Learning New Auction Format by Bidders in Internet Display Ad 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 data set on internet display ad auctions that exploits a staggered adoption by different publishers (sellers) of first-price auctions (FPAs), in place for the traditional second-price auctions (SPAs). Event study regression estimates indicate a significant jump, immediately after the auction format change, in revenue per sold impression (price) of the treated publishers relative to that of control publishers, ranging from 35% to 75% of pre-treatment price levels of the treated group. Further, we observe that in later auction format changes the lift in price relative to 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 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. In contrast, under first-price auctions (FPAs), Bayes Nash equilibrium requires 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 in 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 found discrepancy 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.

However, there have been few field studies about learning in auctions. A notable exception is Doraszelski et al. (2018), which analyzes bidders’ learning when a new auction market is introduced. Understanding bidders’ responses after a market design change is fundamental for policy makers as well as profit maximizing platforms as they consider different potential alternatives to implement. For example, in the real-time sponsored search advertising market — one of the largest auction markets world-wide — there was an historical dilemma between using second-price and first-price auctions and the potential implications for bids and revenues. A similar discussion arose in the last 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 gets introduced into the marketplace. We investigate this question in the setting of internet display ad auctions. To quantify bidders’ responses to the format change over time, we exploit staggered adoptions by different publishers (sellers) of first-price auctions (FPAs), in place for 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 a new environment (FPA)? (2) How do different bidders react to the format change?

We use daily-level 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 (number of auctions resulting in sale) on the platform and the aggregate revenue (sum of 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 waves: (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 back then (control group).

Our results show that the average revenue per sold impression (average price) jumped considerably relative to the control publisher and took place immediately after the format change to FPAs. The magnitude of this jump ranges from 35% to 75% of pre-treatment price level of the treated group. Further, in the last three format changes, we observe that the lift in price relative to SPAs dissipates over time in 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 bidder valuations’ second order statistic 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 lift is transitory, we believe, strongly suggests initial insufficient bid shading, followed by reduction in price as bidders learned to shade their bids under FPA.

It is interesting to observe that the price level under FPA and SPA eventually converge. This is reminiscent of the celebrated revenue equivalence theorem by Vickrey (1961); Myerson (1981); Riley and Samuelson (1981). We think this result is quite remarkable specifically because we do not believe that the prerequisites for the revenue equivalence theorem (such as bidder symmetry) hold in our setting (Maskin and Riley, 2000).

Furthermore, it took less time for the average prices to go down to the price level under SPA in the 2020 format changes compared to the change in 2019, and then compared to the change in 2017. This pattern suggests that bidders learned over time how to better shade their bids from 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, but filling such gaps in the theory is important for market design. In the short-run,
economic actors may have trouble bidding optimally and it may appear that first price auctions drive revenue increases. However, over the long run, as buyers adjust to market dynamics and learn how to bid more effectively, the revenue gains for publishers dissipate. As a result, it is easy for myopic market designers to infer the wrong conclusions from implementing auction logic changes. While we believe there were other compelling reasons for internet display ad auctions to switch to FPAs, a compelling rationale did not seem to be that they make publishers or exchanges more money in the long-run.

We also study the heterogeneity of the effect of format change across bidders. Specifically, we estimate the impact on price by an event study design, separately for advertisers that use the bidding algorithm provided by the ad exchange and the rest of the bidders. We find that, in three out of four format changes, the latter type of bidders/advertisers see a bigger increase in price than the former type of advertisers. This suggests that heterogeneity of bidders’ sophistication impacted how they responded to the format change: advertisers that use the ad exchange’s bidding algorithm were more sophisticated in bidding, so they shaded 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.

Apart from the literature in auctions mentioned above, our work contributes to the literature in operations management and management science studying different market design aspects of the display advertising industry; see, e.g., Celis et al. (2014), Golrezaei et al. (2021), Agarwal et al. (2020), and Fridgeirsdottir and Najafi-Asadolahi (2018). More broadly it is also related to work in operations using quasi-experimental data to study important changes in digital platforms, like in 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 switch 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 studies regressions and interpretation of our regression estimates. We also conduct several robustness checks here. Section 4 augments our main analysis by investigating the heterogeneity of response in spend across different types of bidders. Section 5 concludes.
2 Institutional Background and Data

2.1 The Industry of Display Advertising

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

![Diagram of display ad auctions with real-time bidding](image)

Figure 1: Diagram of display ad 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 ad contents. The process of RTB starts when an internet user visits that web page (1), whether on a computer or on 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 ad be served, which is called ad request or ad call (2). The ad exchange then decides which advertiser will serve the ad by an auction. For many digital publishers, there are additional systems that make decisions before the ad request hits the Ad Exchange and after the exchange selects a winning bid. However, for the publishers in this study, Figure 1 is a useful depiction of the process during the study 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 ad 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 ad content to the internet user (5).

This entire process (internet user’s visit to a webpage until 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 by 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 shift 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 to FPAs announced in March 2019.\footnote{https://www.blog.google/products/admanager/simplifying-programmatic-first-price-auctions-google-ad-manager/} 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 high as 70% (Bender, 2016). As a result, the selling side had developed yield-enhancing technologies, such as “hard floors” (reserve price) and “soft floors”.\footnote{Soft floors work as follows: If there are bids above the soft floor, the winner — the bidder with the highest bid — will pay the higher of the soft floor and the second highest bid (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.} One such technology, Dynamic Price Floors, which is adjusting the price floors programmatically and in real-time (Bender, 2016), was criticized as opaque (Doherty, 2014). Ad buyers were especially concerned that the price floors were manipulated so they got very close to the highest bid, essentially requiring them to pay what they bid (Caruso, 2015): they even had suspicions that the price floors may be set after the bids are submitted (Benes, 2017). (This is exactly the incentive compatibility concern raised by Akbarpour and Li (2020) about SPAs). First-price auctions have been seen as a way to solve this transparency concern, while ostensibly solving seller’s concerns about the gap between the first and second highest bid (Sluis, 2017).\footnote{The demand for switch to FPAs out of transparency concerns was strengthened by the growth of header bidding, as explained in Despotakis et al. (Forthcoming). 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 from a major ad exchange platform operated by Xandr. The data are aggregated in the following manner. Seller 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, for instance, a given publisher earned $X by selling $Y impressions to a given bidder.\footnote{In this example, the number of impressions $Y$ does not count auctions that did not result in the delivery of ad contents for reasons such as: (1) no bids meet reserve price, or (2) the ad contents were not delivered because of server timeouts.} 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.

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”). Global Company has several different functionalities, and has a website (publisher) for each functionality in each of virtually all countries/jurisdictions 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.

![Figure 2: Types of publishers and dates of format changes. The four columns on the right indicate treatment-control pairs in the event studies regression (“T” indicates the treatment group and “C” indicates the control group). The gray bars represent periods under SPA and the orange ones under FPA.](image)

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

1. Publishers of 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 on a country level: all publishers in smaller countries/jurisdictions switched in September (“September Publishers”), and all publishers in larger countries/jurisdictions switched in February publishers.

...
February ("February Publishers"). The data period is June 2011 to September 2019. We compare September Publishers as treatment group to February Publishers as control group.

2. European Media Company A, operating internationally, changed the auction format for its publishers in Country X to FPA on September 17, 2019. These publishers, as treatment group, are compared to other publishers of European Media Companies. 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 them as treatment group to (i) all publishers of Company A outside of Countries X and Y and (ii) all publishers of Company C as 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 it as treatment group to (i) all publishers of Company A outside of Countries X and Y and (ii) all publishers of Company C as control group. The data period is January 2017 to August 2020.

Switching to FPAs was a big business decision. As such, 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, so it took more time 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 changed in response to the format change from SPAs to FPAs. Table 1 shows a pre-post comparison at the level of treatment-control group level for each of the four format changes. Each of Panels A to D corresponds to one set of auction format change. For each of these changes, we consolidate all the number of sold impressions and seller’s (publisher) revenue, separately for all treated publishers (left two columns) and all control publishers (right two columns), for the 30-day period immediately before format

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5 For European Media Companies, we exclude certain minor/inactive publishers so we have enough observations near the format change date. For the format change in September 2019, we only include publishers that sold at least 10,000 impressions and 100 USD in every month from August 2017 to August 2019. For the two format changes in 2020, we only include publishers that sold at least 1,000 impressions in every month from October 2019 to July 2020. These included publishers account for more than 90% of impressions and revenue for the indicated periods. The number of publishers in Table 1 does not count such excluded publishers.
change and another 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 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, Country X, 21% for Company B, and 80% for Company A, 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 average price level differs substantially across publishers.\textsuperscript{6}

Figure 3 visualizes this observation by plotting the weekly time series of average price. In this plot, we aggregate revenue and number of sold impressions of all treated publishers and all control publishers for each week, and compute average price by dividing revenue by number of impressions in each week. 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, the plot exhibits a spike in 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: it is February Publishers that exhibit a jump in price. Similar observation holds for Company A, 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 did not affect the average price for European Media Companies, at least in an obvious manner.

### 3.2 Event Studies Regression

#### 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.

We first aggregate data to a 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:

\[
y_{pt} = \alpha_p + \sum_{k \leq k_0, k \neq -1} \beta_k D_p \cdot 1(K_t = k) + \gamma t + \gamma_{p,dow(t)} + \gamma_{p,dom(t)} + \gamma_{p,month(t)} + \gamma_{p,eoq(t)} + \epsilon_{pt},
\]

where \( p \) indicates a publisher, \( t \) indicates a day, \( y_{pt} \) indicates average price, \( \alpha_p \) indicates publisher

\textsuperscript{6}The 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 of ad spaces because they are media companies that earn a significant portion of revenue from selling ads. In contrast, the Global Company has its main business that does not depend on ad revenue.
Panel A: Global Company

|                         | September publishers | February publishers |
|-------------------------|----------------------|---------------------|
| Number of publishers    | 160                  | 38                  |
| 8/22–9/20/2017          | 82/9–20/2017         |
| Number of impressions [000 000] | 7359.72           | 12697.97            |
| Revenue [000 USD]       | 4478.60              | 15088.52            |
| Average price [1/1000 USD] | 0.61               | 1.19                |

Panel B: European Media Companies, first batch

|                         | Company A, Country X | Other |
|-------------------------|----------------------|-------|
| Number of publishers    | 44                   | 32    |
| 8/18–9/16/2019          | 8/18–9/16/2019       |
| Number of impressions [000 000] | 521.16             | 642.98 |
| Revenue [000 USD]       | 421.16               | 855.28 |
| Average price [1/1000 USD] | 4.71               | 1.33  |

Panel C: European Media Companies, second batch

|                         | European Media Company B | Other |
|-------------------------|--------------------------|-------|
| Number of publishers    | 15                       | 48    |
| 3/2–3/31/2020           | 4/1–4/30/2020            |
| Number of impressions [000 000] | 39.09               | 188.68 |
| Revenue [000 USD]       | 119.92                  | 260.27 |
| Average price [1/1000 USD] | 3.07                | 1.38  |

Panel D: European Media Companies, third batch

|                         | Company A, Country Y  | Other |
|-------------------------|-----------------------|-------|
| Number of publishers    | 1                     | 48    |
| 5/2–5/31/2020           | 5/2–5/31/2020         |
| Number of impressions [000 000] | 7.63                | 219.36 |
| Revenue [000 USD]       | 10.81                 | 246.32 |
| Average price [1/1000 USD] | 1.42                 | 1.12  |

Table 1: Comparison of number of impressions, revenue and average price for the 30-day period before and after auction format change. The left two columns summarizes 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 the time. The number of impressions and revenue are summed up for such publishers, separately for the 30-day period indicated in the second line of each Panel. Average price is obtained by dividing revenue by the number of impressions.
Figure 3: Weekly time series of average price by each publisher group as defined in Table 1. The top panel plots time series for September publishers and February publishers of Global Company, and the vertical lines indicate their dates of format change. The middle panel plots time series for European Media Companies, separately for Company A, Country X and others. The vertical line indicates the date of format change by publishers of Company A, Country X. The bottom panel plots time series for European Media Companies that did not switch to FPA 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.
fixed effect, and $\gamma_t$ indicates time (day) fixed effect. We also include publisher-specific seasonality fixed effects $\gamma_{p,dow(t)}$, $\gamma_{p,dom(t)}$, $\gamma_{p,month(t)}$, and $\gamma_{p,eq(t)}$. In other words, we have the following fixed effects, separately for each publisher $p$: (i) day of week (7 fixed effects per publisher before removing perfect multicollinearity), (ii) day of month (30 fixed effects per publisher),\(^7\) (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 altogether, and another for days other than at the end of quarter).

The coefficients of interests are $\beta_k$. The variable $D_p$ is the treatment indicator taking 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 $k$ at the bottom and a positive number $\bar{k}$ at the top). In the estimation, we take $k = -65$, $\bar{k} = 65$ and plot estimates for $-60 \leq k \leq 60$. We omit the parameter for $k = -1$, hence all estimates are with respect to the day before the auction format change.

We create a dataset for each treatment-control 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 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 Set 3 and 4. The data are winsorized by capping the values of $y_{pt}$ at 0.1 percentile from below and at 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).

### 3.2.2 Identifying Assumptions

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

\(^7\)We use the same fixed effect for the 30th and 31st days of the month, as there are fewer observations on the 31st day.
(2003); Angrist and Pischke (2009).

On a different note, our event study estimates may potentially reflect market equilibrium effects: if, for instance, average prices of treated publishers go up, buyers may substitute from treated publishers to control publishers.\textsuperscript{8} We believe 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 switch by European Media Company A in 2019, no control publishers operate in Country X (because there were few suitable candidates on the exchange). In 2020, the control group does include publishers operating in Country Y, but they occupy only 3.3\% of impressions and 12.6\% of revenue earned by all the control publishers.

3.2.3 Estimation Results

![Graphs showing estimation results 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{8}Technically, this is a violation of the stable unit treatment value assumption (SUTVA; Imbens and Rubin, 2015, p. 10).
Figure 4 indicates the point estimates and 95% confidence intervals for $\beta_k$’s for different pairs of treatment and control groups. In each of the four treatment-control pairs, we observe an immediate jump in 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 next day of format change ($\beta_1$) by 0.45/1000 USD, relative to the counterfactual price level if these publishers were to continue to run SPAs. This lift in price is substantial: it is 73% of average price of September Publishers during the 30-day period immediately before the change (shown in Table 1). Average price under FPAs continues to be higher than SPAs until $k = 60$.

The top right panel shows estimates for publishers of Company A, Country X for the September 2019 format change. $\beta_1$ is estimated to be 1.62/1000 USD, which is 34% of average price of publishers of Company A, Country X during the 30-day period immediately before the format change. This time, the lift in average price is transitory: Estimated effect diminishes over time and becomes insignificant as $k$ nears 60. The bottom two panels show estimates for the two batches of format changes in 2020, with left panel showing effects for Company B after April 1 and right panel showing effects for Company A, 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 price level during the immediately preceding 30-day period). Again, the lift in average price under FPAs diminishes over time and becomes insignificant as $k$ nears 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, so the average revenue is the mean of the maximum of 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, instantly after the format change, at a level sustained by the equilibrium. Compared to these predictions, we observe that average prices went up initially upon all format changes compared to the level under SPAs, and the lift dissipated over time for the three format changes in 2019 and 2020. We interpret this *transitory* lift in prices as evidence that (i) some bidders shaded their bids insufficiently under the new regime of FPAs compared to their rational, best-response strategy, and (ii) they gradually learned to shade their bids to a level sustained by 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 price level under FPAs eventually falls down 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 by Vickrey (1961); Myerson (1981); Riley and Samuelson (1981). We believe this result is noteworthy and intriguing specially considering that we do not believe the prerequisites for the revenue equivalence theorem (such as bidder symmetry) hold in our setting (Maskin and Riley, 2000).

Second, we note that it took less time for the average prices to go down to the level under SPAs in 2020 compared to 2019, and then compared to 2017: In the 2017 format change, after 60 days the average price was still not coming down after the initial jump. In contrast, in the 2019 change, the average price came back to the SPA level in 60 days. This period until price decrease shortened to 30 days in the 2020 format changes. We interpret this as evidence of long-term learning that bidders got better and faster in adjusting their bids, either through (or both of) their first-hand experience of format changes or by industry-wide learning.

3.4 Role of Ad Campaign Budgets

A potential concern for the above interpretation relates to the role of ad campaign budgets (see, for instance, Balseiro et al. (2015) for a theoretical treatment of budget constraints in display ad auctions). One may be concerned that bidders spend a fixed amount of budget on the treated publishers, and whatever phenomena taking 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, on the results above. Most bidders/advertisers buy impressions from multiple publishers and they usually do not set fixed budgets for a particular publisher or a group of publishers.

To support this claim, we present two pieces of evidence, one using cross section of ad campaigns and another using time series of bidders’ spend. First, we take the cross section of all ad campaigns by advertisers that used Xandr’s DSP service including its bidding algorithm and bought from our treated publishers near the format change dates (30 days before or after the format change). For each such ad campaign, we compute the fraction of its spend on treated publishers (i.e., compute the dollar amount it 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 ad campaigns in an ascending order of the computed fraction, and plot the cumulative percentage in those ad campaigns’ total spend on the treated publishers. Figure 5 shows such cumulative percentage plot.
for ad campaigns that bought from Global Company September Publishers, separately for the 30-day period before the format change (in solid line, “Pre”) and the 30-day period after (in dashed line, “Post”). We observe that the share of September Publishers varies considerably across campaigns. The midpoint of the solid line indicates that 55.2% of September Publishers’ revenue from ad campaigns using Xandr’s DSP service during the 30-day period come from ad campaigns that spent less than 55% on September Publishers (i.e., spent more than 45% on other publishers). Figure B.1 shows plots for the other three groups of treated publishers, with similar observations. These figures indicate that advertisers buy from a diverse set of publishers and not just from treated publishers.

Second, the time series of bidders’ spend on treated publishers exhibits quite a bit of change after the switch to FPAs, and such change shows 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 its spend as the ratio of that bidder’s spend on the treated publishers during the 7-day period after the format change to the spend during the 7-day period after the format change. Figure 6 shows the histogram of such growth rates for bidders buying from September Publishers (unit of observation is a bidder). They are color-coded by each bidder’s importance in September Publishers’ revenue, i.e., whether (i) the bidders are top 5 bidders in terms of spend on September Publishers, (ii) they otherwise spend at least 1,000 USD for 7 days before the format change, and (iii) others. 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 revenue across bidders. These facts suggest that the bidders do not have a fixed budget on treated publishers.

### 3.5 Robustness Checks

We rerun the event studies regression in equation (1) by replacing the outcome variable (left-hand-side variable) with $\log y_{pt}$, log of average price. Figure A.1 shows the estimates. Apart from showing some pretrends — which is the reason why we prefer $y_{pt}$ instead of $\log y_{pt}$ as the main specification — the basic observation stays the same, i.e., (i) significant jump after the format change, and (ii) decline in the lift in approximately 60 days (Company A, Country Y) or 30 days (Company B and Company A, Country Y).

To investigate whether seasonality adjustments are affecting the estimates, we also estimate the event studies 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 event study
Figure 5: Cumulative percentage of Global Company September Publishers’ revenue from ad campaigns that used Xandr’s DSP service. The horizontal axis represents the share of September Publishers within each such ad campaigns’ spend, rounded to nearest multiple of 10%. The revenue and share are computed separately for 30 days before the format change (“Pre”) and for 30 days after (“Post”).

Figure 6: Histogram of growth rates of bidders’ spend on Global Company September Publishers from 7 days before format change to 7 days after, color-coded by the importance of each bidder in September Publishers’ revenue during the 7-day period before change (as captioned).
regression as in (1), except that \( y_{pt} \) is replaced with \( \tilde{y}_{pt} \) and the seasonality fixed effects (\( \gamma_{p,\text{dow}(t)} \), \( \gamma_{p,\text{dom}(t)} \), \( \gamma_{p,\text{month}(t)} \), and \( \gamma_{p,\text{eoq}(t)} \)) are removed; See Appendix A.2 for details. In the second method, we estimate (1) without any seasonality fixed effects. Figures A.2 and A.3 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.3 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 studies regression by picking hypothetical dates for format change that are one year before the actual dates. Figure A.4 shows the results. The estimates are no longer statistically significant in three out of four pairs. For the remaining pair (Company A, Country Y vs. its controls), the estimated effects of hypothetical format change are negative.

4 Bidder Heterogeneity

To investigate further the relation between response in revenue/spend and bidders’ behavior, we estimate how the effect of format change on spend differs across different types of bidders. For that purpose, we classify bidders into different levels of sophistication as below, and then estimate the following regression equation:

\[
y_{pbt} = \alpha_{pb} + \sum_{k \leq k \leq K, k \neq -1} \beta_{bk} D_{pb} \cdot 1(K_i = k) + \gamma_t + \gamma_{pb,\text{dow}(t)} + \gamma_{pb,\text{dom}(t)} + \gamma_{pb,\text{month}(t)} + \gamma_{pb,\text{eoq}(t)} + \epsilon_{pbt}.
\]

Here, \( b \) indicates the type of bidders as we define below. The difference with the main regression specification (1) is the additional index \( b \): (i) the outcome variable \( y_{pbt} \) is now the average spend 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 seasonality fixed effects \( \gamma_{pb,\text{dow}(t)}, \gamma_{pb,\text{dom}(t)}, \gamma_{pb,\text{month}(t)}, \gamma_{pb,\text{eoq}(t)} \) 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. For that purpose, we classify the bidders into three types, “large”, “medium” and “small,” as follows. We calculate each bidder’s spend on the treated publishers for 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 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 response in spend is largest among
“small” bidders and smallest among “medium” bidders, while “large” bidders’ responses were in between the other two types.

We next use a classification of bidders that are 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 call them the “AppNexus/Xandr bidder.” Since the AppNexus/Xandr bidder uses the bidding algorithm by Xandr, which coordinated the format change from SPA to FPA, it was arguably more sophisticated than other bidders in changing its bidding algorithm.

![Figure 7: Effects of format changes on spend for the AppNexus/Xandr bidder and non-AppNexus/Xandr bidders for Global Company September Publishers.](image)

Figure 7 shows the estimated effects when Global Company September Publishers changed to FPAs. We observe that spend by non-AppNexus/Xandr bidders jumped immediately ($\beta_{b1} = 0.56/1000$ USD, or 84 percent of 30 days average price before format change) and that increase persisted for 60 days, while spend by the AppNexus/Xandr bidder increased only moderately ($\beta_{b1} = 0.20/1000$ USD, or 39 percent of 30 days average price before format change) and became statistically insignificant after 6 days. These suggest that the AppNexus/Xandr bidder adjusted to the new environment of FPA more quickly than other bidders with its sophisticated bidding algorithm incorporating bid shading, suggesting the lift in revenue is the result of less-than-optimal bid shading by unsophisticated bidders. Figure C.2 shows estimates for other publishers, and we observe a pattern similar to Global Company September Publishers. The exception is Company B, which sees a larger increase in spend by the AppNexus/Xandr bidder. For Company B, un-
like other publishers, the AppNexus/Xandr bidder represents only a small fraction of impressions and revenue (3.5 percent of impressions and 5 percent of revenue for 30 days before the format change) and even reduced the number of impressions by 80% (comparing 30 days prior to 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 only buys 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’ spend: as different bidders compete for the same impressions, change in bidding behavior by some bidders affect which bidders win the auctions, changing the composition of impressions (market equilibrium effect) We understand that the change in composition only attenuated 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 spend 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 pushes down their average spend than the level when there were no change in the composition of impressions (i.e. if the bidders would purchase the same set of impressions). In contrast, advertisers that constitute the AppNexus/Xandr bidder would lose auctions for impressions for which they have lower willingness to pay. This increases their average spend than when there were no compositional effects of the format change.

5 Conclusion

Using the data of internet display ad auctions, we have analyzed the impacts of auction format change from second price auctions (SPAs) to first price auctions (FPAs). By estimating event studies regressions, we find that average price jumps up immediately after the format change from SPAs to FPAs, which attenuates over time. We take this as evidence of suboptimal, insufficient bid shading by some bidders. Comparing across different instances of format changes, we also find evidence that bidders learn over time about how 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 — shade their bids more aggressively than non-AppNexus/Xandr bidders once the format is 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 for a simulation of bids, for each bidder, in a counterfactual world where they shaded their bids rationally, and compare that with the actual bidding.
A Robustness Checks

A.1 Log Average Price as Outcome Variable

Figure A.1: 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.2 Alternative Seasonality Adjustments

Figure A.2 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, so subtracting this seasonal component from $y_t$ gives the deseasonalized time series $\tilde{y}_{pt}$.

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

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

Figure A.3 estimates the main regression (1) but without any seasonality fixed effects.

Figure A.2: Estimates of $\beta_k$ under “two-step” method.
Figure A.3: Estimates of $\beta_k$ when no seasonality adjustments are made.
A.3 Falsification Test with Hypothetical Event Dates

Figure A.4: 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 such ad campaigns’ spend, rounded to nearest multiple of 10%. The revenue and share are computed separately for 30 days before the format change (“Pre”) and for 30 days after (“Post”).
Figure B.2: Histogram of growth rates of bidders’ spend 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 (as captioned; “AppNexus/Xandr” indicates the AppNexus/Xandr bidder as explained in Section 4).
C Bidder Heterogeneity

Figure C.1: Estimated lift in bidders’ spend on Global Company September Publishers, separately for “large”, “medium”, and “small” bidders. A bidder is classified as “large” if their share of September Publishers’ aggregate revenue during 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 spend per sold impression, separately for AppNexus/Xandr bidder and for other bidders.
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