{1}(a_i = a) \mathbb{1}(y_{i,a} = 1),$$

where $\mathbb{1}(a_i = a)$ indicates whether ad a is shown in impression i and $\mathbb{1}(y_{i,a} = 1)$ is an indicator for whether this impression is clicked. Clearly, ad a only extracts utility when his ad is being shown and clicked in an impression. We further assume that $\mathbb{1}(a_i = a)$ is independent of CPC_{ia} with respect \mathcal{G}_a . Now, we define the expected utility function EU_a as the expectation over impressions as

follows:

$$\begin{aligned}
EU_a(b_a; \mathcal{G}_a) &= \mathbb{E}_{\mathcal{G}_a} [(v_a^{(c)} - CPC_{ia}) \mathbb{1}(a_i = a) \mathbb{1}(y_i = 1)] \\
&= (v_a^{(c)} - c_a(b_a)) \pi_a(b_a) \mu_a \\
&= (v_a^{(c)} - c_a(b_a)) \frac{b_a q_a}{b_a q_a + Q_{-a}} \mu_a
\end{aligned} \tag{A.23}$$

where $\mu_a = \mathbb{E}_{\mathcal{G}_a} [\mathbb{1}(y_i = 1)]$ is the average probability of click that ad a expects to receive. The second line of Equation (A.23) is resulted because of the independence of $\mathbb{1}(a_i = a)$ and CPC_{ia} with respect \mathcal{G}_a .

Now, to write the FOC, we need to take the first derivative of the expected utility function for ad a . We can write:

$$\frac{\partial EU_a(b_a; \mathcal{G}_a)}{\partial b_a} = (v_a^{(c)} \pi'_a(b_a) - c_a(b_a) \pi'_a(b_a) - c'_a(b_a) \pi_a(b_a)) \mu_a \tag{A.24}$$

Now, to satisfy the FOC, we need to have $\frac{\partial EU_a(b_a^*; \mathcal{G}_a)}{\partial b_a^*} = 0$, where b_a^* is the equilibrium bid. Using Equation (A.24), we can write the FOC as follows:

$$\begin{aligned}
v_a^{(c)} &= c_a(b_a^*) + \frac{c'_a(b_a^*) \pi_a(b_a^*)}{\pi'_a(b_a^*)} \\
&= c_a(b_a^*) + \frac{c'_a(b_a^*) b_a^*}{1 - \pi_a(b_a^*)},
\end{aligned} \tag{A.25}$$

where the second line is because we have $\frac{\pi_a(b_a)}{\pi'_a(b_a)} = \frac{b_a}{1 - \pi_a(b_a)}$ which is easy to show:

$$\frac{\pi_a(b_a)}{\pi'_a(b_a)} = \frac{\frac{b_a q_a}{b_a q_a + Q_{-a}}}{\frac{q_a Q_{-a}}{(b_a q_a + Q_{-a})^2}} = \frac{b_a (b_a q_a + Q_{-a})}{Q_{-a}} = \frac{b_a}{1 - \pi_a(b_a)} \tag{A.26}$$

Now, to complete the proof, we need to show that the second-order condition (SOC) is also satisfied. We start by writing a useful property in the relationship between the first and second derivative of the allocation function:

$$\frac{\pi'_a(b_a)}{\pi''_a(b_a)} = \frac{\frac{q_a Q_{-a}}{(b_a q_a + Q_{-a})^2}}{\frac{-2q_a^2 Q_{-a}}{(b_a q_a + Q_{-a})^3}} = \frac{(b_a q_a + Q_{-a})}{2q_a} = -\frac{b_a}{2\pi_a(b_a)} \tag{A.27}$$

We can now write the second derivative of the expected utility function as follows:

$$\begin{aligned}
\frac{\partial^2 EU_a(b_a^*, \mathcal{G}_a)}{\partial b_a^{*2}} &= \mu_a \left((v_a^{(c)} - c_a(b_a^*)) \pi_a''(b_a^*) - c_a'(b_a^*) \pi_a'(b_a^*) - c_a'(b_a^*) \pi_a'(b_a^*) - c_a''(b_a^*) \pi_a(b_a^*) \right) \\
&= \mu_a \left(\frac{c_a'(b_a^*) \pi_a(b_a^*)}{\pi_a'(b_a^*)} \pi_a''(b_a^*) - 2c_a'(b_a^*) \pi_a'(b_a^*) - c_a''(b_a^*) \pi_a(b_a^*) \right) \\
&= \mu_a \left(c_a'(b_a^*) \pi_a(b_a^*) \left(\frac{\pi_a''(b_a^*)}{\pi_a'(b_a^*)} - 2 \frac{\pi_a'(b_a^*)}{\pi_a(b_a^*)} \right) - c_a''(b_a^*) \pi_a(b_a^*) \right) \\
&= \mu_a \left(c_a'(b_a^*) \pi_a(b_a^*) \left(\frac{2\pi_a(b_a^*)}{b_a^*} - 2 \frac{1 - \pi_a(b_a^*)}{b_a^*} \right) - c_a''(b_a^*) \pi_a(b_a^*) \right) \\
&= \mu_a \left(-\frac{2}{b_a^*} c_a'(b_a^*) \pi_a(b_a^*) - c_a''(b_a^*) \pi_a(b_a^*) \right) \\
&= \mu_a \pi_a(b_a^*) \left(-\frac{2}{b_a^*} c_a'(b_a^*) - c_a''(b_a^*) \right)
\end{aligned} \tag{A.28}$$

In the equation above, we know that both μ_a and $\pi_a(b_a^*)$ are positive, so it is sufficient to show that $-\frac{2}{b_a^*} c_a'(b_a^*) - c_a''(b_a^*) \leq 0$, which is resulted from the assumption in Proposition 2. Thus, the SOC is satisfied and this completes the proof.

H Analysis of Cost-per-Click Payment Mechanism

We now present an analysis of targeting under the Cost-per-Click (CPC) mechanism, where an advertiser's bid indicates the maximum price he is willing to pay per click. In this case, having a more accurate estimation of match values for impressions does not change advertisers' bidding behavior because they do not pay per impression. Theoretically, if advertisers have infinite budget, they should bid their valuation for click, even if they know they have higher CTR for some impressions.

However, the ad-network has an incentive to make more efficient matches in order to generate more clicks since clicks are their main source of revenue. For example, if there is an advertiser with a very high bid but very low CTR, the ad-network cannot make money by selling the slot to this advertisers. Let v_{ia} and m_{ia} respectively denote the valuation for click and the match value for advertiser a for impression i . The maximum revenue that platform could get is then $\max_a v_{ia} m_{ia}$. Thus, defining b_{ia} as advertiser a 's bid on impression i , the platform should sell the ad slot to $\arg\max_a b_{ia} m_{ia}$ and charge her the minimum bid with which she still wins. It generates the expected revenue of the second-highest $b_{ia} m_{ia}$. (In fact, this is how Google's sponsored search auctions work.)

No Targeting	Perfect Targeting
<p>For both impressions:</p> <p><u>Bids:</u> Advertiser 1: $b_{11} = b_{21} = 1$ Advertiser 2: $b_{12} = b_{22} = 1$</p> <p><u>Match values:</u> Advertiser 1: $m_{11} = m_{21} = 0.3$ Advertiser 2: $m_{12} = m_{22} = 0.2$</p> <p><u>Outcomes:</u> Advertiser 1 wins both impressions and pays $\frac{0.2 \times 1}{0.3} = 0.66$ per click</p> <p>Platform's expected revenue: $R = 0.66 \times (0.5 + 0.1) = 0.4$</p> <p>Advertiser's expected surplus: $W_1 = (1 - 0.66) \times (0.5 + 0.1) = 0.2$ $W_2 = 0$</p> <p>Total expected surplus: $S = 0.6$</p>	<p>For User 1's impression:</p> <p><u>Bids:</u> Advertiser 1: $b_{11} = 1$, Advertiser 2: $b_{12} = 1$</p> <p><u>Match values:</u> Advertiser 1: $m_{11} = 0.5$, Advertiser 2: $m_{12} = 0.1$</p> <p><u>Outcome:</u> Advertiser 1 wins User 1's impression and pays $\frac{1 \times 0.1}{0.5} = 0.2$ per click</p> <p>For User 2's impression:</p> <p><u>Bids:</u> Advertiser 1: $b_{11} = 1$, Advertiser 2: $b_{12} = 1$</p> <p><u>Match values:</u> Advertiser 1: $m_{11} = 0.1$, Advertiser 2: $m_{12} = 0.3$</p> <p><u>Outcome:</u> Advertiser 2 wins User 2's impression and pays $\frac{1 \times 0.1}{0.3} = 0.33$ per click</p> <p>Platform's expected revenue: $R = 0.2 \times 0.5 + 0.33 \times 0.3 = 0.2$</p> <p>Advertiser's expected surplus: $W_1 = (1 - 0.2) \times 0.5 = 0.4$ $W_2 = (1 - 0.33) \times 0.3 = 0.2$</p> <p>Total expected surplus: $S = 0.8$</p>

Table A6: Example depicting no targeting and perfect targeting under CPC pricing mechanism.

Table A6 shows how the example in §6.1 in the main text of the paper generalizes to the CPC case. Although CPC and CPI have different properties, we can easily prove that their revenue is the same under different levels of targeting. This stems from the fact that under second-price auction, bidders bid their valuation. Thus, the platform's expected revenue from impression i under both mechanisms is the second highest $v_{ia}m_{ia}$, as long as the match-values (or targeting strategies) are the same under both mechanisms. Conceptually, there exists a one-to-one mapping between CPC and CPI mechanisms if and only if there is a one-to-one mapping between the targeting regime and resulting match-value matrix. In the CPI mechanism, m_{ia} enters the advertisers' bidding strategy, i.e., the targeting decision is made by the advertisers. The ad-network's decision consists of whether to share targeting information with advertisers or not. In contrast, under the CPC mechanism, the ad-network directly decides the extent of targeting to engage in and the advertisers always bid their valuation.

Our empirical results suggest that under the CPI mechanism, ad-networks may have incentive to limit behavioral targeting. In the CPC context, this translates to the following result: the ad-network has an incentive to not use behavioral information for targeting, as compared to contextual information. In both cases, the platform has an incentive to protect users' privacy by ensuring that behavioral information is not used for targeting purposes. In sum, the empirical estimates of platform's revenue, advertisers' revenues, and the implications for user-privacy are similar in both settings.

I Robustness Checks for Analysis of Revenue-Efficiency Trade-off

I.1 Alternative Methods for Estimation of Click Valuations

As discussed in §6.3.2 in the main text of the paper, we make three simplifications to derive Equation (15).

1. **Simplification 1:** Advertisers' probability of winning an impression is approximately zero, i.e., $\pi_a(b_a) \approx 0$, for all a .
2. **Simplification 2:** Advertisers' cost-per-click is approximately their bid, i.e., $c_a(b_a) \approx b_a$, for all a .
3. **Simplification 3:** The first-order condition shown in Equation (14) is satisfied for all advertisers, including reserve price bidders.

If one or more of these simplifications fail in our data, our estimates of click valuations may be biased. This, in turn, can affect our main qualitative findings. Therefore, we now present six alternative methods to estimate click valuations that progressively relax these simplifications and show that our main findings are robust to these simplifications.

Table A7 gives an overview of the set of simplifications that each alternative method relaxes. We now describe each of these methods in detail.

1. **Alternative Method 1 (AM1):** In this method, we relax Simplification 1, but retain Simplifications 2 and 3.

Specifically, instead of assuming that $\pi_a(b_a) \approx 0$, we estimate the advertiser's expected probability of ad allocation directly from the data as:

$$\hat{\pi}_a(b_a^*) = \frac{\sum_{i=1}^{N_F} \mathbb{1}(a_i = a)}{\sum_{i=1}^{N_F} e_{i,a}}. \quad (\text{A.29})$$

Simplification	Main	AM1	AM2	AM3	AM4	AM5	AM6
Zero winning probability ($\pi_a \approx 0$)	✓	×	×	×	×	×	×
Pay-your-bid cost function ($c_a(b_a) \approx b_a$)	✓	✓	×	×	×	×	×
First-order condition satisfied for reserve price bidders	✓	✓	✓	✓	×	×	×
Parametric cost function	✓	✓	✓	✓	✓	✓	×

Table A7: Table of simplifications imposed by each estimation method

This is the total number of impressions showing ad a divided by the total number of impressions ad a bid on (i.e., participated in the auction for). This is a consistent estimator of the proportion of impressions that ad a will win in the platform.

Since we still assume that advertisers pay their own bid per click (Simplification 2), we have $c_a(b_a) = b_a$. This gives us the click value estimates as:

$$\hat{v}_a^{(AM1)} = b_a^* + \frac{b_a^*}{1 - \hat{\pi}_a(b_a^*)}, \quad (\text{A.30})$$

2. **Alternative Method 2 (AM2):** In this method, we relax both Simplifications 1 and 2. Like AM1, here also we estimate the probability of winning (proportion of impressions allocated) from the data using Equation (A.29). In addition, we no longer assume that advertisers pay their bid. Instead, we model their payment upon winning as a linear function of their bid such that $c_a(b_a) = \gamma_a b_a$. Then, using Equation (14), we can write:

$$\hat{v}_a^{(AM2)} = \hat{c}_a(b_a^*) + \frac{\hat{c}_a(b_a^*)}{1 - \hat{\pi}_a(b_a^*)} \quad (\text{A.31})$$

This is because if $c_a(b_a)$ is linear, we have $c_a(b_a) = c'_a(b_a)b_a$. Hence, we only need to estimate $\hat{c}_a(b_a^*)$, which is the average cost-per-click for ad a .

3. **Alternative Method 3 (AM3):** This method is similar to AM2. The main difference is that, here we model the cost function more flexibly by allowing it to be a quadratic function of bids. We can characterize our cost function as $c_a(b_a) = \gamma_a b_a + \gamma b_a^2$. Note that the coefficient for b_a is ad specific, but the one for b_a^2 is the same for all ads. This is because we cannot identify advertiser-specific curvature since advertisers do not change their bids.

We can estimate this quadratic cost function from the data using the following regression model:

$$CPC_i = \gamma_a b_a + \gamma b_a^2 + \epsilon_i, \quad (\text{A.32})$$

where CPC_i is the actual cost-per-click for impression i .

Once we have the estimates, $\hat{\gamma}_a$ and $\hat{\gamma}$, we can estimate click valuations using Equation (14) in the main text of the paper as follows:

$$\hat{v}_a^{(AM3)} = \hat{c}_a(b_a^*) + \frac{b_a^*(\hat{\gamma}_a + 2\hat{\gamma}b_a^*)}{1 - \hat{\pi}_a(b_a^*)} = \hat{c}_a(b_a^*) + \frac{\hat{c}_a(b_a^*)}{1 - \hat{\pi}_a(b_a^*)} + \frac{\hat{\gamma}b_a^*}{1 - \hat{\pi}_a(b_a^*)} \quad (\text{A.33})$$

Equation (A.33) is very similar to Equation (A.31), except for the last term $\frac{\hat{\gamma}b_a^*}{1 - \hat{\pi}_a(b_a^*)}$, which is added to incorporate the curvature in the relationship between bid and cost-per-click. Of course, if the relationship is linear, (A.33) will be identical Equation (A.31).

While both AM2 and AM3 allow the cost-per-click to differ from the actual bid, they formulate an advertiser's cost-per-click only as a function of their own bids, and not that of its competitors. Given Proposition 2, our click valuation estimates are valid to the extent that our parametric cost functions estimate $c'_a(b_a^*)$ well. Nevertheless, in AM6, we estimate the advertisers' cost function without imposing any functional form assumptions, and allow it to depend on other advertisers' bids as inputs.

4. **Alternative Method 4 (AM4):** In this method, we relax all three simplifications. We build on AM3 and incorporate the fact that there is a reserve price r_0 for all impressions (i.e., advertisers need to bid higher than or equal to this amount).

In the presence of a reserve price, equilibrium bids may not satisfy the first-order condition since they may be right-censored. That is, there could have been bids lower than r_0 without the reserve price. For reserve-price bidders, we know that the participation constraint $v_a^{(c)} \geq r_0$ is satisfied. On the other hand, we know that $b_a^* \leq r_0$ which implies that $v_a^{(c)} \leq r_0 \left(1 + \frac{1}{1 - \hat{\pi}_a(b_a^*)}\right)$. Thus, for reserve bidders, we have $v_a^c \in [r_0, r_0(1 + \frac{1}{1 - \hat{\pi}_a(b_a^*)})]$. As such, if such valuations come from a uniform distribution in this range, our estimates will be:

$$\hat{v}_a^{(AM4)} = \begin{cases} r_0 \left(1 + \frac{1}{2(1 - \hat{\pi}_a(b_a^*))}\right) & \text{if } a \text{ is a reserve bidder} \\ \hat{v}_a^{(AM3)} & \text{otherwise} \end{cases}, \quad (\text{A.34})$$

where the estimated click valuations for a reserve bidder a is the mean of uniform distribution $\mathcal{U}\left(r_0, r_0 \left(1 + \frac{1}{1 - \hat{\pi}_a(b_a^*)}\right)\right)$.

5. **Alternative Method 5 (AM5):** In this method, we follow all the steps in AM4, but draw a value from distribution $\mathcal{U}\left(r_0, r_0 \left(1 + \frac{1}{1 - \hat{\pi}_a(b_a^*)}\right)\right)$ for any ad a who bids the reserve price. As

such, our estimates will be:

$$\hat{v}_a^{(AM5)} = \begin{cases} x \sim \mathcal{U}(r_0, r_0(1 + \frac{1}{1-\hat{\pi}_a(b_a^*)})) & \text{if } a \text{ is a reserve bidder} \\ \hat{v}_a^{(AM3)} & \text{otherwise} \end{cases} \quad (\text{A.35})$$

6. **Alternative Method 6 (AM6):** Here, we implement the the non-parametric estimator proposed by Rafieian (2020) for quasi-proportional auctions. This is a structural approach to estimate click valuations that relaxes all the simplifications made earlier and incorporates the full structure of the setting. The main difference between his approach and the alternative methods AM1–AM5 is in the operationalization of the cost function. Unlike the earlier methods, which parameterized the cost function, he employs a fully non-parametric method for modeling the cost distribution. As such, advertisers’ expected cost function is obtained by taking the expectation over the distribution of auctions they participate in. We refer readers to Rafieian (2020) for more details.

Results from Alternative Methods for Click Value Estimation

We first illustrate the empirical CDFs of all these alternative methods as well as the main method used in the paper. As we can see from Figure A.5, the estimated value distributions are not very different. This is mostly due to the fact that Simplification 1 is mostly valid (i.e., there are many bidders and no one has disproportionately high chance of winning), which in turn, makes the approximation method used in (15) quite reasonable.

Next, we use the click value estimates from each of these alternative methods to estimate the market outcomes – total surplus, platform revenues, and advertisers’ surplus. The results are shown in Table A8. While these estimates are quantitatively different from those presented in Table 5, notice that our main qualitative results remain the same: we find a monotonic relationship between total surplus and the granularity of targeting, but platform revenues are maximized when the platform limits the targeting level to the contextual targeting. In particular, we expect that results from AM6 to be the most accurate since it is the most assumption-free method, and even here the main qualitative finding holds.

Further, we find that the results from AM1 are the closest to the results in the main text (Table 5). This is because AM1 still uses the approximation that $CPC_a \approx b_a$. On the other hand, the results from AM2 to AM6 are very close quantitatively. This is because they all relax Simplification 2 and estimate the cost function from the data. As a result, the magnitude of total surplus and platform revenues is smaller (because advertisers in a quasi-proportional auction submit higher bids when they know they are not exactly charged their submitted bids). However, the main qualitative

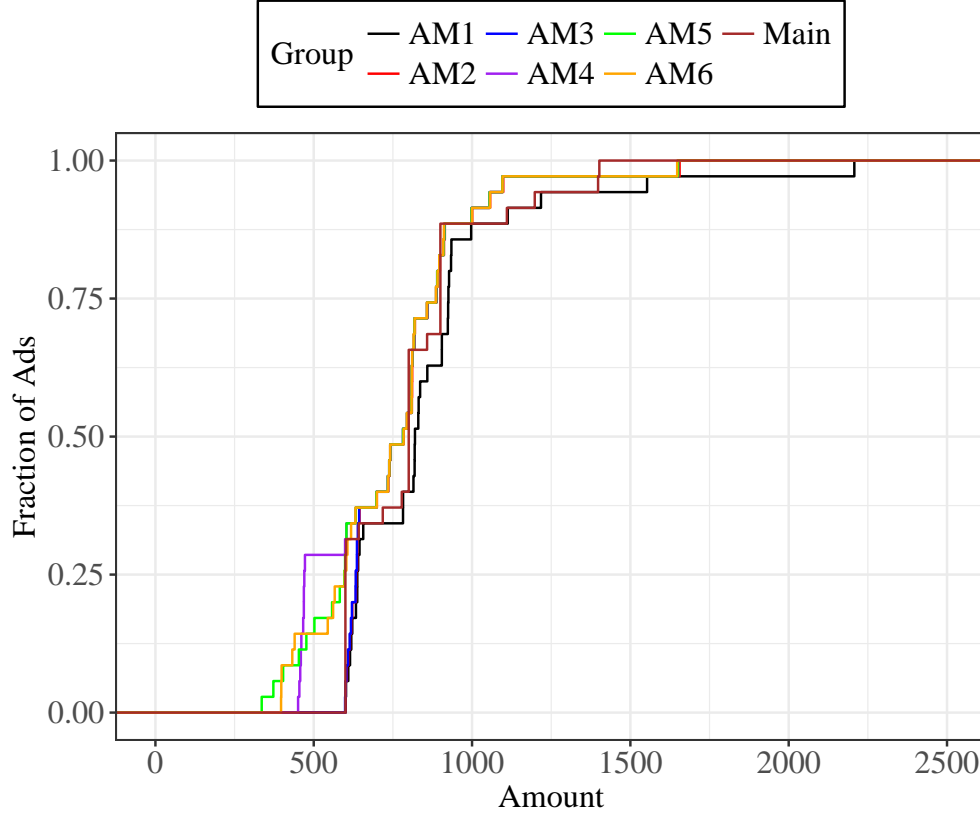


Figure A.5: Empirical CDF of estimated value distributions using alternative methods

findings remains the same under all these methods, since the main source for these findings is the heterogeneity in match valuations induced by more granular targeting.

I.2 Adding Noise to Match Valuations

As discussed in §6.3.3 in the main text of the paper, our assumption that advertisers can obtain match values estimated in our machine learning framework may not be realistic. As such, we consider various scenarios here to reflect cases in which advertisers can only obtain a noisy version of our estimates.

I.2.1 Identically Distributed Noise Across Ads

First, we consider the case that an identically distributed noise is added to any element in the match value matrix. We operationalize this noise as follows:

$$\hat{m}_{i,a}^{(\nu)} = \hat{m}_{i,a} \epsilon_{i,a}, \quad (\text{A.36})$$

Targeting	Total Surplus	Platform Revenue	Advertisers' Surplus
<i>A. Alternative Method 1 (AM1)</i>			
No Targeting	8.54	8.36	0.18
Contextual Targeting	9.09	8.49	0.60
Behavioral Targeting	9.32	8.47	0.85
Full Targeting	9.60	8.48	1.12
<i>B. Alternative Method 2 (AM2)</i>			
No Targeting	7.96	7.93	0.03
Contextual Targeting	8.62	8.09	0.53
Behavioral Targeting	8.83	8.05	0.78
Full Targeting	9.09	8.05	1.04
<i>C. Alternative Method 3 (AM3)</i>			
No Targeting	7.91	7.89	0.02
Contextual Targeting	8.61	8.07	0.53
Behavioral Targeting	8.81	8.04	0.77
Full Targeting	9.08	8.04	1.04
<i>E. Alternative Method 4 (AM4)</i>			
No Targeting	8.02	7.91	0.11
Contextual Targeting	8.61	8.08	0.53
Behavioral Targeting	8.82	8.03	0.79
Full Targeting	9.08	8.04	1.04
<i>D. Alternative Method 5 (AM5)</i>			
No Targeting	8.02	7.91	0.11
Contextual Targeting	8.61	8.08	0.53
Behavioral Targeting	8.82	8.03	0.79
Full Targeting	9.08	8.03	1.05
<i>F. Alternative Method 6 (AM6)</i>			
No Targeting	8.03	7.91	0.12
Contextual Targeting	8.61	8.08	0.53
Behavioral Targeting	8.82	8.03	0.78
Full Targeting	9.08	8.04	1.04

Table A8: Platform revenues, advertisers' surplus, and total surplus for different levels of targeting using different methods to estimate click valuations. The numbers are reported in terms of the average monetary unit per impression.

where $\epsilon_{i,a} \sim \mathcal{U}(1 - \nu, 1 + \nu)$. As such, advertisers obtain estimates $\nu \times 100$ percent lower or higher than the estimate from our ML framework. For any noise distribution, we make the entire matrix and follow the procedure presented in §6.3.4 in the main text of the paper to estimate the average surplus, revenue, and advertisers' surplus. The results are shown in Table A9. We find that noise-adding can increase the revenue under full targeting by distorting efficiency. This is in line with Athey and Nekipelov (2010) who find that the platform's optimal decision is to use imperfect CTR estimates in a cost-per-click setting. Interestingly, we find that full and contextual targeting yield almost the

Targeting	Noise (ν)	Total Surplus	Platform Revenue	Advertisers' Surplus
No Targeting	0.05	8.36	8.30	0.06
Contextual Targeting	0.05	8.99	8.44	0.55
Behavioral Targeting	0.05	9.18	8.35	0.82
Full Targeting	0.05	9.43	8.35	1.08
No Targeting	0.1	8.36	8.30	0.06
Contextual Targeting	0.1	8.99	8.44	0.55
Behavioral Targeting	0.1	9.17	8.36	0.82
Full Targeting	0.1	9.37	8.35	1.02
No Targeting	0.15	8.36	8.30	0.06
Contextual Targeting	0.15	8.99	8.44	0.55
Behavioral Targeting	0.15	9.16	8.36	0.80
Full Targeting	0.15	9.29	8.35	0.93
No Targeting	0.2	8.36	8.30	0.06
Contextual Targeting	0.2	8.99	8.44	0.55
Behavioral Targeting	0.2	9.14	8.36	0.78
Full Targeting	0.2	9.20	8.37	0.82
No Targeting	0.25	8.36	8.30	0.06
Contextual Targeting	0.25	8.99	8.44	0.55
Behavioral Targeting	0.25	9.13	8.37	0.76
Full Targeting	0.25	9.10	8.41	0.70
No Targeting	0.3	8.36	8.30	0.06
Contextual Targeting	0.3	8.99	8.44	0.54
Behavioral Targeting	0.3	9.12	8.38	0.74
Full Targeting	0.3	9.01	8.47	0.54

Table A9: Platform revenues, advertisers' surplus, and total surplus for different levels of targeting when adding an identically distributed noise to match values. The numbers are reported in terms of the average monetary unit per impression.

same results when $\nu = 0.3$. Thus, we can interpret contextual targeting as a noise-adding strategy.

I.2.2 Differentially Distributed Noise Across Ads

Here we consider a more realistic case wherein ads with more impressions (more data) have better estimates (less noisy). Similar to the case with identical noise, we operationalize the differential noise as follows for any ad a :

$$\hat{m}_{i,a}^{(\nu_a)} = \hat{m}_{i,a} \epsilon_{i,a}, \quad (\text{A.37})$$

where $\epsilon_{i,a} \sim \mathcal{U}(1 - \nu_a, 1 + \nu_a)$. As such, the noise is different for each ad. Since the error rate is proportional to the square root of number of observations, we write:

$$\nu_a = \frac{\nu}{\sqrt{N_a}},$$

where N_a is the number of impressions ad a has in our Filtered sample. Now, for any ν , we can make the entire match value matrix and estimate the market outcomes. The results are shown in Table A10. Again, we find that the platform benefits when advertisers have imperfect estimates of their match valuations. Comparing the results in Table A9 and A10, we find that the total surplus declines faster with a differentially distributed noise: when the platform's revenue is the same under full and contextual targeting, the total surplus is higher under contextual targeting. Given the absence of privacy costs under contextual targeting, our results in both tables indicate that platforms benefit most when allowing only contextual targeting.

Targeting	Noise (ν)	Total Surplus	Platform Revenue	Advertisers' Surplus
No Targeting	10	8.36	8.30	0.06
Contextual Targeting	10	8.99	8.44	0.55
Behavioral Targeting	10	9.18	8.35	0.82
Full Targeting	10	9.42	8.34	1.08
No Targeting	20	8.36	8.30	0.06
Contextual Targeting	20	8.99	8.44	0.55
Behavioral Targeting	20	9.17	8.35	0.82
Full Targeting	20	9.35	8.32	1.03
No Targeting	30	8.36	8.30	0.06
Contextual Targeting	30	8.99	8.44	0.55
Behavioral Targeting	30	9.16	8.35	0.80
Full Targeting	30	9.24	8.31	0.93
No Targeting	40	8.36	8.30	0.06
Contextual Targeting	40	8.99	8.44	0.55
Behavioral Targeting	40	9.14	8.35	0.79
Full Targeting	40	9.12	8.32	0.80
No Targeting	50	8.36	8.30	0.06
Contextual Targeting	50	8.99	8.44	0.55
Behavioral Targeting	50	9.12	8.35	0.77
Full Targeting	50	8.99	8.35	0.65
No Targeting	60	8.36	8.30	0.06
Contextual Targeting	60	8.99	8.44	0.55
Behavioral Targeting	60	9.10	8.35	0.75
Full Targeting	60	8.93	8.36	0.57
No Targeting	70	8.36	8.30	0.06
Contextual Targeting	70	8.99	8.43	0.56
Behavioral Targeting	70	9.09	8.34	0.75
Full Targeting	70	8.86	8.39	0.47
No Targeting	80	8.36	8.30	0.06
Contextual Targeting	80	8.99	8.43	0.55
Behavioral Targeting	80	9.07	8.34	0.73
Full Targeting	80	8.80	8.44	0.36

Table A10: Platform revenues, advertisers' surplus, and total surplus for different levels of targeting when adding an differentially distributed noise to match values. The numbers are reported in terms of the average monetary unit per impression.

References

- S. Athey and D. Nekipelov. A structural model of sponsored search advertising auctions. In *Sixth Ad Auctions Workshop*, volume 15, 2010.
- L. Breiman, J. Friedman, C. J. Stone, and R. A. Olshen. *Classification and Regression Trees*. CRC press, 1984.
- T. Chen and C. Guestrin. Xgboost: A Scalable Tree Boosting System. In *Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 785–794. ACM, 2016.
- J. Friedman, T. Hastie, R. Tibshirani, et al. Additive Logistic Regression: A Statistical View of Boosting (with Discussion and a Rejoinder by the Authors). *The Annals of Statistics*, 28(2):337–407, 2000.
- J. H. Friedman. Stochastic Gradient Boosting. *Computational Statistics & Data Analysis*, 38(4):367–378, 2002.
- T. Hastie, R. Tibshirani, and J. Friedman. *The Elements of Statistical Learning*. NY Springer, 2001.
- D. W. Hosmer Jr, S. Lemeshow, and R. X. Sturdivant. *Applied Logistic Regression*, volume 398. John Wiley & Sons, 2013.
- G. A. Johnson, R. A. Lewis, and D. Reiley. Location, Location, Location: Repetition and Proximity Increase Advertising Effectiveness. *Available at SSRN 2268215*, 2016.
- J. Levin and P. Milgrom. Online Advertising: Heterogeneity and Conflation in Market Design. *The American Economic Review*, 100(2):603–607, 2010.
- H. Li and P. Kannan. Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment. *Journal of Marketing Research*, 51(1):40–56, 2014.
- D. F. McCaffrey, B. A. Griffin, D. Almirall, M. E. Slaughter, R. Ramchand, and L. F. Burgette. A tutorial on propensity score estimation for multiple treatments using generalized boosted models. *Statistics in medicine*, 32(19):3388–3414, 2013.
- H. B. McMahan, G. Holt, D. Sculley, M. Young, D. Ebner, J. Grady, L. Nie, T. Phillips, E. Davydov, D. Golovin, et al. Ad Click Prediction: A View from the Trenches. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1222–1230. ACM, 2013.
- R. Pieters, E. Rosbergen, and M. Wedel. Visual Attention to Repeated Print Advertising: A Test of Scanpath Theory. *Journal of Marketing Research*, pages 424–438, 1999.
- O. Rafieian. Revenue-optimal dynamic auctions for adaptive ad sequencing. 2020.
- O. Rafieian and H. Yoganarasimhan. How does variety of previous ads influence consumer’s ad response? Technical report, Working paper, 2020.
- N. S. Sahni. Effect of temporal spacing between advertising exposures: Evidence from online field experiments. *Quantitative Marketing and Economics*, 13(3):203–247, 2015.
- E. H. Simpson. Measurement of Diversity. *Nature*, 1949.

- W. Vickrey. Counterspeculation, Auctions, and Competitive Sealed Tenders. *The Journal of finance*, 16(1): 8–37, 1961.
- J. Yi, Y. Chen, J. Li, S. Sett, and T. W. Yan. Predictive Model Performance: Offline and Online Evaluations. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 1294–1302. ACM, 2013.
- H. Yoganarasimhan. Search personalization using machine learning. *Management Science*, 66(3):1045–1070, 2020.
- T. Zhang, B. Yu, et al. Boosting with Early Stopping: Convergence and Consistency. *The Annals of Statistics*, 33(4):1538–1579, 2005.