LemonAds: Impression Quality in Programmatic Advertising

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Completed Research Paper

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Abstract

The display advertising practice relies on the real-time exchange of large volumes of impressions. Advertisers and publishers typically carry out their transactions through Reservation contracts, Real Time Bidding (RTB), or a mixture of the two. The co-existence of multiple transaction methods is problematic since impression quality is difficult to assess. As such, the display advertising market is characterized by high uncertainty and asymmetric information. In this paper, we use viewability as a measure of impression quality and show how the co-existence of different transaction methods leads to allocation and pricing inefficiencies. Using bid-request level data from a European Demand Side Platform, we find that publishers who engage in both Reservation Contracts and RTB offer higher quality impressions through Reservation Contracts, while allocating the remaining lower quality impressions to RTB. We find that, by doing so, publishers can leverage on asymmetric information on impression quality to extract excess profit from advertisers.

Keywords: Programmatic Advertising, RTB, Information Asymmetry, Display Advertising, Impression Quality

Introduction

Display advertising is the leading format of choice for marketers, with banners and videos combined making up to 46% of the market in the first half of 2018 (IAB/PwC, 2018). With a total market size of upwards of 88 billion USD in 2017, and year-on-year growth of approximately 22% (IAB/PwC, 2018), the digital advertising market shows how marketers and publishers are turning to almost entirely digital-focused strategies. Real-time transactions allowed by the Programmatic Media Buying (PMB) infrastructure hold the promise for marketers to deliver the right content, to the right user, in the right context. Recent reports highlight the market's belief in the PMB infrastructure as the present and future of digital advertising, with an estimated 90% of the total display ads transacted via PMB by 2020 (Fisher, eMarketer, 2018). As the digital advertising market continues to grow, however, the stakes for the actors involved keep on increasing. While the outlook on the technology adoption seems overall positive, advertisers are still facing the difficulties of transacting in a highly complex and often opaque market. The role of the buy-side, in fact, is especially problematic. The inherent credence nature of the advertising impression product, combined with a variety of technological solutions and transaction methods, turned the digital advertising market into an extremely complex entity, often confusing and alarming the advertisers. This was especially evident in 2017 when large corporations such as Procter & Gamble decided to revise all of their digital advertising contracts in favor of more accountable agreements (Faull & Drum, 2017). Despite the advertisers' call for help has not been left unheard and industry professionals are working towards higher levels of transparency and overall accountability (IAB, 2015), the digital advertising market is still vexed by inefficiencies.

In this paper, we focus on two foundational traits of the current PMB-driven advertising markets, namely transaction methods and impression quality. Advertisers and publishers typically transact impressions via either Reservation Contracts, Real-Time Bidding auctions (RTB), or a mixture of the two. Reservation Contracts are bilateral agreements between advertisers and publishers regarding the volume of advertising to serve on the publisher's outlet at a given price. Historically, Reservation Contracts have been the only way to transact advertising spaces. In recent years, however, technological advancements have facilitated the diffusion of large-scale open electronic auction markets for impression transactions (RTB). RTB works by matching the demand and supply of advertising impressions by first or second price sealed bid auction in real time. In a context of difficult measurability such as that of digital advertising, however, the co-existence and the heterogeneous adoption of multiple transaction methods are problematic. Since publishers can decide the portion of their impression stock destined to each transaction method, the advertisers will ultimately bear the information risk deriving from the selection process. Analogously to Akerlof's Market for Lemons (1978), publishers may hold private information about the quality of an impression and act strategically upon it by allocating different impression quality tiers to different transaction methods. Since this strategic allocation is driven by information only available to the publisher, advertisers are exposed to potential losses. Publishers who engage in such practices, in fact, may price the impression stock sold on RTB at the market price for impressions with similar disclosed features (i.e. dimensions or position on the UI), despite it may carry lower expected quality. Measuring impression quality, however, is difficult. Despite its historical use as a performance-advertising device, advertisers increasingly use display advertising as a branding tool (IAB/Deloitte, 2018). As such, broadly-defined performance measurement becomes fuzzier, and typical metrics such as clicks and conversions are less informative. We, therefore, focus on impression viewability, constructed as the probability of a target consumer ultimately seeing a served impression. Not all impressions, in fact, carry the same expected probability of effectively reaching a target customer, and thus the number of served impressions may be misleading when evaluating a campaign's performance. The use of this straightforward, although uncommon, measure helps us establish a lower bound of impression quality, leaving further effectiveness considerations out of the picture. The metric, in fact, does not depend on the target user's propensity to buy, but rather only on her interaction with the publisher's website. Since publishers have private information on the use of their digital outlets, we can realistically think that they may have better viewability estimates than their counterparts. In this sense, viewability can serve as a proxy for impression quality, and thus inform our investigation on the ongoing market dynamics.

In the present work, we aim to investigate the information dynamics of the PMB-driven advertising markets. Specifically, we are interested in understanding the implications of the strategic allocation of impressions to Reservation Contracts and RTB by publishers who engage in both transaction methods. Our research question thus concerns whether the co-existence and heterogeneous adoption of multiple transaction methods in PMB allows publishers to allocate their impression stock strategically according to its quality constructed through viewability, therefore exposing advertisers to potential losses. We thus introduce the LemonAds construct. We define LemonAds those impressions sold on RTB that, despite being indistinguishable from the other impressions in terms of disclosed features and pricing, carry a higher risk of not being viewable in force of undisclosed strategic allocation efforts deployed by the publishers.

The answer to our question is not straightforward. While current theoretical literature has recently found the co-existence of RTB and Reservation Contracts to be convenient for both advertisers and publishers (Sayedi, 2018), we take a slightly different approach by involving impression quality information and heterogeneous transaction method adoption into our work. We formulate and test two hypotheses. First, we investigate whether publishers who engage in both transaction methods offer different impression quality in terms of viewability when transacting via RTB as opposed to Reservation Contracts. Then we investigate if the impressions sold from such publishers on the RTB market differ in quality from those offered by publishers who only sell via RTB.

We perform our empirical analysis on a unique bid-request level dataset from a major European Demand-Side Platform. We find that publishers may leverage private information to offer better impression quality through Reservation Contracts, thus altering the average impression quality offered in RTB auctions. We then further investigate the relationship between viewability and floor-pricing. We find that, by strategically allocating impressions across transaction methods, publishers may extract opportunistic revenues from the RTB market.

The present work contributes to the extant literature on digital advertising markets in two ways. First, we introduce the concept of impression quality as disconnected from common performance measures. The literature has so far considered all served impressions to be homogeneous in quality and relied the evaluation of advertising effectiveness on the advertisers' communication strategy. Impressions, however, are not all equal, and publishers play a fundamental role in shaping the success of a display advertising campaign. Our use of viewability as a quality metric allows for an objective measurement of service quality, reducing to a certain extent the credence features of impression transactions towards a more experiential type of consumption. Second, we are the first to our knowledge to investigate the consequences of information asymmetries in digital advertising markets empirically. As such, we open the debate for a more widespread interest towards PMB-driven advertising markets beyond theoretical modeling and into empirical testing. Finally, our work contributes to practice, by informing marketers of the potential losses deriving from the information exploitation in the digital advertising market. Moreover, our findings may allow practitioners to screen RTB impressions in a simple way, thus reducing the negative impact of the information asymmetries on their campaigns.

Related Literature

This work relates to the following research streams:

Programmatic Media Buying and Real Time Bidding

Current research on programmatic advertising belongs for the most part to the computer science and operations research fields. Researchers have investigated several aspects of the PMB infrastructure including bid optimization (e.g. Lee et al. 2013, Zhang et al. 2014), ad performance optimization (Chen et al. 2011), impression pricing across transaction methods (Bharadwaj et al. 2010, Chen et al. 2014) , and revenue management (Radovanovic & Heavlin, 2012; Balseiro et al. 2014). As the literature on programmatic advertising focuses mostly on pricing and revenue management, some aspects of the PMB infrastructure are still under investigated. This is the case of impression quality (Muthukrishnan, 2009). In this paper, we aim to contribute to the programmatic advertising literature by investigating the effect of heterogeneous impression quality, constructed through viewability, on publishers and advertisers' revenue streams.

Market Design in Digital Advertising

Market design is a fundamental issue in digital advertising. Although at first mostly studied in the search-advertising domain (e.g. Varian, 2007; Edelman et al., 2007; Katona & Sarvary, 2010; Yao & Mela,2011; Athey & Ellison, 2011; Varian & Harris, 2014; Almadoss et al. 2015), the interest towards the subject has broadened with the widespread adoption of complex electronic markets for display impression transactions. While, historically, display impressions were transacted only through Reservation Contracts, the current landscape has evolved. Despite the persistence of Reservation Contracts, more and more impression transactions happen via Real-Time Bidding auctions. The most common auction form in RTB advertising markets is the Vickrey-Clark-Groves auction (Clarke, 1971; Groves, 1973; Vickrey, 1961). Thanks to its straightforward dominant strategy of bidding the buyer's true valuation, it is widely accepted as a mechanism design for impression transactions, which pricing under competition is often unknown to the seller. While auctions are in principle more efficient than bilateral negotiations in allocation and pricing (e.g., Harris et al. 1981), this depends on the information levels and the buyer's knowledge of their true valuation (Arnosti et al., 2016). A growing body of literature has thus started to focus on information dynamics in advertising markets. Sun et al. (2016) designed a Two-Call auction mechanism to counteract the effects of asymmetric information in ad exchanges. Wilbur and Zhu (2009) investigated the implications of fraudulent information disclosure in ad auctions. Frick et al. (2018) find that incentive misalignments between advertisers and buy-side brokers may lead to incorrect performance evaluation and ultimately hurt the firm's advertising strategy. Asdemir et al. (2012) and Hu et al. (2015) investigate the incentive issues in performance metric selection, showing how the choice of Cost per Mille (CPM), Cost per Click (CPC) or Cost per Action (CPA) as a preferred target may change the incentives and ultimately the revenues of advertisers and publishers. While these efforts have started shedding light upon the market design issues of digital display advertising, the implications of the co-existence of Reservation Contracts alongside RTB auctions are still relatively unexplored. Sayedi (2018) has recently tapped into the issue. His findings suggest that publishers who transact through both Reservation Contracts and RTB maximize their revenue when selling a large portion of their impressions in Reservation Contracts. His work, however, considers impressions as homogeneous in quality. In the present work, we take a step further and include viewability as an impression quality measure to evaluate the implications of information imbalances and contractual strategies in the display advertising markets.

Display Advertising Effectiveness

The literature on display advertising effectiveness is a well-established one. Researchers have thoroughly studied the ad features that enhance campaign performance. For example, Machanda et al. (2006) studied the effect of repeated exposure, ad creative variance, and targeting on repeated purchase, Bleier and Eisenbeiss (2015) investigated how personalization, placement, and timing contribute to banner effectiveness, and Hoban and Bucklin (2015) looked at display advertising effectiveness along the customer journey. Moreover, a large part of the literature has focused on targeting and personalization (e.g., Lambrecht and Tucker, 2013; Lu and Yang, 2016; Goldfarb and Tucker, 2011), and privacy issues (e.g., Johnson, 2013). Despite a growing body of research, advertising effectiveness remains elusive. Dalessandro et al. (2012), suggest that the very performance metrics chosen for attribution may change the incentive-equilibria between advertisers and publishers, thus hurting performance measurement. Causal inference of advertising effectiveness is also problematic. Johnson et al. (2017), for example, proposed the Ghost Ads methodology to overcome the experimental design challenges of ad effectiveness estimation. Moreover, while effectiveness is the goal of digital advertising efforts, it is not a clean measure for market design. As advertising effectiveness depends both on the advertiser's and on the publisher's effort levels (Yu et al., 2016), it cannot cleanly be used to inform advertisers when deciding upon their true valuation of an impression. As not all served ads are ultimately viewed by the target users, in this work, we use actual ad views (Ghose and Todri, 2016) to establish a clean and objective lower bound of advertising quality and thus contribute to the ad effectiveness literature.

Impression Viewability

Impression viewability is a fundamental, yet understudied element of display advertising. Since programmatically traded impressions are generally paid on a CPM basis, oftentimes advertisers pay for impression stocks that are not viewed by the target consumers. This generally happens due to the position of the ad on the page and the scrolling habits of the target user. Fulgoni (2016) reports that practitioners' evidence attests the average impression viewability to be around 50 percent. Since seeing an ad is a necessary condition for consumer engagement, the viewability issue is fundamental to the advertisers. Although viewability is an increasingly popular metric among practitioners, the academic literature on the subject is still scant. In recent years Ghose and Todri (2016) introduced viewability in their empirical study of ad effectiveness, stressing its importance for attribution modeling and causal inference of advertising effects. Zhang et al. (2015) studied viewability metrics, and concluded that to consider an impression as viewable, at least 75 percent of the ad pixels should show in the target user's viewport for at least two continuous seconds. This finding challenges the industry standard of 50 percent of the ad pixels for one continuous second (Fulgoni & Lipsman, 2017). Bounie et al. (2017) model the effect of the introduction of viewability metrics, and show that higher viewability rates may finally hurt the user experience, exposing firms to the risk of a wider-spread adoption of ad blocking technologies. Despite an initial interest towards the subject, viewability remains largely understudied. In this paper we contribute to the scientific literature on impression viewability by using it as a proxy metric for advertising quality. In doing so, we place basic user engagement as a necessary condition for advertising effectiveness, and study the consequences of the transactional choices of the publishers on the advertisers' engagement performance.

Hypotheses

In the context of Information Systems and Organizational Science literature, the impact of IT on the evolution of a market has different and contradicting effects. On the one hand, IT makes it easier to coordinate a multitude of transactions with various counterparts in open markets (Malone, 1987), while, on the other hand, IT makes for an easier formation and maintaining of long-term contracts with a limited network of counterparts (Clemons 1993). In PMB, this double push towards open and private marketplaces has led to the co-existence of different transaction models that have so far competed to attract market share in the digital advertising environment. Looking at the market through the lenses of the IT Adoption in E-Procurement theoretical argument in the context of Risk Augmented Transaction Costs Theory (Kauffman, 2004), end-buyers in the PMB supply chain (the Advertisers) are exposed to a trade-off between procurement and uncertainty costs whenever they want to establish their preferred transaction means. Open markets offer lower search costs and faster agreements alongside with higher risks in terms of security, supply variance, and financial settlements. In force of this trade-off, firms self-select into either open or private platforms (Kauffmann, 2004). Interestingly, in PMB markets, firms seem to adopt hybrid quasi-market strategies, often employing a mixture of both private and open market transactions.

Reservation contracts generally include specifications on service quality and penalties for underdelivery. With advertisers getting more and more conscious about user engagement metrics, viewability ratios may well be a contracting feature (Bounie et al., 2017). Since publishers own private information about the quality of their impression stock (Yu et al., 2016), they can allocate ad slots to different transaction methods in order to fulfill their contractual obligations with advertisers. Publishers, for example, may know in advance the probability that a user will scroll to the bottom of a particular landing page, and thus have a better estimate of the potential viewability of an impression than their counterparts may have. Chen et al. (2014), in fact, observe how on average directly traded inventories in PMB tend to be of higher quality than those traded via RTB. Since viewability is only known ex-post, however, if the viewability of impressions on RTB differed from those sold through Reservation Contract while keeping all other quality signals constant, there may be evidence of the exploitation of private information. By leveraging on private information, in fact, publishers may prioritize higher viewability impressions to Reservation Contracts, leaving the remaining ones to be traded via RTB. This leads to our first hypothesis:

Hypothesis 1: Impressions sold via RTB by publishers who engage in both Reservation Contracts and RTB transactions will be less viewable than those offered through Reservation Contracts by the same publishers, keeping all other quality signals constant.

Moreover, since the adoption of private and open transaction methods is heterogeneous across publishers, impression stock's quality in RTB may differ depending on the transactional strategy deployed by the publisher. By prioritizing higher quality impressions to Reservation Contracts, in fact, publishers who engage in both private and RTB transactions may pollute the RTB market with lower quality impressions. Since this strategic allocation may derive from the exploitation of private information, we hypothesize that these impressions are indistinguishable from other impressions in terms of disclosed quality signals, according to our definition of LemonAds. This leads to our second hypothesis:

Hypothesis 2: Impressions sold via RTB by publishers who engage in both Reservation Contracts and RTB transactions will be less viewable than those offered by publishers who only transact their stock via RTB, keeping all other quality signals constant.

Setting and Data

The PMB supply chain connects advertisers with target consumers by allowing the real-time transaction of large amounts of impressions. Because advertisers often trust their campaign management on third-party brokers, we collected our data through a major European Demand Side Platform (DSP). DSPs operate as demand-side brokers in the PMB environment and manage clients' digital advertising campaigns by buying impressions on their behalf. Having a common bid management system for all the impressions in our dataset allows us to analyze multiple advertisers' campaigns while controlling for the effect a single bid-optimization backend.

Figure 1 shows an overview of the PMB process. Programmatic transactions of impressions start with a user-initiated access to a mobile app or website (1). Once a user opens a mobile application or lands on a web page, pre-defined spaces on the user interface are made available to advertisers as bid requests (2). Bid requests thus appear on ad exchanges, where advertisers and demand-side brokers can decide to submit a bid (3). Publishers signal impressions bound to Reservation Contracts with deal identifiers to make them recognizable in real time to their buy side counterparts. The rest of the impressions are auctioned off through first or second price sealed bid auction. Once all the transactions are cleared (4) and all impressions paid for their CPM cost, the ads are finally served on the user's device (5).

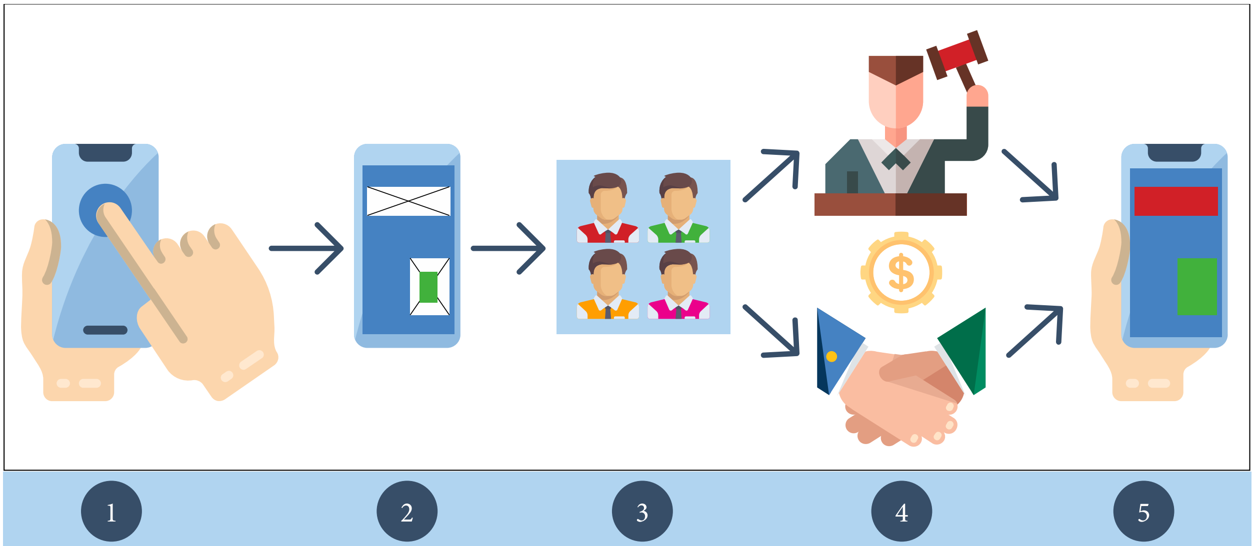

Figure 1. Programmatic Transaction of Impressions

The conditional structure of the bidding decision-making process required the collection of a large number of additional observations. Since we can only observe viewability for impressions that our partner company ultimately served, there is an underlying risk of algorithmic bias in our data, driven by the DSP's bidding strategy. The DSP may in fact cherry-pick impressions considered to be of higher quality, hence potentially biasing our estimates. We thus collected both bid requests on which the DSP did not bid and bid requests on which the DSP bid but ultimately lost, alongside our main observations of interest. These additional observations allow us to model the decision-making process that leads to one impression being served, and thus isolate the effect of publishers' transaction method choice on impression viewability.

Our database includes a random sample of over 9 million bid requests originating from European mobile app publishers over the course of four days. Of these available impressions, our partner company bid on 214,347 and won 44,600. The bids originated from multiple campaigns ran by our partner company's clients in April 2019. We also collected all the impression-related variables available to the partner company (Table 1). These variables are sanctioned by the IAB standards (IAB 2016), and are the same across all publishers and advertisers.

43% of the impressions in our dataset were transacted via RTB, while the rest were sold through Reservation Contracts. 76% of the publishers offered Reservation Contracts alongside RTB transactions.

Table 1. Summary Statistics

Variable	Description	Observations	Mean	SD	Min	Max
Bid Confirmed	If the advertiser bid (1) or not (0) on an impression	9,118,458	0.02	0.15	0	1
Won	If the advertiser won (1) or not (0) an impression	9,118,458	0.00	0.07	0	1
Viewable	If a won impression was ultimately viewed (1) or not (0) by the customer	9,118,458	0.00	0.05	0	1
Open Market	If the transaction happened on the Open RTB Auction (1) or Reservation Contract (0)	9,118,458	0.43	0.50	0	1

Has Private	If the publisher offers Reservation Contracts (1) or not (0)	9,118,458	0.76	0.43	0	1
Auction Type	If the impression was offered through a first (1) or second (2) price auction	9,111,868	1.60	0.49	1	2
Banner Height	Height in pixels of the offered impression	8,824,275	216.37	91.95	50	2560
Banner Width	Width in pixels of the offered impression	8,824,322	316.57	38.15	90	1920
Campaign	Advertiser's campaign unique identifier	9,118,458			0	11451
Client Id	Advertiser's unique identifier	9,118,458			0	5363
Bid Price	Advertiser's bid	876,228	1.78	1.76	0	50
Impression Floor	Impression's floor bid	5,950,917	2.93	30.97	0.01	40536.2
Device Make	Brand of the user's device	9,102,621			1	432
Latitude	User position's latitude	9,078,782	52.02	2.56	-37.22	65.67
Longitude	User position's longitude	9,078,782	4.86	5.83	-122.87	175.48

Model Free Evidence

Our model free evidence suggests reasons to believe in the hypothesized effects. Figure 2 shows that on average impressions transacted via RTB tend to be less viewable than those transacted through Reservation Contracts. This first evidence suggests that the impression stock sold through Reservation Contracts may indeed be on average of higher quality with respect to that available on the RTB market.

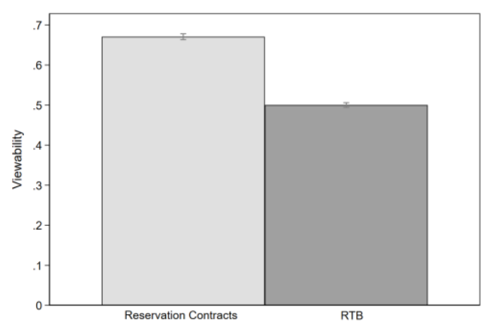

Figure 2. Average Viewability of Impressions

Furthermore, the difference persists when zooming into the impression stock of publishers who operate through both transaction methods (Figure 3). The preliminary finding seems to support our first hypothesis, suggesting that publishers may engage in impression prioritization across markets.

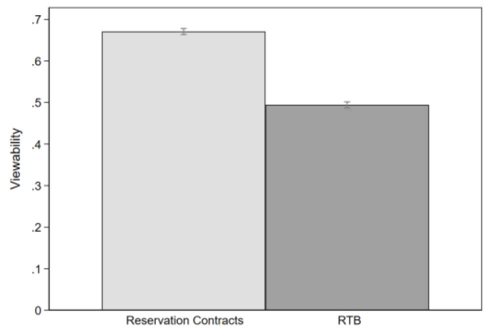

Figure 3. Average Viewability of Impressions Sold By Publishers Who Engage in Both Transaction Methods

Finally, Figure 4 shows that impressions sold via RTB by publishers who engage in both transaction methods tend to be on average less viewable than those offered by publishers who only operate on the RTB market. Our second hypothesis seems thus to be supported by the data, giving us a first glance into the consequences of impression prioritization in the PMB market. Publishers thus seem to engage in strategic allocation of impressions to different transaction methods, and the practice seems to affect the overall impression quality in the RTB market.

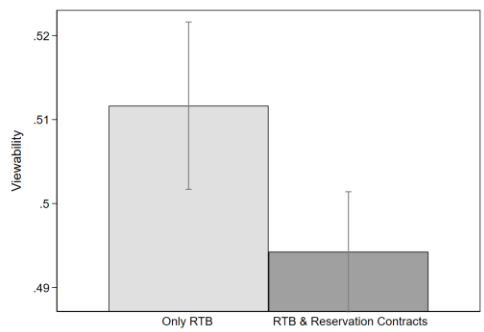

Figure 4. Average Viewability of Impressions Sold via RTB

Empirical Analysis

Model 1

We test our first hypothesis, by comparing the viewability of impressions sold via RTB by publishers who engage in both transaction methods to that of the impressions sold by the same publishers in Reservation Contracts. We thus run the estimation on the subset of the dataset that only includes publishers who engage in both transaction methods.

The process that leads to an impression being viewable is complex and requires careful attention when choosing an estimation strategy. First, because our dataset only reports viewability measures of impressions our data provider won, we risk incurring in selection bias driven by the bidding strategy of our partner firm. Our partner firm may, for example, cherry-pick impressions that have an overall higher likelihood of being viewable based on variables unknown to us. Moreover, our partner company does not use the information on the publisher's choice of transaction methods when bidding. They may thus overestimate the viewability of impressions sold via RTB, hence systematically winning lower-viewability impressions. Second, the probability of winning is a function of the bidding strategy of our partner firm and of the agreements the firm has with its advertising clients. On the one hand, the firm may decide to bid on impressions they have a higher likelihood to win. If more viewable impressions were harder to acquire, the bidding decision may once again bias our viewability estimates downwards. On the other hand, the firm may not bid on potentially winning impressions because of the clients' budget restrictions or because they don't fit with their strategy.

If clients were interested in higher overall viewability in their campaigns, the bidding decision might thus confound our viewability estimates.

We tackle our data limitations by devising a three-equation Conditional Mixed Process model as follows.

Since the probability of winning an impression may be correlated to our main outcome through the unobserved company's estimation of viewability, we need to control for sample selection. We thus model viewability with a 2-stage Heckman Probit using the probability of winning an impression as the selection criterion. This modeling choice allows us to control for the company's bidding strategy also when unobserved expected viewability may influence the impression selection. The probability of winning an impression, however, strongly depends on the bid decision and the bid price. As stated earlier, the bidding decision, and thus the bid price, may correlate with the likelihood of winning and therefore with viewability. We overcome this issue by adding a third equation to the model, in which we estimate the bid price conditional on the decision to bid. As bid price takes positive values only when the company decides to bid, and zero otherwise, we model it via a left-censored Tobit model. Equation 1 to 3 show the full model.

$$Viewable = \beta_0 + \beta_1 OpenMarket + \beta_2 BannerHeight + \beta_3 BannerWidth + \beta_5 ImpressionFloor + \eta\lambda + \epsilon \quad (1)$$

$$Won = \gamma_0 + \gamma_1\, BidPrice + \gamma_3 AuctionType + \gamma_5 Latitude + \gamma_6 Longitude + \mu X + \psi \quad (2)$$

$$BidPrice = \begin{cases} \theta_0 + \theta_1 ClientId + \theta_2 DeviceMake + \phi X + \delta Z + \iota \ \ if\ Bidprice > 0 \\ 0\ if\ Bidprice = 0 \end{cases} \quad (3)$$

Equation 1 and 2 are the two stages of our Heckman Probit model. Equation 1 models our main outcome variable *Viewable* that is a dummy variable that takes value 1 if the end user ultimately viewed the impression, and 0 otherwise. The estimates from our model report the correlation between the independent variables and the probability that a user was ultimately exposed to at least 100% of the impression pixels for one continuous second (*Viewable*=1). Thus the coefficients of the independent variables should be interpreted in terms of the change in Viewability defined as the probability that an end user ultimately sees the ad. The main variable of interest of the outcome equation is *OpenMarket* that is a dummy variable that takes value 1 when an impression was transacted via RTB and 0 if it was transacted through Reservation Contract. Its coefficient β_1 thus represents the variation in the probability that an impression is ultimately viewable when a publisher who engages in both transaction methods decides to sell it via RTB instead of through a Reservation Contract. *BannerHeight* and *BannerWidth* record the dimensions of the impression, and *ImpressionFloor* records the minimum acceptable bid for the impression. Finally, λ is the Inverse Mills Ratio obtained from the estimation of the selection equation (eq. 2), and ϵ is the error term.

Equation 2 models the probability of winning an impression, and it serves as the first stage of the Heckman Probit model. Won is a dummy variable that takes value 1 if the partner company won the impression and 0 otherwise. *BidPrice* records the price bid by our partner company for an impression; *AuctionType* indicates whether the impression was transacted via first or second price sealed-bid auction; *Latitude* and *Longitude* are the geographical coordinates of the user. Finally, *X* contains all the regressors from equation 1, and ψ is the error term. *BidPrice*, *AuctionType*, *Latitude*, and *Longitude* help us identify our selection equation (equation 2). Because the information on viewability is not available to the bidder before the impression is served, *BidPrice* affects our main outcome variable only through the probability of winning an impression. *AuctionType* may change the probability of winning an impression, while, however not affecting the user's actions on the landing page, and thus on the viewability of the impression. Finally, the user coordinates *Latitude*, and *Longitude* help us identify the probability of winning by serving as a proxy for end-user attractiveness, and thus competition. Advertisers may in fact consider users who are in certain areas as more attractive for example because of their potential willingness to pay, or because of their proximity to shopping districts. These practices may entail harsher competition, and hence lower winning probabilities in certain locations. Once again, these two variables only correlate with impression viewability through the probability of winning, since location per se does not influence on-device user behavior.

BidPrice is, however, problematic as the buyer may bid more on impressions on which they have a higher chance to win. Moreover, the variable is left-censored, since it only takes values greater than zero when the buyer decides to bid on an impression. To overcome these limitations, we devise the third equation (equation 3) to control for the bidding decision of the company. We thus specify our third equation as a left-censored Tobit Model and estimate it simultaneously with equation 1 and 2. In equation 3, *ClientId* and *DeviceMake* serve the identification of the full model, X contains all the regressors from equation 1, Z contains all the additional regressors from equation 2, and ι is the error term. *ClientId* is a categorical variable that records the identity of the bidding advertiser. As each advertiser has a personal bidding strategy, this variable helps us identify *BidPrice* and thus the probability of winning beyond the mere attractiveness of the impression. *DeviceMake* is a categorical variable that records the device in use by the target user. Since device ownership may correlate with the end user's willingness to pay, it may affect both the bidding decision and the bid price.

We estimate equation1, 2 and 3 simultaneously via Maximum Likelihood. By allowing the error terms to be correlated, we take into account the strategic interdependence of the three equations. Table 2 shows the results of the estimation.

Results

Table 2. Model 1 Estimation Results

	Heckman Probit (outcome)	Heckman Probit (selection)	Tobit
VARIABLES	Viewable	Won	Bid Price
Open Market	-0.840***	0.672***	0.178***
	(0.012)	(0.006)	(0.005)
Auction Type		0.369***	0.644***
		(0.011)	(0.017)
Latitude		0.060***	-0.041***
		(0.006)	(0.004)
Longitude		-0.014***	0.004***
		(0.001)	(0.001)
Banner Height	0.002*	0.004***	-0.010***
	(0.001)	(0.000)	(0.000)
Banner Width	-0.022***	-0.006***	0.068***
	(0.001)	(0.000)	(0.000)
Impression Floor	0.095***	-0.108***	0.001***
	(0.005)	(0.002)	(0.000)
Bid Price		0.469***	
		(0.002)	
Device Make	No	No	Yes
Client Id	No	No	Yes
λ	-1.027***		
	(0.044)		
Constant	8.454***	-5.822***	-15.145***
	(0.498)	(0.297)	(0.295)
Observations	4,370,613	4,370,613	4,370,613

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2 shows the estimates for model 1. Our model estimates show that impressions sold via RTB by publishers who engage in both transaction methods are on average 84% less viewable than those sold by the same publishers through Reservation Contracts. This result suggests that publishers indeed engage in strategic allocation of impression when deciding how to sell an impression. The Inverse Mills Ratio is significant. This result backs our intuition with respect to selection bias, and supports our modelling choices. Publishers thus seem to cherry-pick transaction methods based on ad quality.

Model 2

We test our second hypothesis by comparing impressions sold via RTB by publishers who sell their impression stock only via RTB to those sold by publishers who engage in both transaction methods. We thus run the estimation on the subset of the dataset that only includes impressions transacted via RTB.

As the impression selection and bidding decision-making processes are the same as stated before, the model specifications remain unchanged. Once again, our model controls for potential selection and strategic decisions by simultaneously estimating a 2-stage Heckman Probit and a left-censored Tobit model as a conditional mixed process. Equations 4,5, and 6 present the full model.

$$Viewable = \xi_0 + \xi_1 HasPrivate + \xi_2 BannerHeight + \xi_3 BannerWidth + \xi_5 ImpressionFloor + \varrho\lambda + \sigma \quad (4)$$

$$Won = \pi_0 + \pi_1\, BidPrice + \pi_3 AuctionType + \pi_5 Latitude + \pi_6 Longitude + \pi X + o \quad (5)$$

$$BidPrice = \begin{cases} \tau_0 + \tau_1 ClientId + \tau_2 DeviceMake + \rho X + \kappa Z + \omega \ \ if\ Bidprice > 0 \\ 0\ if\ Bidprice = 0 \end{cases} \quad (6)$$

The only change with respect to the previous model specification stands in our main variable of interest in equation 1. $HasPrivate$ is a dummy variable that takes value 1 if the publisher also offers Reservation Contracts and 0 otherwise. Its coefficient ξ_1 represents the variation in the probability that an impression is ultimately viewable when bought from a publisher who engages in both transaction methods as opposed to an impression bought from a publisher who only sells via RTB. Table 3 shows the results of the estimation.

Results

Table 3. Model 2 Estimation Results

	Heckman Probit (outcome)	Heckman Probit (selection)	Tobit
VARIABLES	Viewable	Won	Bid Price
Has Private	-0.124***	0.126***	0.159***
	(0.028)	(0.008)	(0.007)
Auction Type		0.144***	-0.490***
		(0.011)	(0.012)
Latitude		0.068***	-0.052***
		(0.007)	(0.004)
Longitude		-0.008***	0.005***
		(0.001)	(0.001)
Banner Height	-0.001	0.002***	-0.006***
	(0.001)	(0.000)	(0.000)
Banner Width	0.005*	-0.005***	0.055***
	(0.003)	(0.000)	(0.000)
Impression Floor	0.140***	-0.194***	0.407***
	(0.009)	(0.005)	(0.003)
Bid Price		0.692***	
		(0.003)	
Device Make	No	No	Yes

Client Id	No	No	Yes
λ	0.412***		
	(0.080)		
Constant	-1.946**	-5.299***	-10.866***
	(0.956)	(0.337)	(0.251)
Observations	2,427,411	2,427,411	2,427,411

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Our analysis supports our second hypothesis. By strategically allocating higher quality impressions to Reservation Contracts, publishers pollute the market with impressions that are 12% less viewable than the average of the market. Once again, the Inverse Mills ratio is significant. We further discuss the implications of our findings in the following section.

Further evidence: floor pricing and LemonAds

We extend our empirical investigation by taking a closer look at the relationship between floor pricing and viewability. The floor price is the minimum amount an advertiser must bid to have the chance to win an impression. Publishers assign a floor price to each impression, and it can be interpreted as the publisher's reservation utility for the single impression.

Analyzing the relationship between viewability and floor pricing helps us dig deeper into the market implications of our findings and investigate the existence and the potential impact of LemonAds. The viewability differentials from our empirical analysis, in fact, only paint half of the picture. Publishers, in fact, could price their impressions' floor bid according to their viewability potential. In this way, they could eventually cover the information risk to which they expose the advertisers by strategically allocating their impression stock. Moreover, advertisers could use floor price as a quality signal, and cherry-pick impressions at each price point to insure themselves against potential losses. If any of these two scenarios were to be true, then the publisher's choice of transaction method would not affect the advertisers' performance, thus casting doubt on the implications of our findings.

We therefore investigate the viewability of impressions at various floor-price points using the marginal effects from our main models.

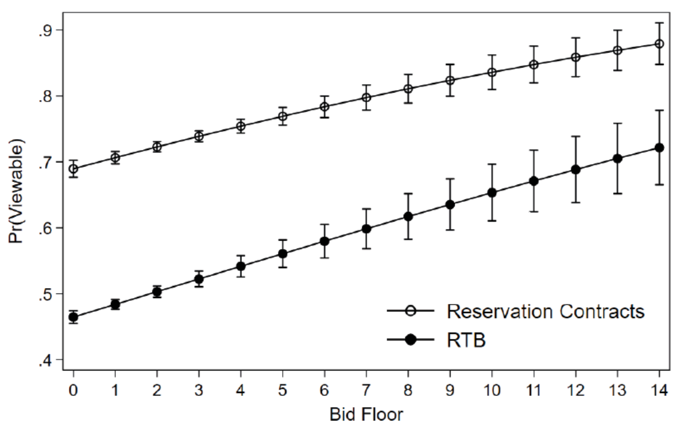

Figure 5. Viewability of Impressions Sold by Publishers Who engage in Both Transaction Methods

Figure 5 compares impressions sold via RTB and through Reservation Contracts by publishers who engage in both transaction methods. While the viewability greatly differs, pricing doesn't. At the same price level, an impression bought from the same publisher through different transaction methods will eventually have a different viewability. This effect sheds some light on the revenue management tactics of publishers. By allocating impressions strategically to both transaction methods, in fact, publishers seem to be able to extract higher revenues from less viewable impressions. For example, to buy an impression that has the same expected viewability as one sold at the entry-level Reservation Contract price (0-1 USD interval) via RTB from the same type of publisher, an advertiser will have to spend a minimum of thirteen to fourteen times more.

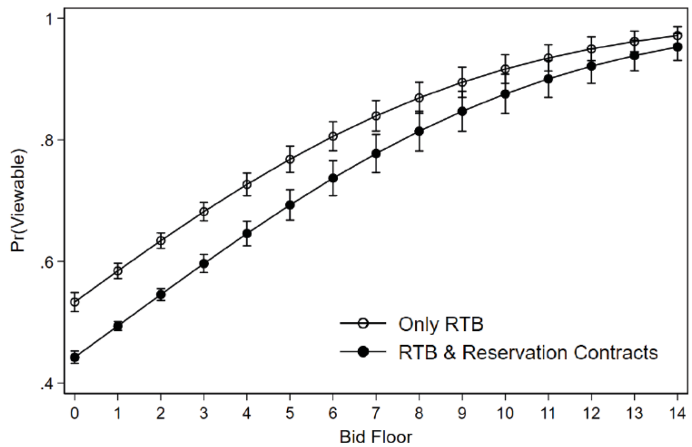

Figure 6. Viewability of Impressions Sold via RTB

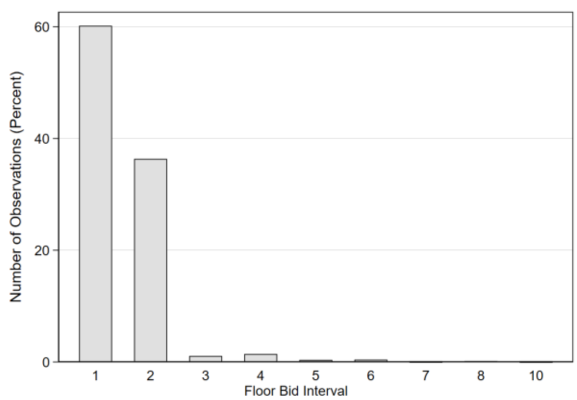

Figure 7. Frequency of Impressions Sold at Each Floor Bid Interval

Figure 6 compares impressions sold via RTB by publishers who only sell via RTB and those who also offer Reservation Contracts. Once again, viewability differs by publisher type at each floor pricing point. The evidence from Figure 6 suggests that publishers may be extracting opportunistic revenues from the RTB market by prioritizing higher quality impressions to Reservation Contracts. For example, an impression floor-priced in the 0-1 USD interval offered by a publisher who only operates on the RTB market will have the same viewabilitity of an impression floor-priced in the 2-3 USD interval sold by a publisher who also offers Reservation Contracts. While the effect seems to wear off and lose significance for impressions priced 8USD and above, Figure 7 show that such impressions are eventually very rare. Figure 6 gives a visual representation of LemonAds. Keeping all other variables constant, in fact, those impressions sold by publishers that engage in both transaction methods tend to carry a lower expected viewability. It is important to stress how the information available to the buy side is not sufficient to distinguish these impressions from the rest of the impressions sold on RTB. Our further analysis thus highlights the existence of LemonAds and gives insight on the monetary risk the advertisers are exposed to when transacting on RTB with publishers that engage in both transaction methods. Our findings suggest that advertisers may be able to reduce their monetary risk by screening impressions sold by publishers that engage in both transaction methods when buying impressions on RTB.

Conclusions

In the present work, we moved a first step towards understanding the information dynamics at work in the digital advertising markets. Our findings suggest that publishers who sell their impression stock both via RTB and through Reservation Contracts may offer higher quality impressions in terms of viewability to their private counterparts, dumping their lower quality stock on the RTB market. This practice not only seems to affect the average quality of the impressions sold on the RTB market but also seems to help publishers reap higher profits.

Our work thus contributes to the extant literature in two ways. First by introducing the concept of LemonAds, and showing how expected impression quality is used by opportunistic publishers as a revenue management tool. Despite the debate about impression quality is ongoing in the industry, its strategic use has so far been neglected by the literature because of a lack of reliable measures. By using viewability data, we were able to single out a lower bound of impression quality and thus investigate the strategic and monetary implications of quality heterogeneity and transaction methods in the PMB market. This leads to our second contribution. Our empirical approach to the PMB market dynamics highlights the publishers' information exploitation tactics. Thanks to our novel interpretation of viewability, we were able to infer about impression quality in spite of the credence nature of the advertising product. We believe that by presenting a simple way to proxy for service quality in advertising markets, we may help the future Information Systems and Marketing research efforts to shed light on more advertising market dynamics that have been neglected because of the overall lack of measurability.

Our additional analyses show the economic implications of the selective allocation of impressions. By exploiting private information, publishers are able to systematically extract price-to-viewability ratios far superior than the average of the market. Since the information advantage of the publishers originates from their knowledge of user behavior on their outlets, advertisers have currently no way to defend themselves against this practice.

Our work wants to inform PMB market players about the potential risks deriving from information asymmetries in the digital advertising markets. We thus presented an intuitive way to screen opportunistic publishers based on their transactional strategies. By taking into account the publishers' impression allocation, in fact, advertisers can select more price effective impressions, hence improving their performance.

While the digital advertising literature has mostly focused on advertising effectiveness, the empirical analysis of the underlying market dynamics has been for the most part neglected. Shifting the focus from advertising as just a means to an end to an understanding of advertising as a product in itself means moving closer to today's reality. The advertising market generates millions each second, and is for the most part unregulated. Opportunistic practices such as those described in this work are common, and market players are often left alone when faced with such reality.

With this paper, we aim to shed light on a small fraction of the dynamics currently in place in the digital advertising markets. We believe that the potential for empirical research on PMB is consistent, despite the rarity of reliable data. There are vast possibilities for future research. Since PMB-driven markets are highly complex and populated by a multitude of different players, research on incentive conflicts and information asymmetries has the potential to inform the growth of a largely understudied market entity.

Finally, the present work wants to signal the need for market regulation in the PMB ecosystem. While regulation could prove difficult for a highly decentralized and fast-moving market, today's market practices are far from sustainable. Open electronic markets bare the promise of efficient pricing and information transparency beyond any bilateral agreement. Only a correctly regulated electronic market, however, can protect its players from opportunistic practices and ensure the perpetuation of its existence.

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