No More Chasing Waterfalls: A Measurement Study of the Header Bidding Ad-Ecosystem

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ABSTRACT
In the last few years, Header Bidding (HB) has gained popularity among web publishers and is challenging the status quo in the ad ecosystem. Contrary to the traditional waterfall standard, HB aims to give back control of the ad inventory to publishers, increase transparency, fairness and competition among advertisers, thus, resulting in higher ad-slot prices. Although promising, little is known about this new ad-tech protocol: How does it work internally and what are the different implementations of HB? What is the performance overhead, and how does it affect the user experience? Does it, indeed, provide higher revenues to publishers than the waterfall model? Who are the dominating entities in this new protocol?

To respond to all these questions and shed light on this new, buzzing ad-technology, we design and implement HB-Detector: a holistic HB detection mechanism that can capture HB auctions independently of the implementation followed in a website. By running HB-Detector across the top 35,000 Alexa websites, we collect and analyze a dataset of 800k auctions. Our results show that: (i) 14.28% of the top Alexa websites utilize HB. (ii) Publishers tend to collaborate mostly with a relatively low number of demand partners, which are already big players in waterfall standard, (iii) HB latency can be significantly higher than waterfall, with up to 3x latency in the median cases.

KEYWORDS
Header Bidding, Digital Advertising, Ad Transparency, RTB, Waterfalling, AdTech

1 INTRODUCTION
The largest portion of the digital advertisements we receive today while browsing the web follows a programmatic ad-purchase model which enables advertisers to perform dynamic pricing and user targeting. Upon a website visit, a real time auction gets triggered, usually via the real-time bidding (RTB) protocol [23], for each available ad-slot on the user’s display. These auctions are hosted in remote marketplace platforms called Ad Exchanges (ADXs) (e.g., AppNexus, Microsoft Ad Exchange, OpenX, Rubicon Project) that collect the bids from their affiliated Demand Site Platforms (DSPs) (e.g., Google DoubleClick, MediaMath, TubeMogul). The DSP with the highest bid will win, pay the second best price and deliver its impression to the available ad-slot on the user’s display.

However, there are more than one ad networks that can provide bids for an ad-slot. In the traditional standard for ad-buying, called waterfaling, the different ad networks (ADXs with their affiliated DSPs) are prioritized in hierarchical levels. Thus, when there is no bid from ad network #1, then a new auction is triggered for ad network #2 and so forth. Apart from the auction-based ad purchase, there are also other non-programmatic channels like direct orders from advertisers who run static campaigns for a certain number of impressions targeting not a user but the entire audience of a specific website (e.g., an ad regarding super bowl on espn.com). Alternatively, if there is neither a direct order nor a bid in these auctions, the ad-slot may be filled via a different channel for remnant inventory called fallback or backfill (e.g., Google AdSense).

The process of ad prioritization among the above different channels and the different ad networks in waterfall standard

1according to Vickrey type of auctions[42]
is managed through the publisher’s ad server or Supply Side Platform (SSP) (e.g., DoubleClick for Publishers (DFP)). Priorities are typically set not at real time but based on the average price of the past purchases for each channel. As a consequence, in waterfall standard not all ad partners have the ability to compete simultaneously. As a result, the publishers do not get the optimal charge price, since an ad-slot may not be sold in the higher price (e.g., if the winning bid in the auction of ad network #1 is 0.25$, the ad slot will be sold even if there was a bid of 0.55$ in ad network #2). Apart from the potential loss of money for the publishers, there is also a significant lack of transparency, since besides the winning bidder, the publishers do not know who else bids for their ad-slots and for how much. In addition, the lack of control restricts the publishers from choosing demand partners, or different sale channels at real time (e.g., to get a high price (e.g., through RTB) when the quota of direct sold ads has not yet been depleted).

To remedy all the above, Header Bidding [44] has been recently proposed and has started to gain wide acceptance among publishers [18, 21, 30, 40]. As depicted in Figure 1, HB is an additional auction that takes place not on the ad server this time, but inside the header field of a HTML page, before anything else is loaded on the page. It allows publisher to simultaneously get bids from all sale channels (e.g., direct orders, programmatic auctions, fallback) and demand partners (e.g., DSPs, ADXs, ad agencies). This not only gives the control back to the publisher but also higher revenues, since it guarantees that the impressions with the higher price will get bought and rendered [10]. On the advertiser’s side, HB promotes fairness since there are no priorities. Consequently, any advertiser could win any auction, as long as it bids higher than others. This makes small advertisers competitive compared to bigger ones, which on the waterfall model would have higher priority.

Although there is a lot of research regarding the waterfall standard [6, 7, 28, 29, 32], we know very little about the innovative and rapidly growing mechanism of HB. Specifically, how is HB implemented? What is the current adoption of HB on the web? What is the performance overhead and how it affects the page rendering time? How many bids can the average publisher receive? What are the average charge prices and how do these compare to the ones of the waterfall standard? Which are the big players and how is the market share divided?

To respond to all these questions, we design HBDetector: a novel methodology to detect HB auctions on the web independently of the HB implementation a website may use. By crawling the top 35,000 Alexa websites, we collect a rich dataset of 800k auctions, which we analyze and present the first of its kind, full-scale study of HB. In summary, in this paper we make the following main contributions:

(1) We study the HB ecosystem and discover different HB implementations (i.e., Client-side, Server-side and Hybrid).
(2) We propose HBDetector, the first of its kind, implementation-agnostic detection mechanism, capable of detecting HB auction procedures on the Web.
(3) By implementing and running HBDetector\(^2\) across the top 35,000 Alexa websites, we collect a dataset of 800k auctions and find 14.28% of the sites using HB.
(4) We analyze the collected dataset and conduct the first full scale study of HB aiming to shed light on how this innovative technology of HB works. The results of this study show that: (i) 14.28% of the top Alexa websites utilize HB, and this portion has been rising through the years. (ii) Publishers tend to collaborate mostly with a relatively low number of Demand Partners, which are already big players in waterfall standard, (iii) HB latency can be significantly higher than waterfall, with up to 3x latency in the median cases, and up to 15x in some extreme, 10% of cases.

2We plan to open-source HBDetector after paper’s publication

2 BACKGROUND ON HEADER BIDDING

HB is considered one of the most important advancement in ad tech since the introduction of real-time bidding (RTB) [43]. The main purpose of HB was to replace the traditional, and currently dominant, waterfall standard [1, 4, 17] and its hierarchical model, with a more fair, broadcast model (see Figure 1) that will:

i. enhance the transparency in the ad ecosystem,
ii. give back to publishers the control of the selling process of their ad inventory,
iii. increase the competition among advertisers, and, thus, iv. increase the revenue for the publishers

Figure 1: High level overview of the HB. The absence of priorities aims to provide fairness and higher competition among advertisers and increased revenue for the publisher.
2.1 Protocol Description

Contrary to the traditional waterfall standard, in HB the ad auction does not take place in a remote ADX, but on the user side. The process of HB, as depicted in Figure 2, is the following:

**Step 1** When a user visits a website, the HTML page is fetched. As soon as the header of the HTML is rendered in the browser, user tracking code and the third party library responsible for the procedure of the HB is loaded as well.

**Step 2** Then, the HB library sends (in parallel) HTTP POST requests to the Demand Partners (e.g., DSPs, ad agencies, ADXs which conduct their own RTB auctions) requesting for bids. These bid requests also include information about the current user (such as interests and cookies). Such information can be used by the Demand Partners to decide whether and how much they will bid for an ad-slot in the particular user’s display. Note, that if a Demand Partner does not respond within a predefined time threshold, its bid is not taken into account.

**Step 3** As soon as the Demand Partners respond with their bids (and their impressions), the collected responses are sent to the publisher’s ad server. The ad server will check the rest of the (non-programmatic) available channels (e.g., direct order, fallback) and will find the best option for the specific ad-slot.

**Step 4** As soon as the impression gets rendered on the user’s display, a callback HTTP request notifies the winning Demand Partner that its impression was rendered successfully on the user’s browser, and the ad price that was charged (winner notification).

In theory, with this new protocol, the publisher has the total control over the ad inventory they provide, knowing exactly how much the Demand Partners value each slot, and the actual amount of money they are willing to pay for it. In addition, there is full transparency, since the publisher can have access to all bids and decide at real time the best strategy it needs to follow without needing to trust any intermediates. However, as we will show later in Section 4, this transparency and control is not always applicable under the various types of HB we have detected.

2.2 HB Implementation & Performance

To implement the above protocol, publishers need to include HB third party libraries in their webpages. Although there does not exist a common standard for HB yet, the vast majority of publishers use the open-source library of Prebid.js [35], supported by all major ad companies.

This library includes: (i) the core component which is responsible to issue the bid requests and collect the responses, which are later sent to the publisher’s ad server, (ii) the adapters which are plugged into the core and provide all necessary functionality required for each specific Demand Partner. Prebid.js is supported by more than 200 Demand Partners (e.g., AppNexus, Criteo, OpenX, PulsePoint) that provide their own adapters [34].

The non-hierarchical model of HB produces much more network traffic than the waterfall standard. Indeed, HB sends one request for each and every collaborating Demand Partner. This can result to an increased page latency, especially when some Demand Partners take too long to respond. To make matters worse, as soon as they receive a bid request, some of these Demand Partners may run their own auctions inside their own ad network, with their own affiliated bidders (as depicted in Figure 1). This increased page latency raises significant concerns. Indeed, 40% of the publishes already mention that such latency is capable of impacting their users’ browsing experience [8, 9, 13].

3 METHODOLOGY FOR MEASURING HB

3.1 Detection Mechanism

In order to detect if a webpage is using HB for delivering ads to its users, we need to detect HB-related activity originating from the said webpage. As explained earlier, this is typically happening due to a library (typically implemented in Javascript) embedded in the header of the page. There are three main ways to detect if HB is present in a webpage:
(1) Perform static analysis of the page and identify tags of scripts that load known HB libraries such as prebid.js, gpt.js or pubfood.js.

(2) Detect DOM-related events that are triggered due to HB embedded in the webpage.

(3) Detect web requests sent from the page to HB entities.

The first method is straightforward to implement with the following steps: Download the webpage source code and use regular expressions to detect all know HB libraries. However, we note that just detecting these libraries is not enough, as false positives or false negatives could occur. Indeed, false positives could occur if the publisher decides to misuse names of existing HB libraries for other purposes. Also, if a publisher decides to rename the HB library it uses, or use a new library unknown to the detection tool, this would lead to false negatives.

The second method is more difficult to implement, but offers better detection rates with reduced false positives and negatives, and thus, harder to evade. This method monitors the DOM events that are triggered in a webpage, events that are sent to notify the code of interesting activity that has taken place on the page. Events can represent everything from basic user interactions to automated notifications happening on the page. Most HB libraries trigger events in several phases of an auction (initiation of the auction, bid collection, winning bidder, etc.). If such an event is detected, we can almost be certain that it is because of HB. Even better, by “tapping” on these events [27] we can collect information about HB that the first method is not able to detect.

The third method is similar to the second: monitor the web requests of a page in real-time, and detect all the request to and received from the known HB demand partners. By constructing a list containing all the known HB Demand Partners, we can check all the incoming and outgoing webRequests to the browser, and keep all relevant ones.

In this paper, we implemented HBDetector, a tool which combines the second and third methods to increase detection performance. HBDetector ads a content script in the header of each webpage when the page is loaded. This script monitors the webpage’s activity for various events and requests sent or received by the page, and keeps the ones relevant to HB. (an overview of the tool is illustrated in Figure 3).

HB events that our tool detects are the following:

- `auctionInit`: the auction has started
- `requestBids`: bids have been requested
- `bidRequested`: a bid was requested from specific partner
- `bidResponse`: a response has arrived
- `auctionEnd`: the auction has ended
- `bidWon`: a bid has won
- `slotRenderEnded`: the ad’s code is injected into a slot
- `adRenderFailed`: an ad failed to render

![Figure 3: Overview of the HBDetector mechanism. After the user accesses a webpage, all the incoming and outgoing WebRequests are inspected to detect HB partners. A content script is also injected in the header of the webpage to detect HB events about the auction performed.](image)

Table 1: Summary of our crawled data.

| Data                                | Volume   |
|-------------------------------------|----------|
| # of websites crawled               | 35,000   |
| # of websites with HB               | 4998     |
| # of auctions detected              | 800,000  |
| # of bids detected                 | 250,000  |
| # of competing Demand Partners      | 84       |
| # weeks of crawling                 | 5        |

In this work, we focus on three of these events: `auctionEnd`, `bidWon`, and `slotRenderEnded`. The `auctionEnd`, as its name states, is triggered after the auctions for the ad-slots have finished, i.e., the Demand Partners have submitted their offers. The `bidWon` event is triggered after the winning Demand Partner (s) have been determined. Finally, the `slotRenderEnded` event is triggered when an ad has finished rendering successfully on an ad slot. Using APIs and documentation provided by the HB libraries [22, 33], as well as in-depth reverse-engineering of the libraries available in the market, we were able to collect several metadata about the auctions, such as the Demand Partners who bided, the CPM (cost per million) spent, the ad size, the winning Demand Partner, currency, dimensions, etc.

We also constructed a list with all the known HB Demand Partners. We collected and combined several lists used by HB tools designed to help publishers fine tune their HB on their websites. Using this list, we can infer all the `WebRequests` about HB without altering them, in order to detect when a request to a Demand Partner is sent, and when an answer is received. The HBDetector is written in a few hundred lines of Javascript as a Google Chrome browser extension.
3.2 Data Crawling

We used our tool to detect which websites employ HB, by crawling the top 35,000 Alexa websites. We detected HB in ∼5,000 of the websites. Then, we crawled these 5,000 websites every day for a period of 34 days, collecting metadata about the HB auctions, and performance exhibited from the various websites using HB. In Table 1, we provide a summary of the data collected.

We note that we detected 800k auctions but received 250k bids. One could expect that each auction should have at least a bid. Indeed this would be the case if actual users were involved and Demand Partners were interested in them. However, given that our crawler has no profile, some HB partners were not interested to bid. Also, due to non-transparency in Server-Side HB, not all bid prices were available to our tool.

4 THE FACETS OF HEADER BIDDING

In this section, we analyze the crawled data and present results and observations we have made about the HB adoption over time and types of HB we identified from our exploration.

4.1 Header Bidding Adoption

Since this is a new ad programmatic protocol, we explore the general adoption of HB through time. We select the top 100 publishers, based on Alexa rankings [3] that we have identified they use HB using our tool. To analyze the adoption rate, we downloaded snapshots of their webpages using the Wayback Machine [24], and statically searched for HB libraries in their source code. Figure 4 shows the yearly breakdown of HB found in these websites. Interestingly, we observe a yearly steady increase of the HB adoption. Also, about 30% of these websites were early adopters and started using HB 5 years ago. Because we performed a static analysis looking for HB libraries and components in their websites’ code, we cannot detect HB with 100% accuracy. For this reason, we don’t see 100% HB adoption in 2019 as we should. This is an expected result, as publishers can change the name of the library they use.

4.2 Types of Header Bidding Detected

Our in-depth investigation of the HB ecosystem and the data collected revealed that this new programmatic advertising protocol is currently being deployed in three facets:
- Client-Side HB
- Server-Side HB
- Hybrid HB

In the next paragraphs we analyze each one, including the steps taken for the execution of the protocol, and potential consequences it may have.

4.3 Client-Side HB

In Client-Side HB, as the name implies, the HB process happens in the user’s browser. Figure 5 describes how Client-Side HB works. The user’s browser:

- step 1 requests the website,
- step 2 receives the website’s header,
- step 3 sends available ad-slots to participating partners,
- step 4 receives their bids,
- step 5 sends the received bids to the ad-server,
- step 6 receives the winning bid(s) from the ad-server,
- step 7 notifies the winning partner,
- step 8 and receives the winning impression(s).

Client-Side HB’s main goal is to improve fairness and transparency. Publishers can choose the Demand Partners they want to collaborate with, regardless of their market cap. What matters is if their bids are competitive enough. Also because the whole HB process is performed at the client side, and then sent to the publisher’s ad-server, it is completely transparent to the publisher and, in theory, to the user.

The publisher can know at any time which partners bid, for which ad-slots they were interested, how much they were willing to pay, etc. On the down side, Client-Side HB is harder to set up. Publishers need to have good technical understanding to set up and tune their HB library. Also, they need to set up and operate their own ad-server, a task which is not
trivial. Finally, because of the increased number of messages to be sent and received, or due to a bad configuration in the HB library, longer latencies may be observed.

From the user’s point of view, the only thing that can be observed is an increased latency for the loading of the webpage when it employs Client-Side HB. However, the user cannot be aware of all the HB activity happening in the background. This is where our HBDetector tool can help increase transparency of the protocol from the point of view of the end-user, and measure non-obvious aspects such as the communication and time overhead for the browser during Header Bidding, winning bids, etc.

4.4 Server-Side HB

In Server-Side HB, a single request is sent to a Demand Partner’s server, which is responsible to do the whole HB process and send back to the client only the winning impressions. As Demand Partners in this scenario are considered all the possible advertising partners (SSPs, DSPs) that take part in the auction. Figure 6 shows the Server-Side HB model. The user’s browser:

step 1 requests the website,
step 2 receives the website’s header,
step 3 sends the available slots to the ad-server,
step 4 receives the winning impression(s).

Obviously, in this model the publisher needs to trust that the Demand Partner (i.e., the server handling all requests) is honest and will select the best bids as winners, thus providing the best possible profits to the publisher.

Server-Side HB requires the least effort from the publishers to setup their HB. However, in exchange for setup convenience, it reduces transparency to the minimum, since the publishers have no way of knowing the Demand Partners participating in the auctions or their actual bids. Publishers don’t need to tune their library, nor set up an ad-server. They just add to their webpage a pre-configured library, provided by the Demand Partner they choose to collaborate with. Also this setup could make small players less competitive, compared to big ones with better infrastructure and higher influence to the market, because publishers could tend to trust the latter ones. In effect, the Server-Side HB has re-enabled the dominant players in RTB to regain control of the ad-bidding process which was momentarily transferred on the user browser.

From the user’s point of view, this setup lacks transparency and does not offer many insights on how the whole HB process either works, performs, or what impact it has on the user’s browser: all auctions are done in the background, at the ad-server’s side. This setup brings back the pros and cons of the typical RTB with ADXs playing the crucial and controlling role in the protocol.

4.5 Hybrid HB

As its name states, this is a hybrid model that combines Client-Side HB with Server-Side HB (Figure 7). In this model, the user fetches the webpage which will then request bids from independent demand partners (as in the Client-Side HB model. When it receives the bid responses, it sends them to the ad-server along with the available slots. The ad-server then performs its own auction (as in the Server-Side HB model) and picks the final winning impression(s) from all collected bids (both from the client and server side). This model tries to combine the pros of Client-Side HB and Server-Side HB, while avoiding their cons. It is a semi-transparent model with a certain degree of fairness, which requires a moderate degree of effort for the setup. Publishers can choose the Demand Partners they will collaborate with directly, so they can know the bids they are willing to pay. Also they don’t need to operate their own ad-server, so the programmatic effort is reduced to tuning with the selected Demand Partners.

4.6 Facet Breakdown

The 3 facets of HB that we observed and described above have the following breakdown. We notice that the server-side currently comprises the larger portion of the market with 48%. Then, the hybrid is second with 34.7% and the client-side is third with 17.3%. This means that publishers are
preferring the centralization and control offered by a server-side (or hybrid) model, which imposes reduced overhead and increases speed of transactions. As we will see in the next section, this highly skewed breakdown towards server-side or hybrid is due to the presence of Google’s DFP, which participates in many of these HB auctions.

**Finding:** HB has been increasing its presence in the market for the last 5 years.

**Finding:** There are 3 types of configurations for HB: client-side, server-side, and hybrid model.

5 ANALYZING THE HB ECOSYSTEM

In this section, we analyze the data crawled under different dimensions:

- number, diversity and combinations of Demand Partners participating in HB (Section 5.1),
- latencies measured with respect to the overall HB process, publishers and participating partners (Section 5.2),
- auctions performed, bids received, bids taken into account or got lost (Section 5.3),
- properties of ads delivered: ad-slot prices paid and comparison with RTB prices. (Section 5.4)

5.1 Who’s Involved in Header Bidding?

Here, we examine the properties of Demand Partners across the websites crawled and investigate who are the dominant entities, how many partners participate per website, their frequent combinations, if this has any association with the performance of Header Bidding, etc.

**Who dominates the market?**

First, we examine the popularity of each Demand Partner across all websites. We define as popularity the percentage of sites that a given Demand Partner participates in its HB process. In total, we find 84 unique Demand Partners. Figure 8 shows the 11 most popular Demand Partners. Google’s DoubleClick for Publishers (DFP) is the most popular partner, with more than 80% of publishers utilizing it. The DFP can be used both as an ad-server and as a server-side HB solution. Thus, it is not strange that most of the publishers choose it over setting their own ad-server. We can also see that the list of top Demand Partners is full of popular “waterfalling” partners, such as AppNexus, Rubicon and Criteo. This means that these companies have already invested in the HB protocol and process early on, capitalizing on their knowledge and market share in RTB, and that most publishers tend to choose these traditional big ad-partners over smaller ones.

**Finding:** Google dominates the HB market with more than 80% of the market share.

**How many Demand Partners are typically used?**

A website can use more than one Demand Partner during the HB auction. But given that the more partners used could impact the loading time of the website, a question is what is typically employed by publishers. Figure 9 shows the ECDF of the number of Demand Partners found on each website. We can see that more than 50% of the websites use only one Demand Partner. However, about 20% of the publishers collaborate with 5 or more Demand Partners, and about 5% of publishers collaborate with ten or more Demand Partners.

**Finding:** Although most publishers use only one Demand Partner, 5% of publishers use several partners - sometimes more than 10.

**What are the most common combinations of Demand Partners?**

Demand Partners can appear on a website in different combinations. Given that we already identified 3 types of HB setup (client-side, server-side and hybrid), it is interesting to see how publishers select different Demand Partners to participate in their HB auctions. We should keep in mind that the mixture of partners selected can impact the performance of HB with respect to delays and prices achieved. Also, frequently selected combinations may reveal typical or unlike...
5.2 Header Bidding Latency

In this section, we set out to explore various aspects of Header Bidding such as the imposed latency measured from different vantage points, with respect to overall latency, publishers using it, number of partners participating.

How much latency does HB add?

The total latency of HB on a publisher’s webpage is defined as the time from the first bid request to a Demand Partner (step 1 in Fig. 2) until the ad-server is informed and responds (step 3 in Fig. 2). In Figure 11, we show the total time needed from the HB to process the bid requests and responses. We see that the median latency is about 600ms (point 1 in figure), which can be a noticeable overhead in the loading time of a webpage. However, some websites suffer a much higher overhead. Indeed, about 35% percent of the websites suffer more than one second of latency, and as much as 4% of websites suffer more than 5 seconds of overhead.

Based on our description so far, one might expect that a timeout would be used during the HB, to cut off responses from slow Demand Partners. Although many of the wrappers use a time out of 3 seconds, publishers are able to set their own threshold by making some changes in the wrappers. Unfortunately, our results indicate that at least 10% of the websites exceed the threshold of 3 seconds (point 2 in figure), and some even need 20 seconds before the HB is completed!

Finding: HB can add significant latency in loading of a webpage: 0.6 seconds for the median website and more than 3 seconds in 10% of the websites examined.

Does publisher popularity associate with HB latency?

As a next step, we study the latency measured with respect to the ranking of each website. Someone could expect that highly ranked publishers seek to have lower latencies for their websites, and therefore add partners in their HB process who demonstrate lower latencies. Also, higher-ranked websites may have available more resources to use in their HB planning, which could lead to reduced latencies and better performance. In Figure 12 we show the latency of publishers vs. their Alexa ranking. We note that, although the gradient of the linear fit is very small, it is still non-zero and positive. This could indicate that, indeed, some higher-ranked publishers may attempt to reduce latency of their page by selectively adding HB partners. However, for the general case, it seems that publishers can exhibit a wide range of latencies due to HB, regardless of their ranking.

Finding: Higher-ranked publishers may achieve better HB latencies, but overall, website popularity does not significantly associate with HB latency.

Do multiple Demand Partners impact HB latency?

As we mentioned earlier, a publisher may choose to use several Demand Partners at the same time. Although this decision may increase competition for the ad-slots offered, and can drive-up the bidding prices, and consequently the publisher’s revenue, it may also increase the latency of the
webpage to load on the user’s browser, and decrease the quality of the overall user experience. For this, we explore the impact that the number of Demand Partners can have on the user experience (with respect to latency).

Figure 13 shows the latency of websites vs. the number of Demand Partners each website has. We observe that publishers who use only one Demand Partner have a small latency of 268.2 ms. As can be seen by the second y-axis, this is the majority of websites. Also, publishers with two Demand Partners have a latency of 1091.6 ms. Publishers with more than two Demand Partners have a median latency in the range of 1.3-3 seconds.

**Finding:** Publishers who use more than one Demand Partner in their HB auctions tend to have significantly higher page load times (at least 1 second extra delay).

### Does HB partner popularity associate with HB latency?

Next, we study the latency of all 84 Demand Partners detected, ranked based on their popularity in our dataset. In Figure 14 we show the average latency observed per partner, when computed across all the websites each partner was found. We observe an upward trend for their latencies.

**Finding:** Demand Partners who are more popular tend to demonstrate lower latencies in HB.

### How many HB bids are lost?

Next, we analyze the portion of bids lost per auction. As lost bids we define all the responses about bids from Demand Partners which arrive too late, i.e., after the request to the ad server is sent from the browser. Thus, it is important to understand what is the portion (and number) of bids that were received from the browser, that came too late and were not considered in the HB auction. In Figure 15, we show the ECDF of the portion of such lost bids with respect to the total number of bids received at a website at a HB auction.

We see that in 50% of the cases with lost bids, almost 50% of the bid responses come too late to be considered in the auction by the ad server. Also, for 10% of the auctions, more than 80% of the bids are lost. In results not shown here for brevity, we measured that in 60% of the auctions, there was only one lost bid, in 40% of the auctions we had at least two lost bids, and in 20% of the auctions we had at least four lost bids. All these lost bids point to the possible loss of revenue from the publisher. This could be the result of a poorly defined wrapper that sends the request to the ad server the same time it sends the requests to Demand Partners, without waiting for their responses first.

**Finding:** In more than 50% of the auctions, at least half of the bids are not considered in the auction, due to being delivered too late, leading to potential loss of revenue for the publisher.

#### 5.3 Header Bidding Ad-slots Auctioned

In this section, we investigate the properties of the auctioned ad-slots, such as the size, the number auctions per website and how this impacts the overall performance of the protocol.

### How many ad-slots are auctioned per webpage?

We start by investigating the number of ad slots available for auction. These are the possible ad slots that the publisher provides to the partners to place their advertisements. In Figure 16, we plot the ECDF of the number of ad slots across the websites with HB. We observe that the median website has around 4 available slots. However, about 10% of the websites have more than 10 slots, and 3% of the websites provide more than 20 slots for auction.

Requesting bids for 20 ad-slots on a single page can be considered odd. Therefore, we manually investigated such cases, and to our surprise, we found that some publishers request auctions for more slots than they have available for
Figure 16: Auctioned ad slots across websites. The median website has about 4 available ad-slots, and 90% of websites have 10 ad-slots. We speculate they do that due to either bad configuration of their wrapper (i.e., they use the same HB wrapper for all the devices they serve without customizing the requests), or because they want to receive bids for multiple versions of the same ad-slots, for better optimization of the publisher’s HB process later on.

Finding: We observe that the median website has around 4 available slots. Although most websites have a small number of available slots, some websites request auctions for more slots than they have available for display!

Does the number of auctioned ad-slots impact latency?

Next, we checked if the HB latency is associated with the number of ad-slots auctioned. Intuitively, we may expect that the more slots are to be auctioned, the more time the HB will take. However, given that a lot of Demand Partners invest significant computing resources to parallelize and optimize bidding computations, the above statement may not hold. In Figure 17, we plot the latency of HB based on the number of slots auctioned in the website. In the majority of cases, this latency includes the communication to the ad-server. In Client-Side HB we cannot know the ad-server (since each publisher uses their own), so we have no means to infer this latency. We observe that the total latency tends to increase with the number of slots auctioned. In fact, when there are 1-3 ad-slots auctioned, the median latency is 0.3-0.57 seconds, but when the slots are 3-5, the median latency ranges to 0.57-0.92 seconds. Interestingly, we observe that even if there is only one ad-slot to be auctioned, the latency can still vary a lot per auction, from a few tens of milliseconds to almost 2 seconds. This can be due to extra latencies as result of internal auctions that might occur to each Demand Partner.

Finding: More ad-slots in a webpage generally lead to higher latencies in the HB process.

What are the most popular ad-slots auctioned?

Finally, we analyze the most popular dimensions of HB ad slots. Our findings are presented in Figure 18. We see that the most common ad size is the 300x250 (side banner) and the 728x90 (top banner). These two are popular banners in both mobile and desktop advertising, and they match results observed in the past for RTB [32]. Due to the increase of mobile browsing, publishers can choose these specific sizes to keep the HB configuration simple and well defined for multiple devices (as they don’t need to set multiple sizes for different devices, and fewer auctions need to occur on the Demand Partners’ side).

Finding: Most popular ad-slots auctioned in HB for a webpage are 300x250 (side banner) and 728x90 (top banner).

5.4 Header Bidding Charge Prices

In this section, we discuss the ad-slot charge prices of HB and how they vary depending on the size of ad-slot. We were able to detect the ad prices using HBDetector. In case of Hybrid and Client-Side HB, most of the prices are transparent to the client and easy to extract from the bid response messages. In contrast, in Server-Side HB the prices are not trivial to detect. We analyze in depth the auction metadata, and based on several heuristics we find and extract the prices whenever they are included.

What are the HB partners willing to pay?

First, we analyze the prices bided by the Demand Partners during the auctions. In Figure 19, we show the CDF of the baseline charge prices (in CPM or cost per thousand ad impressions) that advertisers are willing to spend for the ad-slots auctioned. We observe that more than 10% of the prices are more than 0.5 CPM which is lower but comparable to regular waterfelling prices, as claimed in past studies (found
Finding: HB partners are willing to pay relatively high prices even with no prior knowledge for the user.

What are the HB partners paying per ad-slot?

Second, we compare ad-slot sizes with prices paid for each size. In Figure 20 we plot the prices (in CPM) for each ad-slot. We see that in the recorded dimensions, the median cost ranges from 0.00084-0.096 CPM. The most expensive ad-slot (based on median price) is 120x600 with 0.096 CPM. The cheapest ad-slot is 300x50 (which also happens to have the least ad-area) with 0.00084 CPM. Also, the most popular ad-slot size, which is 300x250, has a median cost of 0.031 CPM. Previous studies on waterfalling [32] find the prices of 300x250 slot ranging between 0.1 and 1.4 CPM with a median of 0.19 CPM. These prices are higher than the ones found in our HB study, but we should again consider that our detected prices are for baseline users that Demand Partners have no prior knowledge.

Finding: Popular ad-slots in HB cost prices comparable to RTB prices.

6 RELATED WORK

User data and their economics have long been an interesting topic and attracted a considerable body of research [2, 11, 19, 20, 29, 32, 36, 37, 39, 41, 45]. In particular, in [2], Acquisti et al. discuss the value of privacy after defining two concepts (i) Willingness To Pay: the monetary amount users are willing to pay to protect their privacy, and (ii) Willingness To Accept: the compensation that users are willing to accept for their privacy loss. In two user-studies [11, 39] authors measure how much users value their own offline and online personal data, and consequently how much they would sell them to advertisers. In [37], authors propose "transactional" privacy to allow users to decide what personal information can be released and receive compensation from selling them.

Papadopoulos et al. in [32] set out to explore the cost advertisers pay to deliver an ad to the user in the waterfall standard and RTB auctions. In addition, they study how the personal data that users leak while browsing (like location and interests) can affect the pricing dynamics. The authors propose a methodology to compute the total cost paid for the user even when advertisers hide the charged prices. Finally, they evaluate their methodology by using data from a large number of volunteering users. Olejnik et al. in [29] perform an analysis of cookie matching in association with the RTB advertising. They leverage the RTB notification URL to observe the charge prices and they conduct a basic study to provide some insights into these prices, by analyzing different user profiles and visiting contexts. Their results confirm that when the users’ browsing histories are leaked, the charge prices tend to be increased. In [31], the authors measure the costs of digital advertising on both the user’s and the advertiser’s side in an attempt to compare how fairly these costs are distributed between the two. In particular, they compare the cost advertisers pay in waterfall standard with the costs imposed on the dataplans, the battery efficiency and the privacy of the specific user.

In [26], the authors briefly describe HB and focus on optimizing its bidding strategy and the produced yield. They consider revenue optimization as a contextual bandit problem, where the context consists of the information available about the ad opportunity, such as properties of the internet user or of the provided ad slot. In [19], authors use a dataset of users’ HTTP traces and provide rough estimates of the relative value of users by leveraging the suggested bid amounts for the visited websites, based on categories provided by the Google AdWords. FDTV [20] is a plugin to inform users in real-time about the economic value of the personal information associated to their Facebook activity. In [25], Iordanou et al. try to detect both programmatic and static advertisements in a webpage, using (i) a crowdsourcing and (ii) a crawling approach to determine the criteria with
which ads are displayed. They find biases on ads depending on age, income and gender of users.

Bashir et al. in [7], study the diffusion of user tracking caused by RTB-based programmatic ad-auctions. Results of their study show that under specific assumptions, no less than 52 tracking companies can observe at least 91% of an average user’s browsing history. In an attempt to shed light upon Facebook’s ad ecosystem, Andreou et al. in [5] investigate the level of transparency provided by the mechanisms “Why am I seeing this?” and Ad Preferences Page. The authors built a browser extension to collect Facebook ads and information extracted from these two mechanisms before performing their own ad campaigns and target users that used their browser extension. They show that ad explanations are often incomplete and misleading. In [6], the authors aim to enhance the transparency in ad ecosystem with regards to information sharing, by developing a content agnostic methodology to detect client- and server- side flows of information between ad exchanges and leveraging retargeted ads. By using crawled data, the authors collected 35.4k ad impressions and identified 4 different kinds of information sharing behavior between ad exchanges.

7 SUMMARY AND DISCUSSION

Header Bidding (HB) has gained popularity among Web publishers, who have been eager to regain control of their ad inventory and how much it is sold to the online advertisers. Proponents of HB have touted that this new ad-tech protocol increases transparency and fairness among advertisers, since more partners can directly compete for an ad-slot. This, in theory, can boost the revenue of publishers who can select the Demand Partners that are competing for the publishers’ ad-slots, and also remove intermediaries from the ad-selling process.

However, our present study challenges a lot of these arguments. Specifically, we investigate and present in full detail the different implementations of HB and how each of them works. Based on these observations, we design and implement HBDetector: a first of its kind tool to measure in a systematic fashion the evolving ecosystem of HB, its performance and its properties.

7.1 Lessons Learned

By running HBDetector across the top 35,000 Alexa websites, we collected data about 800k HB auctions and performed the first in-depth analysis of HB. Overall, the lessons learned from this study can be summarized as follows:

• Depending on the publisher’s needs, Header Bidding can be implemented in 3 different ways: (i) Client-Side HB, (ii) Server-Side HB and (iii) Hybrid HB.
• Google (DoubleClick) dominates the HB market with more than 80% of market share.
• Most publishers use only one Demand Partner, but some use more than 10.
• DoubleClick for Publishers (DFP) dominates as a single partner, while it also appears in 51% of the competing groups of Demand Partners in HB.
• HB can impose 0.6 seconds of latency to the median website and more than 3 seconds to 10% of websites.
• HB latency does not get affected drastically from the publisher’s ranking.
• Publishers with more than one Demand Partner have higher page load times: Users visiting publishers who use only one Demand Partner face a small latency of 268.2 ms. When the website uses 2 Demand Partners this latency increases to 1091.6 ms and in case of 3, latency may reach as high as 3 seconds.
• More popular Demand Partners tend to have lower latencies.
• Most websites have a small number of available ad-slots per webpage (i.e., around 4 ad slots for the median case), but some auctions request for more ad-slots than they have available.
• As expected, the more ad-slots there are in a webpage, the higher the overall latency of HB will be. In fact, when there are 1-3 ad-slots auctioned, the median latency is 0.3-0.57 seconds, but when the slots are 3-5, the median latency ranges to 0.57-0.92 seconds.
• Side banner and top banner are the most popular ad-slots auctioned in HB.
• In more than 50% of auctions, half of bid responses arrive too late to be considered due to high latency, which could result in loss of revenue for the publishers.
• Demand Partners are willing to pay high prices even without prior knowledge for the visiting user.

7.2 Commoditization of Ad Supply

Header Bidding was introduced to put Demand Partners under pressure for more competitive pricing (and loosen Google’s grip on the market). Indeed, it has changed the hierarchy on the supply side. Demand Partners that could previously claim exclusive access to a publisher’s inventory (and thus higher positions in the waterfall) are no longer able to do so. Instead, HB enabled all Demand Partners regardless of their size or relationship with publishers, to compete for the same inventory, thus commoditizing supply [14].

However, as measured in this study, big companies such as DoubleClick, AppNexus, Rubicon, Criteo, etc., took advantage of their existing dominance in the ad-market and placed themselves again in a very centralizing (and process controlling) position within the HB ecosystem. Google, in
particular, handles as much as 80% of HB auctions. In general, we identified that Server-Side HB dominates this market with 48% of auctions handled by a single partner/ad-server.

7.3 Non-Viable Performance Overheads

The fear of latency has kept some premium publishers away from header integrations and continues to make others wary about embracing HB. Results of this study verify the concerns of publishers [12, 16] regarding the latencies imposed on the user side, measured up to 0.6 seconds for the median case and may even reach as high as 3 seconds. It is of no doubt that for the publishers that do the utmost to provide readers with a high-quality experience, such latency is capable of significantly degrading the user experience.

Although Header Bidding tech promises multiple in-parallel bid requests to Demand Partners that can provide the best possible ad price to the publisher, Javascript on the users’ end is single-threaded. That means even if the HB provider’s wrapper performs well-optimized asynchronous ad calls, these still need to stand in the network queue, thus increasing not only the overall HB execution time but also the entire webpage’s loading time. These delays can have adverse effects on user’s browsing experience while loading a HB-enabled webpage.

7.4 Loss of Bids

The broadcasting nature of Header Bidding results in an enormous amount of bid requests to multiple Demand Partners. As measured in this study, the median webpage has 4 ad-slots which means that 4 parallel auctions take place, where each of them request bids from numerous DSPs. This overwhelming volume of bid requests significantly increases the needed processing power for ADXs and the decision engines of DSPs, thus skyrocketing their infrastructure costs [15]. Indeed, companies that started supporting HB experienced increases of up to 100% in the bid requests they received [38] (i.e., between 5 million and 6 million requests per second) for the very same number of available ad-slots as before. Interestingly, the same partners may in fact compete for the same ad-slots more than once: in the HB and then in the regular waterfall model, since the publisher may still fall back to the waterfall if the HB does not reach high enough prices for the auctioned slots [15].

Apart from skyrocketing the infrastructure costs, the increased amount of bid requests also increases the response time for DSPs, causing lots of delayed bids, and in some cases (up to 50% for the median case) bids that arrive after the publisher’s set threshold. These lost bids not only are wasted network resources and processing power from the point of view of the Demand Partners, but also loss of potentially higher revenues for publishers.

7.5 User Data Leaking

Besides the performance overhead on the browser, the broadcasts of HB have also a significant impact on the privacy of end users. Programmatic advertising implies that the served ads are targeted based on the user’s interests, age, gender, etc. [20, 32]. This practice obviously raised a lot of controversy around the implications on users’ privacy, which has already been studied in the context of the traditional waterfall model [6, 7, 31]. Unfortunately, HB leads to even higher levels of privacy erosion, as the user’s information is sent to a larger number of third parties.

User-side effects: In the case of the waterfall standard, publishers move their inventory from one market to the next which means that waterfalling limits how much user data the bidders can collect. For example, if the first tier ad network (or ADX) in the waterfall wins 50% of the auctioned ad-slots, then subsequently, half of the ad-slots that are for sale won’t get passed along to other networks. So, each network only obtains user data from whoever they sell impressions to, which is only a portion of the total audience that the total ad-slots in the auction are sold to.

Contrary to that, HB allows, due to its broadcasting nature, each and every collaborating Demand Partner (e.g., ad networks, DSPs, ad agencies) to get notified simultaneously about the auction, and receive information about the current user. To make matters worse, in some cases these collaborating Demand Partners conduct their own auctions and may send user data along with their bid requests to several other potential bidders, without requiring from them to place any bid or spend any money for that, allowing these 2nd-auction partners to hoover user data passively for free (e.g., by always bidding low). So it is apparent, that the more partners the publisher collaborates with, the more third parties have access to a visitor’s data, which can then leak out further from there.

Publisher-side effects: Apart from the above user privacy implications, the user data leaked from HB auctions can be problematic for the publishers as well. Indeed, the leaked data can devalue publisher’s inventory by enabling re-targeting companies to use data leaked from HB appearing on premium publishers to target users while they are visiting other, non-reputable (or even fake news distributing) websites that sell ad-slots of lower values.

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