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AN EMPIRICAL ANALYSIS OF THE VALUE OF INFORMATION SHARING IN THE MARKET FOR ONLINE CONTENT

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I. INTRODUCTION

This paper studies the importance of consumer-related information to the market for display advertising and, in turn, to the publishers who produce and distribute online content. Our study is based on two primary data sets. The first is a large, impression-level database of advertising placements during a one-week period in August 2013, provided by two anonymous companies that operate advertising exchanges with automated bidding. These data form the basis for an econometric analysis that allows us to measure the premium paid by advertisers for ads served to customers with cookies, and ultimately to assess the added economic value generated by information sharing in the online content market. The second data set, provided by Adomic, measures the relative prevalence of ads generated by different advertising models based on observations of display ad placements for the top 4000 publishers. This data set allows us to assess the relative significance of third party advertising technology models to the industry in general, and to smaller, "long-tail" web sites in particular.

The results of our econometric analysis corroborate and extend an emerging body of empirical work documenting the value of information sharing in online advertising. Our estimates indicate that advertisers place significantly greater value on users for whom more information is available, and our results are highly significant both in a statistical and economic sense: after controlling for other factors, the availability of cookies to capture user-specific information is found to increase the observed exchange transaction price by at least 60 percent relative to the average price (for users with "new" cookies), and by as much as 200 percent (for users with longer-lived cookies). In addition, the Adomic data reveal that even the largest publishers rely on third-party technology models to serve approximately half of their advertising impressions, while "long-tail" publishers rely upon third-party technology models for up to two thirds of their advertising volumes.

The remainder of this paper is organized as follows. Section II provides an overview of the industry, and describes the structure of some of the key business models taking shape as online advertising markets evolve over time. Section III briefly reviews some key findings that have emerged from prior studies of online advertising markets. Section IV describes the dataset compiled for our econometric analysis, and reports the results obtained when our econometric model is applied to the data. Section V describes the patterns that emerge from the Adomic data, and their implications for the role of third-party advertising technology models in the industry. Section VI concludes.

II. ADVERTISING AND THE MARKET FOR ONLINE CONTENT

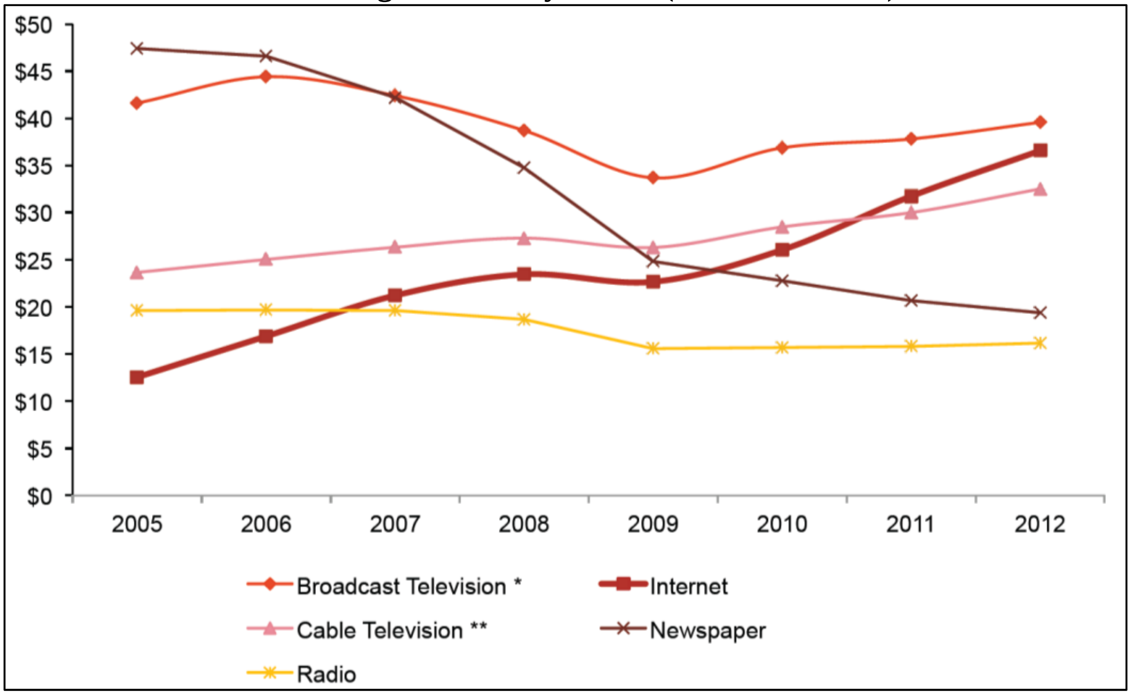
In recent years, advertising delivered over the Internet has become a significant source of revenue for web-based businesses, and now ranks among the largest segments of the advertising industry overall. This Section describes broad trends in the industry, and also provides an overview of the business models that have evolved in recent years.

A. Size, Revenues, Growth

Advertising delivered over the Internet has become increasingly central to the advertising industry. As seen in Figure 1, Internet advertising revenues have grown more rapidly than any other media type since 2005, surpassing cable television advertising revenues in 2011. As of 2012, Internet-based advertising revenue exceeded $36 billion, and was second only to Broadcast Television.[1]

[1] Interactive Advertising Bureau, "IAB internet advertising revenue report: 2012 full year results," (April 2013), [hereafter *IAB Report 2012*] available at: http://www.iab.net/media/file/IAB_Internet_Advertising_Revenue_Report_FY_2012.pdf, at 19-20.

Figure 1:
Advertising Revenue by Media (2005 – 2012, $B)



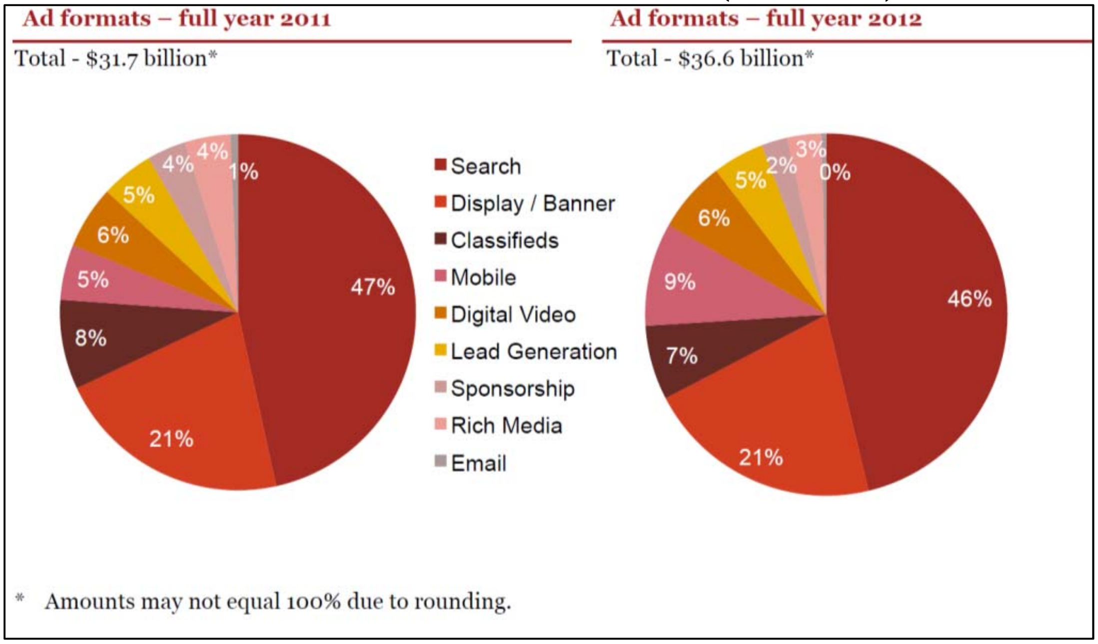
Source: *IAB Report 2012* at 20. * Broadcast Television includes Network, Syndicated and Spot television advertising revenue. ** Cable Television includes National Cable Networks and Local Cable television advertising revenue.

Display advertising represents a large share of Internet advertising. The Interactive Advertising Bureau defines "display-related advertising" as consisting of (1) display and banner ads (in which an advertiser pays for space to display a static or linked banner or logo); (2) rich media ads (which integrate some component of streaming interactivity); (3) digital video ads (which appear before, during, or after digital video content, such as an online news clip); or, (4) sponsorship ads (in which the advertiser pays for custom content).[2] As seen in Figure 2, these categories collectively accounted for nearly $12 billion in revenues in 2012, roughly one third of the industry total.[3]

[2] Interactive Advertising Bureau, "IAB internet advertising revenue report: 2012 full year results," (April 2013), available at: http://www.iab.net/media/file/IAB_Internet_Advertising_Revenue_Report_FY_2012.pdf, at 12 and at 21-22.

[3] As seen in Figure 2, these four categories collectively accounted for approximately 21% + 3% + 6% + 2% = 32 percent of industry revenues in 2012 (which totaled $36.6 billion).

Figure 2:
Distribution of Internet Ad Revenues (2011 - 2012)



Source: *IAB Report 2012* at 12.

B. Structure, Business Models, and the Role of Advertising

The display advertising marketplace is both dynamic, in the sense that new technologies and business models are constantly emerging, and complex, in the sense that some individual firms frequently perform multiple functions (i.e., they are vertically integrated). As of 2013, display advertising is sold through at least four different channels: Publisher Direct Advertising, Advertising Networks, Real-Time Ad Exchanges, and Remnants.

Both Advertising Networks and Ad Exchanges are third-party intermediaries that facilitate transactions between the ultimate buyer (the advertiser) and the ultimate seller (the publisher). Third party-mediated transactions are increasingly delivered through automated placement or optimization. Impressions delivered in this fashion are sometimes described as Programmatic.[4]

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[4] See Gabe Gottlieb, "RTB Reality Check," OMMA RTB Chicago (2013), available at http://www.adomic.com/data. See also "Advertisers Continue Rapid Adoption of Programmatic Buying," *eMarketer* (Nov 26, 2013), available at http://www.emarketer.com/Article/Advertisers-Continue-Rapid-Adoption-of-Programmatic-Buying/1010414.

Publisher Direct Advertising typically commands the highest price, and is sold directly by the publisher (although an advertising agency may also be involved). A 2007 IAB benchmarking study found that seven large publishers sold roughly half of their inventory directly. The study also found a substantially higher price for advertising sold directly than for advertising sold to an ad network. Publisher Direct advertising commanded a price per thousand USD ("CPM") of $10 to $20, compared to CPMs of $0.60-$1.10 for advertising sold through networks.[5]

Some direct advertising is sold based on "endemic" targeting; for example, an ad may automatically target all visitors to the sports car part of a particular website. Endemic advertising may also be sold with an audience overlay, such as men aged 18-49 who visit the sports car part of the site. This audience overlay may also include geographic targeting, to limit the ad to a particular geographic market.

Advertising Networks act as audience aggregators, allowing smaller-scale publishers to market their own inventory while capturing the efficiencies of larger audience size. Advertising networks pool inventory from multiple publishers, package it according to the demographic and other characteristics of the audience, and sell impressions to advertisers.[6]

Increasingly, advertising networks and other advertising intermediaries are transitioning to auction-based business models known as Ad Exchanges.[7] These markets have developed in roughly the last five years, and grown substantially. Typically, the highest bid wins the auction, and the price paid is the price of the second highest bid. Publishers may refuse to accept certain bids because they have an exclusive arrangement with a competing seller, because they do not

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[5] Bain/IAB Digital Pricing Research, (August 2008), available at: http://www.iab.net/media/file/Bain_IAB_Digital_Pricing_Research.pdf.

[6] *See* http://www.youtube.com/watch?v=zZOXuljhOmI (AdXTraining)

[7] *See* http://www.youtube.com/watch?v=MBhnB-sWqy8 (OpenX); http://www.youtube.com/watch?v=-DiIsrJUsRU (Acuity).

want a certain type of advertising on their site, or because the bid does not exceed their reserve price (i.e., the price at which they have already sold the impression either directly or through an ad network). Examples of ad exchanges include DoubleClick (Google), OpenX, RightMedia (Yahoo!), and AppNexus.

Buyers in ad exchanges may participate either through the use of bidding rules, or by real-time bidding. Buyers using bidding rules specify the prices they are willing to bid for impressions that meet certain criteria. Buyers using real-time bidding make separate, independent bids for each impression based on the unique information available about the visitor. One advertising exchange reports that real-time bids are on average 140% higher than rules-based bids, which suggests that the value of user-specific information is significant.[8]

Advertising sold through auctions may go through at least two types of intermediaries: Sell-Side Platforms (SSPs) and Demand-Side Platforms (DSPs). First, publishers may pass availabilities through SSPs (or "yield managers"). SSPs contract with publishers on a commission basis, taking a fee for their services and passing the remaining revenue to the publisher.[9] The seller provides information about, among other things the page, location, browser information, the IP address, and the SSP's unique ID for that user. The SSP may augment the information with its own information about the user, based on either purchased data or its own knowledge of the user's browsing history. SSPs then pass this information to potential bidders. Third party cookies are integral to the SSP process.

Second, advertisers may contract with a DSP (or "demand-side platform")[10] to purchase advertising availabilities in the auction market. Using third party cookies, the DSP can match an SSP's user ID to its own user ID to further augment the information available about the user,

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[8] *See* http://www.youtube.com/watch?v=MBhnB-sWqy8 (OpenX)
[9] http://www.youtube.com/watch?v=_sGZxtnGZRY (AdXTraining)
[10] http://www.youtube.com/watch?v=jTBcz5R_IgE (adform)

combining the data from the SSP with its own user-specific data. The DSP will then determine bids for the availability for each participating advertiser. Each advertiser may also have information about the particular user; if so, that information is also incorporated in determining the advertiser's bid. In some instances, a DSP is unable to match a particular user to any other information. Bids for these users would reflect the bids that would be expected in a market without third party cookies.

When the DSP submits a bid to the SSP, it includes the URL of the advertisement that the advertiser wants to serve to that user. Generally the DSP will pass bids from all of its participating advertisers, rather than narrowing bids to the top bid, because the bid density is important to the efficient functioning of the auction market. The SSP aggregates the bids from all participating DSPs and provides the information to the seller. The seller selects the winning bidder, and serves the advertisement as part of the page.

III. THE VALUE OF INFORMATION SHARING: PRIOR RESULTS

Prior studies have found that information sharing generates substantial economic value, and that efforts to curtail information sharing through regulation risk destroying some or all of that value. In a relatively early study, Anderson, Silver, and Gordon (2009) observed that "[a]dvertising networks increasingly are defining the future of the online content business,"[11] and that "[a] driving force in the growth of online ad networks is their capacity to target advertising based on individual users' behavior rather than content topics or a site's overall demographics."[12] Goldfarb and Tucker (2011) analyzed the reactions of more than three million users randomly exposed to online display advertising to investigate how advertising effectiveness changed in

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[11] Scott Anderson, Mike Silver, and Rich Gordon, "Online Ad Networks: Disruption–and Opportunity–for Media Businesses," Media Management Center, Medill School Kellogg School of Management (2009) at 5, available at: http://mediamanagementcenter.sectorlink.org/research/adnetworks.pdf.

[12] *Id.*

Europe following the enactment of the 2002 E-Privacy Directive. The authors found that, post-regulation, advertising effectiveness fell by approximately 65 percent in Europe on average, relative to the rest of the world.[13] Analyzing a survey of ad networks, Beales (2010) finds that CPMs are significantly higher for behaviorally targeted ads, that behavioral targeting is more successful than standard run of network advertising, and that targeting generates greater consumer utility from more relevant advertisements.[14] More broadly, Deighton and Johnson (2013) found that, as of 2012, producers of goods and services spent over $150 billion to purchase marketing services that could not have been performed without individual-level consumer data.[15]

The value of information sharing is also apparent in the efforts of industry participants to develop new technologies which could serve as a complement to (or even substitute for) the industry-standard method of using cookies. Efforts to "create a standardized tracking system that improves on cookies,"[16] have been spurred in part by a desire to obtain more reliable information about mobile users.[17]

IV. MODEL, DATA, AND RESULTS

Our econometric analysis measures the premium paid by advertisers for impressions served to customers with cookies, after controlling for other factors. As explained below, our results indicate that the added economic value generated by information sharing in advertising is quite substantial, with cookies estimated to increase advertiser willingness-to-pay by at least 60

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[13] Avi Goldfarb and Catherine Tucker, "Privacy Regulation and Online Advertising," 57(1) *Management Science* (2011), 51-71.

[14] Howard Beales, "The Value of Behavioral Targeting," (2010), available at http://www.networkadvertising.org/pdfs/Beales_NAI_Study.pdf.

[15] John Deighton and Peter A. Johnson, "The Value of Data: Consequences for Insight, Innovation & Efficiency in the U.S. Economy," Data-Driven Marketing Institute (October 2013), available at http://ddminstitute.thedma.org/#valueofdata.

[16] Suzanne Vranica and Christopher Stewart, "Advertisers Worry About Changes to 'Cookies'," *Wall Street Journal* (Sept. 19, 2013). http://online.wsj.com/news/articles/SB10001424127887324807704579085592617339648

[17] *Id.*

percent (for users with recent cookies) and by as much as 200 percent (for users with longer-lived cookies).

A. Data and Model

For our econometric analysis, we assembled a large, impression-level database of advertising placements provided by two anonymous companies ("Company 1" and "Company 2"), both of which operate advertising exchanges with automated bidding. Company 1 is significantly diversified, operating multiple Internet-based enterprises in addition to its online advertising exchange. In contrast, Company 2 is specialized as an advertising exchange. Each company extracted a random sample of impressions during a one week period in August 2013. The full dataset for Company 1 consists of approximately two million impressions, while Company 2 provided approximately 1 million impressions. Both samples were restricted to U.S. users based on IP addresses.

For each impression, we observe the cleared auction price, expressed in CPM; this forms the dependent variable in our regression analysis. The key independent variable of interest is a binary indicator of whether each impression is associated with a cookie. Another key independent variable of interest is the age of the cookie, expressed in days. Finally, the regression analysis incorporates a variety of control variables. These include:

- *Ad Size*: Equal to the product of the width and the height of the ad, measured in pixels.
- *Publisher Reach*: Monthly unique US viewers for each publisher, as reported by Quantcast.
- *RTB:* Indicator variable for impressions purchased not by the ultimate publisher, but instead by a real-time bidding website or similar entity.[18]

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[18] In some cases, the Companies' databases explicitly identified RTB sites. In others, RTB sites were identified based on the publisher website, which each Company provided for each impression.

- *Fixed Effect Control Variables*: A series of categorical variables that control for additional impression-level attributes, including operating system, desktop/mobile, fold position (e.g., above or below), browser type, language, and media type (e.g., banner vs. video).

Summary statistics for the key regression variables are displayed in Table 1. The mean CPM ranges from \$0.29 (Company 2) to \$0.47 (Company 1). For each of the two companies, a high percentage of impressions have a cookie (89 percent for company 1, 96 percent for company 2). The average cookie age differs significantly across the two samples: For Company 1, the mean age is more than 84 days. In contrast, the average cookie in Company 2's dataset is just over a week (8.54 days) old.

Table 1:
Summary Statistics

	Mean	**SD**	**Min**	**Max**
Company 1				
CPM	0.47	0.96	0.0	166
Cookie	0.89	0.32	0.0	1
Cookie Age (Days)	84.23	161.20	0.0	2669
RTB	0.12	0.33	0.0	1
*Ad Size (10k Pixels, width*height)*	7.07	9.73	0.7	409
Observations	**1,965,727**			
Company 2				
	Mean	**SD**	**Min**	**Max**
CPM	0.29	1.17	0.0	100
Cookie	0.96	0.19	0.0	1
Cookie Age (Days)	8.54	28.93	0.0	920
RTB	0.23	0.42	0.0	1
*Ad Size (10k Pixels, width*height)*	6.20	3.08	0.0	96
Observations	**999,999**			

The regression model for each Company can be written as follows:

$$P_i = \beta_0 + \beta_1 Cookie_i + \beta_2 CookieAge_i + \sum_k \beta_k X_{ki} + \varepsilon_i$$

Above, P_i is the clearing price for an individual impression (CPM). *Cookie* takes a value of one if the auctioned impression has a cookie associated with it, and zero otherwise. *CookieAge* is equal to the age of the cookie in days, and defaults to zero whenever *Cookie* is zero. The covariates are denoted X_{ki}. Our hypotheses are (1) all else equal, impressions with cookies are more valuable to advertisers than those without $(\beta_1 > 0)$; and (2) all else equal, the longer a cookie exists, the more information it conveys, and the more valuable it becomes to advertisers $(\beta_2 > 0)$.

B. Results and Interpretation

Regression results for Companies 1 and 2 are displayed in Table 3. For each Company, the basic model regresses CPM against *Cookie*, *CookieAge*, and *AdSize*, in addition to a number of fixed effect controls. The full model includes all of these variables, in addition to *Reach* and *RTB*, while allowing for the effect of *Reach* to interact with both *Cookie* and *RTB*.

Table 3:
Regression Results [Dependent Variable = CPM]

	Company 1		Company 2	
	Basic Model	**Full Model**	**Basic Model**	**Full Model**
Cookie	0.3003***	0.338***	0.102***	0.2199***
	(0.00216)	(0.00327)	(0.0041)	(0.00986)
Cookie Age (Days)	0.00068***	0.00065***	0.00517***	0.00476***
	(5.98E-06)	(6.570E-06)	(0.00011)	(0.00011)
*Ad Size (10k Pixels, w*h)*	0.0015***	0.0015***	0.016***	0.0139***
	(0.000066)	(6.81E-05)	(0.0008)	(0.00058)
Reach (1M Viewers)		0.00084***		-0.00109***
		(5.51E-05)		(5.09E-05)
*Cookie * Reach*		-0.00099***		-0.00066***
		(0.000056)		(4.22E-05)
RTB		-0.2324***		-0.1704***
		(0.002037)		(0.0046)
*RTB * Reach*		0.00325***		0.00145***
		(3.26E-05)		(3.67E-05)
Obs.	1,965,727	1,602,891	999,999	698,441
R-Squared	4.2%	5.4%	16.6%	18.0%
Adj. R-Squared	4.2%	5.4%	16.6%	18.0%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust t statistics in parentheses. Fixed effects suppressed for operating system, desktop, mobile, fold position, browser, language, and media type.

Regardless of how the model is specified, or which Company is analyzed, the results consistently indicate that the presence of a cookie has a positive effect on advertiser willingness to pay, which is highly statistically and economically significant. For Company 1, *Cookie* increases CPM by more than \$0.30, exceeding 60 percent of the sample mean of \$0.47. For Company 2, the magnitude of the *Cookie* effect from the full model (approximately \$0.20), is comparable (between 60 and 70 percent) when measured relative to that Company's sample mean (approximately $0.29).

The effect of *CookieAge* is also highly statistically significant for both Companies; however, the economic effect is an order of magnitude larger for Company 2: In this case, a 30-day-old cookie has a predicted CPM approximately $0.14 higher than an impression with 'new' cookie (but with otherwise identical characteristics).[19] Thus, for Company 2, adding a cookie with a month's worth of information increases the value of an impression by approximately 125 percent, relative to the sample mean.[20] Similarly, the effect for a cookie with two months' worth of information is approximately 175 percent,[21] while a 90-day-old cookie would exceed the sample mean by more than 200 percent.[22] These estimates are consistent with our priors for Company 2, which hypothesize that the presence of older cookies cause an impression to sell for a substantial premium relative to new cookies, reflecting the cookie's ability to facilitate learning about users over time.

For Company 1, each 30-day increment of *CookieAge* increases the predicted CPM by significantly less (approximately $0.02) than for Company 1.[23] Thus, although the initial effect of a "new" cookie on CPM is higher for Company 1 than for Company 2, adding two or even three months' worth of information contributes less to the premium that the advertiser is willing to pay to Company 1. Interestingly, this result is also consistent with our priors for Company 1, which hypothesize that it is often able to supplement the information available through cookies with information gleaned from its diversified businesses. Given that these non-cookie sources

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[19] Multiplying the Company 2 coefficient on *CookieAge* by 30, one obtains $30*0.00476 \approx 0.14$.

[20] Equal to $(0.2199 + 0.14)/0.29$. Approximately nine percent of the one million impressions provided by Company 2 had cookies with an age greater than or equal to 30 days.

[21] Equal to $(0.2199 + 0.14*2)/0.29$. Approximately five percent of the one million impressions provided by Company 2 had cookies with an age greater than or equal to 60 days.

[22] Equal to $(0.2199 + 0.14*3)/0.29$. Approximately four percent of the one million impressions provided by Company 2 had cookies with an age greater than or equal to 90 days.

[23] Multiplying the Company 1 coefficient on *CookieAge* by 30, one obtains $30*0.00065 \approx 0.0195$.

would not be available to (less diversified) Company 2, it makes sense that, once a user has been associated with such information, any subsequent cookie-based learning would generate less value for Company 1 than for Company 2. Thus, cookies appear to be particularly valuable to companies that lack alternate sources of information about the user.[24]

Finally, the coefficient on the interaction term *Cookie*Reach* is negative and statistically significant for both Companies. Thus, all else being equal, cookies confer more value to smaller publishers (i.e., those with less reach). This result is consistent with the evidence presented in the next Section, which shows that "long tail" publishers tend to rely particularly heavily on third party advertising technology models.

V. THE PREVALENCE OF THIRD-PARTY ADVERTISING TECHNOLOGY MODELS: EMPIRICAL EVIDENCE

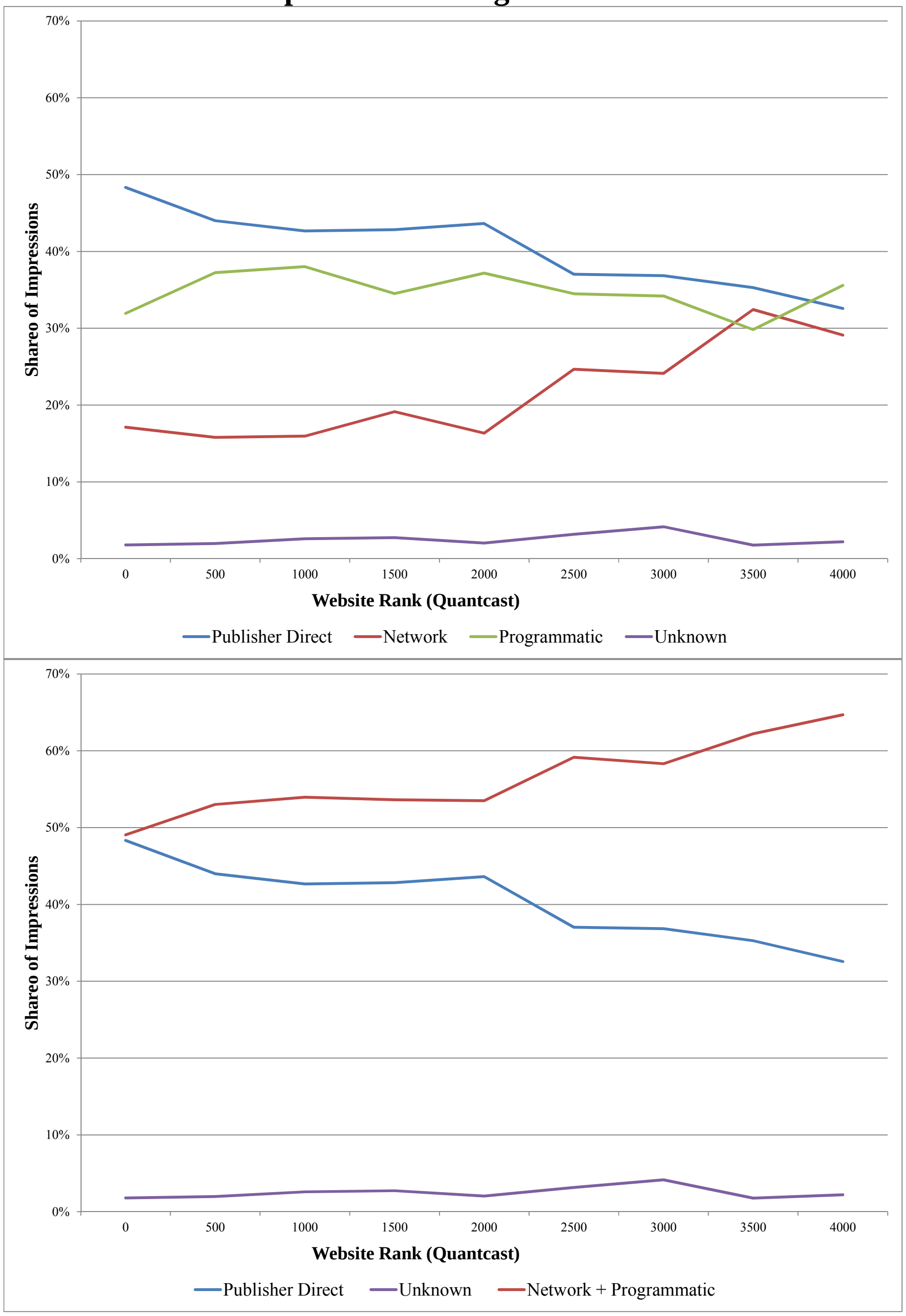
To assess the relative significance of third party advertising technology models for the industry, and for "long-tail" web sites in particular, we analyzed a dataset compiled by Adomic, a firm specializing in the analysis of online advertising patterns on behalf of agencies, publishers, and other clientele. The Adomic data set was compiled between August and November of 2013, and measures the relative prevalence of ads generated by different categories of advertising models based on observations of display ad placements for the top 4000 publishers.

Adomic divides publishers into cohorts based on their Quantcast rank. The first cohort contains the top 500 sites, the second contains 501 to 1,000 (and so on). For each cohort, Adomic measures the relative prevalence of advertising based on the relative frequency of three different categories of online advertising. The first category is *Publisher Direct*, which encompasses

[24] As discussed in the Appendix, in addition to calculating the effect of cookies relative to the sample mean, we also calculated the impact of cookies relative to impressions for which cookies were not present. We found that prices for impressions with new cookies were roughly three times as high as those for impressions without cookies, and prices for impressions with 90-day-old cookies were as much seven times as high as for impressions without cookies.

impressions sold directly by publishers to advertisers. The second category, *Network*, captures impressions sold in bulk, with transactions facilitated by third party ad networks such as Advertising.com. The final category, *Programmatic*, is similar to the second, except that it focuses exclusively on impressions delivered via automated placement or optimization, through services such as the Google Display Network (GDN). Because both Network and Programmatic capture third-party advertising technology models these two categories are displayed both separately and as a single aggregate in Figure 3.

Figure 3:
Share of Impressions among Sites that Advertise



Source: Adomic

As shown in the bottom panel of Figure 3, Network and Progra7mmatic ads together account for a plurality of advertising among publishers in the top cohorts, and a clear majority of advertising in the smaller publisher cohorts. Overall, third-party advertising technology models account for roughly half of advertising activity among top-ranked websites, and roughly two-thirds of advertising activity among websites in lower cohorts. Thus, although even the largest publishers rely on third-party advertising models, the Adomic data reveal that long-tail websites are disproportionately dependent on these intermediaries.

VI. CONCLUSION

At a time when "traditional media" face considerable challenges to their underlying business models, online advertising constitutes a dynamic and rapidly expanding component of the digital economy. The advent of information sharing in the market for online content has created unprecedented opportunities for the exchange of information to more efficiently connect consumers with the ultimate suppliers of the products they value the most. The value of this form of information sharing has been documented elsewhere, and is further corroborated by our econometric analysis, which indicates that advertisers place significantly greater value on users for whom more information is available. In addition, our analysis reveals that even the largest publishers rely on third-party technology models for approximately half of their advertising needs, while "long-tail" publishers rely even more heavily on these models.

APPENDIX

In addition to calculating the impact of cookies on impression prices relative to the sample mean, we also calculated the mean impact of both new and 90-day-old cookies on prices relative to the prices of otherwise identical cookies not associated with cookies. The results (calculated from the full model regression analysis, evaluated at the mean or modal value of other characteristics for each company) are shown in Figure A-1 below, which shows that, for company one, impressions accompanied by new cookies were 3.3 times more valuable than those without cookies, and impressions accompanied by 90-day-old cookies were 3.7 times as valuable as those without cookies. For company 2, new cookies increased the value of impressions by a factor of 2.9, while 90-day-old cookies raised the value by a factor of 7.1.

Figure A-1:
Impact of Cookies on Impression Prices
(Multiple, Relative to Impressions without Cookies)