THE IMPLICATIONS OF IMPROVED ATTRIBUTION AND MEASURABILITY FOR ANTITRUST AND PRIVACY IN ONLINE ADVERTISING MARKETS

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INTRODUCTION

The digital revolution has often been heralded for the transformation it has produced in advertising. The ability to collect data about the individual, automatically parse it, and then serve ads on that basis has transformed advertisers' ability to target ads and show specific ads to specific groups of consumers. This targeting revolution has led to the emergence of paid search advertising, where search engines serve ads on the basis of billions of possible search terms. In online display advertising, the targeting revolution has led to contextually targeted banner ads that accurately match an ad to the content the consumer is reading. This same revolution has also led to behaviorally targeted banner ads where the advertiser can use past browsing behavior to target ads.

The digital advertising revolution's implications for measuring advertising effectiveness are far less discussed in academic literature.[1] Tracking a user's clickstream across websites allows far more accurate measurement of different advertisements' performance.[2] Though this revolution has not attracted much academic interest, the advertising industry has responded swiftly to the increased potential for accurately measuring advertising effectiveness. A new type of advertising firm and technology has emerged, specializing in the measurement and attribution of advertising performance. By 2009, 31% of Internet firms were actively using cross-channel attribution technologies.[3] These technologies allow advertisers to assess and compare the relative performance of different online, and sometimes offline, advertising platforms. Advertising platforms can include search advertising, display advertising, social media, and direct mail campaigns.

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[1] *See* Avi Goldfarb & Catherine Tucker, *Online Advertising*, *in* 81 ADVANCES IN COMPUTERS 289, 296 (Marvin V. Zelkowitz ed., 2011).

[2] *Id.*

[3] *See generally* John Lovett et al., *A Framework for Multicampaign Attribution Measurement*, FORRESTER (Feb, 19. 2009), http://www.iabcanada.com/wp-content/uploads/2010/09/Forrester_AFrameworkForMulticampaignAttribution.pdf.

The existing theoretical literature on advertising and technology implies that there may be positive effects on consumer welfare when firms can accurately measure the relative return on investment of different advertising campaigns and channels.[4] This Article attempts to provide some initial empirical tests of this theory by looking at the evolving behavior of advertisers after adopting an attribution technology.

This Article uses two different datasets tracking advertiser behavior after the adoption of new technologies that facilitate attribution. One dataset is based on advertising allocation decisions within a single large platform. The other dataset is based on advertising allocation decisions across different paid search providers and display advertising campaigns. Analysis of this data suggests that the ability of firms to gauge ad performance allows firms to use far more refined targeting criteria. Better tracking of ad performance substantially reduces the cost of advertising by allocating campaign dollars to advertising platforms that give a higher return on investment.

This Article analyzes the effect of attribution technologies on consumer welfare by tracking advertiser behavior after the adoption of new attribution technologies. Part I introduces the history and development of attribution technologies by providing background information on online advertising. Part I also introduces a theoretical framework based on existing literature on attribution technologies. Part II conducts an empirical analysis of advertisers' behavior after adopting attribution technology. Part III discusses the policy implications of the empirical data presented in Part II.

I. THE EVOLUTION OF ATTRIBUTION TECHNOLOGIES

"I know half my advertising is wasted, I just don't know which half."[5] This quote has been variously attributed to Henry Ford and John Wanamaker.[6] It illustrates that the biggest problem advertisers face is that they know advertising is useful, but they do not know which particular advertising is useful.

Substantively, there are three steps in measuring the effectiveness of advertising: (1) Observing whether or not a consumer is actually exposed to an ad; (2) observing whether or not the consumer takes the action that the advertising is intended to promote; and (3) identifying which, if any, of the

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4 *See, e.g.*, Simon P. Anderson & Stephen Coate, *Market Provision of Broadcasting: A Welfare Analysis*, 72 REV. ECON. STUD. 947, 948-49 (2005).

5 Goldfarb & Tucker, *supra* note 1, at 292.

6 *See, e.g.*, *id.* (attributing the quote to John Wanamaker); Torin Douglas, *Tough Sell for Britain's Mad Men?*, BBCNEWS (last updated Nov. 2, 2010, 9:15 AM), http://www.bbc.co.uk/news/uk-11674865 ("Lord Leverhulme, the founder of Unilever, and the car manufacturer Henry Ford are both credited with the dictum . . . .").

multiple potential ads that a consumer was exposed to was actually responsible for the consumer taking the action.

Offline, all of these steps are hard. The first step is hard because advertisers in traditional media do not track individuals and what ads they see. It is hard for advertisers to know whether a particular person has been exposed to a television, print or radio ad.[7] There are a few traditional media techniques that help advertisers track exposure, like embedding an identifying code in a Macy's coupon in a newspaper or making a TV "infomercial" that uses an identifiable phone number. The second step is difficult because, in the offline world, many retailers do not observe exactly who purchases their products. It is unrealistically expensive for those retailers to monitor whether the same person who was exposed to their ads also purchased the product. Last, even if firms can observe that someone saw an ad and then bought the product, it is not clear that there is a causal link between the two. This is the classic endogeneity problem of advertising.[8] It could be merely that the kind of person who chose to be exposed to that kind of advertising is also more likely to purchase the product.[9] For example, even with the coupon, Macy's cannot observe whether the people who used the coupon would have bought the product anyway. These are all well recognized as limitations of empirical studies in offline advertising.

A. *The Growth of Attribution Technologies Online*

By contrast, the history of online advertising over the past decade has entailed the development of techniques and tools that specifically address all of offline media's shortcomings. This development has led to exponential growth in firms that specialize in what is often referred to as "'cross-channel attribution.'"[10] Typically, cross-channel attribution technologies do four things. First, they collate data on who has been exposed to what ads across a firm's many advertising campaigns.[11] Second, they match this data with whether or not there is a record that individual has converted.[12] For online businesses, the conversion is usually a sale.[13] For offline businesses, the conversion may be registering on the website or using an electronic

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7 *See* Gert Assmus et al., *How Advertising Affects Sales: Meta-Analysis of Econometric Results*, 21 J. MARKETING RES. 65, 65-74 (1984).

8 Goldfarb & Tucker, *supra* note 1, at 292.

9 *Id.*

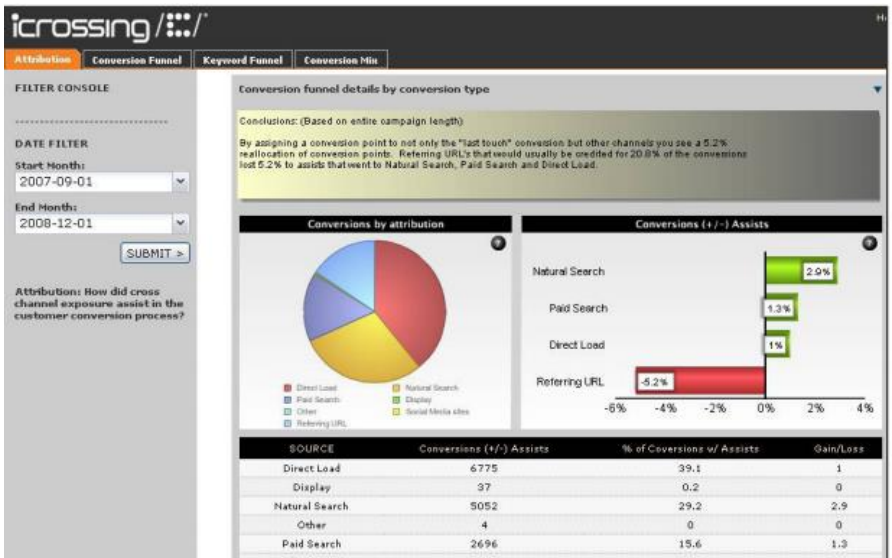
10 *See* Econsultancy & Google Analytics, *Marketing Attribution: Valuing the Customer Journey*, GOOGLE 2 (Apr. 2012), https://docs.google.com/viewer?url=http://ssl.gstatic.com/think/docs/marketing-attribution-valuing-the-customer-journey_research-studies.pdf&chrome=true.

11 *See* Lovett, *supra* note 3, at 6.

12 *Id.* at 6-7.

13 *Id.* at 7-8.

coupon.[14] Third, they use a probability model to assess which combination of ads contributed to the successful outcome.[15] Fourth, they go on to automate and optimize the adjustment of media spend on behalf of the advertiser, to reflect the relative return on investment of different advertising channels.[16]



Data Source: Interest2Action, Merchantize; Data Timeframe: Conversions that took place from September 2008-December 2009, adjustable through the provided drop down menus.

Figure 1: iCrossing

Figure 1 is a screenshot of a cross-channel attribution provider's website, showing that these technologies typically provide easy-to-read dashboards that allow easy attribution of conversions in different advertising channels.

At the turn of the twenty-first century such technologies were unheard of, but now they are widely used. According to Forrester, 52% of 275 website decision makers surveyed in 2008 agreed that such cross-channel attribution technologies would enable them to spend marketing dollars more effectively.[17] Thirty-one percent reported that they were actively using attribution technologies.[18] A more recent survey by Econsultancy suggests

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14 *See, e.g.*, Goldfarb & Tucker, *supra* note 1, at 292 (describing conversion through the use of coupons).

15 *See* Lovett, et al., *supra* note 3, at 4-5.

16 *Id.* at 7.

17 *Id.* at 1.

18 *Id.*

that 62% of marketers and 77% of agencies are using attribution technologies.[19] The Econsultancy results are based on a survey fielded to marketers and agencies between September 26 and October 23 of 2011, yielding 607 responses. The regional decomposition of advertisers was: 44% North America, 33% United Kingdom, 12% Europe (non-UK), 6% APAC, 5% other.[20]

B. *Collection of Data on Advertising Exposure*

Attribution technology evolved in part due to the relative ease of collecting data for the paid search and online display advertising channels. Search advertising allows advertisers to easily track website visitors who navigated to the website because the visitor clicked on an online search ad. Such visitors are usually directed to a specific "landing page" or visit an identifiable URL.[21] Further, advertisers can use their internal server logs to track a visitor's behavior when the visitor reached the website after clicking on an ad associated with a particular search term.[22]

At first, online banner ads were much like electronic billboards. Advertisers could not track exposure unless a consumer clicked on the online ad directly.[23] As click rates fell and advertisers began to use display ads primarily for branding, "impressions" (i.e., whether a consumer was directly exposed to an ad) rather than clicks became crucial for understanding an ad's effectiveness.[24] In response to this need, advertisers developed systems of tracking exposure to ads via the use of "pixel tags."[25] Very simplistically, pixel tags work as follows: each time a user visits a website with a pixel tag embedded in an ad, the pixel tag downloads from a remote server. The advertiser or advertising network is then able to record the time and page that person saw (with the associated IP address and/or cookie).[26]

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19 Econsultancy & Google Analytics, *supra* note 10, at 1.

20 *Id.*

21 *See* Goldfarb & Tucker, *supra* note 1, at 297.

22 Tat Y. Chan et al., *Measuring the Lifetime Value of Customers Acquired from Google Search Advertising*, 30 MARKETING SCI. 837, 840-41 (2011).

23 *See, e.g.*, Patrali Chatterjee et al., *Modeling the Clickstream: Implications for Web-Based Advertising Efforts*, 22 MARKETING SCI. 520, 520-21 (2003) ("When a consumer clicks on a banner ad, a *click-through* is recorded in the server access log.").

24 *See* Chrysanthos Dellarocas, *Double Marginalization in Performance-Based Advertising: Implications and Solutions*, 58 MGMT. SCI. 1178, 1178 (2012).

25 Goldfarb & Tucker, *supra* note 1, at 297 & n.1.

26 One issue in online display advertising is that it has been hard for advertisers to observe whether a consumer was actually exposed to an ad. Sometimes banner ads can be at the bottom of a webpage but be unseen by the browser. This has been addressed by the Interactive Advertising Bureau in its recent "Guidelines for the Conduct of Ad Verification" and by the development of "above" and "below the fold" categories for ads. *See Guidelines for the Conduct of Ad Verification*, INTERACTIVE ADVER.

Data is easy to collect for display, like paid search and organic search advertising channels. Recently, however, the ambitions of many attribution technology developers have broadened to encompass many new digital advertising channels.[27] Figure 2 shows that attribution technologies are developing the ability to compare the relative performance of organic leads, online videos, Twitter, Facebook, and mobile advertising.

Another recent development is that attribution technologies are able to integrate offline media, including television, radio, print, and direct mail, into their attribution models.[28] This is pertinent because competition policy has often treated the online advertising market as separate from the offline advertising market.[29] These new technologies allow advertisers to substitute between offline and online channels, suggesting that online and offline advertising channels may turn out to be far easier substitutes than previously supposed. This substitution is unlikely to be instantaneous in the cases of buying radio and television ads or planning a direct mail campaign, due to longer lead times. With this caveat, however, these advances do echo earlier evidence of substitution between offline and online advertising markets, as presented by Professors Goldfarb and the Author.[30]

C. *Collection of Data on Conversion*

As long as a transaction is conducted or initiated online, it is relatively straightforward to link the activity to previous advertising exposure. For search advertising, tracking is relatively straightforward, as the search ad directs the consumer straight to the webpage where such transactions can be tracked.[31] However, as Professor Chrysanthos Dellarocas pointed out, such models can lead to coordination conflicts.[32] Over the past few years, display ads have developed a similar capacity. Display ads can use a combination of cookies and pixel tags to match a "conversion event" on an advertiser's

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BUREAU (Feb. 14, 2012), http://www.iab.net/media/file/Ad_Verification_Conduct_Guidelines_2012.pdf.

27 *See* David S. Evans, *The Online Advertising Industry: Economics, Evolution, and Privacy*, 23 J. ECON. PERSP. 37, 38-42 (2009).

28 Ari Osur, *The Forrester Wave: Interactive Attribution Vendors, Q2 2012,* FORRESTER, 3 (Apr. 30, 2012), http://www.adometry.com/landing-pages/forresterreport-website/adometry-forresterreport-q2-2012.pdf.

29 Avi Goldfarb & Catherine Tucker, *Substitution Between Offline and Online Advertising Markets*, 7 J. COMPETITION L. & ECON. 37, 37 (2011).

30 *See generally* Avi Goldfarb & Catherine Tucker, *Advertising Bans and the Substitutability of Online and Offline Advertising*, 48 J. MKTG. RES. 207 (2011); Avi Goldfarb & Catherine Tucker, *Search Engine Advertising: Channel Substitution When Pricing Ads to Context*, 57 MGMT. SCI. 458 (2011) [hereinafter Goldfarb & Tucker, *Search Engine Advertising*].

31 Search engines have even experimented with a cost-per-action model of payment that facilitated such linkages even more.

32 *See* Dellarocas, *supra* note 24, at 1179.

website with an individual user profile, which records the various display advertising campaigns that users have seen previously.[33]

D. *Attributing Causality*

Attribution technologies do two things that depart from previous practice. First, they use large-scale probability models, which attempt to disentangle patterns from variation in exposure to different ads.[34] These models also take into account correlations among the rates of ad impressions, website visits, and website conversions.[35] In other words, the sheer scale of data collection that is possible in an online environment allows advertisers to tease apart effective and ineffective advertising.[36]

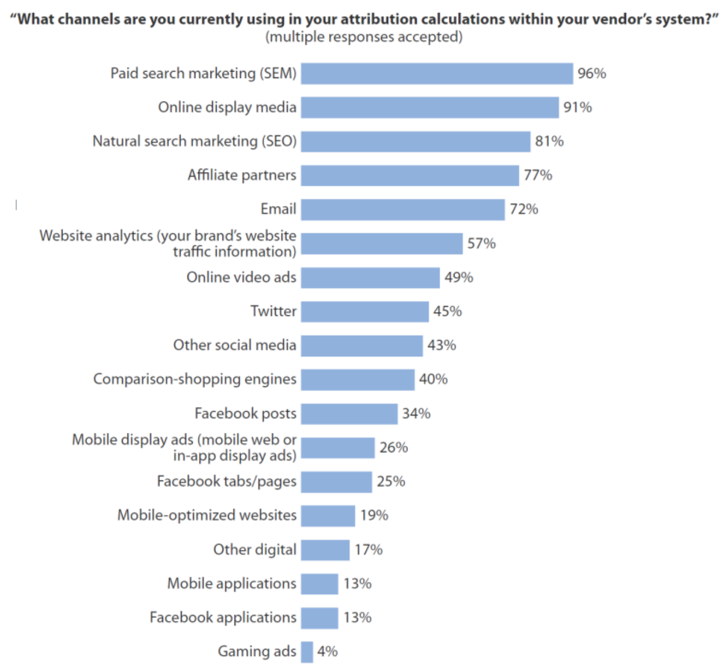

Figure 2: Advertising Channels Linked to Attribution

Source: Forrester Research Interactive Attribution Customer Reference Survey

33 *See* Goldfarb & Tucker, *supra* note 1, at 297-99.

34 *See* Econsultancy & Google Analytics, *supra* note 10, at 2.

35 Michael Braun & Wendy Moe, Online Advertising Response Models: Incorporating Multiple Creatives and Impression Histories 2-3 (Apr. 7, 2012) (unpublished manuscript), *available at* http://ssrn.com/abstract=1896486.

36 *Id.* at 4.

Second, and even more novel, are advertisers' attempts to recognize that, typically, it is not a "single advertising event" that leads a consumer to ultimately convert. Instead, a combination of events influences the consumer's decision to convert. Figure 3 describes the different steps in a typical consumer's path towards conversion for a consumer product. Echoing older marketing models of a "funnel," these "attribution funnels" recognize that there are different stages in the purchasing process. The "attribution funnels" also recognize that different advertising media may play different roles. Prior to the evolution of advertising technologies, advertisers tended to focus on the "last click" and attributed the entire motivation for conversion to this "last click." Such procedures, however, ignored other media that had built brand and product awareness. In particular, those procedures tended to favor "search advertising" over "display advertising," as paid search ads are often the last ads that a consumer sees. Figure 4 summarizes the different attribution methods that typical attribution technologies use. Figure 4 suggests that while "last click" is still prevalent as an attribution methodology, other methods are growing. Figure 5 shows that often these technologies allow clients the flexibility to choose the parameters of their own attribution algorithm.

Figure 3: Different Advertising Events Can Lead to Conversion

E. *Automation of Media Spend Based on Return on Investment*

One of the major changes in the past three years is that attribution technologies have begun to automate ad allocation across channels depending on relative return on investment.[37] In other words, the advertiser does not have to actively change and manage its campaigns in response to information about better-performing advertising platforms.[38] Instead, the attribution technology automatically allocates a larger advertising budget to better-performing advertising.[39]

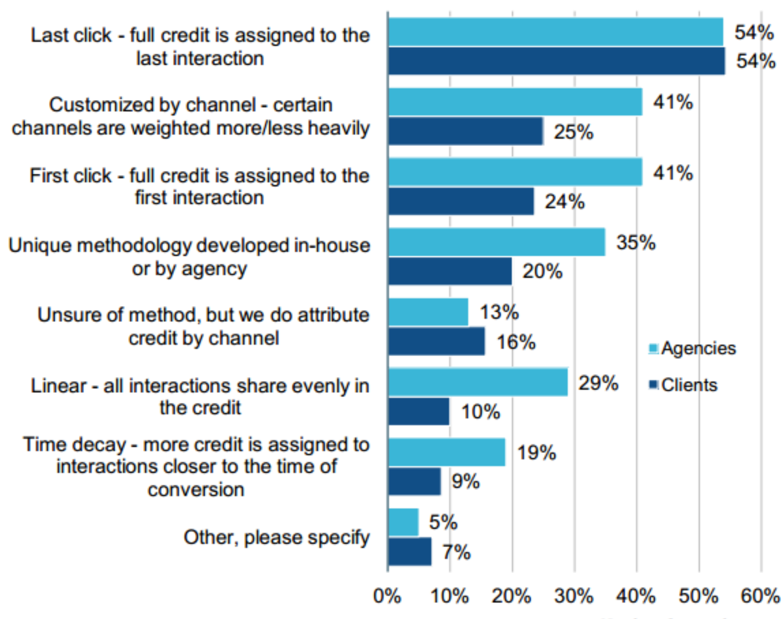

Figure 4: Range of Attribution Methods

Forrester suggests that half of all vendors offer the capacity to allocate the budget to more effective advertising. According to Forrester, 30% of reference clients used the budget allocating capacity.[40] Figure 6 summarizes advertisers' current use of such attribution technologies. It is noticeable that 64% of clients are already using technologies to evaluate the relative performance of different advertising channels and allocate advertising appropriately.

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37 *See* Econsultancy & Google Analytics, *supra* note 10, at 9.

38 *Id.*

39 *Id.* at 10.

40 Osur, *supra* note 28, at 4.

Attribution technologies, by brokering data across multiple advertising platforms, help reduce fears that the importance of data for measurement and targeting might lead to a natural monopoly in online advertising.[41] By brokering data across multiple platforms, attribution technology agencies reduce the tendency of the advertising-supported Internet toward concentration. Attribution technologies also increase the ability of smaller advertising platforms to compete.

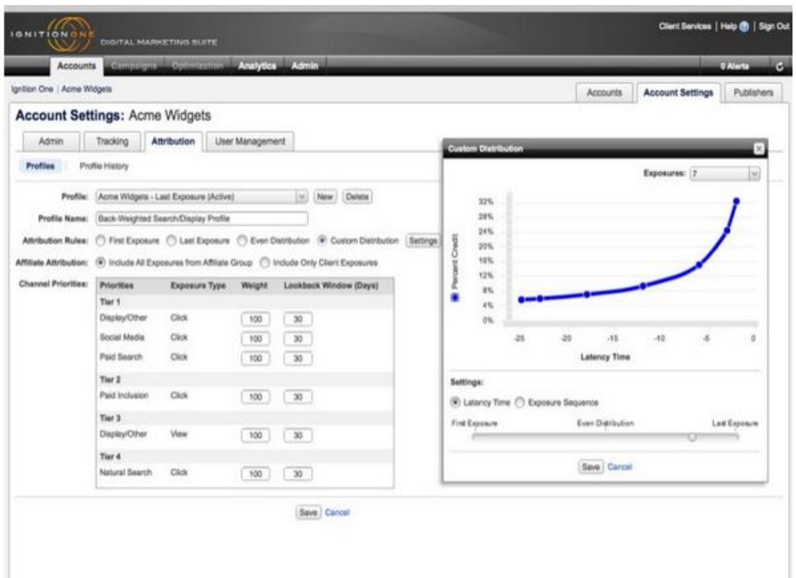

Figure 5: Attribution Technologies Allow Some Flexibility in How Attribution is Performed

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41 Eric K. Clemons & Nehal Madhani, *Regulation of Digital Businesses with Natural Monopolies or Third-Party Payment Business Models: Antitrust Lessons from the Analysis of Google*, J. MGMT. INFO. SYS., Winter 2010-11, at 43, 49.

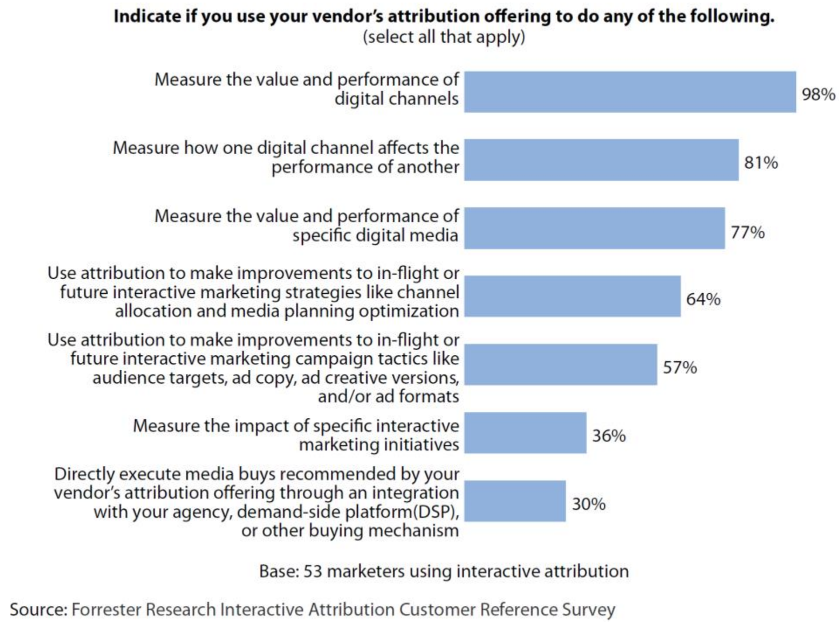

Figure 6: How Advertisers Use Attribution Services

Figure 6 summarizes survey responses about technologies' effects on individual advertisers' behavior. Figure 7 emphasizes that one of the major effects of such technologies is to facilitate transition between different advertising channels, such as search and display. Figure 7 provides further evidence that one of the consequences of such technologies has been a shift away from print media toward more effective digital media. This evidence again appears to support an interpretation of widespread substitution between offline and online advertising channels.[42]

This Article also examines the potential consequences of attribution technologies on advertising market prices and outcomes. Therefore, Section F of this Part turns to the theoretical literature on advertising technologies and market outcomes to build a theoretical framework before moving to more detailed data.

42 Goldfarb & Tucker, *supra* note 29, at 44.

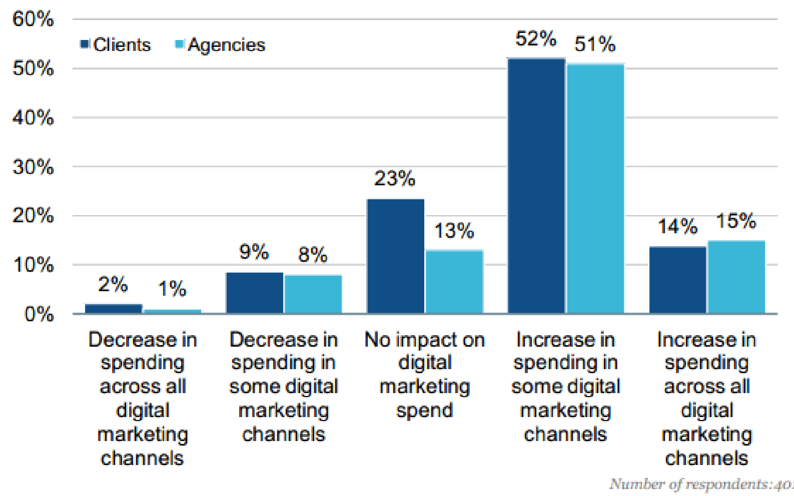

Figure 7: Changes to Attribution Behavior from Attribution

F. *Theoretical Effects of Increased Measurability*

This Article addresses the likely implications of this burgeoning cross-channel attribution technology for consumers and advertisers. Earlier work, such as Professor Yu Jeffrey Hu's work, points out that the increased measurability of online advertising means that online advertising platforms can offer performance-based pricing in ways impossible with traditional advertising or in the more general two-sided market.[43] This performance-based pricing can lead to an increase in incentives for advertising platforms to perform well.[44] Such work, however, does not address the implications of the increased comparability of different advertising channels for advertising and their customers in general.

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[43] Yu Jeffrey Hu, Performance-Based Pricing Models in Online Advertising 2-3 (Mar. 2004) (unpublished manuscript), *available at* http://papers.ssrn.com/sol3/papers.cfm?abstract_id=501082.

[44] *Id.* at 4.

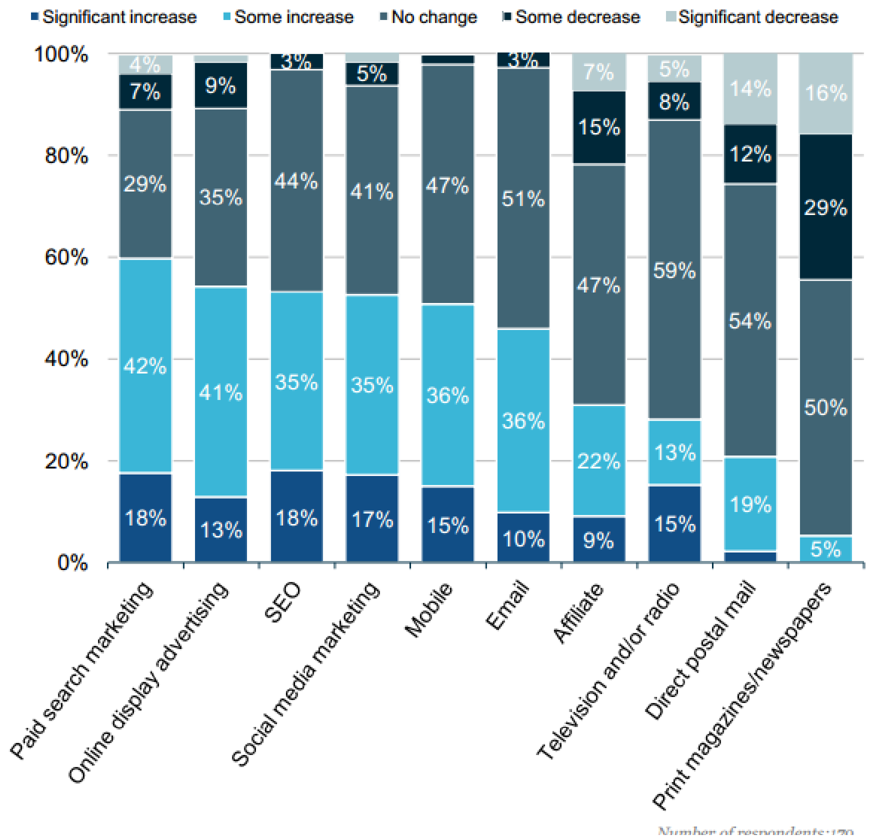

Figure 8: Changes to Channel Investments Resulting from Attribution

Since the work of Professors Gene M. Grossman and Carl Shapiro,[45] there has been a slew of theoretical literature studying the potential effects of improvements in targeting technology on advertising markets, where targeting is often modeled as ensuring that ad exposures are not wasted.[46] However, there has been little literature that directly models the implications for advertising platform competition when advertising becomes more measurable and conversions are better attributed.

The literature on the implications of targeting improvements may still be relevant. This is because, from a practical standpoint, improved targeting is modeled as reducing the proportion of consumers who see ads that are

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45 *See generally* Gene M. Grossman & Carl Shapiro, *Informative Advertising with Differentiated Products*, 51 REV. ECON. STUD. 63 (1984) (observing that improvements in advertising efficiency increase market competitiveness and drive down prices).

46 *See* Lola Esteban et al., *Informative Advertising and Optimal Targeting in a Monopoly*, 49 J. INDUS. ECON. 161, 161-63 (2001) (employing a monopoly model to examine how targeted advertising affects market outcomes); Ganesh Iyer et al., *The Targeting of Advertising*, 24 MARKETING SCI. 461, 472-73 (2005) (discussing the effects of targeting on advertising strategies in competitive markets).

not relevant for them. Cross-channel ad attribution technology should achieve a similar outcome, although the process is different from targeting technologies. The difference in process is simply that targeting technologies *prospectively* identify "better eyeballs" through a theory about who may be responsive customers. Attribution technologies *retrospectively* use better data to identify campaigns that were more successful and, therefore, presumably reached "better eyeballs."[47] However, the end result of facilitating ads reaching more receptive eyeballs is similar. This difference in nuance may be absent in the theoretical literature because, for reasons of simplicity, theory models focus on a static rather than multiple-period model of advertising allocation.

This insight enables this Article to revisit the original cost function $A(\Phi; \alpha)$ that Professors Grossman and Shapiro hypothesized as applying to advertising.[48] In their model, Φ captures the fraction of the target population that is exposed to a message, and α captures advertising technology, which drives the total and marginal advertising costs.[49] Attribution technology and automated cross-channel attribution could lead to a reduction in α if an ad can be delivered to the population Φ with less waste and more accuracy.[50] The next question is: due to these reduced costs, what will be the equilibrium effects on advertising prices and competition?

Earlier work in this area, such as Professor Ambarish Chandra's study of newspaper advertising prices, suggested that improved targeting could lead to higher prices in advertising markets.[51] The increase is due to advertising platforms' ability to capitalize on delivering better performance to advertisers and to the increased attractiveness of advertising, leading advertisers to bid up prices.[52]

Recent literature has challenged such findings when it comes to the digital era.[53] For example, Professors Dirk Bergemann and Alessandro Bonatti studied the impact of targeting on competition between advertising platforms.[54] They point out that improvements in targeting technology, by reducing the number of advertisers competing for each consumer, actually

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47 Another relevant branch of theory was developed by Professor Hanna Halaburda and Yaron Yehezkel, who studied how asymmetries in quality information can spur concentration of market power to be welfare-improving. Hanna Halaburda & Yaron Yehezkel, *Platform Competition Under Asymmetric Information* 2 (Harvard Bus. Sch., Working Paper No. 11-080, 2011), *available at* http://www.hbs.edu/faculty/Publication%20Files/11-080.pdf.

48 Grossman & Shapiro, *supra* note 45, at 65-66.

49 *Id.*

50 *Id.* at 70-71.

51 *See* Ambarish Chandra, *Targeted Advertising: The Role of Subscriber Characteristics in Media Markets*, 57 J. INDUS. ECON. 58, 60 (2009).

52 *Id.* at 59.

53 *See, e.g.*, Dirk Bergemann & Alessandro Bonatti, *Targeting in Advertising Markets: Implications for Offline Versus Online Media*, 42 RAND J. ECON. 417, 419 (2011).

54 *Id.* at 418.

reduce the pricing power of a dominant platform, meaning that advertisers pay lower prices.[55] Similarly, Professors Susan Athey and Joshua S. Gans suggest that improved targeting actually increases effective supply of advertising if advertising space is limited.[56] Translating this result to the question of measurability implies that improved measurability may reduce the pricing of advertising in the presence of platform competition. Improved measurability encourages advertisers to jettison unfruitful campaigns and therefore increases the availability of space to display effective campaigns. Professors Jonathan Levin and Paul Milgrom go even further, suggesting that the thinness of markets implied by excessively fine targeting can lead to downward distortions in prices and allow advertisers to game publishers by paying low prices for valuable inventory.[57]

Therefore, the consumer welfare effects of improved measurability would seem likely to be positive if the reduced prices of advertising for advertisers are passed on to consumers. A key condition for this positive outcome, however, is that firms actually behave in the manner the latter set of theories predicts. Another key condition is that firms use the improved measurability to increase the efficiency of advertising allocation by seeking out sets of target consumers for whom there is less of a price premium.

II. EMPIRICAL ANALYSIS OF ADVERTISING OUTCOMES IN THE PRESENCE OF ATTRIBUTION TECHNOLOGIES

This Article uses two different datasets to explore the predictions of the theoretical literature. The first is data on advertising allocation decisions within a single media platform after the introduction of a technology that improved the measurability of advertising.

The advantage of initially focusing on the effects of a single-channel attribution technology is that the effects are relatively clear-cut and easy to understand. However, of course, cross-channel attribution technologies probably have the most potential for transformative effects of online advertising markets. This Article also uses a second dataset that traces out the advertising allocation decisions of advertisers after adopting a media attribution system that allowed them to compare the performance of search advertising and display.

In all cases, the data analysis is relatively simple and descriptive. There is no access to a counterfactual in this data—that is, what would have happened if the advertiser had not adopted the technology—so this Article

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55 *Id.* at 419.

56 Susan Athey & Joshua S. Gans, *The Impact of Targeting Technology on Advertising Markets and Media Competition*, 100 AM. ECON. REV. (PAPERS & PROC.) 608, 608 (2010).

57 Jonathan Levin & Paul Milgrom, *Online Advertising: Heterogeneity and Conflation in Market Design*, 100 AM. ECON. REV. PAPERS & PROC. 603, 606 (2010).

does not make strong causality claims. However, the simple comparative statistics do allow for the study of whether the observed changes in advertiser behavior are in line with the theoretical literature described in Section I.F.

A. *Analysis of a Single-Channel Attribution Technology*

This dataset stems from a single firm's advertising allocation decisions on an individual media platform. Keywords could be used as a basis to target ads, which were based on users' characteristics that they had shared on the platform. A second-priced position auction priced the display advertising on this platform. This auction mechanism is the same as major search engine platforms use. It works similarly to the mechanism that Professors Benjamin Edelman, Michael Ostrovsky, and Michael Schwarz; Professor Varian; and Professors Athey and Ellison describe—advertisers choose which keywords to use in advertising their products and bid the maximum amount they would be willing to pay for a click.[58] Very roughly, the advertiser pays the price of the second-highest bid for that ad slot, though this is adjusted to reward advertisers who achieve high click-through rates. The advantage of this type of price mechanism for advertisers is that prices reflect demand for that particular ad slot. The advantage of this type of price mechanism for advertising platforms is that it allows the automation of price setting.

At the starting point of a dataset, the firm adopted a tracking system that allowed it to measure the relative effectiveness of different campaigns for the first time. The tracking system allowed the firm to automatically use this information to allocate its advertising more efficiently. The firm shared data that spanned the three months after initial adoption. This Article compares ad performance for the 9,665 separate campaigns run in the first week after using this new attribution technology, with the ad performance of the 11,798 campaigns that were run in the final week of the data. Table 1 reports summary statistics for this data. An observation is a campaign launched on a particular day. On average nearly 30,000 different people saw each campaign, which in industry terminology is an impression. Click-through rates were quite low, in line with the rest of the display ad industry, at less than 0.002%.

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58 *See generally* Susan Athey & Glenn Ellison, *Position Auctions with Consumer Search*, 126 Q. J. ECON. 1213, 1214-16 (2011) (examining the interplay between consumer behavior and sponsored search auctions); Benjamin Edelman, Michael Ostrovsky & Michael Schwarz, *Internet Advertising and the Generalized Second-Price Auction: Selling Billions of Dollars Worth of Keywords*, 97 AM. ECON. REV. 242, 242 (2007) (analyzing "generalized second-price" auctions); Hal R. Varian, *Position Auctions*, 25 INT'L J. INDUS. ORG. 1163, 1164 (2007) (presenting a game theoretic model on online ad auctions).

	Mean	Std Dev	Min	Max
Clicks	16.15	70.79	39	2691
Impressions	29,388.80	117,621.16	55,497	4,726,149
Click-Through Rate	0.002	0.05	0	1
Cost Per Click (USD)	1.08	0.53	0	4
Number Targeting Criteria	8.19	4.51	0	21
Observations	21,463			

Table 1: Summary Statistics for Single-Channel Attribution Technology Data

Figure 9 reports the change in click rates for the average campaign at the beginning and end of this period. Figure 10 reports the change in impressions. Figure 11 shows how the change in impressions translates into click rates. Generally, these statistics suggest that there was little change in actual advertising and exposures from the adoption of this technology. Therefore, it is natural to ask what the technology actually achieved.

To determine what the technology actually achieves, it is important to look at the cost of each of these clicks. For this platform, the advertiser paid each time a consumer clicked on an ad, so this was the major driver of costs. Figure 12 shows how the cost per click changed. There is a striking reduction. In other words, one of the major benefits of the adoption of this attribution technology may have been a large reduction in costs.

The next question is, how did this happen, given the relative lack of change in click-through rates and ad exposures? Figure 13 gives some idea about the mechanism behind the change in costs. The firm (presumably as a result of adopting this attribution technology) substantially increased the number of criteria it used when selecting its target market. Consistent with the predictions of Professors Bergemann and Bonatti, this increase in the thinness of the market led to lower prices per click.[59]

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59 *See* Bergemann & Bonatti, *supra* note 53, at 419.

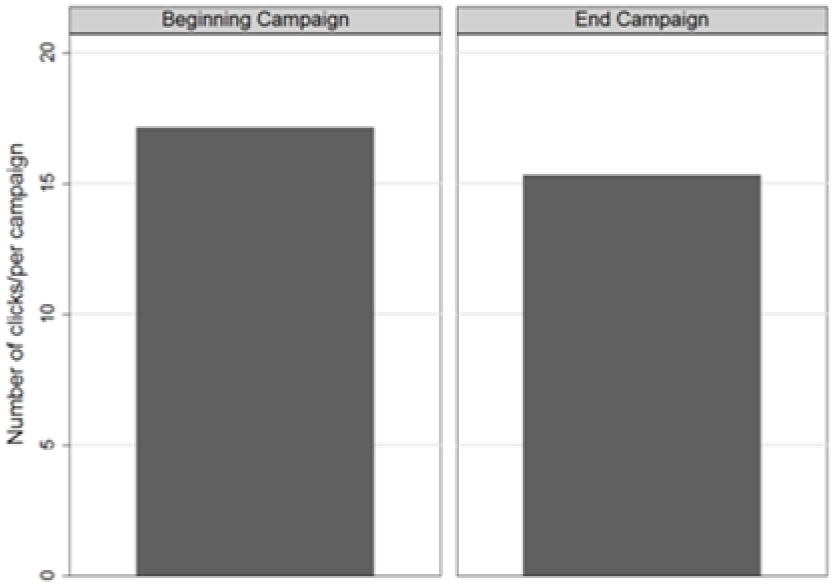

Figure 9: Single Channel: Change in Number of Clicks for an Average Campaign

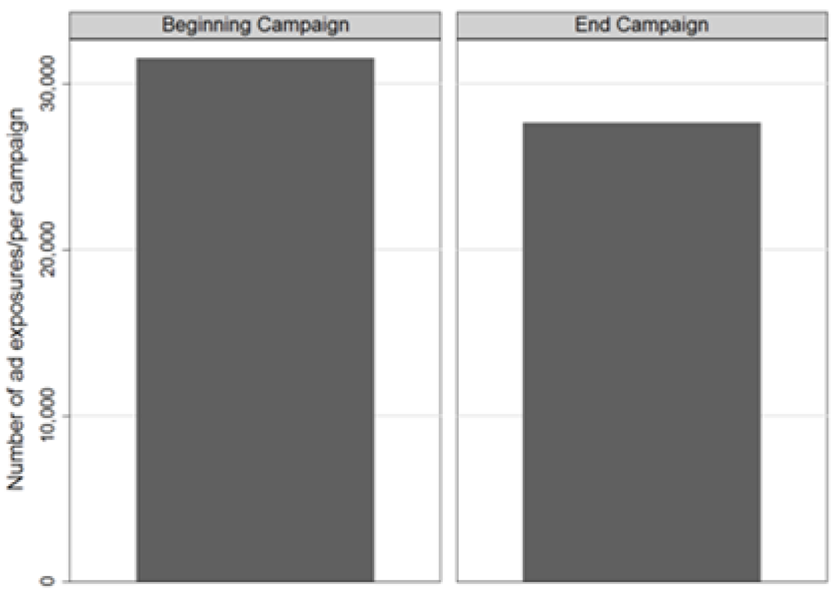

Figure 10: Single Channel: Change in Number of Exposures of Ads for an Average Campaign

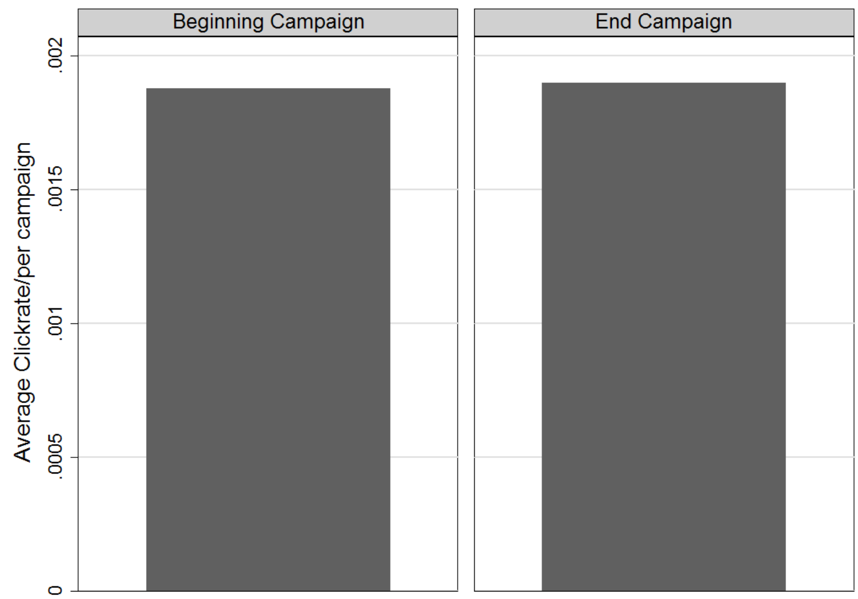

Figure 11: Single Channel: Change in Click-Through Rate of Ads for an Average Campaign

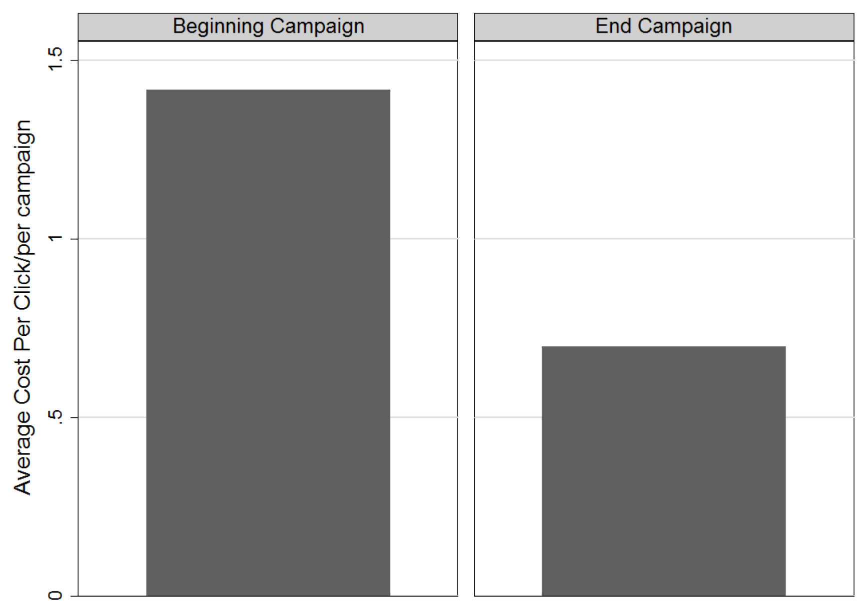

Figure 12: Single Channel: Change in Cost per Click of Ads for an Average Campaign

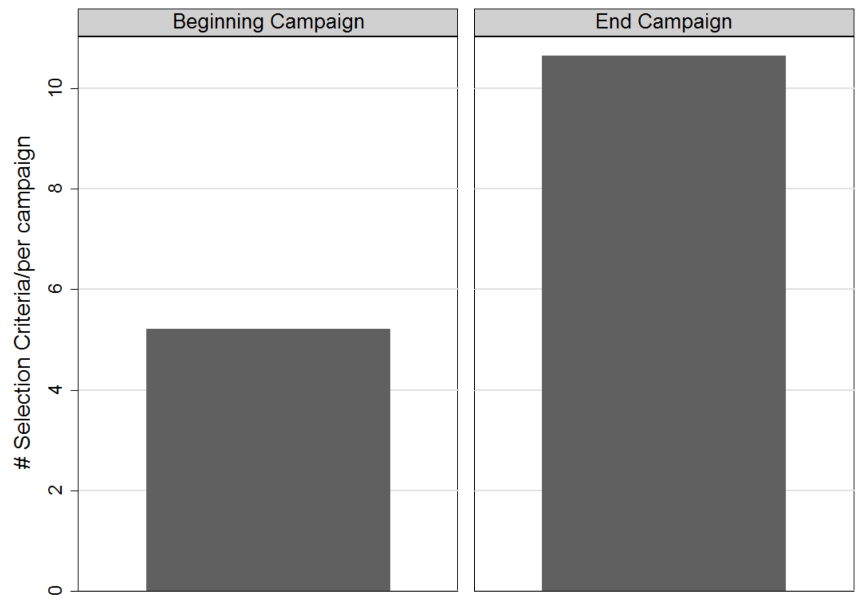

Figure 13: Single Channel: Change in Number of Targeting Criteria for Ads in an Average Campaign

B. *Analysis of a Cross-Channel Attribution Technology*

A firm that allows cross-channel attribution of different forms of online advertising campaigns provided the second dataset. It allows this Article to examine the evolution over three quarters of data of advertising campaigns by a single advertiser who had adopted an attribution technology. This attribution technology allowed the advertiser to easily compare the conversion performance of each different campaign. In this attribution platform, unlike the previous data, the information concerning advertising cost is stored on the advertiser's local server. Initially, this Article simply documents patterns in the data suggestive of substitution across advertising platforms toward advertising campaigns that were more successful. This Article then collects additional external data changes in pricing of the paid search campaigns that the changing substitution patterns imply.

Table 2 reports summary statistics for this external data. An observation in this data is a single user who has been exposed to a variety of advertising campaigns. Typically the user is observed for forty days. It is immediately apparent that paid search ad exposures are a small proportion of total advertising exposures for the typical individual. This small proportion is presumably because anyone can potentially see a display ad for a new cellphone. However, users are only exposed to a paid search ad for a new cellphone if they are actively in the market for a new cellphone, which is a potentially a very small proportion of the population.

An observation in the data analysis is a campaign that either started in the first, second, or third quarter. This Article analyzes data at the campaign level rather than the user level because this Article focuses on changes in campaign-level performance. This Article has data on 883 such campaigns that were initiated over three quarters. Fifty-eight percent of these campaigns were search campaigns, and the remaining campaigns were a mixture of untargeted display ads, behaviorally targeted display ads, and social media ads.

	Mean	Std Dev	Min	Max
Average # Days User Exposed to Ads for Campaign	40.82	41.77	0	218
Average # of Search Ads Seen	0.02	0.27	0	58
Average # of Display Ads Seen	45.55	137.25	0	4,954
Average # of Untargeted Display	32.73	105.87	0	4,954
Average # of Behaviorally Targeted Display Ads Seen	11.78	70.38	0	2,549
Average # of Social Media Display Ads Seen	1.05	13.11	0	2,850
Proportion of Conversions	0.02	0.15	0	1
Observations	358,776			

Table 2: Summary Statistics for Cross-Channel Attribution Technology Data

Figure 14 traces the improvement in conversion rates associated with campaigns across three quarters after the adoption of the cross-channel attribution technology. Figure 14 suggests that, over time, the conversion rates associated with the average advertising campaign increased.

Of course, a natural question is whether the improvement can be attributed exclusively to the attribution technology. Because this Article does not observe a counterfactual—what would have happened if the firm had not adopted an attribution technology—this Article does not make strong causal claims. This Article simply presents the data as correlational. However, it is worth noticing that there does appear to be an appreciable increase in terms of orders of magnitude from the baseline. Such a large change does not support an alternative explanation resting on small incremental changes within a firm. It also does not appear that there are any clear seasonal trends (such as the holiday season) that would otherwise explain the observed pattern.

These statistics were next decomposed by advertising channel. Figure 15 suggests there was an improvement in conversion probabilities for online display advertising. Figure 16 suggests there was a large improvement for search. Both increases were large. The effect on search is larger in absolute terms because search started off at a higher baseline conversion rate. This may be because people who are interested enough to search are also going to be more likely to buy. Figure 16 suggests that the improvement was reasonably equal across Google and its competitors. This observation reassures that the attribution technologies do not appear to favor one advertising platform over another.

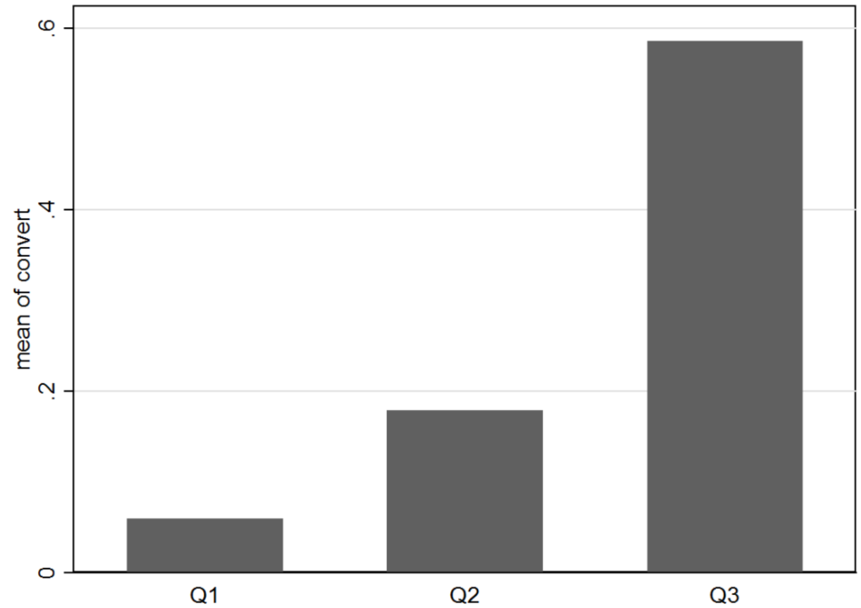

Figure 14: Cross-Channel: Change in Conversion Rate Associated with Campaign Over Time

Figure 17 examines how length (the search term's number of characters) is used for targeting campaigns over time. It suggests that, much like the example of the single-channel attribution technology, some of the improvement in conversions can be traced back to the use of more detailed criteria to target ads.

The next question is whether the increase in conversion rates affects prices in the advertising markets. In particular, do these higher conversion rates come at a higher cost? Direct pricing data is not accessible, so data was collected using Google's Traffic Predictor tool on the likely cost per click of each of the different paid search ads for this firm.[60] In general, Figure 18 shows the price per click dropped somewhat for search ads. However, it was startling how the effective cost per conversion fell far more rapidly, as Figure 19 shows. The difference in price decline between Figure 18 and Figure 19 makes sense, given that advertisers could already use the internal search engine metrics to improve cost per click. However, only with the evolution of attribution technologies could advertisers improve cost per conversion.

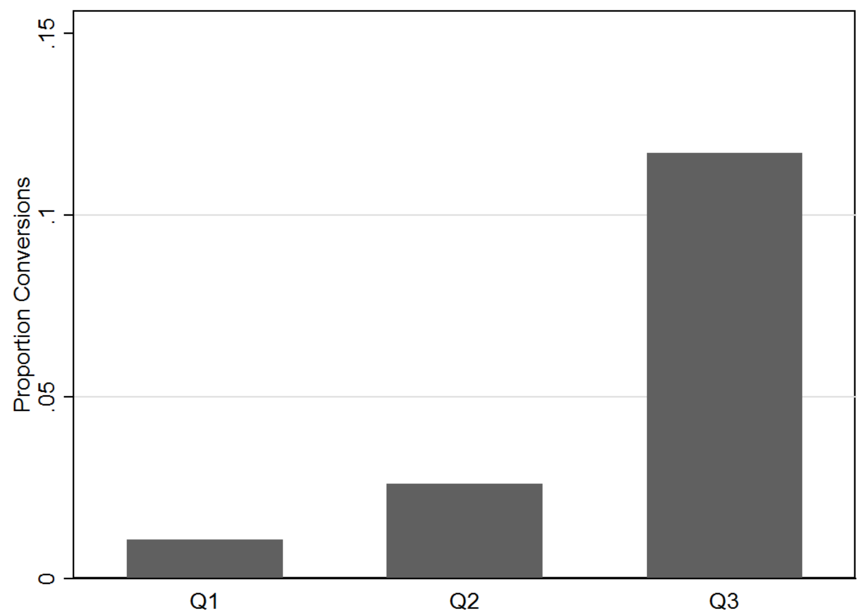

Figure 15: Cross-Channel: Change in Conversion Rate Associated with Display Campaigns Over Time

60 Though it is expected that this predictor tool gives unbiased estimates of prices, ex post the prices paid may differ depending on how the search engine rates that advertiser's quality. *See* Goldfarb & Tucker, *Search Engine Advertising*, *supra* note 30, at 460.

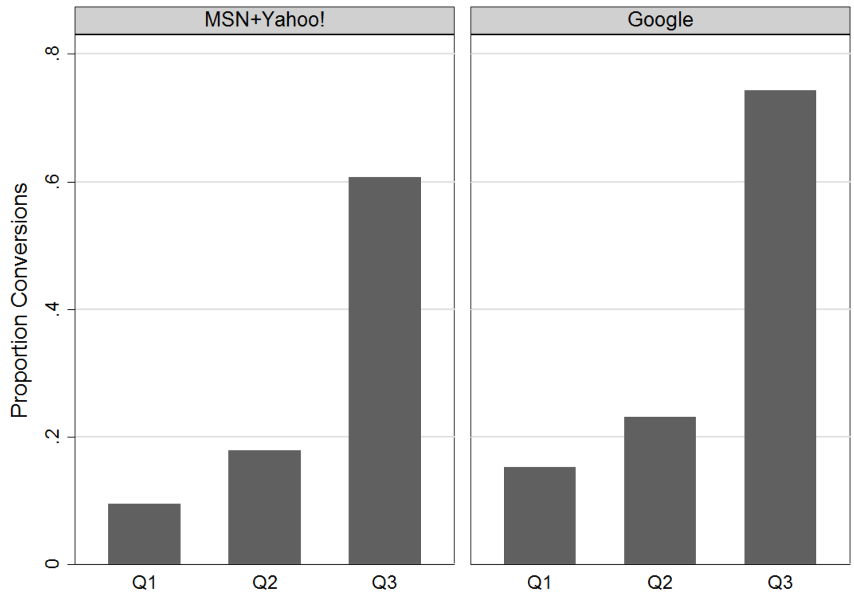

Figure 16: Cross-Channel: Change in Conversion Rate Associated with Different Campaigns at Different Paid Search Providers Over Time

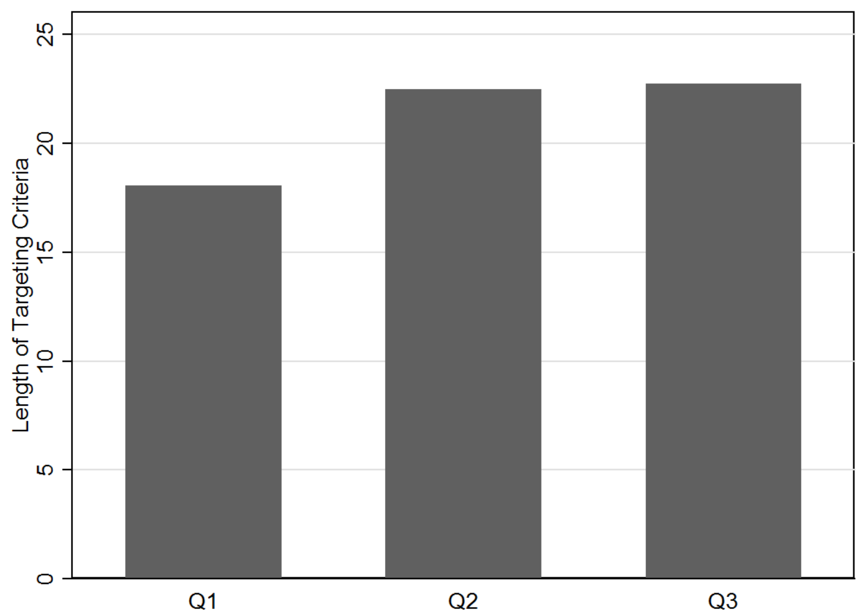

Figure 17: Cross-Channel: Length of Targeting Criteria for Paid Search Ads Over Time

Due to the fact that there is less transparency in display advertising markets, the data do not contain likely cost estimates for the display campaigns. There is, however, useful data about the typical length of a display advertising campaign or how long it ran before the advertiser pulled it. This can act as a proxy for costs because the number of impressions typically determines the price of display campaigns. The length of the campaign determines the number of impressions. Of course, making this comparison assumes that in each case the reach (or number of impressions) on each day was similar for each campaign.[61] If less effective campaigns were running for less time after the adoption of the attribution technology, it would imply that the platform was able to reduce costs. Figure 20 suggests that indeed this was the case. By the final quarter, underperforming campaigns were being run for a substantially shorter time.

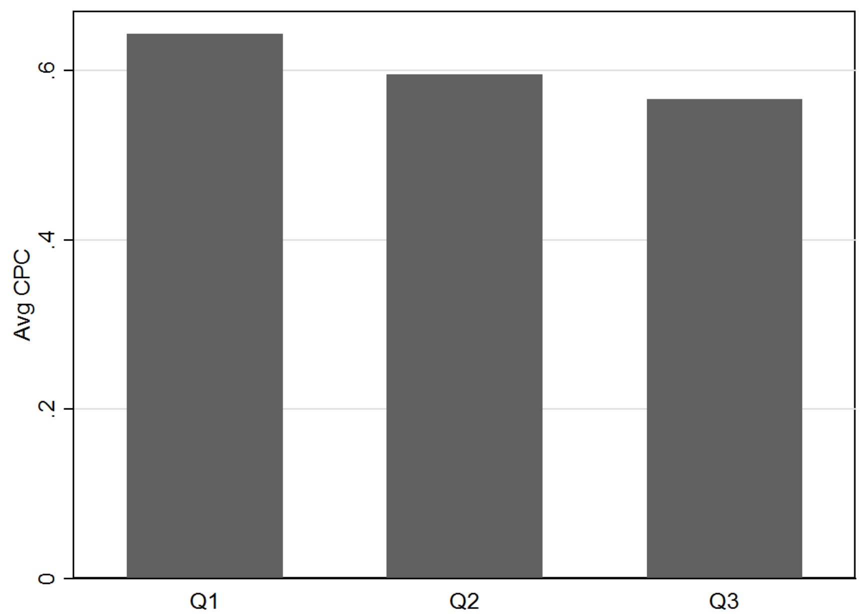

Figure 18: Cross-Channel: Price Paid per Click for Search Ads Over Time

61 A quick comparison of impressions data rules out alternative, more mechanical explanations for Figure 20, such as the number of daily impressions for each campaign increasing over time.

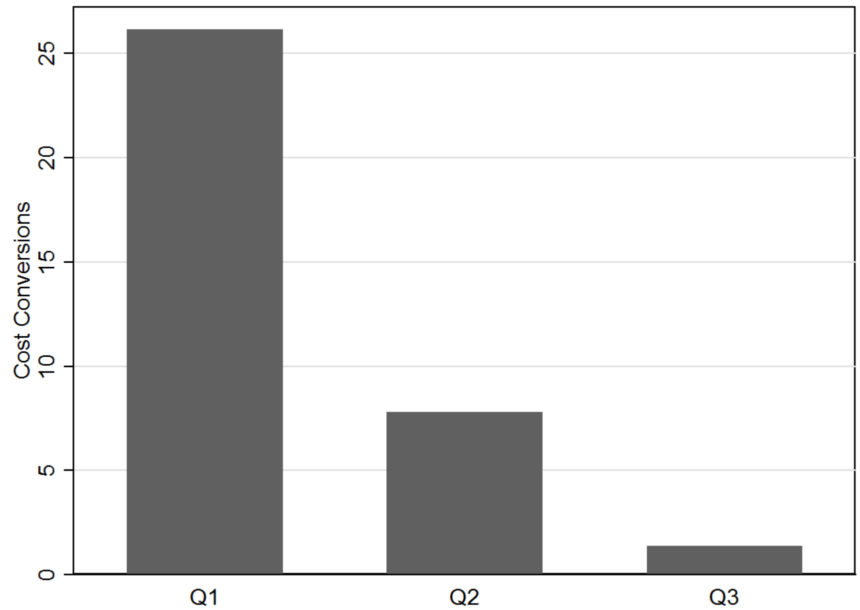

Figure 19: Cross-Channel: Paid per Conversion for Search Ads Over Time

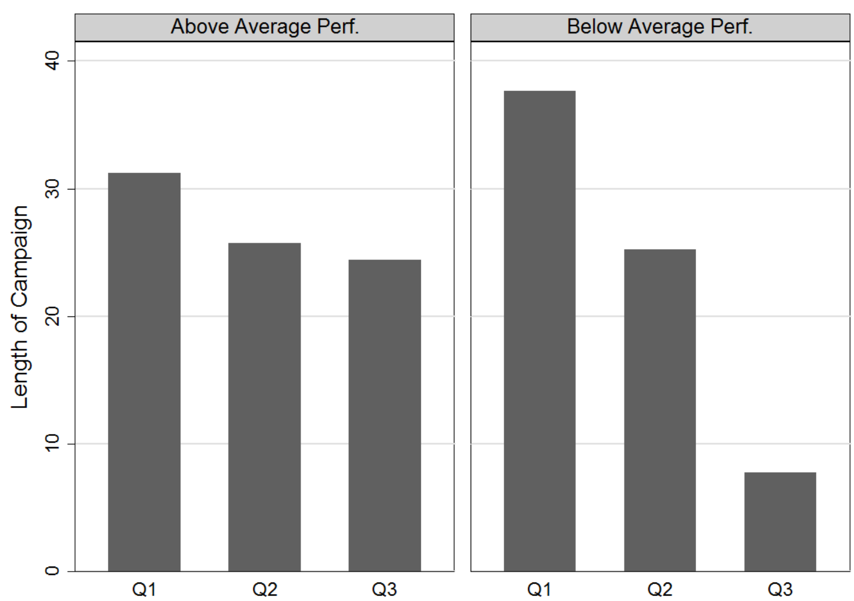

Figure 20: Changing Length of Campaign for Display Ads by Campaign Success

One general concern with the interpretation of these results is that conversions are so high for paid search. This is a concern because there is always the potential for advertising exposure data to reflect an endogeneity bias.[62] The concern is that consumers exposed to these campaigns would have purchased anyway, for reasons this Article does not observe, even in the absence of advertising. This Article does not have the data to address this concern directly. It is, however, relatively straightforward to address such endogeneity problems with a randomized test, sometimes referred to as a split-test or an "a+b" test. Under these tests, consumers are randomly assigned to either see the ad in question or see a placebo ad for something like the Red Cross. The automation inherent in online advertising facilitates the use of such large-scale field tests. Large-scale field tests can evaluate the type of advertising that has the largest incremental effect rather than advertising's simple association with the largest average effect.[63] The use of such field experiments to improve ad performance has been discussed as the next wave of improvements by various cross-channel attribution providers. Such data may be available in future studies to validate identification.[64]

III. IMPLICATIONS AND POLICY DISCUSSION

There are two separate sets of policy implications that can be drawn from this analysis.

The first set of policy implications concerns the consequences of these new attribution technologies for understanding how advertising markets work. Theory suggests that attribution technologies could have two potential conflicting implications. First, if attribution technologies lead advertisers to cluster and target just a few small groups of receptive user eyeballs, then this could cause higher prices paid for advertising.[65] Alternatively, if attribution technologies lead advertisers instead to substitute away from

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62 Randall A. Lewis et al., *Here, There, and Everywhere: Correlated Online Behaviors Can Lead to Overestimates of the Effects of Advertising*, *in* PROCEEDINGS OF THE TWENTIETH INTERNATIONAL WORLD WIDE WEB CONFERENCE 157, 158 (2011), *available at* http://www.www2011india.com/proceeding/proceedings/p157.pdf.

63 *See, e.g.*, Avi Goldfarb & Catherine Tucker, *Online Display Advertising: Targeting and Obtrusiveness*, 30 MARKETING SCI. 389, 389 (2011) (analyzing data from a large randomized field experiment on online advertising campaigns); Anja Lambrecht & Catherine Tucker, When Does Retargeting Work? Information Specificity in Online Advertising 3 (May 6, 2013) (unpublished manuscript), *available at* http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1795105 (describing a field experiment evaluating the relative effectiveness of generic and dynamic retargeting).

64 Anto Chittilappilly, *Using Experiment Design to Build Confidence in Your Attribution Model*, METRICS INSIDER (July 11, 2012, 10:33 AM), http://www.mediapost.com/publications/article/178511/using-experiment-design-to-build-confidence-in-you.html?print#axzz2TQ9hYXUg.

65 Chandra, *supra* note 51, at 59.

higher-priced advertising options and target increasingly "thinner" markets, this could lead to lower prices paid by advertisers for advertising.[66] These competing hypotheses in the theoretical predictions make the consequences of cross-channel attributions an empirical question—one this Article seeks to answer.

In two different datasets, there is repeated evidence that the use of attribution (and improved advertising measurement) technologies appear to be associated with lower prices for advertising. This Article presents evidence that these lower prices appear to be associated with advertisers using the attribution technologies to identify subsets of consumers and then advertising to those consumers. The advertising platform is unable to charge a premium because there are fewer other advertisers bidding up prices. These more nuanced subsets of consumers are, therefore, advantageous for the advertiser.

This Article also presents evidence that, in general, advertisers use these attribution technologies to allocate resources across online and display advertising. Advertisers also use attribution technologies to facilitate substitution across these different media platforms. Theoretically, this evidence is important for competition policy. It is important both for understanding the right market definition and because it helps alleviate concerns that the economies of scope in the data collection for measurement purposes might favor any one advertising platform.[67]

Given this set of apparent benefits, the second set of policy implications concerns the potential consequences of inhibiting the diffusion and use of attribution and measurement technologies. Most obviously, a great deal of anonymized data, commonly about an individual cookie, underlies these attribution technologies. Policymakers involved in privacy policy globally are currently discussing the scale and scope of data collection for ad analytics.[68]

As Professor David S. Evans, Thomas M. Lenard and Paul H. Rubin, among others, have set out, there is a trade-off between the protection of online consumer privacy and a firm's ability to use prior clickstream data to target ads effectively.[69] There are reasons to think that, for policymakers, data used for advertising analytics may even be a more problematic policy question than clickstream data used for targeting. Unlike the benefits of "targeted ads," which might include more relevance and less irritation for

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66 Bergemann & Bonatti, *supra* note 53, at 419.

67 *See generally* Clemons & Madhani, *supra* note 41, at 73-74.

68 *See* Avi Goldfarb & Catherine E. Tucker, *Privacy Regulation and Online Advertising*, 57 MGMT. SCI. 57, 57 (2011).

69 *See* Evans, *supra* note 27, at 55-58; Goldfarb & Tucker, *supra* note 68, at 57; Thomas M. Lenard & Paul H. Rubin, *In Defense of Data: Information and the Costs of Privacy*, 2 POL'Y & INTERNET 149, 166-69 (2010).

consumers, the benefits of ads with better-measured performance are not immediately obvious to consumers.

Instead, this Article's findings suggest that the benefits of better advertising analytics are indirect, because such technologies lead advertisers to pay lower prices for ads. These lower costs should translate to lower end prices for consumers in competitive markets. It seems likely that when deciding whether to share data for advertising analytics purposes, consumers may not internalize the general welfare gains of providing better information to advertising platforms, because the welfare gains are not immediately apparent to the consumer. Consumers' lack of awareness of welfare gains may lead to extremely low "opt-in" rates for consumers when it comes to acceptance of third-party cookies designed to perform third-party advertising analytics, such as those used for the technologies studied in this Article.

As of 2012, privacy policy makers in the European Union and the United States disagree when it comes to privacy policies surrounding the use of third-party cookies for advertising measurement and attribution.[70] Specifically, the W3C standards-setting organization currently contemplates exempting third-party cookies from opt-in requirements for the US "Do Not Track" standard if they enable "Frequency Capping," "Financial Logging and Auditing," and "Aggregate Reporting."[71] Such uses could conceivably allow attribution technologies such as the ones studied in this Article to persist. By contrast, the EU Working Party 29 takes the view that for the proposed "Do Not Track standard" to be in compliance with EU law, for companies serving cookies to European citizens, "Do Not Track must effectively mean '*Do Not Collect*' without exceptions."[72]

These issues are going to be even more pronounced when it comes to new technologies that try to allow advertisers to do multi-channel attribution involving mobile ads or offline advertising, such as direct mailing or television. Obviously, to ensure effective multi-channel attribution requires a far greater scale of data and scope of data collection about an individual consumer. Policymakers will have to trade off the increased scope and scale of data collection with the welfare benefits of increasing the ability of advertisers to switch to lower-priced and more effective platforms more globally than they do now.

In general, it is noticeable that in discussions over privacy policy there has been scant attention paid to the potential implications for competition

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70 Jonathan R. Mayer & John C. Mitchell, *Third-Party Web Tracking: Policy and Technology*, *in* 2012 IEEE SYMPOSIUM ON SEC. & PRIVACY 413, 417-18 (2012).

71 World Wide Web Consortium, Tracking Compliance and Scope (Apr. 30, 2013) (Working Draft), http://www.w3.org/TR/tracking-compliance.

72 *Working Party on the Protection of Individuals with Regard to the Processing of Personal Data Opinion 04/2012 on Cookie Consent Exemption*, at 10 (June 7, 2012), *available at* http://ec.europa.eu/justice/data-protection/article-29/documentation/opinion-recommendation/files/2012/wp194_en.pdf.

policy. In particular, little attention has been paid to the increased difficulty for advertisers to seek lower-priced alternatives in the absence of measurement.[73] The findings of this Article suggest that the benefits of improved substitution between different channels and associated lower prices should be explicitly weighted against the benefits of more stringent privacy regulation.

There are of course limitations to the findings detailed in this Article. First, although the scale and scope of the analyzed datasets are massive in terms of the coverage of customers, the datasets apply to two advertisers and two attribution technologies at a single point in time. This limits generalizability. Second, because this Article lacks a true counterfactual in the data, the evidence presented should be interpreted as merely correlational rather than causative. Third, this Article has not explored the many different ways that advertisers could potentially use cross-channel attribution technologies, such as for offline media planning or as part of a more generalized and rigorous scheme of ad testing. Notwithstanding these limitations, this Article is a useful first step in understanding how the ability to accurately measure advertising performance across advertising channels may affect advertising markets.

73 *See* Goldfarb & Tucker, *supra* note 1, at 310-11.