Research Proposal: On Measuring the Effectiveness of TV Ads: Channel Position Effects

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Despite a long academic literature studying advertising and its effects on market structure (Bagwell, 2007), little is known about the underlying mechanisms through which advertising affects demand, and advertising effectiveness in general. Is advertising driven primarily by information, as argued by Ackerberg (2001) and Blake et al. (2015)? Or does advertising serve as a signal, as suggested by the results of Sahni and Nair (2016)? And, more generally, is there a systematic causal link between product advertising and future sales?

Empirical studies of advertising effectiveness date back to the beginning of the twentieth century (Shryer, 1912). But, the causal interpretation of most of the extant evidence linking advertising to sales is debatable. The empirical literature has been limited by the endogeneity of advertising investments on such media as television and the lack of practical instruments. While some progress has been made using individual-level randomized controlled advertising field experiments (Bertrand et al., 2010; Johnson et al., 2016), the signal to noise ratios in individual-level exposure and purchase data typically require extremely large samples for statistical power Lewis and Rao (2015). Moreover, the temporal separation between the timing of media buying and media exposure limits the practicality of field experiments in domains such as television advertising. The recent empirical literature has relied on natural television advertising experiments to test for advertising effects (Shapiro, 2016; Hartmann and Klapper, 2017; Stephens-Davidowitz et al., 2017). These quasi-experimental approaches require very specific conditions in terms of location and/or timing.

We propose to exploit a large natural experiment to measure the effectiveness of TV advertising on demand for consumer goods. Our identification strategy relies on the quasi-exogenous assignment of television networks to numeric TV channel positions across local cable system in the United States. Martin and Yurukoglu (ming) show that television channel positions in a local

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cable system are largely determined by the timing of the system-channel bilateral negotiations and, as a result, historic order-of-entry of a channel to the cable system. "Position effects" may increase the prominence of content located closer to the top of a list to a viewer, an effect documented for television channel positions (Martin and Yurukoglu, ming) and for organic listings in online search engines (Narayanan and Kalyanam, 2015; Ursu, 2015). Users of a network where a particular channel has a higher position get more exposure to the advertisements carried by this channel. Accordingly, we use the zip-code level variation in advertising exposure induced by network channel position variation across geographic areas to measure advertising effects.

Given a widespread adoption of cable systems and persistent nature of channel positions, we believe that the variation induced by the difference in channel positions creates a great set-up to study short and long-term advertising effectiveness. We can potentially leverage these estimates to test alternative mechanisms of advertising effects, for example, using the new product introductions during the sample period (Ackerberg, 2001). The general purpose applicability of our proposed approach is further extended by the wide array of product markets that use television advertising.

Our proposed approach consists of identifying the marginal effect of television advertising on sales using the incremental advertising exposures associated with geographic variation in a network's channel position. The empirical strategy contains four steps:

1. Establish the differences in content and ads carried by channels.
2. Establish the differences in channel positions across cable systems and the exogeneity of these position differences.
3. Show that there are effects of channel positions on viewership (first stage).
4. Use the positions of channels as an instrument for viewership to estimate its effect on product sales (second stage).

The approach requires four key Nielsen datasets:

1. FOCUS data: lists of the channel positions across cable systems.
2. NLTV data: zip-code level viewership information
3. AdIntel data: the schedules for each advertisement's air time across channels
4. HMS and RMS: local sales and marketing data for consumer packages goods brands that advertise on television

We have access to the dataset (3) and (4) through the Kilts Center for Marketing at the University of Chicago Booth School of Business. However, the datasets (1) and (2) (FOCUS and NLTV) are not currently available through the Kilts Center or through any other academic source. We are therefore requesting access to FOCUS and NLTV through the NBER's new media

data arrangement. Ideally, we would like to get FOCUS data and NLTV daily viewership data by zip-code level for 2006-2015. The local viewership information is critical to the first stage of our identification strategy as we propose to correlate viewership levels with channel positions. We then project the incremental viewership associated with position differences onto sales in the second stage. Nielsen is currently willing to sell these data for the years 2011-2013 at an academic rate of $65,000.

In order to check the feasibility of our empirical strategy, we have conducted some preliminary analysis of the AdIntel and RMS data. First, we have confirmed that there is an overlap in the product categories present in the AdIntel and RMS data: 53.4% (655 out of 1226) of the categories present in the RMS data are present in the AdIntel data. This result is encouraging since it confirms that we can track consumer response to advertising on a broad range of products and categories. Second, we have confirmed that there is substantial variation in advertising levels, at the category and product level, across geographic areas and across TV channels. Table 1 reports summary statistics for the distribution of advertising expenditures of the top 5 (by ad spend) CPG categories and brands in the top 50 (by ad spend) TV channels. Consider the top brand, Bud Light, whose advertising varies considerably across the top 50 channels. Bud Light contributes to 1.51% of total advertising spending on one of these 50 channels. But, Bud Light does not advertise at all on 26 of the channels. Therefore, viewers of these different channels receive very different levels of Bud Light advertising, including many viewers receiving no impressions at all. These preliminary findings confirm a necessary condition for our empirical identification strategy: there is advertising exposure variation across the TV channels even for the largest brands and categories. Clearly a key component of our proposed analysis will consist of using the FOCUS data to extract the plausibly exogenous component of this advertising variation to test for a causal effect on sales.

Table 1: Summary statistics of advertising expenditures of Top 5 CPG Categories and Top 5 CPG Brands across Top 50 TV Channels

	Share of channel ad revenue from category/brand				
Category/Brand	Max	Min	Mean	S.D.	# of Channels with zero share
Top 5 Categories:					
Cereal	7.09%	0%	0.89%	0.99%	2
Candy	2.57%	<0.01%	0.87%	0.54%	0
Beer	4.27%	0%	0.86%	1.06%	13
Yogurt	2.08%	0%	0.44%	0.43%	5
Regular Soft Drinks	1.41%	0%	0.26%	0.28%	4
Top 5 Brands:					
Bud Light	1.51%	0%	0.18%	0.31%	26
Cheerios	0.76%	0%	0.17%	0.17%	6
Miller Lite	0.82%	0%	0.12%	0.21%	33
Coors Light	0.71%	0%	0.09%	0.16%	31
Budweiser	0.55%	0%	0.05%	0.103%	29

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