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Abstract. Moment marketing is a new strategy that entails the ability to synchronize online advertising (e.g., sponsored search) in real time with relevant offline events such as TV ads. More and more practitioners are employing this strategy, given the increasing availability of technologies that enable coordination across advertising channels in real time. However, very little is known about the instant impact of TV advertising on the effectiveness of search advertising. We take advantage of a unique opportunity for causal estimation in this research area by leveraging large exogenous variation in TV advertising expenditure over a long period, while at the same time having access to granular consumer search data under relatively stable sponsored search advertising strategies. Utilizing this novel setup, we provide the first empirical evidence that TV-moment-based search advertising could be effective for optimizing sponsored search advertising for both TV-advertised brands and their competitors. We also document the mechanisms driving such cross-channel advertising effects. Specifically, TV advertising can change the quality of online search traffic (e.g., who searches, where they search, and how they search) in the moments following a TV ad, so that an average searcher responds differently to subsequent search results.

1. Introduction

Moment marketing is a rich new area of contextual advertising that entails using offline events to trigger the start of online advertising in real time. Both large companies (e.g., Google, Facebook, AT&T, and Amazon) and niche companies (e.g., 4C, TVTY, Clickon Media, MediaSynced, and TVSquared) are developing products for such cross-channel coordination (Shields 2017). According to TVTY (2016), 81% of surveyed digital marketers have launched moment marketing campaigns, mostly using (their own or competitors') TV advertising as trigger events. The technologies provided by moment marketing companies enable synchronizing search advertising with TV advertising by first detecting TV ads in real time and then automatically coordinating bidding through search engine application programming interfaces. Advertisers are thus able to instantaneously adjust their bidding strategies (e.g., the targeted keywords, the bid amount, the targeted demographics, and the ad copy) based on the detected TV ad. The goal of moment marketing for

sponsored search advertising is to ensure top-ranked search ads with the right messages reach the right consumers at contextually relevant moments.

Many practitioners advocate for TV moment-based search advertising, citing the expected increase in consumer engagement immediately after a TV ad moment. However, there is very little evidence of such an increase, measured in terms of consumer response to search ads. This is true for both practice and the academic literature, mainly because of the newness and novelty of the platforms that enable moment marketing. In this paper, we take advantage of large variation in the TV ad spend by an advertiser that periodically turned its TV advertising off and on over a long period. We also leverage our access to granular consumer search data under relatively stable search advertising strategies on Microsoft Bing, which is rivaled in size only by Google data. This setup brings us closer than ever before to making causal claims about the impact of TV advertising on both sponsored and organic search advertising. It also

enables us to understand how such cross-channel effects vary across search advertisers, and across types of searchers.[1] To the best of our knowledge, this paper is the first in the marketing literature to tackle these research questions.

In comparison with the existing marketing literature that focuses on measuring the relationship between TV advertising and the size of search spikes (Joo et al. 2014, 2016; Hill et al. 2016; Du et al. 2019), with only one study implying a complementary relationship between TV and search advertising (Hill et al. 2016), our paper contributes by taking a large step beyond prior work. We switch the focus to measuring the effectiveness of coordinated advertising through moment marketing for both TV-advertised brands and competitors, using the consumer click-through rate (CTR) as a performance metric.

Our research provides confirmatory evidence of the positive instant impact of TV advertising on the consumer CTR for sponsored search results, for both a TV-advertised brand and its competitors seeking to poach the TV-advertised brand's search traffic by biding on its keywords (Sayedi et al. 2014). We also examine the underlying mechanisms of these cross-channel effects. We find that TV advertising can change the quality of online search traffic (e.g., who searches, where they search, and how they search) in the moments after a TV ad, so that an average searcher responds differently to the sponsored results on the subsequent search engine results page (SERP). That ultimately affects the CTR across all search impressions. Given the current trajectory of advertising toward moment marketing, our research generates timely insights on coordinated advertising. More generally, our research provides important implications for designing effective search advertising strategies.

2. Research Context

Our study is based on multiple data sets from the U.S. pizza (fast food) industry for 2017: consumer query and click behavior data on both sponsored and organic links on Bing, including branded searches for the top three pizza brands and generic searches that contain the word "pizza"; search engine advertising data on Bing; daily television advertising expenditure for the entire pizza industry; and hourly TV advertising expenditure for the top three pizza brands. Our television advertising data are from one of the large suppliers of TV ad viewership data in the United States that can track national TV advertising in real time.

The pizza category has several features that enable us to conduct a cross-channel advertising study. First, pizza advertisers spend a huge amount of money on both TV and search advertising channels (e.g., industry spending on TV advertising alone was over $2 billion in 2017 based on our television advertising data). Second,

pizza is a frequently searched-for product with high market saturation, and over 95% of Bing searches in this category are branded. Third, bidding on the top brands' keywords is an important and potentially effective strategy for a brand to either retain or acquire more consumer impressions, clicks, and, eventually, sales (Barrett 2018). For instance, although there are thousands of local or national pizza brands in this product category, around 50% of Bing searches are for the top three pizza brands. Table 1 reports, for these top three brands, the percentage of how often each brand appears in the sponsored listing for Bing searches in 2017 whose queries contain only a given brand's name. We anonymize these brands in this paper.

However, a general identification issue in this product category is endogeneity. Pizza brands tend to spend more on TV advertising when food consumption demand (or search interest) is high over the course of a day, as indicated in Figure 1. We address this issue by identifying a top pizza brand, referred to as focal brand f, that temporarily decreased its expenditure to close to zero multiple times over a four-month period from May 1 to August 31, 2017 (see Figure 2). We believe that there exists exogenous variation in TV advertising expenditure, conditional on some time fixed effects, that allows us to identify the causal impact of TV advertising on search and subsequent clicks on search results. This is possible because consumer interest in both the focal brand and the entire pizza category is stable over the hours of a week (as shown in Figure 1) and over the weeks of a year (as shown in Figure 3). Furthermore, we find that none of the other top brands turned off their TV advertising during the period when the focal brand's TV expenditure was close to zero (as shown in Figure 2).

Our causal identification strategy relies on the exogenous variation in TV advertising net of these fixed effects, while holding the search advertising side relatively stable over time. The later assumption is also plausible based on the information available to us. We find neither major changes in the Bing search engine nor the search advertising strategies of these top pizza brands during our observation period. It should also be noted that, to our knowledge, moment

Table 1. Poaching Behavior Among the Top Three Pizza Brands

	Keyword f	Keyword c_1	Keyword c_2
Brand f	61%	21%	31%
Brand c_1	80%	93%	83%
Brand c_2	19%	20%	93%

Note. For each brand–keyword combination, we report the percentage of times the brand appears in the sponsored listing among searches containing only a given keyword on Bing in 2017.

Figure 1. (Color online) The Top Three Pizza Brands
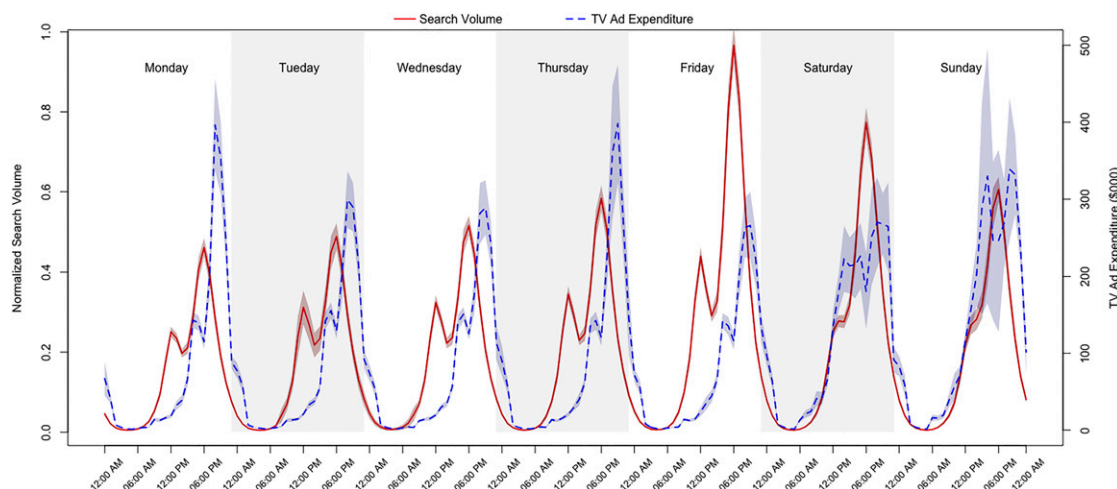
Notes. The solid line indicates the (normalized) average search volume on Bing in 2017, and the dashed line indicates the corresponding average TV advertising expenditure in $1,000. The shaded areas around each line represent the 95% confidence intervals for day-hour observations.

marketing campaigns were not in place for the period in which our data were collected.

We acknowledge the possibility that temporarily turning off TV advertising expenditure could be explained by brand f using a pulsing strategy. This has been recommended as an effective way to generate sufficient ad exposure frequency over a long period with a limited advertising budget (Dubé et al. 2005). Pulsing strategy coordinates ad buys with predictable long-term effects of TV advertising on consumption demand, which we capture using week-of-the-year fixed effects and each brand's

past accumulated TV advertising expenditure. Importantly, we believe pulsing is not a serious concern in our study. This is because our focus is on measuring the instant impacts of TV advertising on consumer click-through tendency for different types of search results, and these relationships are unknown to advertisers ad hoc. Furthermore, it is unlikely that long-term ad buys can be coordinated with the instant effects of TV advertising on search advertising, given the TV advertising scheduling process and the dramatically different institutional features of ad-buy in these two channels.

Figure 2. (Color online) Daily TV Advertising Expenditure
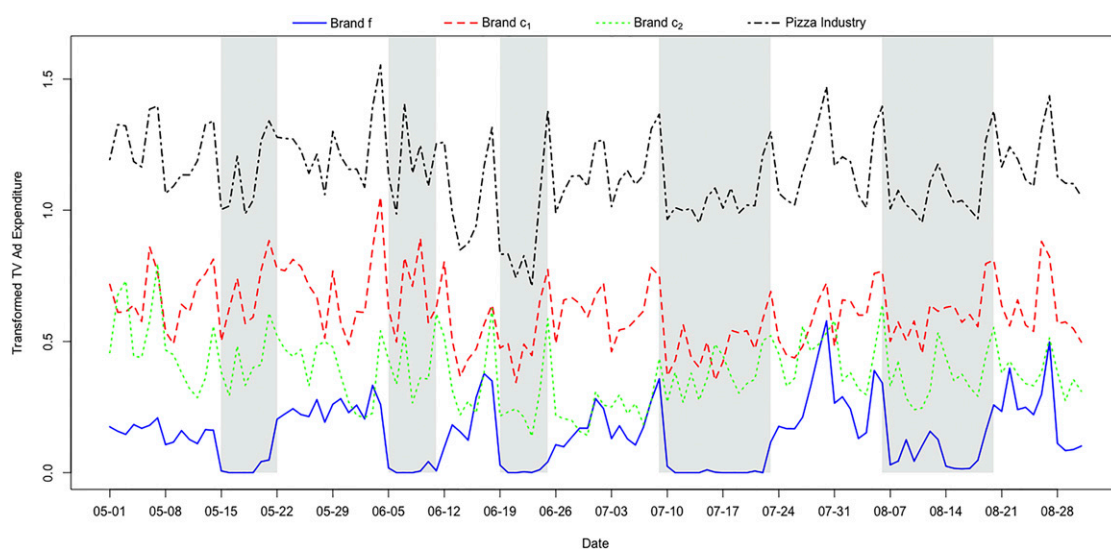
Notes. So as to not reveal the identity of the focal brand through its expenditure relative to other brands or the entire pizza industry, the TV expenditure values in this figure were transformed using the same metric. This does not affect the relative pattern over time or across series.

Figure 3. (Color online) Daily Category Search Volume
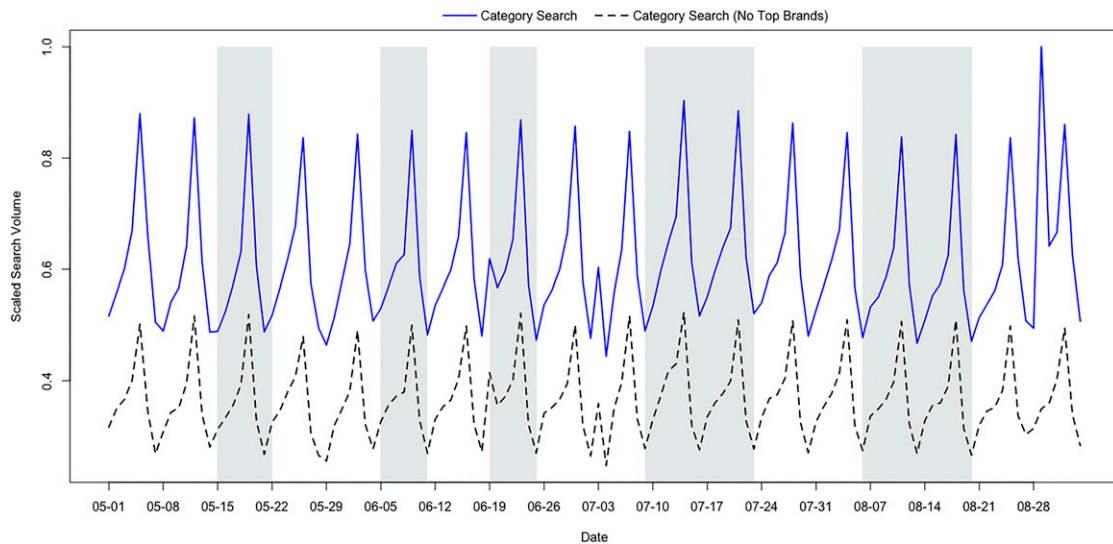
Note. Category search (solid line) represents the total volume of searches whose queries contain either the name of one of the top three brands or the generic word "pizza"; the dashed line represents the search volume for the category with the exclusion of searches for the top three brands.

3. Cross-Chanel Advertising Effects

Moment marketing companies (and search engine advertisers in general) consider the CTR a key performance metric for measuring the relationship between TV and search advertising and for evaluating the performance of synchronization strategies (da Silva 2019). The CTR is considered more generalizable and reliable than other performance metrics, such as conversion to sales, for moment marketing for two reasons. First, the definition of a sale varies across context and industry (e.g., creating an account, a purchase, or a customer inquiry). Second, clicks are observed instantaneously, whereas it takes time for sales to occur. Despite this, the CTR varies by industry, so familiarity with a particular industry is required to assess changes in CTR for a particular advertiser or set of advertisers.

When a moment marketing campaign is triggered, the advertiser automatically bids on a predetermined set of search keywords at the same time. It is expected that this will lead to better outcomes for advertisers (e.g., impressions/clicks/conversions) than if the campaign was not triggered. Although more searches can lead to more clicks, it is unclear whether the likelihood to click (i.e., the CTR) can be improved, as this has not been investigated in the existing literature. Given this background, our main research questions are as follows: Do TV advertisements for a brand have a direct impact on the CTR of its own sponsored search ads? Is the effect different for organic and sponsored ad results? Is there a spillover effect on the search ads of competing brands that attempt to poach the TV-advertised brand's search traffic?

To reduce the confounding factors in this cross-channel study, we focus on searches that satisfy three criteria: (1) a query must contain only the focal brand's name, (2) a query must be issued from the Eastern or Pacific time zone, and (3) the focal brand's ad must be included in the sponsored listings on the SERP. The first criterion is to rule out the possibility that our results are driven by major differences in search advertising at the keyword level, such as keyword frequency, bidding strategy, or the presence of competitors. The second criterion is to ensure the searches were made at the same local time and the same TV advertisements were aired at the same time. For each selected search, we observe the query, time, search device, geographic location, SERP, and subsequent clicks. Note that when the search query contains only the focal brand's name, the focal brand is always in the first position of both the organic and sponsored listings on Bing. We find that in this situation, 6% of clicks are not on the focal brand's results. This percentage of stolen clicks is larger than the estimates of 1%–3% across a wide range of brands reported in Simonov and Hill (2019). This suggests that in the pizza category, competitors are able to poach significant search traffic from the focal brand.

3.1. Analysis of the Advertised Focal Brand

We first measure the cross-channel advertising effects for the focal brand f. We aggregate the data at the hourly level for a total of 3,024 day-hour observations. Across all 2,077 observations whose number of impressions is above zero, the average CTR on the advertised focal brand's organic (sponsored) result is

0.362 (0.383) with a standard deviation of 0.149 (0.153). There is an average of 1.749 mainline ads (those presented at the top of the organic listings) on the SERP, with a standard deviation of 0.395 and an average of 0.551 sidebar ads (presented elsewhere but mainly to the right side of the organic listings) with a standard deviation of 0.305.

For each day-hour observation t, we let M_t denote the number of times that the focal brand appears in both the organic and sponsored listings at time t. We classify the clicks into three categories: Y_{t1} denotes the number of clicks on the focal brand's organic result, Y_{t2} denotes the number of clicks on the focal brand's sponsored result, and $Y_{t0} = M_t - Y_{t1} - Y_{t2}$ denotes a nonclick on the focal brand's results.[2] We model the probability of observing (Y_{t0}, Y_{t1}, Y_{t2}) using a multinomial regression in which a nonclick is the baseline alternative.

The latent utility U_{tj} of alternative $j \in \{1, 2\}$ at time t is parameterized as a linear additive function of brand f's log-transformed total TV advertising expenditure at time t and its past accumulated long-term TV advertising expenditure before time t (i.e., advertising stock). The former is defined as $TV_t^f = \log(a_t^f + 1)$, where a_t^f is brand f's TV advertising expenditure at time t. The latter is defined as $LTV_t^f = \sum_{\tau=1}^{L} \delta^\tau TV_{t-\tau}^f$.[3] We allow the coefficients of these two variables to differ across time, enabling us to investigate how cross-channel advertising effects vary due to consumer demand for pizza. Specifically, we group the 24 hours of a day into seven time windows based on common knowledge of meal times and the search patterns shown in Figure 1: *Inactive*, from 2:00 a.m. to 7:59 a.m.; *Morning*, from 8:00 a.m. to 10:59 a.m.; *Lunch*, from 11:00 a.m. to 1:59 p.m.; *Afternoon*, from 2:00 p.m. to 4:59 p.m.; *Dinner*, from 5:00 p.m. to 7:59 p.m.; *Prime*, from 8:00 p.m. to 10:59 p.m.; and *Late*, from 11:00 p.m. to 1:59 a.m. We also control for time, the number of mainline ads, the number of sidebar ads, and the current and past long-term TV advertising expenditure from the focal brand's major competitors at time t.

Note that we separate competitor c_1's expenditure from the others when specifying the latent utility because, in the next section, we take the perspective of competitor c_1 to examine whether and how the focal brand's TV advertising has spillover effects. There are several reasons for choosing brand c_1. First, brand c_1 is among the top sellers in the pizza category, so there is significant search interest in brand c_1 on Bing. Second, brand c_1 is a major TV as well as search advertiser. In particular, brand c_1 regularly bids on about 80% of the search traffic for the focal brand on Bing (see Table 1), which provides a sufficient number of impressions with both brands f and c_1 in the sponsored listings.

The first two columns of Table 2 report the estimation results. First, we find that for organic results, the focal brand's current TV advertising has a significantly positive (negative) effect on CTR over two major consumption windows, *Afternoon* and *Dinner* (*Lunch* and *Prime*). In comparison, the cross-channel effects on sponsored results are always positively significant over a day (except *Morning*). The effect sizes for sponsored results also tend to be much larger than for organic results. For example, during the *Dinner* window, the relative risk ratio for a one-unit increase in logged hourly TV advertising expenditure is 1.0087 (1.0066) for clicking on a sponsored (organic) result versus nonclicking, holding all the other variables constant. The differences in effect sizes could be driven by an ordering effect: search ads are typically listed above organic results and are thereby more likely to get attention, especially if the traffic is navigational. Similarly, the focal brand's advertising stock has a significantly positive impact on both organic and sponsored results over most time windows, yet with much smaller effect sizes. Finally, for competitor c_1's TV advertising, we find that its instant effects are significantly positive (negative) for the focal brand's sponsored (organic) results, whereas its long-run effects are significantly positive for both types of results. Therefore, competitor c_1's TV advertising may also improve the CTR of the focal brand's search results when consumers search for the focal brand's name. We offer explanation for this counterintuitive finding in Section 4.[4]

3.2. Analysis of a Competitor That Poaches
We now focus on, given the presence of the focal brand in sponsored listings, whether the focal brand's TV advertising has any significant spillover effects on the CTR for competitor c_1, who attempts to poach the advertised brand's search traffic by bidding on its keywords. This analysis is based on the approximately 90% of search impressions for which competitor c_1 also appears in the sponsored listings. Note again that in these cases, brand f is always listed in the first position of both listings, whereas competitor c_1 never appears in the organic listings. Across the 2,042 day-hour observations whose number of impressions is above zero, competitor c_1's CTR is 0.007, with a standard deviation of 0.024; the average position of competitor c_1 is 2.684, with a standard deviation of 0.727; and the average number of mainline (sidebar) ads is 1.821 (0.617), with a standard deviation of 0.396 (0.339).

We model the CTR for competitor c_1's search ads with a regression model similar to that used for the focal brand, but including only two alternatives, clicking and nonclicking. We also control for competitor c_1's ad position. The last column of Table 2 presents the estimation results. We find that the

Table 2. Regression Analysis of CTR

	Advertised focal brand		Competitor c_1
	Organic	Sponsored	Sponsored
$TV_i^f \times Inactive$	−0.0022 (0.0008)***	0.0074 (0.0009)***	0.0149 (0.0096)
$TV_i^f \times Morning$	0.0004 (0.0006)	0.0007 (0.0006)	−0.0100 (0.0066)
$TV_i^f \times Lunch$	−0.0039 (0.0000)***	0.0781 (0.0000)***	23.8661 (0.0000)***
$TV_i^f \times Afternoon$	0.0037 (0.0000)***	0.0038 (0.0000)***	−0.0741 (0.0000)***
$TV_i^f \times Dinner$	0.0066 (0.0010)***	0.0087 (0.0010)***	0.0060 (0.0108)
$TV_i^f \times Prime$	−0.0040 (0.0001)***	0.0027 (0.0001)***	0.0183 (0.0005)***
$TV_i^f \times Late$	0.0056 (0.0011)***	0.0095 (0.0012)***	−0.0171 (0.0112)
$LTV_i^f \times Inactive$	−0.0000 (0.0000)	0.0000 (0.0000)***	−0.0002 (0.0000)***
$LTV_i^f \times Morning$	0.0000 (0.0000)***	0.0000 (0.0000)***	−0.0001 (0.0000)***
$LTV_i^f \times Lunch$	0.0006 (0.0000)***	0.0006 (0.0000)***	−0.1297 (0.0000)***
$LTV_i^f \times Afternoon$	0.0000 (0.0000)***	0.0001 (0.0000)***	−0.0003 (0.0000)***
$LTV_i^f \times Dinner$	−0.0000 (0.0000)***	−0.0000 (0.0000)	−0.0002 (0.0000)***
$LTV_i^f \times Prime$	−0.0001 (0.0000)***	−0.0000 (0.0000)	−0.0004 (0.0000)***
$LTV_i^f \times Late$	0.0001 (0.0000)***	0.0000 (0.0000)***	−0.0002 (0.0000)***
Competitor c_1: $TV_i^{c_1}$	−0.0018 (0.0006)***	0.0070 (0.0006)***	−0.0157 (0.0087)***
Competitor c_1: $LTV_i^{c_1}$	0.0005 (0.0000)***	0.0004 (0.0000)***	0.0019 (0.0001)***
Other competitors: TV_i^{c-1}	0.0047 (0.0008)***	0.0072 (0.0008)***	0.0158 (0.0081)***
Other competitors: LTV_i^{c-1}	−0.0004 (0.0000)***	−0.0004 (0.0000)***	−0.0011 (0.0001)***
Number of mainline ads	−0.3779 (0.0000)***	0.1400 (0.0000)***	0.3594 (0.0002)***
Number of sidebar ads	0.1824 (0.0000)***	0.1818 (0.0000)***	0.0474 (0.0001)***
Position of c_1's ad			−0.5443 (0.0001)***
Time-window fixed effects	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes
Number of observations		2,077	2,042

Note. The baseline alternative in each multinomial regression model is a nonclick on the studied brand.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

instant effects of the focal brand's TV advertising are significantly positive over two major consumption time windows (*Lunch* and *Prime*), but its long-term effects are significantly negative over all time windows. These findings confirm that the positive spillover effects are present only momentarily. In addition, we find that competitor c_1's TV advertising has a significantly negative instant effect on its own poaching strategy, whereas in the long term, the effect is significantly positive. Combined with the findings in the previous section, these findings indicate that competitor c_1's TV advertising can temporarily increase the focal brand's CTR while decreasing its own CTR when poaching the focal brand's search traffic. In the following, we discuss mechanisms that explain these counterintuitive findings.

4. Mechanisms

So far, we have evidence of significantly positive instant effects of TV advertising on the effectiveness of search advertising for both the advertised focal brand and its competitor. Given that a consumer must enter a search query before clicking on a result on the

SERP, we conjecture two possible mechanisms driving these cross-channel advertising effects: a *filtering* mechanism and a *reinforcing* mechanism.

The filtering mechanism works through changes in search demographics. Specifically, the focal brand's TV advertising is likely to trigger searches from consumers who are generally more (less) loyal to the focal (competing) brand, whereas TV advertising from its competitor is likely to filter out searches from consumers who are generally less (more) loyal to the focal (competing) brand. Otherwise, if TV advertising simply leads to more searches from the same composition of consumers, the resulting CTR would remain similar, unless this can be explained by the changes in individual consumers' attention or engagement level.

The reinforcing mechanism suggests that the same consumer's click-through tendency for the same search result is higher when the consumer is exposed to more TV advertising; that is, under the reinforcing mechanism, consumers' existing patterns are strengthened with more exposure to advertising. In contrast to the filtering mechanism, this entails no change in search demographics.

4.1. Mediation Analysis

To determine whether our data confirm these mechanisms and provide suggestive evidence regarding which is dominant, we first conduct mediation analysis (MacKinnon 2012). The top diagram in Figure 4 shows a two-variable model in which the independent variable, *TVAd* (X), influences the dependent variable, *Clicks* (Y). The coefficient β_0 represents the total effect between X and Y without considering other variables. The bottom diagram in Figure 4 presents a three-variable model in which there is an underlying mediation relationship of *TVAd* (X) with *Searches* (M) to *Clicks* (Y). This pathway is the indirect effect of X on Y, which works through the mediator M. Coefficient β_1 represents the relationship of X with M, and coefficient β_2 represents the relation of M with Y, adjusted for the effects of X. Furthermore, β_0' denotes the relationship of X with Y, that is, the direct effect of X on Y absent the mediator M. Conceptually speaking, the total effect β_0 can be broken into two parts: the direct (partial) effect β_0', which captures our reinforcing mechanism, and the indirect effect $\beta_1\beta_2$, which captures our filtering mechanism. Therefore, the filtering mechanism is the only driver if both β_0 and $\beta_1\beta_2$ are significant, but β_0' is not significant. The reinforcing mechanism is a partial driver if both $\beta_1\beta_2$ and β_0' are significant.

Section B of the online appendix presents the detailed estimation results. Here, we summarize the main findings and their implications. First, we find that the focal brand's current TV advertising has a significantly positive impact on searches and impressions (see Table A2 in the online appendix), suggesting that coefficient β_1 in the mediation model is statistically significant as expected. Second, for click-through counts, we find that the focal brand's current TV advertising has a statistically significant positive impact on the focal brand's organic and sponsored results over most time windows. The same is also true for competitor c_1's search ads over several consumption windows (see Table A3 in the online appendix). Thus, coefficient β_0 in Figure 4 is also statistically significant, as expected. Third, for the regression model of Y on X while controlling for M, we find that the coefficients of M (i.e., β_2) are still positively significant. However, the coefficients of X (i.e., β_0') become nonsignificant in all cases, except for the focal brand's sponsored result over two major consumption windows. In conclusion, these findings suggest that the total effect of TV advertising on click-through tendency is mostly explained by indirect effects through searches (i.e., the filtering mechanism), rather than direct effects (i.e., the reinforcing mechanism).

4.2. Evidence Based on Effect Differences Between States

To further test and understand these mechanisms, we compare cross-channel advertising effects in two representative states, denoted by H_f and H_{c_1}, where the respective headquarters of brands f and c_1 are located. This is informative because we expect consumers from a given pizza brand's headquarter state to exhibit more loyalty to the locally based brand than its competitor. Table 3 presents evidence that confirms our expectation. For each variable–state combination, Table 3 reports the mean and standard deviation over 126 daily observations. The first row is the search volume of brand f relative to brand c_1 (denoted by S_f/S_{c_1}) within each state. On average, there are almost two times as many searches for brand f as for brand c_1 in state H_f, but only half as many in state H_{c_1} ($p < 0.001$). The remaining rows in Table 3 report CTRs on different types of search results for searches that contain only the focal brand's names. We also find that the CTR for the focal brand's organic and sponsored results is significantly higher in its headquarter state H_f than in state H_{c_1} ($p < 0.001$). However, we find no significant differences in the CTR for the competitor c_1's sponsored results in these two states ($p = 0.487$).

We now examine whether the focal brand's TV advertising is more likely to increase searches from state H_f than from state H_{c_1}, as predicted by the filtering mechanism. We run a linear regression model of the focal brand's log-transformed search volume at the state-day-hour level. For the independent variables, there are state-specific intercepts, as well as interaction terms between state indicators and (current and past long-term) TV advertising from the focal brand f and its competitor c_1, respectively. The state-specific coefficients are comparable in this case. As before, we control for the same time fixed effects and (current and past long-term) TV advertising expenditure from the other pizza brands. There are 6,048 observations, and the R^2 of the model is 0.9221.

For ease of comparison, Table 4 reports only the estimated state-specific coefficients. We find that the

Figure 4. Path Diagram and Equations for Mediation Analysis

TV Ad (X) — β_0 → Clicks (Y)

The Regression Model:
$$Y = \alpha_0 + \beta_0 X + \varepsilon_0$$

Searches (M), with β_1 and β_2

TV Ad (X) — β_0' → Clicks (Y)

The Mediation Model:
$$M = \alpha_1 + \beta_1 X + \varepsilon_1$$
$$Y = \alpha_2 + \beta_0' X + \beta_2 M + \varepsilon_2$$
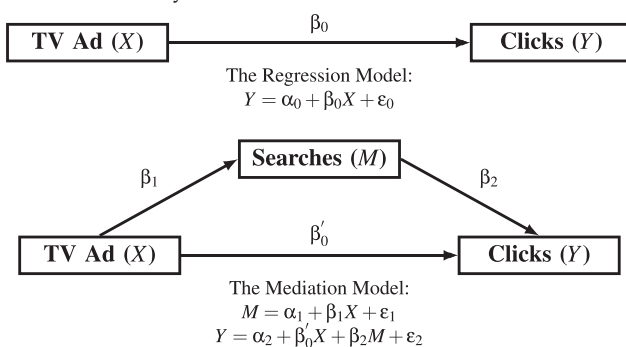
Table 3. Comparing State-Level Consumer Behavior

	State H_f	State H_{c_1}
Search ratio S_f/S_{c_1}	1.9684 (0.3597)*	0.5861 (0.1221)
CTR on f's organic result	0.3564 (0.0691)*	0.3094 (0.0764)
CTR on f's sponsored result	0.4270 (0.0808)*	0.3923 (0.0826)
CTR on c_1's sponsored result	0.0120 (0.0104)	0.0109 (0.0131)

Notes. For each state, we report the sample mean and the standard deviation (in parentheses) over 126 daily observations. Search ratio is the relative (branded) search volume of brand f to that of competitor c_1. The CTR is based on searches that contain only the focal brand's name. An asterisk indicates that the average in state H_f is significantly larger than in state H_{c_1} ($p < 0.001$), based on a paired-sample t-test.

Table 4. Comparing the Effects of TV Advertising on Search Volume Between States

	State H_f	State H_{c_1}
TV_i^f	0.0220 (0.0034)***	0.0113 (0.0034)***
LTV_i^f	0.0000 (0.0000)	−0.0001 (0.0000)
$TV_i^{c_1}$	0.0196 (0.0036)***	−0.0458 (0.0036)***
$LTV_i^{c_1}$	−0.0020 (0.0005)***	−0.0019 (0.0005)***

Notes. We report the estimated state-level coefficients from a linear regression model of log-transformed state-day-hour-level search volume on TV advertising, while controlling for time fixed effects.
***$p < 0.01$.

focal brand's current TV advertising has a significantly positive impact on search volume in both states, whereas the effect in its headquarter state is almost two times as large as the effect in competitor c_1's headquarter state. These findings confirm that consumers who are more loyal to the focal brand are more likely to respond to its TV advertising. In comparison, competitor c_1's current TV advertising has a significantly negative impact on search volume for the focal brand in state H_{c_1}, but a significantly positive impact in state H_f. This suggests that the competitor's TV advertising has a positive instant effect on searches from consumers loyal to the focal brand. At the same time, it prevents less loyal consumers from searching for the focal brand. In the long term, however, the competitor's TV advertising reduces searches for the focal brand in both states.

Given that consumers' loyalty to the focal brand differs dramatically between these two states (as shown in Table 3), we can view the states as distinct consumer segments in the pizza category. The reinforcing mechanism predicts that the focal brand's TV advertising will increase both segments' CTR on its own search results. We test this hypothesis by replicating the CTR regression analysis described in Section 3. We use data for each state separately, but, for simplicity, consider only one coefficient for the focal brand's TV advertising. Table 5 presents the estimation results. We find that the focal brand's current TV advertising has a significantly positive impact on both organic and sponsored results in state H_f. In state H_{c_1}, however, the effect is significantly negative for sponsored results and not significant for organic results. In addition, the instant effect of the competitor's TV advertising is significantly negative in state H_{c_1}. In state H_f, however, the effect is significantly positive for the focal brand's sponsored result and not significant for its organic results. Therefore, these observations imply that the same TV advertising may have opposite effects on the CTR for different consumer segments. In particular, the focal

brand's TV advertising may improve the effectiveness of its search advertising only for loyal consumer segments.

4.3. Summary
Considered together, the results of the mediation analysis and the state-level analysis provide strong and consistent evidence supporting the filtering mechanism, but weak and inconsistent evidence for the reinforcing mechanism. Therefore, we conclude that the filtering mechanism is the main driver of our observed cross-channel advertising effects. This also explains the previous counterintuitive finding that competitors' TV advertising can temporarily increase the focal brand's subsequent CTR, while decreasing its own CTR, when poaching the focal brand's search traffic after a TV moment. This occurs because of the filtering mechanism, whereby competitors' TV advertising filters out consumers who are less (more) likely to click on the focal brand's (competitor's) results on the SERP.

We close our study of the mechanisms by analyzing additional search demographics. The details are reported in Sections B.3 and B.4 of the online Appendix. We find confirmatory evidence that TV advertising has significant impacts on other search demographics such as search keyword and search device. For example, the focal brand's TV advertising is more likely to trigger instant navigational searches than informational searches, which is consistent with Joo et al. (2016). It is also more likely to trigger searches from mobile devices (than from computers) during the *Dinner* window and/or weekends (which represent times when consumers have more leisure time to use mobile devices).

5. Conclusion and Discussion
As one of the first papers on moment marketing, we not only show that cross-channel advertising can be effective, but also describe and provide evidence for the mechanisms underlying these effects. Specifically, we

Table 5. Regression Analysis of the CTR on the Focal Brand's Search Results in Each State

	State H_f		State H_{c_1}	
	Organic	Sponsored	Organic	Sponsored
Focal brand: TV_i^f	0.0216 (0.0052)***	0.0247 (0.0051)***	−0.0006 (0.0070)	−0.0163 (0.0066)***
Focal brand: LTV_i^f	0.0000 (0.0000)	−0.0000 (0.0000)	−0.0000 (0.0001)	0.0003 (0.0000)***
Competitor c_1: $TV_i^{c_1}$	0.0039 (0.0024)	0.0235 (0.0023)***	−0.0311 (0.0036)***	−0.0172 (0.0036)***
Competitor c_1: $LTV_i^{c_1}$	−0.0024 (0.0001)***	−0.0030 (0.0001)***	−0.0027 (0.0001)***	0.0028 (0.0001)***
Other competitors: $TV_i^{c_{-1}}$	0.0339 (0.0025)***	0.0356 (0.0024)***	0.0394 (0.0034)***	0.0058 (0.0035)***
Other competitors: $LTV_i^{c_{-1}}$	0.0009 (0.0001)***	0.0007 (0.0001)***	0.0012 (0.0001)***	−0.0013 (0.0001)***
Number of mainline ads	−0.5562 (0.0001)***	0.3347 (0.0001)***	−0.4433 (0.0001)***	0.2799 (0.0001)***
Number of sidebar ads	0.1055 (0.0000)***	0.3971 (0.0000)***	0.2221 (0.0001)***	0.3867 (0.0001)***
Time-window fixed effects	Yes	Yes	Yes	Yes
Day-of-week fixed effects	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes
Num. obs.	1,841		1,663	

Note. The baseline alternative in each multinomial regression model is a nonclick on the studied brand.
 *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

show that TV moment-based channel coordination is effective for optimizing sponsored search advertising. This strategy is effective because TV advertising has the potential to improve the quality of online search traffic (e.g., who searches, where they search, and how they search), so that in the moments after a TV ad, the average searcher is more engaged with the subsequent organic and/or sponsored results on the SERP. This ultimately improves the CTR across all search impressions. However, our findings suggest that this filtering effect is not long lasting, further confirming the value of investing in coordinated search advertising in real time at contextually relevant moments. Our research contributes to the existing cross-channel literature and provides insights on the recent moment marketing strategy.

With the understanding that our findings may be specific to the pizza industry, we believe our research has important managerial implications for both marketers and academics. To design a more effective coordination strategy between TV and search advertising, it is first important to understand the heterogeneity in consumers' responsiveness to TV advertising across factors such as TV ad content, timing, keywords, demographics, location, and device. These factors can be leveraged for better customization and targeting in the search channel in real time. For instance, based on the content (e.g., promotion, new product/service, or event) or brand featured in a TV ad, advertisers can allocate more budget for keywords appearing in the ad to capture triggered online traffic. They can also allocate their budget differently based on a searcher's engagement with the advertised brand, which can be inferred by the searcher's demographic information provided by the search engine. In addition, advertisers can synchronize search ads, using similar language and

visuals across advertising channels targeted to different demographics (rather than generic messages), to better attract consumers' attention. Furthermore, with the large amount of consumer browsing data collected online, marketers can infer the purchase funnel of individual searchers (e.g., whether the customer has already purchased a product/service). Advertisers can leverage this to personalize search ad copy with the aim of better resonating individual searchers' needs (e.g., add-on products or upgrades for existing customers versus promotions and deals for potential new customers) triggered by the same TV moment. If consumers exhibit heterogeneous responses to an TV ad on different types of devices, because of factors such as ad timing (e.g., consumers may search more on mobile devices in their leisure time) or ad content (e.g., certain types of information are searched for more often on computers/laptops than on mobile devices), advertisers can adjust their strategies across devices for more effective campaigns.

More generally, if consumers click on organic search results much more frequently when firms spend more on television advertising, firms do not necessarily need to increase their spending on simultaneous search advertising (Blake et al. 2015). However, our research findings imply a complementary relationship between TV and sponsored search advertising, which is consistent with the defensive motivation for a TV-advertised brand to bid on its own branded keyword suggested in the existing literature (Desai et al. 2014, Simonov et al. 2018). Therefore, instead of smoothing out their search advertising budget over a day, advertisers can allocate more budget during certain TV moments and less during other times, while holding the total budget fixed. This could ultimately improve the return on investment for search advertising.

Finally, although systematically experimenting with TV advertising expenditure is still rare, we showcase that having large exogenous variation in TV advertising expenditure is a prerequisite for understanding how TV advertising influences the effectiveness of search advertising, particularly in light of new and novel developments in the field, such as moment marketing solutions.

Our research opens up a rich stream of research directions for moment-based coordination across different advertising channels. First, as discussed above, factors that could help advertisers design more effective moment marketing campaigns could be explored. Second, the performance of such channel coordination could be evaluated using other metrics such as conversions to sales. Because in the pizza category consumers who click are more likely to be at the bottom of the consumer purchase funnel, our findings suggest moment marketing has value for improving the conversion rate from clicks to sales. Third, our proposed filtering mechanism is inferred from aggregated data, so using individual-level TV viewing and search data could help develop a deeper understanding of moment marketing. Last, we believe that the filtering mechanism of TV advertising can be generalized to other types of offline events suitable for moment marketing, which could be an interesting and important direction for future research.

Acknowledgments

Endnotes

[1] Alternatively, the advertiser could simultaneously trigger different search advertising campaigns across randomly selected searchers at the same TV ad moment to rule out confounding factors such as timing, TV channel/program, and TV ad copy. However, based on our conversations with the company with which we collaborated (one of the top companies selling moment marketing business solutions), such randomization was not yet ready to be implemented at scale using real-time moment marketing technology at the time of writing this paper.

[2] We ignore approximately 0.1% impressions that generate clicks on both types of listings (i.e., clicks on the advertised brand's organic and sponsored results are considered substitutions in our data).

[3] The literature on advertising carryover effects (Leone 1995, Jedidi et al. 1999, Dubé et al. 2005, Shapiro et al. 2020) suggests that the typical lag of TV advertising is more than six months, so we control for advertising stock over the past 120 days (i.e., $L = 4,320$), given that we have TV advertising data for only 2017. We set the hourly decay parameter as $\delta = 0.9994$, which is equivalent to the weekly decay of close to 0.89 that has been commonly used in recent studies (Dubé et al. 2005, Shapiro et al. 2020). We replicate our analysis using alternative δ and L to assess the sensitivity of our results. We find that our main findings are robust to both parameters, but the instant effects of TV advertising tend to be slightly less statistically significant with a much smaller L. This is because a smaller L leads to significantly less variation in the advertising stock, and hence it becomes

more difficult to distinguish the instant effects from the long-term effects. Details are presented in Section A of the online appendix.

[4] For the other control variables in Table 2, we find that the number of mainline ads has significantly negative (positive) effects on the focal brand's organic (sponsored) results, whereas the number of sidebar ads has positive effects across both the organic and sponsored results. This can be explained by the significant negative relationship between these two variables (-0.375, p-value < 0.001); in other words, more sidebar ads (or fewer mainline ads) makes the focal brand more visible, so consumers click on it more often. In order to not reveal the original scale of searches/impressions/clicks in the data (through the simulated data provided online), we do not report the log-likelihood for all the multinomial regression models in this paper.

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