Bidders’ Responses to Auction Format Change in Internet Display Advertising Auctions*

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Abstract

We study actual bidding behavior when a new auction format gets introduced into the marketplace. More specifically, we investigate this question using a novel dataset on internet display advertising auctions that exploits a staggered adoption by different publishers (sellers) of first-price auctions (FPAs), instead of the traditional second-price auctions (SPAs). Event study regression estimates indicate that, immediately after the auction format change, the revenue per sold impression (price) jumped considerably for the treated publishers relative to the control publishers, ranging from 35% to 75% of the pre-treatment price level of the treatment group. Further, we observe that in later auction format changes the increase in the price levels under FPAs relative to price levels under SPAs dissipates over time, reminiscent of the celebrated revenue equivalence theorem. We take this as evidence of initially insufficient bid shading after the format change rather than an immediate shift to a new Bayesian Nash equilibrium. Prices then went down as bidders learned to shade their bids. We also show that bidders’ sophistication impacted their response to the auction format change. Our work constitutes one of the first field studies on bidders’ responses to auction format changes, providing an important complement to theoretical model predictions. As such, it provides valuable information to auction designers when considering the implementation of different formats.

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1 Introduction

The auction literature has thrived in the past several decades, starting with classical theoretical work such as Vickrey (1961) and followed by more recent advances in empirical studies, particularly those using structural econometric approaches (see, e.g., Hendricks and Porter, 2007; Athey and Haile, 2007). Most of this literature assumes that auction bidders are rational and play Bayesian Nash equilibrium strategies, following the game-theoretic tradition. The equilibrium prediction is simple with second-price auctions (SPAs) under private values: truthful bidding is a dominant strategy. By contrast, under first-price auctions (FPAs), Bayesian Nash equilibrium strategies require more sophistication from bidders: they should optimally shade their bids to balance the trade-off between paying lower prices and decreasing their chances of winning (Vickrey, 1961).

At the same time, economists and scientists in other fields are becoming increasingly aware that agents consistently deviate from rational behavior, as illustrated in the seminal work of prospect theory by Kahneman and Tversky (1979). Moreover, an extensive experimental literature, surveyed in Kagel (1995) and Kagel and Levin (2016), has challenged bidders’ rationality predictions from auction theory. For example, contrary to equilibrium predictions, the literature has observed higher prices in first-price auctions compared to Dutch auctions (Cox et al., 1982). More broadly, as researchers came to find discrepancies between predictions by conventional auction models and reality, they also got interested in how bidders learn or adjust their bidding strategies over time. For instance, Kagel et al. (1987) study bidding when experiment subjects participate in auctions repeatedly.

Despite all these works, to the best of our knowledge, there have been few field studies about learning in auctions. A notable exception is Doraszelski et al. (2018), who analyze bidders’ learning when a new auction market is introduced. Understanding bidders’ responses to a market design change is fundamental for policy makers as well as profit-maximizing platforms as they consider which auction format to implement among the various alternatives. For example, in the real-time sponsored search advertising market—one of the largest auction markets worldwide—there was a historical dilemma between using second-price and first-price auctions and the potential implications for bids and revenues. A similar discussion arose in the past few years in the display advertising industry regarding a transition from the traditionally used second-price auctions to first-price auctions (see Section 2.1).

Thus motivated, in this work we present one of the first field studies in the literature, investigating bidders’ responses to a change from one canonical auction format to another. Specifically, we study how bidders learn to bid when a new auction format is introduced into the marketplace. We investigate this question in the setting of internet display advertising auctions. To quantify bidders’
responses to the format change over time, we exploit staggered adoptions by different publishers (sellers) of first-price auctions (FPAs), instead of the second-price auctions (SPAs) traditionally used in real-time bidding. We then address two questions: (1) How quickly do bidders learn to bid in the new (FPA) environment? (2) How do different bidders react to the format change?

We use daily revenue data for auctions administered by a major ad exchange platform operated by Xandr (formerly known as AppNexus). The dataset records, for each publisher–bidder pair and on each day, the number of sold impressions (i.e., the number of auctions resulting in a sale) on the platform and the aggregate revenue (i.e., the sum of the auction clearing prices). The scale of the auctions is massive: our data tallies hundreds of millions of auctions each day. To our knowledge, this is the first work in the literature using data studying an auction format change in display ad exchanges.

In our dataset, publishers switched from SPAs to FPAs in four batches: (i) September 2017, (ii) September 2019, (iii) April 2020, and (iv) June 2020. We estimate event study regressions by contrasting these publishers (treatment group) with other publishers that did not switch to FPAs on these dates (control group).

Our results show that, immediately after the format change to FPAs, the average revenue per sold impression (the average price) jumped considerably for the treated publishers relative to the control publishers. The magnitude of this jump ranges from 35% to 75% of the pre-treatment price level of the treatment group. Further, in the last three format changes, we observe that the increase in the price levels under FPAs relative to the price levels under SPAs dissipates over the next 30 to 60 days.

We interpret our results as providing evidence of initially suboptimal, insufficient bid shading from the truthful bidding strategy after the format change from SPA to FPA. If all bidders were behaving rationally, the average price would move from the mean of the second-order statistic of the bidder valuations under SPA (or the reserve price, whichever is higher), to the average highest price under some Bayesian Nash equilibrium that involves bid shading under FPA. Furthermore, it would stabilize at the new level immediately after the format change. The fact that the increase is transitory, we believe, strongly suggests initial insufficient bid shading, followed by a reduction in price as bidders learn to shade their bids under FPA.

It is interesting to observe that the price levels under FPA and SPA eventually converge. This is reminiscent of the celebrated revenue equivalence theorem shown by Vickrey (1961), Myerson (1981), and Riley and Samuelson (1981). We think that this result is quite remarkable in light of the fact that the prerequisites for the standard statement of the revenue equivalence theorem (such as bidder symmetry) generally do not hold in our setting (Maskin and Riley, 2000).1

1Interestingly, a recent study by Balseiro et al. (2021) derives revenue equivalence for standard auctions (including SPAs and FPAs) in a setting that encompasses display ad auctions, i.e., where the bidders have budgets for multiple
Furthermore, it took less time for the price levels under FPAs to go down to the price levels under SPAs following the format change in 2019 compared to that in 2017, and it took even less time following the format changes in 2020 than the format change in 2019. This pattern suggests that bidders learn over time how to better shade their bids using a combination of first-hand experience and industry-wide learning.

Our results suggest that existing auction theory can fail to correctly predict bidder behavior in the short run, which is an important fact for market designers. In the short run, bidders may have trouble bidding optimally and so it may appear that first-price auctions are driving price increases. As a result, it is easy for myopic market designers to draw a wrong conclusion that a format change increases prices. However, over the long run, as bidders adjust to market dynamics and learn to bid more effectively, the price increase dissipates. While we believe that there are compelling reasons for internet display advertising auctions to switch to FPAs, one of them does not seem to be that they make publishers or ad exchanges more money per sold impression in the long run.

We also study the heterogeneity of the effect of the auction format changes across bidders. Specifically, we use an event study design to estimate the impact on price, separately for the bidder representing advertisers that use the bidding algorithm provided by the ad exchange (“App-Nexus/Xandr bidder”) and the rest of the bidders that use other bidding algorithms. We find that, in three out of four format changes, the latter type of bidders see a bigger increase in price than the AppNexus/Xandr bidder. This suggests that the heterogeneity of the bidders’ sophistication impacts how they respond to the format change: advertisers that use the ad exchange’s bidding algorithm are more sophisticated in bidding, and so they shade more than other, “naive” bidders.

Finally, we present several alternative specifications and a falsifying test as robustness checks. We also present evidence that ad campaign budgets play a limited role, if any, in the main results; thus, we believe it is reasonable to interpret our results as a result of auction dynamics.

Our work contributes to the growing literature on first-price auctions in the display advertising industry, such as Balseiro et al. (2021) and Han et al. (2020). These papers use theoretical methods, and our work complements the literature by taking an empirical approach. Our work also contributes to the operations management and management science literatures that study various market design aspects of the display advertising industry; see, e.g., Celis et al. (2014) on the tension between surplus from targeting and market thickness, Golrezaei et al. (2021) on financially constrained buyers, Fridgeirsdottir and Najafi-Asadolahi (2018) on guaranteed delivery contracts (a form of selling ad spaces other than by auctions). Agarwal et al. (2020), Choi et al. (2020), Korula et al. (2016), and Muthukrishnan (2009) provide surveys on various issues around the display advertising industry from the operations, information systems, economics, and computer science perspectives. More broadly, it is also related to work in operations using quasi-experimental data auctions and need to pace their bids to meet the budget constraint.
to study important changes in digital platforms, such as Li and Netessine (2020), Farronato et al. (2020), and Gallino and Moreno (2014).

The rest of the paper is organized as follows. Section 2 provides a detailed background on display advertising in general, and the overall trend of switching from SPAs to FPAs in particular. We then explain our dataset and the particular format changes that we exploit in our event study regressions. Section 3 is the body of our analysis: we present summary statistics, event study regressions, and an interpretation of our regression estimates. We also conduct several robustness checks here. Section 4 augments our main analysis by investigating the heterogeneity of spending responses by different types of bidders. Section 5 concludes. The Appendices present supplementary figures and results under alternative specifications.

2 Institutional Background and Data

2.1 The Display Advertising Industry

Digital advertising is a huge industry, with $129 billion spent in the U.S. in 2019, which is more than half of total media advertising spending (Skai, 2019). Digital advertising consists mainly of two forms: (1) display advertising, which allows website publishers to monetize the ad spaces on their websites, and (2) search advertising, which shows ads that are relevant to search terms entered on search engines. Display advertising accounted for $70 billion in the U.S. in 2019 (Skai, 2019). A significant portion of display advertising ($22 billion in the U.S. in 2019; Fisher, 2020) is sold using auctions with real-time bidding (RTB), which is the focus of this study.

Figure 1: Diagram of display advertising auctions with real-time bidding. Source: Yuan et al. (2014), modified by the authors.

Figure 1 is a diagram, simplified for presentation, that explains how these auctions are run. The website publisher prepares a web page that contains ad spaces, which are slots on the web page dedicated for advertising contents. The process of RTB starts when an internet user visits
that web page (1), whether on a computer or a mobile device. The web browser loads the HTML source code of the web page, which contains a code snippet to show the ad content. The browser, by loading that code snippet, sends a request to the ad exchange that an advertising be served, which is called an ad request or ad call (2). The ad exchange then uses an auction to decide which advertiser will serve the ad. (For many digital publishers, there are additional systems that make decisions before the ad request reaches the ad exchange or after the ad exchange selects a winning bid. However, for the publishers in this study, Figure 1 is a useful depiction of the process during the data period.)

Typically advertisers retain intermediaries, called demand-side platforms (DSPs), that submit bids to the ad exchange on their behalf. The ad exchange requests bids from the DSPs (3), and the DSPs submit bids on behalf of advertisers based on the parameters that the advertisers configure in their advertising campaigns (4). When bids are collected, the ad exchange determines the winning bidder and the auction price, and the winning advertiser (selected by the winning bidder) gets to serve its advertising content to the internet user (5).

This entire process (starting from the internet user’s visit to a webpage and ending with the ad content being served) is automated and completed in milliseconds. The ad exchange runs hundreds of billions of such auctions every day. Each instance of serving an advertisement in one ad space is called an impression. There is, in principle, one auction per impression. If the web page contains multiple ad spaces (e.g., at the top of the page and in the right column), there are multiple auctions and multiple impressions each time a user loads that page.

Traditionally, display advertising was sold using second-price auctions in parallel with the tradition of search advertising (Edelman et al., 2007; Wang et al., 2017). However, there has been a growing trend of shifting from second-price auctions to first-price auctions to sell display ads, culminating in Google’s decision to change its auction format for Google Ad Manager from SPA to FPA announced in March 2019.2 This movement started with the selling side’s desire to extract revenue above the second-highest bid: often, publishers observed a large gap between the highest and second-highest bids, sometimes as much as 70% (Bender, 2016). As a result, the selling side developed yield-enhancing technologies, such as “hard floors” and “soft floors.”3 One such technology, Dynamic Price Floors, which adjusts the price floors programmatically and in real time (Bender, 2016), was criticized as opaque (Doherty, 2014). Advertisers were especially concerned that the price floors were manipulated so that they got very close to the highest bid,

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2https://www.blog.google/products/admanager/simplifying-programmatic-first-price-auctions-google-ad-manager/

3Hard floors are traditional reserve prices. Soft floors work as follows. If there are bids above the soft floor, the winner, i.e., the bidder with the highest bid, will pay the soft floor or the second-highest bid, whichever is higher (second-price auction). If all bids are below the soft floor, the winner will pay her own bid (first-price auction). Zeithammer (2019) analyzes equilibrium bidding in auctions with soft floors.
essentially requiring them to pay what they bid (Caruso, 2015): they even had suspicions that the price floors were being set after the bids had been submitted (Benes, 2017). (This is exactly the incentive compatibility concern regarding SPAs raised by Akbarpour and Li, 2020). First-price auctions have been seen as a way to solve this transparency concern, while ostensibly solving sellers’ concerns about the gap between the highest and second-highest bid (Sluis, 2017). The advent of header bidding also strengthened the argument for the adoption of FPAs (Despotakis et al., 2021). This work excludes data of publishers running header bid auctions.

### 2.2 Data and Auction Format Change from SPAs to FPAs

Our goal is to investigate bidders’ responses to the switch from SPAs to FPAs by publishers. For this purpose, we use the dataset of a major ad exchange platform operated by Xandr. The data is aggregated in the following manner. Publisher revenue and the number of sold impressions are tallied for all auctions run on each day, separately for each publisher–bidder pair. In other words, our data records that a given publisher earned $X by selling Y impressions to a given bidder.4 We do not have auction-level data such as revenue and losing bids for each auction. We focus on real-time bidding (RTB) auctions with no pre-negotiated deals between the publisher and any bidders.5

We use data on two sets of publishers: publishers owned by a company that operates globally (“Global Company”), and publishers owned by three different media companies operating in Europe (“European Media Companies”). The Global Company has several different functionalities, and each functionality has a website (publisher) in virtually every country/jurisdiction across the world. The three European Media Companies have many websites (publishers) such as those for newspapers and magazines: one such company, Company A, has many publishers in different parts of Europe, while the other two companies, Companies B and C, operate exclusively in one European country, Country Y.

We compare four sets of treatment–control pairs of publishers (Figure 2):

1. Publishers of the Global Company switched to FPA in two waves: a large majority of publishers on September 21, 2017, and the remaining publishers on February 1, 2018. The change took place at the country level: all publishers in smaller countries/jurisdictions switched in September (“September Publishers”), and all publishers in larger countries/jurisdictions switched in February (“February Publishers”). The data period is June 2011 to September 2019. We compare September Publishers (treatment group) to February Publishers (control group).

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4 In this example, the number of impressions Y excludes auctions that did not result in the delivery of advertising contents for reasons such as server timeouts or failure of bids to meet the reserve price.

5 For example, Kim et al. (2021) studies the impact of deals on publisher revenue.
Figure 2: Types of publishers and dates of format changes. The four columns on the right indicate treatment–
control pairs in the event study regressions (“T” indicates the treatment group and “C” indicates the control
group). The gray bars represent periods under SPA and the orange bars represent periods under FPA.

2. European Media Company A, operating internationally, changed the auction format for its
publishers in Country X to FPA on September 17, 2019. We compare these publishers (treatment
group) to other publishers of European Media Companies, i.e., publishers of Company
A outside of Country X and publishers of Companies B and C (control group). The data
period is January 2017 to August 2020.

3. All publishers of European Media Company B, operating in Country Y, switched to FPA
on April 1, 2020. We compare these publishers (treatment group) to (i) all publishers of
Company A outside of Countries X and Y and (ii) all publishers of Company C (control
group). The data period is January 2017 to August 2020.

4. A single publisher of Media Company A, operating in Country Y, switched to FPA on June
1, 2020. We compare this publisher (treatment group) to (i) all publishers of Company A
outside of Countries X and Y and (ii) all publishers of Company C (control group). The data
period is January 2017 to August 2020.

Switching to FPAs was a big business decision. As a result, the Global Company piloted FPAs
in smaller markets (September Publishers) before adopting them worldwide. The European Media
Companies are smaller and have less capabilities to “test and learn” like the Global Company does,
and so it took longer for them to embrace the change.
3 Aggregate Response at the Publisher Level

3.1 Summary Statistics

As a motivating fact, we compare how the average auction clearing price changes in response to the format change from SPAs to FPAs. Table 1 shows a pre–post comparison at the treatment–control group level for each of the four format changes. Panels A to D each correspond to one batch of auction format change. For each of these changes, we aggregate the number of sold impressions and the publishers’ revenue, separately for all treated publishers (left two columns) and all control publishers (right two columns), and separately for the 30-day period immediately before the format change and the 30-day period immediately after the format change. We then compute the average price by dividing the revenue by the number of sold impressions.

For all format changes, we observe that the average price for treated publishers exhibits a significant increase after the format change: 39% for September Publishers (from $0.61/1000 to $0.85/1000), 21% for Company A in Country X, 21% for Company B, and 80% for Company A in Country Y. The corresponding numbers for control publishers are smaller in magnitude and sometimes negative (−8%, 5%, −20%, and 15%, respectively). We see this increase in price across all format changes even though the price levels differ substantially across publisher groups.7

Figure 3 visualizes this observation by plotting the weekly time series of the average price. In this plot, we aggregate the revenue and the number of sold impressions for all treated publishers and all control publishers in each week, and compute the average price by dividing the revenue by the number of sold impressions. The top panel shows the time series for the Global Company, and the two vertical lines indicate format change dates for September Publishers and February Publishers. Looking at the first format change, we observe a spike in the average price for September Publishers immediately after they switched to FPAs, but the trend is stable for February publishers. The pattern is reversed in the February 2018 switch: the plot exhibits a spike in the average price for February Publishers. A similar observation holds for Company A in Country X (Figure 3, middle panel) and the 2020 format changes (Figure 3, bottom panel). Somewhat surprisingly, the surge in coronavirus cases in Europe and the ensuing social disruption starting in March 2020...

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6For European Media Companies, we exclude certain minor/inactive publishers in order to have enough observations around the format change date. For the format change in September 2019, we include only publishers that sold at least 10,000 impressions and earned $100 USD every month from August 2017 to August 2019. For the two format changes in 2020, we include only publishers that sold at least 1,000 impressions every month from October 2019 to July 2020. The included publishers account for more than 90% of impressions and revenue in the indicated periods. The number of publishers in Table 1 does not count the excluded publishers.

7The difference in price levels across publishers is due mainly to the quality of ad spaces. For instance, European Media Companies tend to have higher-quality ad spaces because they are media companies that earn a significant portion of revenue from selling ads. By contrast, the Global Company has its main business that does not depend on advertising revenue.
did not affect the average price for European Media Companies, at least in any obvious manner.

3.2 Event Study Regressions

3.2.1 Specification

As Table 1 and Figure 3 indicate, the publishers that switched to FPAs experienced a surge in average prices. In this section, we formalize this observation through a rigorous event study design that controls for publisher and time fixed effects, as well as seasonality, which is known to be prevalent in the industry.

We first aggregate data to the publisher–day level: we tally the revenue and the number of impressions sold by each publisher on each day, and compute the average price based on them. We then estimate the following regression equation, separately for each treatment–control group pair:

\[ y_{pt} = \alpha_p + \sum_{k = \min(k, 65)}^{\max(k, -65), k \neq -1} \beta_k D_p \cdot 1(K_t = k) + \gamma_t + \gamma_{p, dow(t)} + \gamma_{p, dom(t)} + \gamma_{p, month(t)} + \gamma_{p, eqoq(t)} + \epsilon_{pt}, \]  

(1)

where \( p \) is a publisher, \( t \) is a day, \( y_{pt} \) is average price, \( \alpha_p \) is publisher fixed effect, and \( \gamma_t \) is time (day) fixed effect. We also include publisher-specific seasonal fixed effects \( \gamma_{p, dow(t)} \), \( \gamma_{p, dom(t)} \), \( \gamma_{p, month(t)} \), and \( \gamma_{p, eqoq(t)} \). In other words, we have the following fixed effects, separately for each publisher \( p \): (i) day of week (7 fixed effects per publisher before perfect multicollinearity is removed), (ii) day of month (30 fixed effects per publisher), (iii) month (12 fixed effects per publisher), and (iv) end of quarter (2 fixed effects per publisher, one for the last 14 days of every March, June, September, and December combined, and another for days other than at the end of the quarter).

The coefficients of interests are \( \beta_k \). The variable \( D_p \) is the treatment indicator, which takes a value of 1 if publisher \( p \) is in the treatment group. This is interacted with dummy variables for \( K_t \) (number of days from the date of format change till \( t \), which is censored at a negative number \( k \) from below and a positive number \( \bar{k} \) from above). In the estimation, we take \( k = -65, \bar{k} = 65 \) and plot estimates for \(-60 \leq k \leq 60\). We omit the parameter for \( k = -1 \), and hence all estimates are with respect to the day before the auction format change.

We create a dataset for each treatment–control group pair in Figure 2: there is a single treatment date within each dataset. We truncate the data period before the control publishers (e.g., Global Company February Publishers) switched to FPAs, so that the data period is June 2011 to January 2018 for Set 1, January 2017 to February 2020 for Set 2, and January 2017 to August 2020 for Sets 3 and 4. The data is winsorized by capping the values of \( y_{pt} \) at the 0.1 percentile from below and

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8 We use the same fixed effect for the 30th and 31st days of the month, as there are fewer observations on the 31st day.
### Panel A: Global Company

|                      | September publishers | February publishers |
|----------------------|----------------------|---------------------|
| Number of publishers | 160                  | 38                  |
| Number of sold impressions [000 000] | 7359.72 7627.86 | 12697.97 12976.45 |
| Revenue [000 USD]    | 4478.60 6474.20      | 15088.52 14229.78   |
| Average price [1/1000 USD] | 0.61 0.85 | 1.19 1.10 |

### Panel B: European Media Companies, first batch

|                      | Company A, Country X | Other |
|----------------------|----------------------|-------|
| Number of publishers | 44                   | 32    |
| Number of sold impressions [000 000] | 89.38 51.26 | 522.18 642.98 |
| Revenue [000 USD]    | 421.16 292.71        | 662.10 855.28 |
| Average price [1/1000 USD] | 4.71 5.71 | 1.27 1.33 |

### Panel C: European Media Companies, second batch

|                      | European Media Company B | Other |
|----------------------|--------------------------|-------|
| Number of publishers | 15                       | 48    |
| Number of sold impressions [000 000] | 39.09 27.25 | 188.68 166.63 |
| Revenue [000 USD]    | 119.92 101.41            | 260.27 184.57 |
| Average price [1/1000 USD] | 3.07 3.72 | 1.38 1.11 |

### Panel D: European Media Companies, third batch

|                      | Company A, Country Y | Other |
|----------------------|----------------------|-------|
| Number of publishers | 1                      | 48    |
| Number of sold impressions [000 000] | 7.63 6.13 | 219.36 259.58 |
| Revenue [000 USD]    | 10.81 15.66           | 246.32 334.56 |
| Average price [1/1000 USD] | 1.42 2.55 | 1.12 1.29 |

Table 1: Comparison of number of sold impressions, revenue, and average price for the 30-day period before and after auction format change. The left two columns summarize data for publishers that switched from SPAs to FPAs on September 21, 2017 (Panel A), September 17, 2019 (Panel B), April 1, 2020 (Panel C), and June 1, 2020 (Panel D) (treatment group), and the right two columns summarize data for publishers that did not switch at these times. The number of impressions and the revenue are aggregated for both groups of publishers, separately for the 30-day period indicated in the second line of each panel. The average price is obtained by dividing the revenue by the number of sold impressions.
Figure 3: Weekly time series of the average price by each publisher group as defined in Table 1. The top panel plots the time series for September Publishers and February Publishers of the Global Company, and the vertical lines indicate their dates of format change. The middle panel plots the time series for European Media Companies, separately for the publishers of Company A in Country X and other publishers (publishers of Company A outside of Country X and publishers of Companies B and C). The vertical line indicates the date of format change by publishers of Company A in Country X. The bottom panel plots the time series for European Media Companies that did not switch to FPAs before 2020. The two vertical lines indicate the dates of format change by publishers of Company B and by the publisher of Company A in Country Y.
at the 99.9 percentile from above. The regressions are weighted by the number of impressions sold by publisher \( p \) on day \( t \) so that larger publishers have more influence on the estimates than smaller publishers. In other words, \( y_{pt} \) is an average of “grouped data” (Angrist and Pischke, 2009, p. 92). The standard errors are clustered at the publisher level (Bertrand et al., 2004).

It is worth mentioning how our regression specification stands in relation to the recent literature on event study regressions with two-way fixed effects. First, de Chaisemartin and D’Haultfœuille (2020) and Borusyak et al. (2021) show that (the probability limit of) the estimated coefficient in a static difference-in-differences (DID) regression (i.e., only one coefficient for the treatment effect) is a weighted average of unit- and time-specific treatment effects, where the weights may be negative. As a result, it is possible to obtain an estimate with the wrong sign (e.g., the estimated coefficient may be negative even if all true treatment effects are positive). Second, Goodman-Bacon (2021) shows that the estimated coefficient in a static DID regression may be biased, because it may be confounded by the time-series change in the treatment effect of the treated units. Both these problems arise only if there are units with different event dates, i.e., different cohorts. Thirdly, Sun and Abraham (2021) consider a dynamic specification like ours, i.e., a specification that uses a separate dummy variable for each relative period from the event date. They show that, when there are multiple cohorts, \( \beta_k \) (to use our notation) is a weighted average not only of conditional average treatment effects \( k \) periods after treatment, but also of conditional average treatment effects \( k' \) periods after treatment for all possible \( k' \) corresponding to other cohorts. We note that none of these problems are present in our regressions, as we have a single cohort/event date within each of the four treatment–control comparisons.

### 3.2.2 Identifying Assumptions

The main identifying assumptions of event study regressions are (i) the exogeneity of treatment assignment and (ii) the common trend (parallel trend) assumption (de Chaisemartin and D’Haultfœuille, 2020). As for (i), Section 2.2 explains the high-level motivation for deciding the format change dates. Display advertising is adopting FPAs as an industry trend, and companies that have the capabilities to “test and learn” are doing so first. When deciding on particular dates (i.e., why those dates rather than one week earlier), there are various factors to consider, such as staff availability to support/supervise the process of format change. Overall, the publishers set dates when there are unlikely to be any factors that confound the impact of format change on prices so that their analysts can investigate the impact of the format change. To investigate whether the parallel trend assumption holds (ii), we will discuss the pre-trend (estimates of \( \beta_k \) for \( k < 0 \)) in Section 3.2.3, as in Autor (2003) and Angrist and Pischke (2009).

On a different note, our event study estimates may potentially reflect market equilibrium effects: if, for instance, the average price for treated publishers goes up, bidders may substitute away
from treated publishers to control publishers.\textsuperscript{9} We believe that such concerns are limited in our case, however. For the Global Company, September Publishers and February Publishers serve distinct geographical markets: they serve internet users of different countries and jurisdictions, often using different languages. As for the format change by European Media Company A in 2019, no control publishers operate in Country X (because there were few suitable candidates on the ad exchange). In 2020, the control group does include publishers operating in Country Y, but they occupy only 3.3\% of the impressions sold and 12.6\% of the revenue earned by all the control publishers. See also Section A.1 for a robustness check, where we rerun the event study regression only using publishers outside of Country Y as the control group.

### 3.2.3 Estimation Results

![Graphs showing the effects of format change on average price for different companies and countries.](image)

Figure 4: Estimates of $\beta_k$ (effects of format change on average price). The solid line indicates point estimates, and the band indicates 95\% confidence intervals.

\textsuperscript{9}Technically, this is a violation of the stable unit treatment value assumption (SUTVA; Imbens and Rubin, 2015, p. 10).
of treatment and control groups. In each of the four treatment–control pairs, we observe an immediate jump in the average price for the treated publishers. The pre-trends are either statistically insignificant or, even if they are significant, much smaller in magnitude than the estimated treatment effects.

The top left panel shows estimates for Global Company’s September Publishers. The format change increased the average price on the day following the format change ($\beta_1$) by 0.45/1000 USD, relative to the counterfactual price level that would have been obtained if these publishers had continued to run SPAs. This increase in price is substantial: it is 73% of the average price for September Publishers during the 30-day period immediately before the change (shown in Table 1). The average price under FPAs continues to be higher than SPAs until $k = 60$.

The top right panel shows estimates for the publishers of Company A in Country X with respect to the September 2019 format change. $\beta_1$ is estimated to be 1.62/1000 USD, which is 34% of the average price for the publishers of Company A in Country X during the 30-day period immediately before the format change. This time, the increase in average price is transitory: the estimated effect diminishes over time and becomes insignificant as $k$ approaches 60. The bottom two panels show estimates for the two batches of format changes in 2020, with the left panel showing the effects for the publishers of Company B after April 1 and the right panel showing the effects for the publisher of Company A in Country Y after June 1. The estimates for $\beta_1$ are 1.25/1000 USD for publishers of Company B and 0.89/1000 USD for Company A’s publisher in Country Y (41% and 63% of their respective average price levels during the immediately preceding 30-day period). Again, the increase in the average price under FPAs diminishes over time and becomes insignificant as $k$ approaches 30.

### 3.3 Interpretation of Results

We draw two insights from the results just described. First, the results indicate that at least a subset of bidders responded suboptimally to the format change. Imagine that all bidders were rational and assume, for simplicity, that they have private values: under the SPA, they bid their valuation of each impression, and so the average revenue is the mean of the maximum of the second-highest valuation by bidders and the reserve price. After the format change, the bidders would shade their bids compared to their valuations according to some Bayesian Nash equilibrium. The average price would stabilize, immediately after the format change, at a level sustained by the equilibrium. Contrary to these predictions, we observe that the average price levels initially went up after each of the format changes compared to the average price levels under SPAs, and that the increase dissipated over time for the three format changes in 2019 and 2020. We interpret this transitory increase in prices as evidence that (i) some bidders shaded their bids insufficiently under the new
regime of FPAs relative to their rational, best-response strategy, and (ii) these bidders gradually learned to shade their bids to a level sustained by a rational strategy. It is important to note that the transition to FPA for each publisher was both transparent at the auction level—the auction type was sent in the bid request—and communicated proactively by publishers to demand-side platforms.

Incidentally, the average price level under FPAs eventually falls to the level under SPAs after the three format changes in 2019 and 2020. It is an interesting observation reminiscent of the celebrated revenue equivalence theorem shown by Vickrey (1961), Myerson (1981), and Riley and Samuelson (1981). We believe that this result is noteworthy and intriguing in light of the fact that the prerequisites for the classic revenue equivalence theorem (such as bidder symmetry) generally do not hold in our setting (Maskin and Riley, 2000).¹⁰

Second, we note that it took less time for the average price levels under FPAs to go down to the average price levels under SPAs following the format change in 2019 compared to the format change in 2017, and it took even less time following the format changes in 2020 than the format change in 2019. In the 2017 format change, the average price was still not going down 60 days after the initial jump. By contrast, in the 2019 format change, the average price levels under FPAs went down to the average price levels under SPAs within 60 days. This period until the price decrease was reduced to 30 days in the 2020 format changes. We interpret this as evidence of long-term learning whereby bidders got better and faster in adjusting their bids, whether through their first-hand experience of format changes, industry-wide learning, or a combination of the two.

3.4 Role of Advertising Campaign Budgets

A potential concern with the above interpretation relates to the role of advertising campaign budgets; see, e.g., Balseiro et al. (2015) for a theoretical treatment of budget constraints in display advertising auctions. The concern is that bidders spend a fixed amount of budget on the treated publishers, and whatever phenomena take place after the format change are caused by budget constraints rather than auction dynamics.

We believe that budget constraints play a limited role, if any, in the results discussed above. Most bidders/advertisers buy impressions from multiple publishers and they usually do not set fixed budgets for a particular publisher or group of publishers.

¹⁰We note another difference between our result and the classic revenue equivalence theorem. We compare revenue per sold impression, i.e., revenue per auction where the highest bid exceeds the reserve price, under SPAs and FPAs. On the other hand, the revenue equivalence theorem concerns revenue per available impression, i.e., revenue per auction considering the possibility of not selling the impression (if all bids are below the reserve price), in which case the auctioneer receives its opportunity cost. Unfortunately, due to data limitations, we have not been able to test the equivalence of revenue per available impression under SPAs and FPAs. We do not observe in our data the number of available but unsold impressions nor relevant reserve prices (price floors).
To support this claim, we present two pieces of evidence, one using a cross-section of advertising campaigns and another using the time series of bidders’ spending. First, we take the cross-section of all advertising campaigns by advertisers that used Xandr’s DSP service including its bidding algorithm and bought impressions from our treated publishers around the format change dates (30 days before or after the format change). For each advertising campaign, we compute the fraction of its spending on treated publishers (i.e., compute the dollar amount the advertising campaign spent on treated publishers, divided by the total dollar amount it spent), and round that fraction to the nearest multiple of 10%. We then sort those advertising campaigns in an ascending order of the computed fraction, and plot the cumulative percentage in those advertising campaigns’ total spending on the treated publishers. Figure 5 shows such a cumulative percentage plot for advertising campaigns that bought from Global Company September Publishers, separately for the 30-day period before the format change and the 30-day period after it.

We observe that the share of September Publishers varies considerably across campaigns. For instance, the solid point on the plot indicates that, out of September Publishers’ revenue from advertising campaigns using Xandr’s DSP service during the 30-day pre-period, 68.2% comes from advertising campaigns that spent less than 75% on September Publishers (i.e., spent more than 25% on other publishers). Figure B.1 shows plots for the other three groups of treated publishers, with similar observations. These figures indicate that advertisers/bidders buy from a diverse set of publishers and not just from treated publishers.

Second, the time series of bidders’ spending on treated publishers exhibit quite a bit of tempo-
eral variations after the switch to FPAs, and these variations show diverse patterns across bidders (we are using all bidders here, in contrast to the cross-sectional evidence in the previous paragraph). For each bidder, we compute the growth rate of the bidder’s spending as the ratio of the bidder’s spending on the treated publishers during the 7-day period after the format change to that bidders’s spending on the treated publishers during the 7-day period before the format change. Figure 6 shows the histogram of such growth rates for bidders buying from September Publishers (the unit of observation is the bidder). Bidders are color-coded by their importance to the September Publishers’ revenue, i.e., according to whether (i) the bidders are the top 5 bidders in terms of spending on September Publishers, (ii) they otherwise spend at least 1,000 USD in the 7 days before the format change, and (iii) they spend less than 1,000 USD in the 7 days before the format change. The growth rates show a significant variation from 0 to above 3 (where the horizontal axis is capped) and, importantly, they differ from 1 in many cases. Figure B.2 shows plots for the other three groups of treated publishers; we again see substantial variation in the growth rates of spending across bidders. These facts suggest that the bidders do not have a fixed budget for treated publishers.

![Growth of bidders' spend: Global Company September Publishers](image)

Figure 6: Histogram of growth rates of bidders’ spending on Global Company September Publishers from 7 days before the auction format change to 7 days after it, color-coded by the importance of each bidder to the September Publishers’ revenue during the 7-day period before the change.

### 3.5 Robustness Checks

We first rerun the event study regressions on the European Media Companies using alternative definitions for the control group. First, we use publishers of Company A other than in Country X as the control group to estimate the effects for the publishers of Company A in Country X. In other words, we exclude publishers of Companies B and C that we included in the control group for the main specification. Publishers of Company A are arguably more similar to each other than to publishers of Companies B and C, and therefore a treatment–control comparison without Company
A may potentially be more appropriate. The results are shown in the top panel of Figure A.2, and are similar to the results for the main specification in Figure 4.

Second, to estimate the effects for the publishers of Company B and the publisher of Company A in Country Y, we use publishers of Company A other than in Countries X and Y as the control group. In the main regression specification, we include publishers of Company C as part of the control group. This might raise concerns of confounding through equilibrium effects, as Company C targets internet users in the same geographical region (Country Y) as the treatment group. Excluding publishers of Company C from the control group mitigates such concerns. The results are shown in the bottom two panels of Figure A.2. Again, the results are similar to those for the main specification.

Next, we rerun the event study regressions specified in equation (1) by replacing the outcome variable (left-hand-side variable) with log $y_{pt}$, log of average price. Figure A.2 shows the estimates. Apart from showing some pretrends—which is the reason why we prefer $y_{pt}$ to log $y_{pt}$ as the main specification—the basic observation stays the same, i.e., there is (i) a significant jump in the average price immediately after the auction format change, and (ii) a decline in the increase within approximately 60 days (the publishers of Company A in Country Y) or 30 days (the publishers of Company B and the publisher of Company A in Country Y) after the change.

To investigate whether seasonality adjustments are affecting the estimates, we also estimate the event study regression in two alternative ways. In the first method, we estimate the regression in two steps: we first remove the seasonality of $y_{pt}$ by regressing $y_{pt}$ on dummy variables, separately for each $p$, and obtain a “deseasonalized” time series $\tilde{y}_{pt}$ for each $p$. We then run the event study regression as in (1), except that $y_{pt}$ is replaced with $\tilde{y}_{pt}$ and the seasonal fixed effects ($\gamma_{p,dow(t)}$, $\gamma_{p,dom(t)}$, $\gamma_{p,month(t)}$, and $\gamma_{p,eqq(t)}$) are removed; see Appendix A.3 for details. In the second method, we estimate (1) without any seasonal fixed effects. Figures A.3 and A.4 show estimates of $\beta_k$ for (i) and (ii), respectively. Again, the estimates show patterns similar to Figure 4, although the estimates under Figure A.4 exhibit more fluctuations because of day-of-week effects. These results indicate that the seasonality adjustments in the main regression do not drive our main results.

Finally, as a falsification test, we run the event study regression by picking hypothetical dates for the auction format change that are one year before the actual dates. Figure A.5 shows the results. The estimates are no longer statistically significant in three out of the four pairs. For the remaining pair (the publishers of Company A in Country Y vs. their controls), the estimated effects of the hypothetical auction format change are negative.
4 Bidder Heterogeneity

To investigate further the relation between the effects of the auction format change on publishers’ revenue and bidders’ behavior, we estimate how the effects of the format change on spending differ across different types of bidders. For that purpose, we classify bidders into different levels of sophistication as defined below, and then estimate the following regression equation:

$$y_{pbt} = \alpha_{pb} + \sum_{k \leq k \leq K, k \neq -1} \beta_{bk} D_{pb} \cdot 1(K_t = k) + \gamma + \gamma_{pb, dow(t)} + \gamma_{pb, dom(t)} + \gamma_{pb, month(t)} + \gamma_{pb, eq(t)} + \varepsilon_{pbt}. \quad (2)$$

Here, $b$ indicates the type of bidders. The difference with the main regression specification (1) is the additional index $b$: (i) the outcome variable $y_{pbt}$ is now the average spending per impression by all bidders of type $b$ for each publisher–day pair, (ii) the treatment effects $\beta_{bk}$ are estimated separately for each type $b$, and (iii) publisher fixed effects $\alpha_{pb}$ and seasonal fixed effects $\gamma_{pb, dow(t)}$, $\gamma_{pb, dom(t)}$, $\gamma_{pb, month(t)}$, $\gamma_{pb, eq(t)}$ are made bidder-type-specific.

We first conjecture that larger bidders are more sophisticated and shade their bids more aggressively than smaller bidders once the format switches to FPAs. To see this, we classify the bidders into three types, “large,” “medium,” and “small,” as follows. We calculate each bidder’s spending on the treated publishers in the 30-day period immediately before the format change, and compute each bidder’s share within the total revenue of the treated publishers during that period. For bidders of the Global Company, we classify a bidder as “large” if the share is above 10%, “medium” if the share is above 1%, and “small” if the share is below 1%.

Figure C.1 shows the estimated $\beta_{bk}$ for $b \in \{\text{large}, \text{medium}, \text{small}\}$. However, contrary to our initial hypothesis, we do not see a monotonic pattern: the effect on spending is the highest among “small” bidders and the lowest among “medium” bidders, while “large” bidders’ responses were in between the other two types.

We next use a classification of bidders that is arguably more directly related to bidder sophistication. Some advertisers use Xandr’s DSP service including its bidding algorithm, and Xandr assigns a single bidder ID to such advertisers: we refer to them as the “AppNexus/Xandr bidder.” Since the AppNexus/Xandr bidder uses the bidding algorithm of Xandr, which coordinates the format change from SPA to FPA, this bidder was arguably more sophisticated than other bidders in changing its bidding algorithm.

Figure 7 shows the estimated effects when Global Company September Publishers changed to FPAs. We observe that spending by non-AppNexus/Xandr bidders jumped immediately ($\beta_{b1} = 0.56/1000$ USD, or 84% of the average price for the 30-day period before the format change) and that increase persisted for 60 days, while spending by the AppNexus/Xandr bidder increased only moderately ($\beta_{b1} = 0.20/1000$ USD, or 39% of the average price for the 30-day period before the
format change) and became statistically insignificant after 6 days. These results suggest that the AppNexus/Xandr bidder was able to adjust to the new environment of FPA more quickly than other bidders due to the former’s sophisticated bidding algorithm incorporating bid shading, suggesting the increase in revenue is the result of suboptimal bid shading by naive bidders. Figure C.2 shows estimates for other publishers, and we observe a pattern similar to that of the Global Company September Publishers.\footnote{The $\beta_1$’s for the publishers of Company A in Country X are 2.02/1000 USD for non-AppNexus/Xandr bidders (42% of the average price for the 30-day period before the format change) and 1.16/1000 USD for the AppNexus/Xandr bidder (27%). For the publishers of Company B, they are 1.25/1000 USD (41%) for non-AppNexus/Xandr bidders and 2.98/1000 USD (68%) for the AppNexus/Xandr bidder. For the publisher of Company A in Country Y, they are 0.92/1000 USD for non-AppNexus/Xandr bidders (67%) and 0.76/1000 USD (37%) for the AppNexus/Xandr bidder. The impact for the AppNexus/Xandr bidder becomes statistically insignificant seven days after the format change.} The exception is Company B, which sees a larger increase in spending by the AppNexus/Xandr bidder. For Company B, unlike other publishers, the AppNexus/Xandr bidder represents only a small fraction of impressions and revenue (3.5% of impressions and 5% of revenue for the 30-day period before the format change). It even reduced the number of impressions it bought from publishers of Company B by 80%, when we compare the number for 30 days before and after the format change. We interpret this as an extreme case of the compositional change due to more aggressive bid shading of the AppNexus/Xandr bidder as we explain in the next paragraph: the AppNexus/Xandr bidder buys only impressions with very high willingness to pay after the format change.

There is a caveat about inferring bidding from the event study estimates on bidders’ spending: as different bidders compete for the same impressions, a change in bidding behavior by some bidders will affect which bidders win the auctions, changing the composition of the quality and nature of impressions (market equilibrium effect). We think that such a change in composition only attenuates the event study effects: the difference in bidding between the AppNexus/Xandr bidder and non-AppNexus/Xandr bidders is even larger than the difference in spending indicated...
in Figure 7. As non-AppNexus/Xandr bidders bid higher than the AppNexus/Xandr bidder, they tend to win more impressions, particularly those for which they have lower willingness to pay. This decreases their average spending relative to when there was no change in the composition of impressions (i.e., when the bidders purchased the same set of impressions). By contrast, the AppNexus/Xandr bidder would lose auctions for impressions for which they have lower willingness to pay. This increases the AppNexus/Xandr bidder’s average spending relative to when there were no compositional effects of the format change.

5 Conclusion

Using the data of internet display advertising auctions, we have analyzed the impacts of auction format change from second-price auctions (SPAs) to first-price auctions (FPAs). By estimating event study regressions, we find that the average price jumps up immediately after the format change from SPAs to FPAs, and that the increase attenuates over time. We take this as evidence of suboptimal, insufficient bid shading by some bidders. Comparing different instances of format changes, we also find evidence that bidders learn over time to adjust their bids in response to the format change. Our heterogeneity analysis reveals that the AppNexus/Xandr bidder—who used a more sophisticated bidding algorithm—shaded their bids more aggressively than non-AppNexus/Xandr bidders once the format changed to FPAs, supporting our argument that suboptimal bid shading caused the transitory increase in price.

In future work, we plan to complement the reduced-form analysis of this work with a structural model of bidding using granular, bid-level data for Company B that we collected recently. Such data would allow us to simulate bids, for each bidder, in a counterfactual world where they shaded their bids rationally, and compare that with the actual bidding.

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A Robustness Checks

A.1 Alternative Control Groups within European Media Companies

Figure A.1: Estimates of $\beta_k$ (effects of format change on log average price) using alternative control groups. Top: publishers of Company A in Country X (treatment group) vs. publishers of Company A other than in Countries X and Y. Bottom left: publishers of Company B (treatment group) vs. publishers of Company A other than in Countries X and Y. Bottom right: the publisher of Company A in Country Y vs. publishers of Company A other than in Countries X and Y.
A.2 Log Average Price as Outcome Variable

Figure A.2: Estimates of $\beta_k$ (effects of format change on log average price) when the LHS variable in equation (1) is replaced by $\log y_{pt}$. The solid line indicates point estimates, and the band indicates 95% confidence intervals.
A.3 Alternative Seasonality Adjustments

Figure A.3 uses the estimates under the following “two-step” method:

1. We first regress, for each publisher $p$’s time series $\{y_{pt}\}$,

$$y_{pt} = \gamma_{p,dow}(t) + \gamma_{p,dom}(t) + \gamma_{p,month}(t) + \gamma_{p,eq}(t) + \delta_{pt},$$

using the data before the format change. We weight the observations by the number of impressions.

2. We compute the fitted values of the previous regression $\hat{y}_t$ and subtract its mean $\bar{y}$, which is obtained by regressing $\hat{y}_t$ on a constant.

3. The demeaned fitted value $\hat{y}_t - \bar{y}$ shows the seasonal component, and so subtracting this seasonal component from $y_t$ gives the deseasonalized time series $\tilde{y}_{pt}$.

4. Regress $\tilde{y}_{pt}$ as follows:

$$\tilde{y}_{pt} = \alpha_p + \sum_{k \leq k \leq k, k \neq -1} \beta_k D_p \cdot 1(K_t = k) + \gamma_t + \tilde{\epsilon}_{pt}. $$

Figure A.4 estimates the main regression (1) but without any seasonal fixed effects.

![Figure A.3: Estimates of $\beta_k$ under “two-step” method.](image-url)
Figure A.4: Estimates of $\beta_k$ when no seasonality adjustments are made.
A.4  Falsification Test with Hypothetical Event Dates

Figure A.5: Estimated effects of hypothetical format change on average price. Hypothetical change dates are set as one year before the actual format changes.
B Supplementary Figures on Ad Campaign Budgets

Figure B.1: Cumulative percentage of treated publishers’ revenue from ad campaigns that used Xandr’s DSP service. The horizontal axis represents the share of treated publishers within each ad campaign’s spending, rounded to the nearest multiple of 10%. The revenue and share are computed separately for 30 days before the format change (“Pre”) and for 30 days after it (“Post”).
Figure B.2: Histogram of growth rates of bidders’ spending on treated publishers from 7 days before format change to 7 days after, color-coded by the importance of each bidder in treated publishers’ revenue during the 7-day period before change (“AppNexus/Xandr” indicates the AppNexus/Xandr bidder as explained in Section 4).
Figure C.1: Estimated increase in bidders’ spending on the Global Company September Publishers, separately for “large,” “medium,” and “small” bidders. Bidders are classified as “large” if their share of September Publishers’ aggregate revenue during the 30 days before the format change date (September 21, 2017) is above 10%, “medium” if the share is above 1%, and “small” if the share is below 1%.
Figure C.2: Effects of format changes on spending per sold impression, separately for the AppNexus/Xandr bidder and for other bidders.