Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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MANAGEMENT SCIENCE
Vol. 71, No. 12, December 2025, pp. 10244–10260
ISSN 0025-1909 (print), ISSN 1526-5501 (online)
https://pubsonline.informs.org/journal/mnsc

Lemon Ads: Adverse Selection in Multichannel Display Advertising Markets

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Received: November 3, 2022
Revised: February 26, 2024; July 15, 2024
Accepted: September 25, 2024
Published Online in Articles in Advance: April 23, 2025

https://doi.org/10.1287/mnsc.2022.03407

Abstract. Two auction-based channels play a crucial role in facilitating transactions of ad impressions in display advertising: real-time bidding (RTB), which is accessible to all advertisers, and private marketplace (PMP), which is restricted to a select group of advertisers through invitation-based agreements with publishers. Despite the ongoing discourse on the benefits and drawbacks of these two channels, how their coexistence influences the market dynamics and outcomes remains an open question. In this paper, we investigate this question by focusing on the welfare implications of publishers' channel adoption. First, using a game-theoretic model, we show that publishers who use both RTB and PMP can leverage their private information on impression quality to sell lower-quality impressions at higher prices in RTB, leading to adverse selection and exposing their RTB-only counterparts to losses. To validate our theoretical prediction, we conduct an empirical analysis using a large proprietary data set. The results provide strong evidence of the presence of adverse selection. In particular, we find that, all else being equal, RTB impressions from dual-channel publishers are of significantly lower quality compared with those from single-channel publishers. Our findings shed light on the nuanced dynamics between RTB and PMP and contribute to the understanding of the complex interplay of informational and strategic factors in the display advertising market.

History: Accepted by Anindya Ghose, information systems.
Supplemental Material: The online appendix and data files are available at https://doi.org/10.1287/mnsc.2022.03407.

Keywords: display advertising • real-time bidding • private marketplace • adverse selection • viewability

> In the real world, the critical question was: how, and how well, do markets handle fundamental problems of information? (Stiglitz 2002, p. 467)

1. Introduction

The display advertising market has witnessed tremendous growth over the past decade. The growth is characterized not only by increased investment, but also by a fundamental shift in how ad spaces are bought and sold. In particular, *programmatic ad buying*—an algorithm-driven process that automatically connects ad buyers (advertisers) and sellers (publishers) for real-time ad space allocation—has surpassed traditional guaranteed contracts, significantly improving the efficiency in ad transactions (Interactive Advertising Bureau 2020). According to Statista (2024), the overall spending on programmatic ad buying has surpassed $595 billion in 2024, and is projected to reach $800 billion in 2028.

Two auction-based channels are central to programmatic ad buying: real-time bidding (RTB) and private marketplace (PMP). In both channels, whenever a user visits a publisher's website or mobile app, advertisers can send a bid for each available ad space (known as an "impression") and compete in a real-time auction. The advertiser with the highest bid wins the impression, and her ad is displayed to the user. RTB is open to all advertisers, hence offering reach and efficiency. However, its openness also makes it prone to ad fraud (Choi and Sayedi 2023). In contrast, PMP requires pre-established agreements between advertisers and publishers, allowing only preapproved advertisers to bid for available impressions. Advertisers' eligibility for PMP impressions is assessed in real-time using digital keys, known as deal IDs. PMP offers exclusivity and control and is gaining popularity for its quality assurance. In practice, publishers typically reserve their premium ad inventory for PMP, and, in return, advertisers pay higher prices (Choi et al. 2020).

Although the benefits and drawbacks of RTB and PMP are well recognized, the impact of their interplay on market dynamics and outcomes remains unclear.

A key concern pertains to the disparity between publishers utilizing both RTB and PMP (dual-channel) and those that are limited to RTB (single-channel) due to resource and scalability reasons. In particular, because advertisers often rely on aggregated market statistics to evaluate impression quality at the channel level, dual-channel publishers may have the incentive to leverage their private information on impression quality and sell their lower-quality impressions at higher prices in RTB, leading to a deterioration of the average impression quality in RTB. As a response to the quality decline, advertisers lower (shade) their bids, leaving single-channel publishers with revenue losses. Such an adverse selection problem could potentially unravel ad transactions in RTB, as in the classic lemons market (Akerlof 1970), and affect the competitive landscape of programmatic ad buying.

Motivated by these practical considerations, we analyze the welfare implications of publishers' channel adoption. In particular, we study the following questions: *Do advertisers benefit from the presence of PMP? Under what conditions? How does the coexistence of PMP and RTB affect the strategic interactions between publishers and advertisers and their respective payoffs?*

We develop a parsimonious game-theoretic model to characterize the strategic interactions between publishers and advertisers, considering both single- and dual-channel publishers. Our analysis reveals two important insights. First, advertisers do not necessarily benefit from the availability of PMP. Specifically, given the limited ad inventory available in PMP (Chen 2017a, Publift 2023), restricting ad purchases to PMP is not a viable option for advertisers seeking a balance between quality and reach. Given this constraint, advertisers must rely on both PMP and RTB to meet their advertising needs. However, because advertisers are unable to discern the quality of impressions offered by single- and dual-channel publishers, dual-channel publishers can exploit the information asymmetry by pooling their low-quality impressions with those from single-channel publishers in RTB, leading to adverse selection. Second, dual-channel publishers' impression allocation strategy leads to revenue loss for single-channel publishers, with the extent of the loss depending on market conditions, including market shares of single- and dual-channel publishers and competition on the demand side.

To validate our analytical insights in real-world display advertising markets, we conduct an empirical analysis using detailed transaction data from over 9 million impressions, 44% of which were traded via RTB and the rest via PMP. In line with the industry practice (Munro 2022), we use *viewability*—whether an ad impression had the opportunity to be seen by a user—as the quality metric for impressions.[1] Our results indicate a strong correlation between publishers' channel choices and impression quality. Specifically, we find that, all else being equal, RTB impressions from dual-channel publishers are significantly less viewable than those from single-channel publishers. Our findings remain robust after accounting for demand-side competition, supply-side heterogeneity, and variations in daily and weekly traffic, providing compelling evidence of adverse selection in RTB.

Our research contributes to the understanding of the complex interplay of informational and strategic forces in the display advertising market. Although ad spending on PMP has risen considerably in recent years and surpassed the spending on RTB (Statista 2023), research on the welfare implications of the coexistence of these two channels has been limited (Choi et al. 2020). Our research provides novel insights into how publishers' channel choices affect the competitive dynamics and outcomes. In particular, our findings challenge the widely held belief that PMP benefits both publishers and advertisers, suggesting that quality assurance from PMP cannot effectively address the fundamental problem of information asymmetry in the increasingly complex programmatic ad supply chain. Our research highlights the necessity for regulatory measures to bring transparency to the market.

The rest of the paper is organized as follows. Section 2 reviews related literature; Section 3 introduces our game-theoretic model; Section 4 presents the analytical results; Section 5 details our empirical analysis; and Section 6 discusses the implications of our findings and suggests directions for further research.

2. Literature Review

Our paper contributes to the growing literature that examines design and operational issues in the display advertising market. Early studies primarily focused on negotiating guaranteed contracts between advertisers and publishers. However, the rise of programmatic ad buying has shifted research into the complex interplay among advertisers, publishers, and intermediaries such as ad exchanges, demand-side platforms (DSPs), and supply-side platforms (SSPs). We briefly discuss three streams of research closely related to our paper (see Table 1 for an overview) and refer to Choi et al. (2020) for a more comprehensive review of literature on the display advertising market.

2.1. Ad Inventory Management

Traditionally, publishers contracted with advertisers to deliver a prespecified amount of impressions at a fixed price. Given the inherently stochastic nature of supply (i.e., impressions), publishers risk underdelivering and incurring penalties. Considering this risk, several

Table 1. Overview of Close-Related Research Streams

Research stream	Previous studies	Our paper
Ad inventory management	Impression allocation among different contracted advertisers (Chickering and Heckerman 2003, Vee et al. 2010, Bharadwaj et al. 2012, Turner 2012, Hojjat et al. 2017) or between guaranteed contracts and RTB (Ghosh et al. 2009, Balseiro et al. 2014, Chen 2017b, Sayedi 2018) by monopolistic publishers.	Impression allocation between RTB and PMP with asymmetric channel access.
Pricing	Floor price as a design parameter for publishers to maximize revenue (Amin et al. 2013, Mohri and Medina 2014, Cesa-Bianchi et al. 2015, Leme et al. 2016, Choi and Mela 2023).	Floor price as a design parameter for publishers and a proxy of advertisers' expectation of impression quality.
Information revelation	Trade-offs of information disclosure for monopolistic publishers (Levin and Milgrom 2010, de Cornière and de Nijs 2016, Hummel and McAfee 2015, Ada et al. 2020).	Welfare implications of information revelation for advertisers and publishers under the coexistence of RTB and PMP.
	Impacts of ex ante information asymmetry between advertisers in single-channel (Arnosti et al. 2016, Abraham et al. 2020) and multichannel (Choi and Sayedi 2023) settings.	Information asymmetry between advertisers and publishers in multichannel settings.

studies have explored optimal strategies for impression allocation among contracted advertisers (Chickering and Heckerman 2003, Vee et al. 2010, Bharadwaj et al. 2012, Turner 2012, Hojjat et al. 2017). The increasing adoption of RTB has also fueled research into dynamic impression allocation across different channels. For example, Ghosh et al. (2009) proposed an analytical framework where publishers act both as sellers in RTB and as bidders for contracted advertisers. Balseiro et al. (2014) developed a policy optimizing both guaranteed contracts and RTB, suggesting that allocating high-quality impressions to guaranteed contracts and the rest to RTB could increase publisher revenue. Chen (2017b) took into account both supply and demand uncertainties and characterized the trade-offs between maximizing RTB revenue and reducing underdelivery risks associated with multiple guaranteed contracts. Sayedi (2018) showed that RTB might not replace reservation contracts entirely, and publishers should sell a substantial portion of their ad inventory through reservation contracts to maximize revenue.

Our paper extends the literature on ad inventory management in two ways. First, previous studies primarily focused on revenue maximization from a monopolistic publisher's view, whereas we focus on the welfare implications of publishers' dual-channel inventory coordination for other parties (i.e., single-channel publishers and advertisers) in the market. Second, existing research considered impression allocation via guaranteed contract and RTB. We, on the other hand, analyze impression allocation issues arising from the coexistence of RTB and PMP, viewing the latter as a hybrid of RTB and reservation contracts.

2.2. Pricing

Another major challenge faced by publishers is pricing impressions in different market channels. When impressions are sold via real-time auctions, following the seminal works on optimal auction design (e.g., Myerson 1981, Milgrom and Weber 1982), publishers benefit from setting a reserve price (also known as floor price in the ad industry). Several papers studied floor price optimization in the presence of strategic advertisers (Amin et al. 2013, Mohri and Medina 2014, Cesa-Bianchi et al. 2015). Leme et al. (2016) showed that the floor prices could increase publishers' revenue in uncertain or thin markets. Choi and Mela (2023) empirically estimated advertisers' demand curves, suggesting that optimal floor prices should consider advertisers' budget constraints.

Our paper shares some similarities with this stream of literature by characterizing publishers' optimal floor prices under the coexistence of PMP and RTB. However, we distinguish ourselves by taking into account the informational role of floor prices. In particular, because floor prices reflect publishers' priors on advertisers' quality expectation, they allow us to test our theoretical predictions in an empirical setting and generate nuanced insights about publishers' pricing strategies.

2.3. Information Revelation

The transaction of impressions between publishers and advertisers also involves, implicitly or explicitly, an exchange of information. Several papers have studied the trade-offs for publishers in disclosing more information to advertisers. Levin and Milgrom (2010) and Hummel and McAfee (2015) independently found that sharing impression-level data is not always in publishers' best interest. de Cornière and de Nijs (2016) showed that disclosing consumer-level information may not always maximize social welfare, even if it improves advertiser-consumer matching, because the enhanced targeting capabilities may push advertisers to target only consumers with a low price elasticity, and hence drive up the price. On the contrary, Ada et al. (2020) empirically demonstrated that disclosing contextual information, such as subdomains, to advertisers can increase revenue to both parties. These conflicting results highlight the intricacies of information revelation in display advertising.

Another stream of literature, to which our paper is closely related, studies the implications of ex ante information asymmetries. For example, Arnosti et al. (2016) showed how information asymmetry between performance advertisers and brand advertisers may expose the latter to adverse selection. Abraham et al. (2020) compared first-price and second-price common-value auctions under information asymmetry due to cookie tracking, finding that second-price auctions are susceptible to low-quality impression identification through cookies, potentially reducing publisher revenue. Few papers have analyzed the implications of information asymmetries arising from the coexistence of RTB and PMP. One exception is Choi and Sayedi (2023), where the authors studied revenue implications of information asymmetry between advertisers with and without access to PMP on a monopolistic dual-channel publisher. Our paper differs from Choi and Sayedi (2023) by focusing on how dual-channel publishers' selective allocation of impressions affects single-channel publishers and advertisers in the market. By doing so, we offer nuanced insights into the welfare implications of information asymmetries associated with the disparity of channel adoption.

3. Model Description

In this section, we present a parsimonious game-theoretic model of the dual-channel programmatic advertising market considered in our paper. We begin with an overview of the basic setup before delving into the detailed formulation of the model.

3.1. Market Characteristics

We consider a display advertising market with two publishers that serve a continuum of consumers (e.g., app users) on one side and n ($n \geq 2, n \in \mathbb{N}$) advertisers on the other side. Following prior studies (e.g., Bounie et al. 2017, Choi and Jeon 2023), we consider a "competitive bottleneck" setting (Armstrong 2006) with single-homing consumers and multihoming advertisers (i.e., advertisers are affiliated with both publishers). The rationale is twofold. First, it is motivated by our focus on the first-order interactions between publishers and advertisers under the coexistence of PMP and RTB. Second, in practice, advertisers often target consumers with different online presence patterns to ensure market reach and, hence, interact with different publishers. For convenience, we refer to a publisher as "he/him" and an advertiser as "she/her" in the rest of the paper.

3.2. Impression Allocation

Publishers have the option to sell ad impressions via both PMP and RTB, or to exclusively use RTB. We note that, in practice, the decision on channel adoption involves weighing various factors, such as technical capabilities, operational cost, and audience reach, and how to balance the trade-offs is challenging by itself and entails rich research questions. To balance relevance and parsimony, in our main model, we take publishers' channel adoption choice as exogenous and assume that one publisher, denoted by p_d, offers impressions via both PMP and RTB, whereas the other publisher, denoted by p_s, offers impressions solely through RTB. For simplicity, we set both publishers' operational cost to zero. We also analyze an extension where we endogenize publishers' channel adoption choice (see Online Appendix EC.2.2 for details).

To capture publisher-specific heterogeneity in impression quality, we follow the industry practice (Harvey 2021) and conceptualize the quality of an impression as its probability of attracting consumer attention. In particular, we assume that the quality of impressions from the dual-channel publisher and the single-channel publisher is uniformly distributed in $[0, \overline{q}_d]$ and $[0, \overline{q}_s]$, $\overline{q}_s \leq \overline{q}_d$. Both quality upper bounds are common knowledge among publishers and advertisers. Without loss of generality, we normalize the dual-channel publisher's quality upper bound $\overline{q}_d$ to one.

To model the status quo for PMP transactions where publishers and advertisers agree on the quality of impressions (Newor Media 2022, Publift 2023), we assume that the dual-channel publisher p_d commits to allocating only high-quality impressions, $q_d \geq \theta$ ($0 < \theta < 1$), to PMP. This quality threshold, θ, is communicated to all advertisers.

3.3. Advertisers' Quality Expectation

Advertisers have different ex ante valuation v of an impression, which is assumed to be uniformly distributed in $[0, 1]$. In line with the industry practice, we assume that the materialization of v (e.g., how likely the impression would lead to a sales conversion or an increase in brand awareness) hinges on the quality of the impression.[2] Although advertisers cannot directly observe the quality of impressions, we assume that they can form rational expectations of impression quality at the channel level based on historical data and market reports.[3] We also study an extension where advertisers are able to discern the quality of impressions from different publishers (see Online Appendix EC.2.1).

Let q^{m} denote the expected quality of impressions from market channel $m(m \in \{\mathrm{PMP}, \mathrm{RTB}\})$, and $\hat{q}^{\mathrm{m}}$ denote the advertisers' expectation of this quality. Under the rational expectations framework, we have $\hat{q}^{\mathrm{m}} = q^{\mathrm{m}}$. Specifically, given a quality threshold θ,

- For impressions offered via PMP: advertisers' quality expectation of the impression is

$$\hat{q}^{\mathrm{PMP}} = q^{\mathrm{PMP}} = \int_{\theta}^{1} \frac{1}{1-\theta} q \, \mathrm{d}q = \frac{1+\theta}{2}. \tag{1}$$

- For impressions offered via RTB: let $\eta_d (\eta_d > 0)$ and $\eta_s (\eta_s > 0)$ denote the traffic (i.e., the supply of impression) from publishers p_d and p_s, respectively. Advertisers' quality expectation of the impression is

$$\hat{q}^{\mathrm{RTB}} = q^{\mathrm{RTB}} = \frac{1}{\eta_d \theta + \eta_s} \left(\eta_d \theta \int_0^{\theta} \frac{q}{\theta} \mathrm{d}q + \eta_s \int_0^{\overline{q}_s} \frac{q}{\overline{q}_s} \mathrm{d}q \right) = \frac{\eta_d \theta^2 + \eta_s \overline{q}_s}{2(\eta_d \theta + \eta_s)}. \tag{2}$$

For notation brevity, we will use $\hat{q}$ hereafter to refer to advertisers' quality expectation whenever there is no confusion.

3.4. Advertiser's Payoff

In the main model, we assume that all advertisers have free access to both PMP and RTB. We relax this assumption and consider the costs associated with using PMP in a two-sided endogenous entry extension (see Online Appendix EC.2.2 for details).

Given an impression with a floor price r, the payoff of an advertiser with valuation v can be formulated as a function of her bid β as follows:

$$\Pi_a(\beta) = \begin{cases} v\hat{q} - \max\{r, \beta_{(2)}\}, & \text{if } \beta \geq \max\{r, \beta_{(2)}\}, \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$

where $\beta_{(2)}$ denotes the second highest bid. The payoff function in (3) captures the reality where winning low-quality impressions can result in negative payoffs for advertisers (Perloff 2023).

3.5. Publisher's Payoff

By selling an impression at a floor price r, a publisher receives a payoff

$$\Pi_p(r) = \begin{cases} \max\{r, \beta_{(2)}\}, & \text{if } \beta_{(1)} \geq r, \\ 0, & \text{otherwise}, \end{cases} \tag{4}$$

where $\beta_{(1)}$ denotes the highest bid. Here, we normalize the publisher's reservation payoff (i.e., payoff from outside options) to zero. We note that. in practice, publishers may obtain a nonzero reservation payoff. However, allowing a general reservation payoff would only introduce boundary cases where either one or both publishers choose to take the outside option and exit the programmatic advertising market. Therefore, we focus on the most interesting case, where the reservation payoff can be normalized to zero.

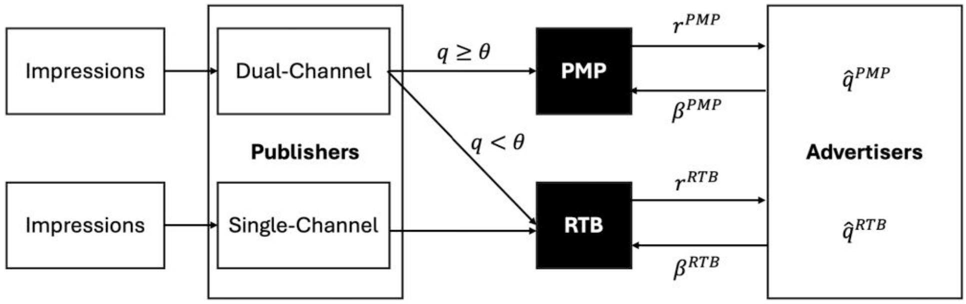
3.6. Sequence of Events

We model the strategic interactions between publishers and advertisers as a three-stage game. Figure 1 provides an overview of the decision processes in this game.

- *Stage* 1. The dual-channel publisher p_d chooses a quality threshold θ for PMP impressions and informs advertisers.
- *Stage* 2. Once a consumer arrives at a publisher's website or app—that is, an impression is available for sale—the publisher observes the impression's quality q, decides on the market channel $m, m \in$ {PMP, RTB}, and sets a floor price r, then notifies advertisers by sending a bid request. Note that for the single-channel publisher p_s, the channel decision is trivial—that is, all impressions are sold via RTB.
- *Stage* 3. Advertisers, upon receiving the bid request, place their bids β based on their valuation v and quality expectation $\hat{q}$ and compete in a second-price auction. The winning advertiser's ad is displayed to the consumer, and the publisher receives a payment equal to the second-highest bid among all participating advertisers.

In the next section, we solve the sequential game using backward induction. We first derive advertisers' optimal bidding strategies, followed by publishers' optimal floor prices, allocation strategies, and the

Figure 1. Overview of the Analytical Model



optimal choice of quality threshold. We then analyze the revenue implications of the dual-channel setting based on equilibrium outcomes. For easier reference, we summarize the key notations used in our model in Table 2. Subscripts and superscripts are used to denote the role of a decision maker and the market channel choice (PMP or RTB), respectively.

4. Equilibrium Analysis

4.1. Characterization of Equilibrium Outcome

We start by analyzing advertisers' optimal bidding strategy. Lemma 1 characterizes the result. All proofs of lemmas and propositions are presented in Online Appendix EC.1.

Lemma 1. *Given any impression of quality q, the optimal bid of an advertiser with valuation v is $\beta^*(v) = \hat{q}v$, where $\hat{q}$ is the advertiser's quality expectation.*

Recall that a bidder's optimal bidding strategy in a standard second-price auction is to bid her true valuation. Lemma 1 states that an advertiser would shade the bid based on her quality expectation, which varies depending on the source of the impression. Specifically, if the impression is offered via PMP, the optimal bid is $\beta^{*\text{PMP}}(v) = v(1+\theta)/2$, which is monotonically increasing in θ; if the impression is offered via RTB, the optimal bid is $\beta^{*\text{RTB}}(v) = v[\eta_d\theta^2 + \eta_s\overline{q}_s]/[2(\eta_d\theta + \eta_s)]$, which is monotonically increasing in $\overline{q}_s$.

Based on the characterization of advertisers' optimal bidding strategies, we can derive publishers' optimal floor prices.

Lemma 2. *Given any impression of quality q and a quality threshold θ for* PMP, *the optimal floor price is $r^* = \frac{\hat{q}}{2}$, where $\hat{q}$ is advertisers' quality expectation.*

Lemma 2 can be viewed as a generalization of the optimal reserve price in single-unit auctions in the presence of bid shading due to quality uncertainty. Specifically, it indicates that the optimal floor price increases in advertisers' rational quality expectation.

Using results from Lemmas 1 and 2, we can derive the dual-channel publisher's optimal allocation strategy as follows.

Proposition 1. *Given any impression of quality q and a quality threshold θ for* PMP, *the optimal channel choice for the dual-channel publisher is $m^* =$* PMP *if $q \geq \theta$ and $m^* =$* RTB *otherwise.*

Proposition 1 states that for any impression that meets the (binding) quality threshold θ, the dual-channel publisher is better off by selling it through PMP. Note that when choosing θ for PMP, the dual-channel publisher faces a quality-quantity trade-off: although a large θ increases advertisers' willingness to pay for PMP impressions, it inevitably leaves out impressions that do not meet the quality threshold. The optimal quality threshold θ^* is characterized in the next lemma.

Lemma 3. *Given $\overline{q}_d = 1$, $0 < \overline{q}_s \leq 1$, and any $\eta_d, \eta_s > 0$, the dual-channel publisher's optimal quality threshold is $\theta^* = \frac{\sqrt{\eta_s^2 + \eta_d\eta_s\overline{q}_s} - \eta_s}{\eta_d}$.*

According to Lemma 3, the optimal quality threshold θ is a function of the dual-channel publisher and single-channel publisher's traffic (η_d and η_s), along with the maximum quality level of the single-channel publisher $\overline{q}_s$.

Proposition 2. *Given $\overline{q}_d = 1$, $0 < \overline{q}_s \leq 1$, and any η_d, $\eta_s > 0$,*

i. *θ^* is monotonically increasing in $\overline{q}_s$ but strictly smaller than $\overline{q}_s$;*
ii. *θ^* is monotonically decreasing in the ratio $\frac{\eta_d}{\eta_s}$.*

Proposition 2 offers two important insights. First, although the quality upper bound of the single-channel

Table 2. Summary of Key Notations

Notation	Description
Decision	
θ	Quality threshold for PMP impressions (publisher's decision)
m	Channel choice for an impression (publisher's decision)
r	Floor price for an impression (publisher's decision)
β	Bid price for an impression (advertiser's decision)
Parameter	
η	The traffic from a publisher
q	The quality of an impression from a publisher's perspective
$\overline{q}$	The quality upper bound
$\hat{q}$	The quality expectation of an impression from an advertiser's perspective
v	Advertiser's private valuation of an impression
Function	
Π_a	An advertiser's payoff function
Π_p	A publisher's payoff function
Π_a^*	An advertiser's maximum expected payoff
Π_p^*	A publisher's maximum expected payoff

publisher imposes a competitive pressure to the dual-channel publisher, the average quality of RTB impressions from the dual-channel publisher is always lower than that from the single-channel publisher. Nevertheless, the expected payment for impressions from the two publishers is the same, as the quality expectation $\hat{q}^{\text{RTB}}$ is based on the entire (pooled) sample rather than individual publishers' inventories. In particular, $\theta^* < \overline{q}_s$ implies $\hat{q}^{\text{RTB}} < \overline{q}_s/2$—that is, the higher-quality impressions from the single-channel publisher are always discounted because of the lower-quality impressions from the dual-channel publisher, which may lead to adverse selection as in the scenario described in Akerlof's market for "lemons" (Akerlof 1970). Second, the traffic (which determines the supply of ad inventory) comparison between the two publishers affects the optimal quality threshold. Specifically, when the dual-channel publisher generates a significantly higher traffic than the single-channel publisher, the former can set a small θ^*, which would aggravate the quality discount effect on the single-publisher's impressions.

4.2. Welfare Implications

The characterization of the equilibrium outcome allows us to examine the welfare implications of publishers' channel choices.

4.2.1. Impact on Advertisers. We start by analyzing the welfare impact on advertisers under the coexistence of PMP and RTB. Lemma 4 summarizes advertisers' maximum expected payoffs under different scenarios.

Lemma 4. *Given* $\overline{q}_d = 1$, $0 < \overline{q}_s \le 1$, *and any* $\eta_d, \eta_s > 0$, *for any advertiser with valuation* $v, v \in [0,1]$, *the maximum expected payoff is*

i. $\Pi_a^{*\text{PMP}}(v) = \frac{(v^n - 2^{-n})\eta_d(1-\theta^{*2})}{2n(\eta_s+\eta_d)}$ *if she purchases solely from* PMP;

ii. $\Pi_a^{*\text{RTB}}(v) = \frac{(v^n - 2^{-n})(\eta_d\theta^{*2} + \eta_s\overline{q}_s)}{2n(\eta_s+\eta_d)}$ *if she purchases solely from* RTB;

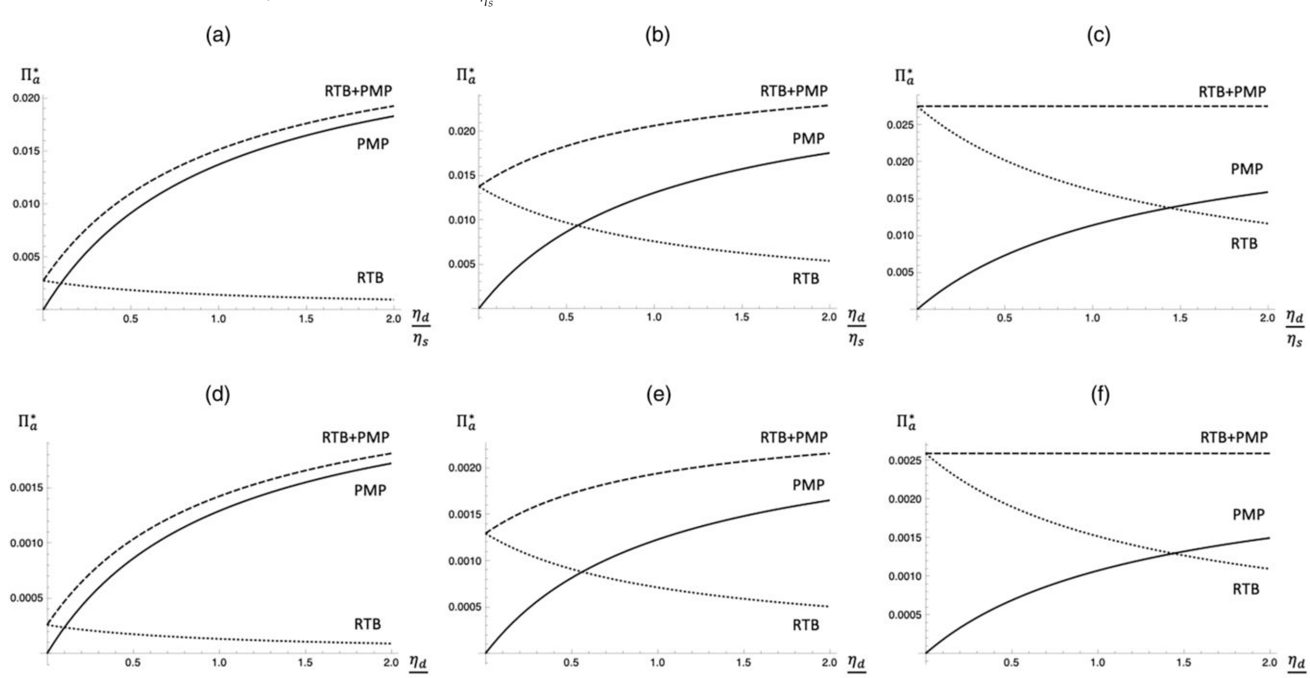
iii. $\Pi_a^{*\text{PMP+RTB}}(v) = \frac{(v^n - 2^{-n})(\eta_d + \eta_s\overline{q}_s)}{2n(\eta_s+\eta_d)}$ *if she purchases from both* PMP *and* RTB.

Lemma 4 indicates that an advertiser's maximum expected payoff depends on the supply (η_s, η_d, and θ^*) from the two publishers, the competitive level on the demand side (which is captured by n), and her channel preferences. The next proposition summarizes advertisers' payoffs across different channel choices.

Proposition 3. *Given* $\overline{q}_d = 1$, $0 < \overline{q}_s \le 1$, *and any* η_d, $\eta_s > 0$, *for any advertiser with valuation* $v, v \in [0,1]$, $\Pi_a^{*\text{PMP+RTB}}(v) > \max\{\Pi_a^{*\text{PMP}}(v), \Pi_a^{*\text{RTB}}(v)\}$.

Proposition 3 states that advertisers achieve higher payoffs by purchasing from both PMP and RTB compared with exclusively from one channel. Figure 2 illustrates the welfare comparison results under various combinations of the $[n, \overline{q}_s]$ values. We make three observations. First, the expected payoff from nonrestrictive purchase is always higher than that from restrictive purchase (i.e., purchasing from PMP or RTB only). Second, the difference between $\Pi_a^{*\text{PMP}}$, $\Pi_a^{*\text{RTB}}$, and $\Pi_a^{*\text{PMP+RTB}}$ varies in η_d/η_s. In particular, when the

Figure 2. Advertiser's Payoff as a Function of $\frac{\eta_d}{\eta_s}$



Notes. This example assumes $v = 0.6$. (a) $\overline{q}_s = 0.1$, $n = 2$. (b) $\overline{q}_s = 0.5$, $n = 2$. (c) $\overline{q}_s = 1$, $n = 2$. (d) $\overline{q}_s = 0.1$, $n = 6$. (e) $\overline{q}_s = 0.5$, $n = 6$. (f) $\overline{q}_s = 1$, $n = 6$.

traffic of the dual-channel publisher exceeds the single-channel's (η_d/η_s is large), the selective allocation of the dual-channel publisher leads to a more pronounced negative effect on the advertiser's payoff if she restricts purchase to RTB. This is consistent with the results from Proposition 2 and Lemma 4. Finally, advertisers' expected payoff decreases as the number of advertisers in the market increases (i.e., the demand-side competition intensifies).

Technically, we can find that $\Pi_a^{*\mathrm{PMP+RTB}}(v)$, which is independent of θ^*, equals the maximum expected payoff for an advertiser with valuation v when neither of the two publishers adopted PMP. At the outset, this result may appear puzzling: Why would quality signaling through PMP not benefit advertisers? The intuition is that the binding quality threshold reduces the supply of PMP impressions, which, in turn, curbs the market reach of advertisers. Note that, in practice, having a broad market reach is critical to the success of an ad campaign (Nielsen 2017): as the average conversion rate for display ads is around 0.55% (Zaric 2023), serving ads to a large audience is not just important, it is necessary. If an advertiser restricts the purchase to PMP, the quality gain cannot offset the loss in market reach. The implication of this result is twofold. First, it highlights a quality versus quantity conundrum similar to that in the context of incentivized word-of-mouth campaigns, where marketers need to decide which endorsers to target (Peng and Van den Bulte 2024). In our case, we find that as long as $q_s > 0$, advertisers are always better off buying from both channels. Second, our finding echoes the ad industry's lament over the insufficient supply on PMP (Chen 2017a), which has prompted practitioners to question the ultimate value of PMP to the display advertising market.

4.2.2. Impact on Publishers. We next proceed to analyzing the welfare implications of the coexistence of PMP and RTB for publishers. Lemma 5 characterizes the equilibrium payoffs of the two publishers.

Lemma 5. *Given $\overline{q}_d = 1$, $0 < \overline{q}_s \le 1$, and any $\eta_s, \eta_d > 0$,*

i. *The single-channel publisher's maximum payoff is* $\Pi^*_{p_s} = \frac{(2^{-n}+n-1)\eta_s(\sqrt{\eta_s^2+\eta_s\eta_d\overline{q}_s}-\eta_s)}{(n+1)\eta_d}$;

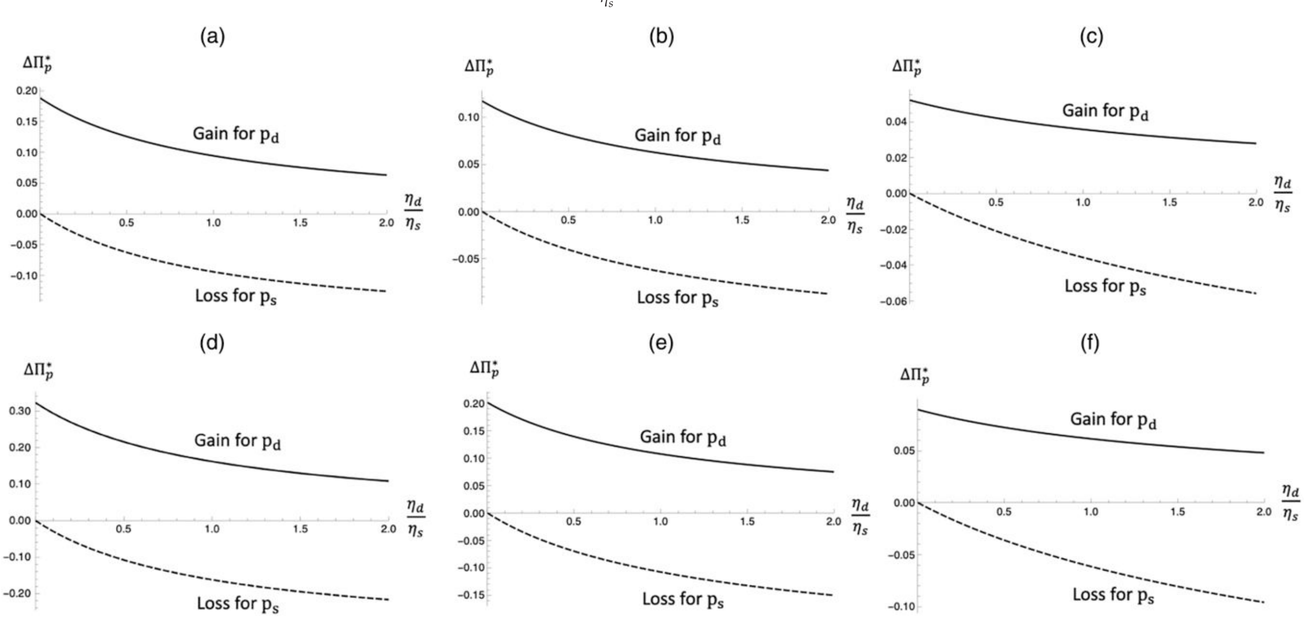
ii. *The dual-channel publisher's maximum payoff is* $\Pi^*_{p_d} = \frac{(2^{-n}+n-1)((\sqrt{\eta_s^2+\eta_s\eta_d\overline{q}_s}-\eta_s)^2+\eta_d^2)}{2(n+1)\eta_d}$.

Based on Lemma 5, we can make a welfare comparison for each publisher. Let $\Pi^*_{p_s,0}, \Pi^*_{p_d,0}$ denote the payoff of the single- and dual-channel publisher in the absence of PMP in the market; $\Delta\Pi^*_{p_s} := \Pi^*_{p_s} - \Pi^*_{p_s,0}$ and $\Delta\Pi^*_{p_d} := \Pi^*_{p_d} - \Pi^*_{p_d,0}$ correspond to the respective payoff differences.

Proposition 4. *Given $\overline{q}_d = 1$, $0 < \overline{q}_s \le 1$, and any η_s, $\eta_d > 0$, $\Delta\Pi^*_{p_s} < 0$; $\Delta\Pi^*_{p_d} > 0$.*

Figure 3 illustrates the insights from Proposition 4 through a series of plots of comparative outcomes of publishers' revenues under different market conditions. The first observation we make is that the coexistence of PMP and RTB always increases the payoff (revenue) of the dual-channel publisher but reduces the payoff (revenue) of the single-channel publisher. Further, we can observe that as the traffic ratio η_d/η_s

Figure 3. Publisher's Revenue Gain/Loss as a Function of $\frac{\eta_d}{\eta_s}$



Notes. This example assumes $v = 0.6$. (a) $\overline{q}_s = 0.1, n = 2$. (b) $\overline{q}_s = 0.5, n = 2$. (c) $\overline{q}_s = 1, n = 2$. (d) $\overline{q}_s = 0.1, n = 6$. (e) $\overline{q}_s = 0.5, n = 6$. (f) $\overline{q}_s = 1, n = 6$.

increases, the extent of revenue losses for the single-channel publisher increases, whereas the magnitude of revenue gains for the dual-channel publisher decreases. The intuition is twofold. First, for any given $\overline{q}_s$, an increase in η_d/η_s leads to a decrease of the optimal quality threshold θ^* (see Proposition 2), which would aggravate the quality discount and, hence, the revenue loss suffered by the single-channel publisher. Second, a small θ^* would reduce the dual-channel publisher's supply on RTB, and thereby, the adverse selection rent extracted through the selective allocation of impressions decreases.

To summarize, our analysis of the equilibrium outcome provides two major insights. First, the availability of PMP does not guarantee benefits for advertisers due to a quality versus reach conundrum: the constrained ad inventory in PMP means that exclusively opting for higher-quality PMP impressions may curb the market reach and, hence, may not be a viable option for advertisers seeking a balance between quality and reach. Advertisers still need to rely on lower-quality RTB impressions to expand their market reach. Second, we show that the disparity in publishers' channel adoption can result in adverse selection, potentially inflicting substantial revenue losses on single-channel publishers. These insights continue to hold after we generalize the analysis to a market with more than two publishers and endogenize the channel adoption decisions of both publishers and advertisers. In particular, we find that as long as there is a nonzero entry cost to PMP, the disparity in publishers' channel adoption will persist, giving rise to adverse selection (see Online Appendix EC.2.2 for more details).

5. Empirical Analysis

To assess whether the analytical insights derived under our game-theoretic model hold in real-world display advertising markets, we conduct an empirical analysis using a large data set of ad transactions, which were retrieved through a demand-side platform managing programmatic ad buying for a vast number of advertisers from both single- and dual-channel publishers in Europe.

5.1. Data

Our data set consists of 9,118,458 bid requests sent from mobile apps to the DSP from April 3 to April 9 in 2019. Each bid request includes (i) supply-side information, such as mobile app/publisher ID, supply-side platform ID, channel (i.e., RTB, PMP), and auction type (first-price or second-price); (ii) ad placement information, such as height, width, and position;[4] (iii) user information, such as user ID, location (latitude and longitude), and device make (e.g., Apple, Samsung); and (iv) floor price, which captures the publisher's pricing decision based on prior knowledge about advertisers' valuation and all the available information (both public and private) about an impression. For each request that our partner DSP bid on, we observe the client (advertiser) ID and the bid price, and for each impression that the DSP won, we have a binary quality measure *Viewable*, which takes the value of one if an impression is visible to a user during a browsing or in-app session, and zero otherwise. The rationale behind our choice of this quality proxy is that, unlike conventional metrics such as click-through rate or conversion rate, viewability does not depend on advertisers' effort but users' browsing behavior, which is jointly affected by users' attributes and publishers' effort. Table 3 illustrates a sample of our data set, encompassing six bidding requests from five different mobile app publishers. Because of space limit, we omit user-related variables in this stylized sample.

In addition to variables recorded in the original data set, we created two categorical variables: *MarketType* and *Format*. *MarketType* classifies impressions into three categories: *SingleRTB* (if an impression was sold by a single-channel publisher via RTB, coded by zero), *DualRTB* (if an impression was sold by a dual-channel publisher via RTB, coded by one), and *DualPMP* (if an impression was sold by a dual-channel publisher via PMP, coded by two). *Format* classifies impressions based on their dimensions (i.e., height and width). The most common formats observed from our data set are 240 × 320 and 250 × 300, which are among the most popular mobile ad formats.

Our empirical analysis primarily focuses on impressions that our partner DSP bid on. After filtering out

Table 3. A Stylized Sample of the Data

App ID	SSP ID	Channel	Auction type	Height	Width	Position	Floor price	Client ID	Bid price	Won	Viewable
9421	431	1	0	240	320	0	1.682	5191	0	0	0
9510	687	0	1	240	320	3	0.761	6734	1.024	1	0
1612	515	1	1	240	320	1	1.883	8182	2.032	0	0
1210	118	0	0	250	300	5	0	6734	1.125	0	0
1871	687	1	1	250	250	1	2.514	5513	3.826	0	0
1612	515	0	0	240	320	0	1.360	5191	1.512	1	1

Notes. Channel: 0, RTB; 1, PMP. Auction type: 0, first-price auction; 1, second-price auction. Position: 0, not disclosed; 1, above the fold; 2, deprecated; 3, below the fold; 4, header; 5, footer; 6, sidebar; 7, full screen. Height and width: in pixels; floor price and bid price: in U.S. dollars.

Table 4. Descriptive Statistics of Key Variables Based on the Subsample that the DSP Bid on: Continuous Variables

Variable	Mean	Median	St. Dev.	Min	Max
Floor price	1.849	1.680	1.132	0	4.510
Bid price	2.872	2.016	1.008	0.100	4.900

impressions with incomplete information and controlling for sparsity, we were left with a total of 433,143 impressions, which account for 95% of the impressions that the DSP bid on. Tables 4 and 5 provide an overview of this subsample.

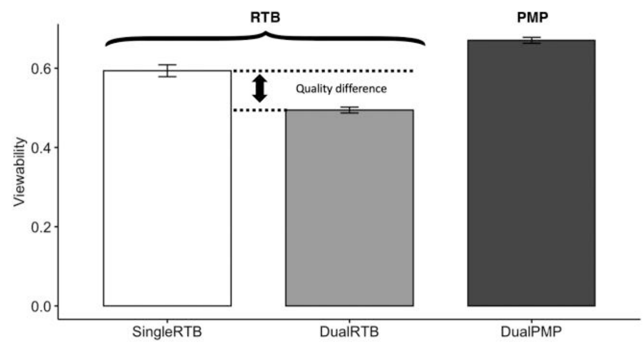
5.2. Model-Free Evidence

We first compare viewability of impressions across the three market types: SingleRTB, DualRTB, and DualPMP. Because viewability is a binary variable, we take the simple average to measure the viewability of impressions from each market type. The descriptive statistics are presented in Table EC.1 in Online Appendix EC.3.1. It is important to note that the DSP assessed viewability postdisplay; hence, we do not have viewability information for impressions that the DSP did not win. We discuss how we address the potential selection bias that arises from the data-generating process in Section 5.3.

Figure 4 shows that PMP impressions from dual-channel publishers indeed have higher viewability than those in RTB. However, in RTB, dual-channel publishers' impressions are less viewable than those from single-channel publishers. We note that such a quality difference by itself does not necessarily mean that there is adverse selection in RTB, unless the quality difference does not correspond to the difference in the average floor price (e.g., the average floor price is comparable or higher for RTB impressions from dual-versus single-channel publishers).

Following this rationale, we compare the viewability of RTB impressions from single- and dual-channel publishers at different floor price levels. Figure 5 shows that, in general, impressions from single-channel publishers have higher viewability than those from dual-channel publishers at the same floor price level. This observation echos the analytical insights in Proposition 2 and suggests overpricing of lower-quality impressions by dual-channel publishers in RTB.

Figure 4. Average Viewability for Different Publisher-Channel Type Combinations



Before moving to the discussion of our empirical strategy, we note that the DSP bid and won a substantial number of impressions with a low floor price from single-channel publishers (see Table 6), which leads to an imbalance in the impressions with a zero floor price between single- and dual-channel publishers. In particular, out of all impressions with a zero floor price that the DSP bid on (won), 4,825 (3,065) were from single-channel publishers, and 888 (263) were from dual-channel publishers. Impressions with a zero floor price typically exhibit lower viewability than those with a positive floor price, as shown in Figure 5. To avoid any potential bias arising from this imbalance, our analysis will focus on impressions with a positive floor price.

5.3. Empirical Strategy

The model-free comparison of impression viewability between single- and dual-channel publishers provides preliminary evidence of adverse selection. In this section, we introduce the empirical strategy that we used to capture and quantify adverse selection in our data set.

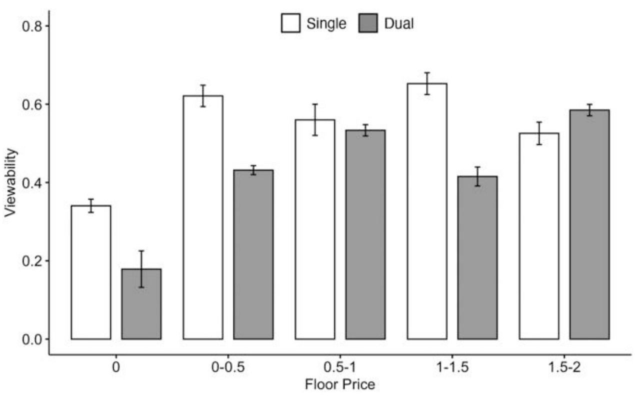
Our empirical analysis follows the rationale that if publishers were to use floor price to truthfully reveal the expected viewability of an impression, then *FloorPrice* would account for a significant amount of the variation in viewability, whereas *MarketType* would have a minimal impact. However, if publishers, depending on their channel choices, choose to withhold private information about low-viewability impressions, *MarketType*

Table 5. Descriptive Statistics of Key Variables Based on the Subsample that the DSP Bid on: Categorical Variables

Variable	Category 1	Category 2	Category 3	Category 4
Market type	0 (8.8%)	1 (25.0%)	2 (66.2%)	
Auction type	0 (14.3%)	1 (85.7%)		
Format	240 × 320 (65.1%)	250 × 300 (33.9%)	250 × 320 (0.7%)	Other (0.3%)
Position	0 (13.4%)	1 (86.5%)	Other (<0.1%)	

Notes. Market type: 0, SingleRTB; 1, DualRTB; 2, DualPMP. Auction type: 0, first-price auction; 1, second-price auction. Position, 0, not disclosed; 1, above the fold.

Figure 5. Average Viewability in RTB



would also explain a significant amount of the variation in viewability, as illustrated by the disparity in Figure 5. Hence, our main outcome variable of interest is *Viewable*, which is a quality proxy of an impression, and the main independent variables are *MarketType* and *FloorPrice*. We also included *Format* and *Position* as controls, as certain formats and positions are more likely to be seen by a user (Harley 2015).

There are two interrelated selection issues in characterizing the relationship between *MarketType* and *Viewable*; both issues are pertinent to the data-generating process. First, the DSP's selection of publishers might be influenced by client preferences. For example, a car manufacturer may assign higher value to traffic from a car review site, irrespective of impression quality, which could skew average viewability. Second, as mentioned in Section 5.1, our analysis is limited to impressions won by our partner DSP, potentially biasing our viewability estimates. For example, if the DSP is more proficient in selecting high-quality (high-viewability) impressions from single-channel publishers than dual-channel publishers in RTB, it might acquire disproportionately more overpriced, low-quality (low-viewability) impressions from dual-channel publishers.

To address these issues, we develop a three-stage model that accounts for the DSP's (unobserved) bidding strategy and the extent of competitive pressure that may affect the main outcome variable (*Viewable*). In particular, we use the two-stage residual inclusion method (Terza et al. 2008) to control for the strategic considerations in the bidding process that influence the DSP's winning probability and a Heckman correction (Heckman 1979) to control for the selection bias related to winning probability. Our three-stage model works as follows:

- In Stage 1, we estimate the DSP's bid price (*BidPrice*) using a linear regression model. The independent variables include *MarketType*, *FloorPrice*, and their interaction; the controls for auction type (*AuctionType*), ad placement characteristics (*Format* and *Position*), and user characteristics (*Latitude*, *Longitude*, and *DeviceMake*); and *ClientID* that serves as an instrument in Stage 2.
- In Stage 2, we characterize the DSP's winning probability using a probit model. To account for unobserved strategic considerations in the bidding process, we use *ClientID* as an instrumental variable. Our selection of this instrument is based on two considerations. First, each client has distinct targeting priorities and budget limitations, making *ClientID* indicative of the heterogeneity in bidding preferences. Second, as *ClientID* remains confidential during auctions, it influences the probability of winning an impression solely through the bid price. Further, we follow Terza et al. (2008) and include both the bid price (*BidPrice*) and the residual (Δ*BidPrice*) from Stage 1 to ensure consistency of the estimation.
- In Stage 3, we estimate impressions' viewability with a probit model, using winning probability derived in Stage 2 as the selection criterion for the Heckman correction. Our exclusion restrictions for identification include *AuctionType*, *DeviceMake*, and the user's physical location (*Latitude* and *Longitude*). *AuctionType* affects the competition level and thereby the winning probability, but does not directly influence viewability; *DeviceMake* is associated with users' perceived willingness to pay (Williams 2018) and, hence, impacts the winning probability, but it does not impact the inherent viewability of an impression; *Latitude* and *Longitude* reflect competitive intensity due to location-based marketing (Andrews et al. 2016) but do not correlate with viewability.

Let $\mathbf{x_1} := (Format, Position)'$, $\mathbf{x_2} := (AuctionType, Latitude, Longitude, DeviceMake)'$. Our three-stage model is specified as follows:

$$\begin{aligned}\text{Stage 1:}\quad & BidPrice\\ &= \gamma_0 + \gamma_1 MarketType + \gamma_2 FloorPrice\\ &\quad + \gamma_3 MarketType \times FloorPrice \gamma_4 \mathbf{x_1}\\ &\quad + \gamma_5 \mathbf{x_2} + \gamma_6 ClientID + \epsilon_1, \end{aligned} \tag{5}$$

Table 6. Floor Prices (in USD) Across Different Market Types

	Impressions that the DSP bid on					Impressions that the DSP won				
Market type	Mean	Median	St. Dev.	Min	Max	Mean	Median	St. Dev.	Min	Max
SingleRTB	0.852	0.660	0.624	0	2.000	0.626	0.360	0.733	0	2.000
DualRTB	0.955	0.850	0.532	0	2.000	0.905	0.710	0.633	0	1.890
DualPMP	2.319	1.690	1.059	0.330	4.510	1.991	1.680	0.792	1.120	4.498

$$\text{Stage 2:}\quad Pr(Won = 1 | MarketType, FloorPrice, \mathbf{x_1}, \mathbf{x_2}, BidPrice, \Delta BidPrice) = Pr(\beta_0 + \beta_1 MarketType + \beta_2 FloorPrice + \beta_3 MarketType \times FloorPrice + \beta_4 \mathbf{x_1} + \beta_5 \mathbf{x_2} + \beta_6 BidPrice + \beta_7 \Delta BidPrice + \epsilon_2 > 0), \tag{6}$$

$$\text{Stage 3:}\quad Pr(Viewable = 1 | MarketType, FloorPrice, \mathbf{x_1}) = Pr(\alpha_0 + \alpha_1 MarketType + \alpha_2 FloorPrice + \alpha_3 MarketType \times FloorPrice + \alpha_4 \lambda + \alpha_5 \mathbf{x_1} + \epsilon_3 > 0), \tag{7}$$

where λ is the inverse Mills ratio, $\epsilon_1, \epsilon_2, \epsilon_3 \sim \mathcal{N}(0,1)$, $cov(\epsilon_1, \epsilon_2) = cov(\epsilon_1, \epsilon_3) = 0$, and $corr(\epsilon_2, \epsilon_3) = \rho$—that is, ϵ_1 is independent of ϵ_2, whereas ϵ_3, (ϵ_2, ϵ_3) follows a bivariate normal distribution. In the estimation, we use the natural logarithm of *FloorPrice* plus one and denote the log-transformed variable by *LnFloor*.

5.4. Estimation Results

We apply the three-stage model to the subsample of impressions that the DSP bid on, excluding those with a zero floor price.[5] Table 7 reports the estimation results. In Stage 1 (column (1)), based on the estimated coefficients for *DualRTB* (0.196***) (where *** indicates $p < 0.01$) and *DualRTB* × *LnFloor* (0.051***), the DSP bid higher for RTB impressions from dual-channel publishers than single-channel publishers for any given

Table 7. Estimation Results from the Three-Stage Model

Variable	Stage 1: Bid Price (1) OLS	Stage 2: Won (2) Probit	Stage 3: Viewable (3) Probit
Intercept	3.126***	−3.431***	−0.262*
	(0.094)	(0.307)	(0.150)
DualRTB	0.196***	0.559***	**−0.789*****
	(0.012)	(0.025)	(0.051)
DualPMP	−0.885***	0.458***	−0.120*
	(0.011)	(0.031)	(0.068)
LnFloor	−0.122***	0.487***	0.044
	(0.014)	(0.030)	(0.058)
DualRTB × LnFloor	0.051***	−0.537***	0.683***
	(0.016)	(0.035)	(0.067)
DualPMP × LnFloor	0.866***	−0.950***	0.305***
	(0.014)	(0.037)	(0.076)
Format(250 × 250)	−1.235***	0.211***	0.402***
	(0.022)	(0.054)	(0.109)
Format(250 × 300)	−1.251***	0.134***	0.403***
	(0.003)	(0.024)	(0.017)
Format(250 × 320)	−0.645***	0.923***	−0.402***
	(0.014)	(0.033)	(0.058)
Position(1)	−0.396***	2.421***	0.202*
	(0.012)	(0.036)	(0.119)
AuctionType(2)	−0.032***	−1.111***	
	(0.012)	(0.021)	
Latitude	−0.014***	0.012**	
	(0.002)	(0.006)	
Longitude	0.003***	−0.008***	
	(0.001)	(0.002)	
BidPrice		0.134***	
		(0.019)	
ΔBidPrice		−0.038**	
		(0.019)	
λ			0.085***
			(0.031)
DeviceMake	Yes	Yes	
ClientID	Yes		
Observations	427,472	427,472	36,901
R^2	0.477		
Adjusted R^2	0.476		
Log likelihood		−112,579.300	−24,055.500
Akaike Inf. Crit.		225,378.600	48,133.010
F statistic	3,474.981***		

Notes. All coefficients are estimated at the impression level. Robust standard errors are in parentheses. λ denotes the inverse Mills ratio. Boldface type indicates that is the core value of interest of the analysis. Inf. Crit., information criterion.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

floor price, holding other impression/user characteristics constant. When comparing the bid price for PMP impressions and RTB impressions from single-channel publishers, the negative main effect of *DualPMP* (-0.885^{***}) may appear to be surprising at first sight but not quite so if we take into account other factors. In particular, recall from Table 6 that most PMP impressions have a high floor price. Given the strong, positive interaction effect of *DualRTB* and *LnFloor* (*DualRTB* × *LnFloor*: 0.866^{***}), the DSP would still bid higher, on average, for PMP impressions than RTB impressions from single-channel publishers. Another important observation we make is that the baseline bid price decreases in the floor price (*LnFloor*: -0.122^{***}), which suggests that the DSP may have allocated more budget to impressions with a high floor price from dual-channel publishers. We note that ad placement characteristics (i.e., *Format*, *Position*), auction type, user characteristics (i.e., *Latitude*, *Longitude*, *DeviceMake*), and *ClientID* also explain a significant amount of the variation in the DSP's bidding strategy (see Table EC.10 in Online Appendix EC.3.2).

Column (2) presents the estimation results from Stage 2. We can observe that the DSP's bidding strategy leads to a higher probability of winning impressions from dual-channel publishers than from single-channel publishers (*DualRTB*: 0.559^{***}, *DualPMP*: 0.458^{***}), although the winning probability decreases as the floor price increases (*DualRTB* × *LnFloor*: -0.537^{***}, *DualPMP* × *LnFloor*: -0.950^{***}). The estimation results shown in column (2) also provide assurance of the effectiveness of our empirical strategy. In particular, the significant estimate for the residuals from Stage 1 (Δ*BidPrice*: -0.038^{**}) (where ** indicates $p < 0.05$) suggests that this term captures a proportion of the unobserved strategic considerations influencing the probability of winning an impression. Further, all exclusion restrictions—that is, *AutionType*, *Latitude*, *Longitude*, and *DeviceMake* (see Table EC.10 in Online Appendix EC.3.2 for detailed results)—are significant.

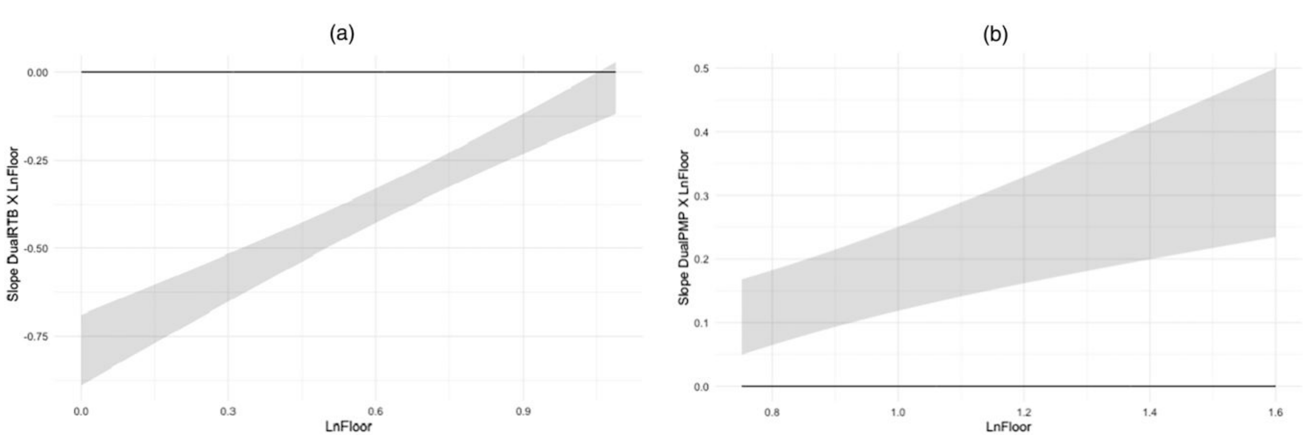
Moving on to the estimation results for viewability (column (3)), we make three main observations. First, the viewability of RTB impressions from single-channel publishers does not vary in the floor price (*LnFloor*: insignificant). Second, RTB impressions offered by dual-channel publishers are less viewable than those from single-channel publishers (*DualRTB*: -0.789^{***}). As the floor price increases, the viewability of these impressions increases (*DualRTB* × *LnFloor*: 0.683^{***}); however, given the range of floor prices (*LnFloor*: 0–1.09) for all impressions won by the DSP, the net effect remains negative; see Figure 6(a) for an illustration. Taken together, these observations suggest that dual-channel publishers are allocating lower-quality impressions to RTB, while matching floor prices of those from single-channel publishers, which are consistent with our analytical insights from Propositions 1 and 2. Third, the viewability of PMP impressions improves significantly in the floor price (*DualPMP* × *LnFloor*: 0.305^{***}). It is worth noting that the negative coefficient of *DualPMP* (-0.120^{*}) (where * indicates $p < 0.1$) is an artifact: because the minimum floor price of PMP impressions won by the DSP is \$1.12 (see Table 6)—that is, *LnFloor* = 0.75—the net effect is still positive, as shown in Figure 6(b). It is worth noting that the estimated coefficient for the inverse Mills ratio is positive (λ: 0.085^{***}), suggesting that the impressions won by the DSP are more viewable than they would be under random selection.

5.5. Robustness Checks

We conduct a series of robustness checks to validate our findings. Table 8 provides an overview, where we list the specific robustness concerns, along with the respective specific strategies taken.

To start with, the observed relationship between market type and viewability may arise spuriously

Figure 6. Visualization of the Net Effect of *DualRTB* and *DualPMP* Under Different Floor Prices



Notes. (a) *DualRTB*. (b) *DualPMP*.

Table 8. Summary of Robustness Checks

Robustness concern	Validation strategy	Result	Reference
Spurious correlation of main dependent variable	Falsification test	Insignificant	Table 9
Demand-side competition	Re-estimate based on different success rates	Significant	Table EC.2
SSP quality heterogeneity	Re-estimate with SSP ID controls	Significant	Table EC.3
App quality heterogeneity	Re-estimate with App ID controls	Significant	Table EC.4
Daily seasonality	Re-estimate based on different times of day	Significant	Table EC.5
Weekly seasonality	Re-estimate for weekdays and weekends	Significant	Table EC.6
Bid price distribution	Re-estimate with log-transformed bid price	Significant	Table EC.7

from the distribution of impressions across different market type categories. To rule out this possibility, we conduct a falsification test by randomly assigning each impression to one of the three market type categories according to the empirical distribution shown in Table 5 and estimating the probit model specified in Equation (7) without accounting for selection issues. Note that the dummy variables *DualRTB* and *DualPMP* no longer reflect the actual choices made by the publishers. We repeat the random assignment and estimation 100 times and calculate the mean and standard deviation of the coefficient for *DualRTB* and *DualPMP*, respectively. We then apply the same probit model to the real data and obtain the estimate of the same coefficients (see Table EC.9 in the Online Appendix). Table 9 summarizes the results of the falsification test, where we denote the coefficients estimated from the real data by α, and those from the randomly shuffled sample by $\tilde{\alpha}$. We can see that the estimates from the randomly shuffled sample are not significantly different from zero but significantly differ from those from the actual data, suggesting that the observed viewability differences from Table 7 are unlikely to be driven by spurious correlation.

Another validity threat to our estimation is the potential confounding effects associated with demand-side competition. Specifically, acquiring high-quality impressions from certain publishers could be challenging due to intense competition. If the low-quality *DualRTB* impressions in our sample were to coincide

Table 9. Results of the Falsification Test

	DualRTB	DualPMP
Mean of $\tilde{\alpha}$	0.001	−0.006
Std. dev. of $\tilde{\alpha}$	0.049	0.052
α	−0.829	−0.120
H0: $\tilde{\alpha} = 0$		
Z-score	0.0247	−0.1208
p-value	1	0.904
H0: $\tilde{\alpha} = \alpha$		
Z-score	−16.951	−2.159
p-value	<0.001	0.031

Note. $\tilde{\alpha}$ denotes the estimated coefficient based on the random assignment of market type categories, whereas α denotes the estimated coefficient based on the real data.

with the limited success purchases from those publishers, our results might reflect competition rather than adverse selection. To assess this possibility, we re-estimate the three-stage model using three subsamples that consist of impressions offered by publishers from which the DSP won at least 100; 300; and 500 impressions, respectively. Table EC.2 in the Online Appendix shows the estimation results for Stage 3, which are largely consistent with those from our main analysis. In particular, the estimated coefficients for *DualRTB* and *DualPMP* remain qualitatively unchanged.

Our third robustness check focuses on the quality differences among SSPs. SSPs, serving as intermediaries that distribute publishers' impressions to the market, often work with multiple publishers simultaneously. In practice, some SSPs may consistently offer lower-quality impressions than others. If our partner DSP happened to have purchased RTB impressions from dual-channel publishers working with lower-quality SSPs, our observed effects could be misleading. We address this concern by including SSP IDs as control variables in the three-stage model. Table EC.3 in the Online Appendix reports the estimation results for Stage 3. We make three observations. First, RTB impressions from dual-channel publishers continue to be less viewable. Second, the viewability improvement associated with the increase in the floor price for these impressions is less pronounced, suggesting that a set of SSPs consistently offer higher-quality, higher-priced impressions. Third, despite the coefficient for *DualPMP* × *LnFloor* remaining positive, the net effect of *DualPMP* reverses and becomes negative, which reinforces the possibility that the higher-quality PMP impressions in our sample may originate from a specific set of SSPs.

In a similar vein, the observed effects may pertain to a specific set of publishers. For example, some publishers may consistently deliver low-quality impressions, yet our partner DSP was not aware of such practices. To rule out this possibility, we include mobile app/publisher IDs as controls and re-estimate the model. Table EC.4 in the Online Appendix shows that after accounting for publisher/app IDs, the estimated effects remain consistent with those from the main analysis, which indicates that our findings regarding the lower viewability of RTB impressions from dual-channel publishers are unlikely to be driven by a few outlier publishers. Note that we cannot include both SSP IDs and app IDs as controls simultaneously in the model, because in combination, SSP IDs and app IDs perfectly identify market type categories for a large number of publishers. In other words, including both controls would lead to severe multicollinearity, which would make the estimated coefficients unreliable.

Because users' online/in-app behaviors exhibit strong seasonality (Kanuri et al. 2018, Zhang et al. 2021), which, in turn, impact both supply- and demand-side dynamics in the display advertising market, we further examined whether the observed adverse selection effects related to impression quality varied at different times of the day and different days of a week. In particular, if certain times of day featured both higher volume and more intense competition for RTB impressions from dual-channel publishers compared with single-channel publishers, the DSP might be more likely to secure lower-quality impressions from these publishers. To assess this possibility, we followed Kanuri et al. (2018) and divided a day into four periods: night (12:00 a.m.–5:59 a.m.), morning (6:00 a.m.–11:59 a.m.), afternoon (12:00 p.m.–5:59 p.m.), and evening (6:00 p.m.–11:59 p.m.). We then re-estimated our three-stage model for each period. Table EC.5 in the Online Appendix reports the results for morning, afternoon, and evening periods, excluding the night due to the low volume of traffic and resulting small sample size. We can observe that the negative effect of *DualRTB* persists throughout the day, with the strongest effects in the afternoon and evening. Similarly, we assessed whether differences in competition between weekdays and weekends could account for our findings. Table EC.6 reports the results, which remain largely consistent with those from the main analysis, except that the net effect *DualRTB* loses significance at high floor prices, primarily due to the limited number of relevant observations in this subsample.

Finally, we re-estimate the three-stage model by using log-transformed bid price in the first stage to alleviate the concern around the distribution of the DSP's bid prices. Table EC.7 in the Online Appendix summarizes the results. We note that the main coefficient estimates of interest remain unchanged (column (3), *DualRTB*: -0.789^{***}, *DualRTB* $\times$ *LnFloor*: 0.683^{***}) compared with the results from the main analysis, and the rest of the coefficient estimates are also consistent with those from Table 7.

Overall, our empirical analysis shows that RTB impressions from dual-channel publishers are of significantly lower quality (i.e., less viewable) than those from single-channel publishers, although the exact size of the quality difference (see Table EC.11 in the Online Appendix) may depend on market conditions, as reflected in our robustness checks. These findings lend strong empirical support to our theoretical predictions of adverse selection in RTB.

6. Conclusion

Display advertising has become an integral part of the digital economy. Despite its exponential growth, concerns over impression quality in programmatic ad buying have escalated, leading many publishers to adopt PMP alongside RTB. In this paper, we study how the coexistence of PMP and RTB affects publishers' decisions on impression allocation and pricing, as well as the competitive dynamics in the display advertising market. Through a combination of game-theoretic analysis and empirical analysis using real-world ad transaction data, we show that the disparity in publishers' channel choices may lead to adverse selection in RTB. Specifically, dual-channel publishers may have the incentive to exploit their information advantage on impression quality to consistently offer lower-quality impressions than their single-channel counterparts, leaving the latter with revenue losses.

Our study contributes to the understanding of the complex interplay of informational and strategic factors in the display advertising market in several ways. To begin with, this is, to the best of our knowledge, the first study that examines the welfare implications of the coexistence of PMP and RTB for both publishers and advertisers. As such, our findings enrich the literature on the effects of publishers' impression allocations policies. Our analysis reveals an unintended consequence of using PMP as a quality-signaling device. Contrary to the common belief of its efficacy in mitigating information asymmetry, we show that PMP's quality-signaling role may aggravate the problem. This is because advertisers, seeking to balance quality with market reach, cannot limit their purchase solely to PMP due to its supply constraints. Such a quality versus quantity conundrum highlights the complexity of addressing the issue of information asymmetry amidst the coexistence of PMP and RTB in the display advertising market. To this point, it is worth noting that although our analysis was geared toward the specifics of display advertising, our findings also contribute to the broader literature on market design by showcasing how adverse selection manifests itself in multichannel markets.

Our study also provides important insights for business practice. First, for advertisers, our findings underscore the importance of strategic planning in navigating the dual-channel market to fulfill their advertising needs. In particular, because purchasing exclusively from PMP is not viable, advertisers and their demand-side partners must develop effective multichannel strategies. Second, for publishers, especially those who cannot afford operating both on and

PMP, our analysis suggests that the ongoing development of viewability technologies may eventually bring a more level playing ground by enabling advertisers to discern impression quality. Hence, transparent pricing is critical for sustaining long-term relationships with advertisers and maintaining a reputable brand in the competitive market. Third, by documenting the potential adverse selection and its effects on market participants, our study suggests the need for regulatory measures to address the issue of transparency within the programmatic advertising market.

We close by acknowledging that our study bears several limitations, which open avenues for future research. For example, our current game-theoretic model has not taken into account the strategic decisions of intermediaries such as SSPs, DSPs, or ad exchanges. Exploring how publishers would allocate and price impressions across channels in the presence of these intermediaries could be an interesting research direction. Further, we note that, in practice, market authorities may conduct periodic or random audits on impression quality. Such a possibility may reduce the extent to which dual-channel publishers can selectively allocate their impressions. Analyzing the implications of policy interventions related to impression allocation will be a fruitful research direction.

Our empirical analysis relies on a sample that consists of bid requests retrieved by a European DSP throughout a week in April 2019. Hence, our results are subject to external validity considerations when it comes to the generalizability of the effect sizes. In addition, although our choice of quality proxy (viewability) allows us to isolate the impact of publishers' information advantage in dual-channel operations, such a quality metric only captures part of the picture. For example, viewable impressions may be placed along with content that is inappropriate or unsafe (e.g., spam, malware, fake news) for a brand's identity, in which case additional quality metrics must be used in conjunction with viewability. Finally, because our data set does not contain competitor bid information, we are not able to estimate the economic impact of dual-channel publishers' selective allocation or perform policy counterfactuals under alternative market structures, such as an RTB-only scenario. Exploring these aspects could lead to deeper insights into the design and operationalization of real-world display advertising markets.

Acknowledgments

The authors are grateful to the department editor (Prof. Anindya Ghose), the anonymous associate editor, and three anonymous reviewers for their helpful comments and suggestions.

Endnotes

[1] According to the Media Ratings Council of the Interactive Advertising Bureau, an ad impression is considered as *viewable* if at least 50% of its pixels are visible for a minimum of one second (Interactive Advertising Bureau 2014).

[2] For example, according by Interactive Advertising Bureau (IAB) (2024) guidelines, "Viewable impressions are required for attribution of outcomes to ad exposures", highlighting that merely serving impressions is not enough.

[3] The rational expectations concept has been widely used in studying market dynamics and performance with strategic participants (Muth 1961, Su and Zhang 2009, Kalkanci and Plambeck 2020).

[4] A full description of ad position is available at https://www.iab.com/wp-content/uploads/2016/03/OpenRTB-API-Specification-Version-2-5-FINAL.pdf, pp. 45–46 (accessed April 3, 2025).

[5] We also run the three-stage model by including impressions with a zero floor price. The main effects remain qualitatively unchanged; see Table EC.8 in the Online Appendix for details.

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