The Welfare Implications of Targeted Television Advertising
NBER-Nielsen Media Project Proposal

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Research Question, Motivation, and Related Literature

The spread of digital TV increasingly enables advertisers to target commercials to specific sets of viewers, selected based on their demographics, viewing habits or even purchase histories. According to the *Wall Street Journal*, NBC Universal will allocate $1 billion of its advertising inventory to targeted segments in 2017 and Credit Suisse forecasts that the market for targeted TV ads may soon be worth $100 billion. This research will quantify how increased targeting of ads affects product market competition (price and advertising levels, market shares, profits, and consumer surplus) in oligopoly markets and consider associated policy implications.

Theoretically, the effects of increased targeting are ambiguous, depending on the distribution of tastes as well as price and advertising elasticities in the population. Targeting allows brands to reach only consumers whose purchase decisions can be affected, increasing the efficiency of advertising dollars. This will tend to raise advertising expenditure and reallocate exposures across consumers (Deng and Mela 2017). However, if competing brands target the same consumers with greater advertising, then this may intensify price competition, lowering prices, and benefitting both targeted and non-targeted consumers (Grossman and Shapiro 1984, Bagwell 2007). On the other hand, targeting may allow firms to target their loyal, inframarginal consumers and to avoid comparison shoppers, softening competition and raising prices (Iyer et al. 2005). Consumers who receive fewer advertising exposures once targeting is possible may experience higher or lower welfare depending on whether firms can also offer these consumers lower prices (e.g., via coupons or store-specific pricing). Targeting may also allow smaller, niche brands, to make use of television advertising, reducing the dominance of the leading firms in an industry.

While theory suggests several possible effects of advertising on product market competition, the vast majority of the empirical literature on non-targeted advertising has been focused on measuring firm- or industry-level advertising elasticities (e.g., Sethuraman et al. 2011); explaining phenomenon such as pulsing (e.g., Dubé et al. 2005); or identifying which economic "view" of advertising (informative, persuasive or complementary) applies in a particular setting (Ackerberg 2003). An exception is Murry (2017) who estimates a structural model to understand the effects, on advertising and prices, of restricted vertical contracting between dealers and manufacturers in the automobile industry. The nascent empirical literature on targeting has focused on how it may raise the efficiency of advertising without allowing for equilibrium price changes (Deng and Mela 2017) and trying to assess how consumers, who may be concerned about their privacy, respond to targeting (Goldfarb and Tucker 2011).

While we aim to provide the first systematic quantification of how targeting affects product market outcomes, our analysis will also be relevant to public policy. In both the US and Europe, targeting has raised concerns about privacy and data protection when broadcasters and advertisers use data on viewing and purchasing. This debate would benefit from an informed view of how targeting affects product market outcomes. Additionally, the distributive effects of targeting are policy relevant. Should all advertisers target similar affluent, white consumers, then this might cause the media industry to invest in programming that only appeals to these consumers or lead to price changes that redistribute surplus across demographics. On the other hand, targeting could

allow firms to promote products that appeal primarily to minority or lower-income consumers, leading to greater diversity in the media landscape.

Our empirical setting is the US beer market. In 2015, the five largest brewers in the United States spent over $1.3 billion on advertising and accounted for over 80% of industry sales. However, beer advertising has been estimated to have almost no effect on total beer consumption (Nelson 2005, Tremblay and Tremblay 2005), suggesting that advertising primarily affects brand-level competition and market shares.

Model, Empirical Approach, and Counterfactuals

Owing to the ambiguity of theoretical predictions, we will quantify the effects of targeting by estimating a structural model. The structure of the baseline model is that manufacturers[1] will simultaneously choose prices and advertising in a static Nash equilibrium.

Our demand framework has two components because we need to model both brand purchases and individuals' exposures to brand advertising. A "media consumption/advertising exposure" model will predict the exposures of individuals with particular demographics and living close to the stores in our sample as a function of a brand's advertising on different channels, and the channels that these consumers watch. Second, a rich, random coefficients "brand choice" model will determine the quantities of different brands that are purchased in a store as a function of individual demographics and preferences, store prices and advertising exposures. These demand models will be combined with a supply-side model, where brands choose prices and advertising levels, which will be used to back out implied marginal costs and will play a critical role in the counterfactuals described below.

The brand sales and price data comes from IRI store-level scanner data from 2000 to 2011. The IRI data is an extended version of the data in the IRI Academic Panel (Bronnenberg et al. 2008), which is possible because one of the authors is an IRI advisory board member. This extended dataset provides us with greater information on the identity and location of stores, allowing us to construct, using data from the Census and the American Community Survey, accurate measures of the demographics of the consumers living close to each store.[2]

The advertising exposure model will be estimated using Nielsen Ad Intelligence and television ratings data, together with our data on local demographics. The Ad Intelligence data will provide weekly data on brand advertising dollars and exposures for different types of television (e.g., national network and cable, and local spot), while demographic- and DMA-specific viewing data for different time periods of the data will allow us to project exposures onto consumers with different demographics living around each store.

To confirm that this type of projection can serve our purpose, we have constructed some measures using inferior data, specifically (i) Kantar Media measures of monthly TV ad units purchased by brand (no channel information) from 2003 to 2011; (ii) data on channel-specific advertising by brand in 2011 (provided to us by Ken Wilbur); and (iii) Simmons Experian estimates of primetime channel viewing by zipcode in 2010, which is an extrapolation from a national survey. Assuming that brands always advertise on the same channels, and viewing habits do not change throughout our sample, we can predict average monthly exposures by zipcode (no demographics) throughout our data. We then estimate several multinomial logit demand models, using IRI store-brand-month sales data for eight leading brands (market size is defined as

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[1] This approach will overlook the fact that equilibrium prices are also determined by distributors and retailers, and that these parties may also engage in some advertising. However, beer manufacturers account for the vast bulk of advertising spending, and almost all spending on television advertising.

[2] We may supplement store-level panel data with household-level purchase data to provide more accurate identification of preference heterogeneity, following Petrin (2002).

maximum observed sales at the store during the sample), where the mean utility of a brand depends on the brand's average price and our zipcode exposure measure for the same month. We also include a variety of fixed effects that, in these regressions, we view as controlling for the endogeneity of prices and advertising.[3] The results are reported in the following table:

	(1)	(2)	(3)	(4)	(5)	(6)
Price ($/24-pack)	-0.152***	-0.159***	-0.164***	-0.169***	-0.167***	-0.180***
	(0.00948)	(0.0105)	(0.00779)	(0.00880)	(0.00867)	(0.0143)
Ad Exposure	0.00302***	0.00143***	0.00159***	0.00157***	0.00246***	0.00223**
	(0.000238)	(0.000132)	(9.97e-05)	(9.40e-05)	(0.000782)	(0.000901)
Month FE	Y	Y	Y	Y	N	N
Store-Brand FE	Y	Y	Y	Y	Y	Y
Brand-Month FE	N	N	N	N	Y	N
Brand-DMA-Month FE	N	N	N	N	N	Y
Product Time Trends	N	Y	Y	N	N	N
DMA Time Trends	N	Y	Y	N	Y	N
Product-DMA Time Trends	N	N	N	Y	N	N
Observations	863,430	863,430	863,430	863,430	863,430	863,430

Note: Robust standard errors clustered on the DMA in parentheses, with *** indicating statistical significance at the 1% level.

Across the specifications, median own price elasticities are between 2.5 and 3, and the advertising coefficients, which are consistently significant, imply an elasticity of 0.03, which is consistent with many estimates in the marketing literature (Sethuraman et al. 2011).[4] We expect to find more convincing, and probably larger, advertising effects if we can use richer data on weekly television advertising (linked to our weekly sales data) and superior ratings-based data on viewing that can capture changes in viewing over our sample. We will also investigate forming alternative exposure measures using both ratings and survey data in order to address measurement error using an instrumental variables strategy. We should also be able to allow for demographic heterogeneity in ad responsiveness, which may be an important motivation for targeting.

We will use the estimated model to perform counterfactuals where we change the ability of brands to target. For example, we will allow brands to control the intensity of advertising around particular stores (geographic targeting) and for particular demographic groups (demographic targeting) based on alternative assumptions about how product market prices and advertising prices can adjust.[6] We will also consider counterfactuals where brands can choose to advertise based on consumers' preferences in order to understand what can happen when advertisers and media companies combine data on viewing and purchases. Finally, we will analyze how our results depend on the assumed structure of the supply-side game because a sequential advertising-then-price structure is likely to change both the amount and the focus of advertising.

Requested Nielsen Data (limited or no alternative funding available)
Ad Intelligence: For the beer sub-group category (F310), weekly data on the following types of television advertising: Network TV; Syndicated TV; Cable TV; Spanish Language Network TV;

[3] In our research we will also investigate a range of alternative ways of trying to address the endogeneity of advertising using information on differences in advertising across DMA borders (as in Shapiro 2016) and instrumental variables that use alternative ways of predicting exposures.
[4] If we make reasonable assumptions on brewer margins, these estimates imply a return on a dollar invested in cable television advertising ranges between $0.90 and $1.10.
[6] Ideally we would want to model the price of advertising as being an endogenous function of advertisers' choices. However, these prices will obviously depend on how advertisers in many other sectors of the economy (which we are not modeling) want to target so we currently plan to understand how our results change when we vary the prices of targeted advertising exogenously.

Spanish Language Cable TV; and, Local Spot TV. For measures where only monthly measures are available, we will use those. For these types of television we want the following fields: Advertiser, Brand Variant, Date, Time, Duration, Daypart, Distributor, Program Type, Impressions Equivalent, GRPE and Total Dollars. For Network, Syndicated and Cable TV (and other TV type for which this data is available, even if only for some DMAs) we want Impressions/GRP estimates broken down by Market Breaks for several demographic categories (Male/Female, Black/White/Hispanic, Age, Education, Household Income). The time period would be 2000 to 2011. If only limited data is available, the leading brands and some data snapshots from several of the later years will be more valuable.

Television Ratings: ratings (household share) network and cable channel viewing during "late fringe", "broadcast prime", "Sat/Sun daytime" and "cable prime'' from the national panel broken down by the demographics listed above (and interactions of these demographics where possible). We would also want DMA-level data on channel viewing (with demographics, where possible). The level of time aggregation could be week or month, but it would be useful to separate weekdays and weekends. We could use several snapshots taken between 2000 and 2011. If only limited data is available, a sample of later years and more popular channels will be more valuable.

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