Non-Informational Advertising Informing Consumers: How Advertising Affects Consumers' Decision-Making in the U.S. Auto Insurance Industry *

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Yi-Lin Tsai† Elisabeth Honka‡

Abstract

We investigate the relationship between both advertising content and quantity and several stages of consumers' decision-making, namely, unaided and aided awareness, search (consideration), and purchase. Understanding how the amount and content of advertisements affect consumers' decision-making is crucial for companies to effectively and efficiently use their advertising budgets. Our unique individual-level data contain information on consumers' purchases, consideration and awareness sets, demographic variables, and perceived prices for consumers between 2008 and 2016. We supplement these data with data on advertising quantities for all and advertising content for the main three media channels (TV, Internet, and magazines). We account for the endogeneity of the advertising decision using the regression discontinuity approach suggested by Shapiro (2018). Our results reveal that advertising quantity significantly increases consumer (unaided and aided) awareness, but has no effect on consideration and choice – a finding consistent with the informative role of advertising. Interestingly, the advertising content that leads to consumers' increased awareness is of non-informational nature implying that the effect on awareness is coming from non-informational content leading to better brand recall. And lastly, our results show no evidence of vulnerable consumers being adversely affected by advertising.

Keywords: Advertising, Advertising Content, Purchase Funnel, Auto Insurance Industry

JEL Classification: D83, G22, M37

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†University of Delaware, yilint@udel.edu.

‡University of California Los Angeles, elisabeth.honka@anderson.ucla.edu.

1 Introduction

Whether, how, and how much consumers are influenced by advertising are crucial questions for marketing managers who spend millions, and in some cases even billions, of dollars on this communication method.[1] The need to answer these questions has given rise to a rich academic literature in both marketing and economics developing theories on how to think about advertising (e.g. information versus persuasion by Chamberlin 1933, complementarity by Becker and Murphy 1993), models on how to quantify its effects (e.g. demand estimation under full versus limited information), and methods to deal with the econometric challenge of advertising endogeneity (e.g. control function approach by Petrin and Train 2010 or field experiments used by Sahni 2015). This paper contributes to the literature on advertising by combining information on each stage of a consumer's decision-making process (awareness, consideration,[2] and purchase) with data on advertising content and quantity to hone in on three main questions: (i) which stage(s) of consumers' decision-making is (are) affected by advertising, (ii) which type of advertising content affects consumers (potentially at which stage), and (iii) to what extent do the effects of advertising differ across groups of consumers.

Knowing which stage(s) is (are) affected by advertising is important for academics, managers, and public policy makers. For academics, it provides empirical evidence of the role of advertising in the marketplace. For example, if advertising only affects consumer awareness for the existence of a brand, its effect is informative. For managers, it informs them which consumer decisions are affected by advertising and thus gives guidance on the situations in which advertising can and should be used as an effective marketing tool. For example, if advertising only affects consumer awareness and a company wants to improve its conversion rate from consideration to purchase, advertising would not be an effective tool to do so. And, lastly, since advertising affecting awareness has been associated with pro-competitive effects and advertising affecting conditional consideration/choice with anti-competitive effects (e.g. Hastings,

[1] For example, P&G spent $8.3 billion on advertising its Pampers brand in 2016 (http://www.businessreviewеurope.eu/marketing/856/Top-20-companies-with-the-biggest-advertising-budget).

[2] In this paper, we use the terms "consider," " search," and "shop" interchangeably.

Hortacsu, and Syverson forthcoming, Honka, Hortaçsu, and Vitorino 2017), policy makers can learn whether advertising in an industry is rather a pro- or anti-competitive strategic tool.

While data on advertising quantity allows researchers to answer the question which stage(s) is (are) influenced by advertising, they are not sufficient to answer other important questions related to the effects of advertising. For example, do any types of advertising content affect each stage equally or do different types of advertising content influence different stages in the decision-making process? It is not far fetched to hypothesize that brand focused advertising might affect consumer awareness, while advertising highlighting specific product attributes might affect conditional consideration and/or conditional choice. Another important question relates to the role of advertising in the marketplace and cannot be answered without information on advertising content: if advertising quantity affects conditional consideration and/or conditional purchase, is the role of advertising to inform or to persuade consumers at that stage? And lastly, do advertising effects differ across consumer groups? For example, are vulnerable consumers adversely affected by advertising compared to the remaining population? This paper addresses these questions.

Our unique main data come from J.D. Power and Associates' annual screener surveys and annual "Insurance Shopping Studies" conducted between 2008 and 2016. The screener surveys provide us with information on a large number of non-shoppers (about 17,000 - 183,000 individuals annually). Non-shoppers are consumers who were not actively shopping for auto insurance during a particular year.[3] From these screener surveys, we have information on non-shoppers' unaided and aided awareness sets and their current insurance provider.[4] Each year, J.D. Power and Associates also conduct "Insurance Shopping Studies" surveying about 15,000 individuals annually. From these "Insurance Shopping Studies," we have information on shoppers' unaided and aided awareness sets, consideration sets and purchase decisions. Additionally, we also have

[3]In this paper, we view shopping, i.e. requesting at least one price quote from an insurance company that is not the consumer's current insurance provider, as a prerequisite for an (active) purchase decision that involves deciding whether to switch auto insurers.

[4]Since non-shoppers do not shop, they do not form consideration sets and do not make an (active) purchase decision, but remain passively insured with the same insurance company.

location and demographic information for all consumers, i.e. shoppers and non-shoppers, and information on the identity of the previous insurance provider and categorical information on insurance premia for shoppers.

We supplement our main data with data on all national and DMA-level advertising quantities (in dollars and units) for all media channels and advertising content for the three main media channels (TV, Internet, and magazines). We employed a team of student research assistants to code the content of all TV, Internet, and magazine ads. The resulting data contain information on the presence or absence of the following two types of content: informational (price/rate/discount, (non-price) product feature) and non-informational (brand name focus, and fun/humor/entertainment). Note that we make a conscious distinction between the terms "informational" and "informative" in this paper. "Informational" refers to the content of ads intended to inform consumers about the product and its characteristics, i.e. talking about price and non-price product features. "Informative" refers to the effect of advertising and its role in consumers' decision-making (Chamberlin 1933).[5]

We quantify the effects of both advertising quantity and advertising content on consumers' (unaided and aided) awareness, consideration, and purchase using a set of linear probability models. We account for the endogeneity of the advertising decision using the regression discontinuity approach suggested by Shapiro (2018). Our results reveal that advertising intensity affects consumer (unaided and aided) awareness, but has no effect on conditional consideration and conditional choice. These findings are consistent with those from Honka, Hortaçsu, and Vitorino (2017) in the context of retail banks and suggest that advertising has an informative effect for financial services. Interestingly, we find that the type of advertising that leads to increased consumer awareness is of non-informational nature (brand-focused and funny/entertaining content) implying that the effect on awareness is coming from non-informational content leading to better brand recall. And lastly, our results show no evidence of vulnerable consumers (i.e. racial

[5] According to Bagwell (2007), "informative" advertising informs consumers about (i) product existence and (ii) price and non-price product characteristics. "Persuasive" advertising (i) alters consumers' taste and (ii) creates spurious product differentiation.

minorities, low education or low income consumers) being adversely affected by advertising.

The contribution of this paper is three-fold: First, we quantify the effects of advertising on each stage of the consumers' purchase process. Understanding how both the amount and content of advertisements affect each stage of consumers' decision-making is crucial for companies to effectively and efficiently use their advertising budgets. Second, access to data on both advertising quantities and advertising content allows us to determine the role of advertising in the U.S. auto insurance industry. Beyond intellectual curiosity, understanding the role of advertising as a strategic tool employed by auto insurance and, more broadly, financial services companies can shape public opinion and public policy (e.g. regulatory measures) for this important part of the economy. And lastly, we contribute to the public policy discussion on whether advertising adversely affects vulnerable consumer groups. With the arrival of Big Data, policy makers have raised concerns that companies might use this information to target vulnerable consumers with misleading offers.

The remainder of this paper is organized as follows: In the next section, we discuss the relevant literature. In Section 3, we describe our data. We introduce our model and estimation approach in the following section. In Section 5, we discuss our results and present robustness checks in the following section. And, finally, we conclude in Section 7.

2 Relevant Literature

Our paper is related to three streams of literature on advertising, consumers' limited information, and demand for financial services. In the following, we review the relevant literature and delineate the positioning of our research vis-a-vis the findings from extant research.

Empirical researchers have long tried to determine the role(s) advertising plays in consumers' decision-making. Most work has focused on finding empirical evidence for the informative or persuasive view of advertising first developed by Chamberlin (1933) (e.g. Ackerberg 2001; Ackerberg 2003; Narayanan, Manchanda, and Chintagunta 2005; Clark, Doraszelski, and Draganska 2009; Ching and Ishihara 2012; Chan, Narasimhan, and Xie 2013; Lovett and Staelin 2016; Honka, Hortaçsu, and Vitorino 2017).[6] Consistent with this literature, if advertising affects consumer awareness of a brand, i.e. informs a consumer of the existence of a product, we deduce that it has an informative component. If advertising affects consideration conditional on awareness and/or choice conditional on consideration, the role of advertising cannot be determined without knowledge of the content of advertisements. This is because both informative advertising, i.e. advertising that informs consumers about product characteristics, and persuasive advertising, i.e. advertising that alters consumers preferences, can influence conditional consideration and conditional choice.

Our focus is on financial services and, more specifically, on auto insurance. There is little academic research that investigates the precise way through which advertising affects consumer demand for financial products. Gurun, Matvos, and Seru (2016) and Hastings, Hortaçsu, and Syverson (forthcoming) explore the effects of advertising in the subprime mortgage and social security markets, respectively, but neither of these studies can differentiate between the awareness and the utility-shifting functions of advertising because of data limitations. Most closely related to our paper is Honka, Hortaçsu, and Vitorino (2017) who investigate the role of advertising in the retail banking industry. However, our paper differs from theirs in several respects: first, the questions both papers can and do answer are different. Honka, Hortaçsu, and Vitorino (2017) find that advertising plays a primarily informative role by informing consumers about the existence of banks. They use their results to quantify branch-advertising substitutability and to analyze the competitive effects of advertising in the retail banking industry. While we also study whether advertising plays an informative and/or persuasive role in the auto insurance industry, we then turn to the content of ads and investigate whether informational and non-informational content have heterogenous effects on the different stages of consumers' decision-making. Further, we study whether advertising has heterogeneous effects

[6] There is little empirical work on the complementary (Stigler and Becker 1977; Becker and Murphy 1993) and signaling views (Nelson 1970; Nelson 1974) of advertising. Recent exceptions are Tuchman, Nair, and Gardete (forthcoming) for complementarity and Sahni and Nair (2016) for signaling. In this paper, we focus on the informative and persuasive roles of advertising.

across different consumer groups. And second, to answer the respective research questions, the empirical approaches are different. While Honka, Hortaçsu, and Vitorino (2017) develop a structural model and address the issue of advertising endogeneity using the control function approach, we use reduced-form modeling and the regression discontinuity approach to address advertising endogeneity.[7]

The majority of the empirical literature on advertising content investigates the effects of specific informational cues on consumers' purchase decisions. Bertrand et al. (2010) conduct a direct mail field experiment and find that showing fewer sample loans or including of a photo of an attractive woman increases the demand for loans. They conclude that advertising content persuades by appealing "peripherally" to intuition rather than to reason. Anderson et al. (2016) investigate the mechanism of comparative advertising in the OTC analgesics industry and find that self-promotion is more effective than outgoing attacks in raising a brand's own perceived quality. Liaukonyte, Teixeira, and Wilbur (2015) study how four different TV ad categories (action, information, emotional and imagery) affect online shopping behavior. They find that action-focus ads increase both website traffic and sales, while information- and emotion-focused ads reduce website traffic but increase sales.

There are a handful of papers that investigate how different types of advertising content (together with advertising quantity) affect consumers' demand for financial services. Using data from Sweden, Cronqvist (2006) finds that only a small fraction of advertisements for funds is informational in the sense that the ads contain information on relevant product characteristics. Further, he finds that advertising affects investors' choices even though it provides little information. Agarwal and Ambrose (2010) use data on home equity credit choices from direct mail and walk-in customers and find non-informational content to influence consumer choices. Gurun, Matvos, and Seru (2016) analyze consumers' borrowing behavior in the context of subprime mortgages. They find that initial/introductory rates are frequently and prominently

[7] The data are also different. While Honka, Hortaçsu, and Vitorino (2017) only have data on consumer (aided) awareness, consideration, and choice for one year and only data on advertising quantities, our data spans a time period of nine years, also includes unaided awareness, and we not only have information on advertising quantities, but also on advertising content.

advertised, while reset rates and other characteristics of mortgages or lenders are rarely advertised. Further, Gurun, Matvos, and Seru (2016) show that expensiveness and advertising intensity of a lender within a market are positively correlated and conclude that their results are consistent with the persuasive view of advertising. And lastly, Mullainathan, Schwartzstein, and Shleifer (2008) investigate whether predictions from their theoretical model of the role of advertising in the mutual funds industry are consistent with empirical patterns. They analyze the content of ads from two business magazines and find that the inclusion of past returns data is used to frame mutual fund investing as grabbing an opportunity rather than as hiring advice. The results from these four papers appear to be broadly consistent with a persuasive role of advertising, i.e. advertising does mostly not contain information on product characteristics, but affects consumer choice. However, what these four papers implicitly assume is that consumers have full information in the sense that they know that all these financial institutions operate in the marketplace. While we use data on advertising content and quantity as do the previous papers, what distinguishes our paper from theirs is that we have information on consumers' awareness and consideration sets allowing us to relax the full information assumption made by previous literature.

As mentioned in the previous paragraph, most empirical demand models have traditionally assumed that consumers have full information due to data limitations. In recent years, a growing stream of papers has acknowledged the importance of consumers' limited information and modeled the different stages of the consumers' purchase process, namely, awareness, consideration, and choice. The papers in this area fall into one of two groups depending on the data and identification strategy used. A first group of papers models at least two stages, usually consideration and choice, and uses purchase data for estimation purposes (e.g. Allenby and Ginter 1995, Siddarth, Bucklin, and Morrison 1995, Chiang, Chib, and Narasimhan 1998, Goeree 2008, Van Nierop et al. 2010, Terui, Ban, and Allenby 2011). A second, smaller group of papers, also models at least two stages, but makes use of available data on each shopping stage by incorporating it directly in the estimation (e.g. Franses and Vriens 2004, Lambrecht, Seim, and Tucker 2011, Chintagunta and Lee 2012, Abhishek, Fader, and Hosanagar 2012, De los Santos, Hortaçsu, and Wildenbeest 2012, Honka 2014, Moraga-González, Sándor, and Wildenbeest 2015, Honka, Hortaçsu, and Vitorino 2017). Our paper belongs to the latter group of papers.

And finally, our research is also related to the literature generally examining consumer purchase behavior for financial services and products. Hortaçsu and Syverson (2004) study consumer purchase behavior for S&P 500 index funds and Allen, Clark, and Houde (2017) look at consumer behavior when buying mortgages. Lambrecht, Seim, and Tucker (2011) study the adoption of Internet-based customer self-service applications such as online payments in the retail banking sector. Dick (2008) and Wang and Ching (2016) develop aggregate-level, structural models of consumer demand for retail bank services. Most closely related to our research project, Cummins et al. (1983), Dahlby and West (1986), Berger, Kleindorfer, and Kunreuther (1989), Honka (2014), and Honka and Chintagunta (2017) estimate demand for auto insurance taking consumers' limited information into account. Just like the previously mentioned group of papers, we also study consumers' purchase process in the auto insurance industry. However, in contrast to the previously mentioned group of papers, we conduct a reduced-form analysis with a special focus on the effects of different types of advertising content.

3 Data

We combine data from several sources to investigate the relationship between advertising and each stage of consumers' purchase process. Our main data come from J.D. Power and Associates who generously shared data from their annual screener surveys and annual "Insurance Shopping Studies" from 2008 to 2016. The data sets contain individual-level information on consumers' awareness[8] and consideration sets,[9] the identity of the purchased option,[10] the identity of the

[8] Unaided awareness: "When you are thinking of auto and home insurance, which companies come to mind?" Aided awareness: "Please review the list below and select ALL the insurance companies that you recognize."

[9] "From which of the following insurance companies did you receive a quote?"

[10] "Which company is your current auto insurer?"

previous insurance provider,[11] location and demographic information, perceived categorical price information,[12] and representativeness weights.[13]

Our data on advertising come from Kantar. Kantar tracks advertising expenditures (in dollars and units) at the national and Designated Market Area (DMA) level. We have annual data from 2008 to 2016. Additionally, for the three main media channels (TV, Internet, and magazines), Kantar supplied us with the creatives, i.e. the files containing the ads.

3.1 Data Processing

3.1.1 Screener Surveys and Insurance Shopping Studies

The screener surveys conducted by J.D. Power and Associates between 2008 and 2016 provide information on a large number of non-shoppers (about 17,000 - 183,000 individuals annually). Non-shoppers are consumers who were not actively shopping for auto insurance during a particular year.[14] From these screener surveys, we have information on non-shoppers' unaided and aided awareness sets and their current insurance provider.[15] Each year, J.D. Power and Associates also conduct "Insurance Shopping Studies" surveying about 15,000 individuals annually. From these "Insurance Shopping Studies," we have information on shoppers' unaided and aided awareness sets, consideration sets, and purchase decisions. Additionally, we also have location and demographic information for all consumers, i.e. shoppers and non-shoppers, and information on the identity of the previous insurance provider and categorical information on insurance premia for shoppers.

[11] "Which company was your auto insurer prior to [pipe in current insurer]?"

[12] "Which auto insurer offered you the lowest price/premium?"

[13] Representativeness weights were calculated by J.D. Power and Associates to ensure that the data and results from an annual study are representative of the U.S. population. Given large differences in sample sizes across years, we modified the representativeness weights to give data from each year the same weight (while leaving the relative weights across individuals within a year unchanged) and use these modified representativeness weights in all descriptive statistics and model estimations.

[14] In this paper, we view shopping, i.e. requesting at least one price quote from an insurance company that is not the consumer's current insurance provider, as a prerequisite for an (active) purchase decision that involves deciding whether to switch auto insurers.

[15] Since non-shoppers do not shop, they do not form consideration sets and do not make an (active) purchase decision, but remain passively insured with the same insurance company.

In our empirical analysis, we focus on respondents living in counties at the borders of the top 130 DMAs.[16] We further focus on the top 22 brands (measured by revenue) that were consistently part of the surveys between 2008 - 2016 and held a joint market share of about 85%. This focus implies that respondents who purchased auto insurance from a brand that is not part of the top 22 brands were removed. Next, we dropped respondents who indicated to be younger than 16 years or older than 85 years. Unfortunately, detailed location information (beyond the state) was not available for respondents from the 2012 Insurance Shopping Study and the 2014 screener survey so these respondents were dropped. These data processing steps left us with our final sample of 303,503 respondents from the screener surveys (251,461 non-shoppers and 52,042 shoppers) located in 1,325 different counties. These 1,325 counties belong to 237 different border regions.[17]

3.1.2 Advertising Quantity

We use total advertising spending per household as our measure of advertising intensity.[18] Following Shapiro (2018), we calculate total advertising spending per household as the sum of DMA-level advertising spending per household and national advertising spending per household. To calculate the former, we divide annual DMA-level advertising expenditures by the number of households in a given DMA-year, and to calculate the latter, we divide annual national advertising expenditures by the number of the households at the national level in that year.

3.1.3 Advertising Content: Magazines, TV, and Internet

We have all ads, i.e. "creatives," placed by auto insurance companies in magazines, on TV, and on the Internet between 2008 and 2016 (both in Spanish and English). Across all auto insurance companies, 368 unique magazine ads, 2,893 unique TV ads, and 5,677 unique Internet

[16]Focusing on respondents living in DMA border counties allows us to apply the approach developed by Shapiro (2018) to account for potential advertising endogeneity (see also Section 4).

[17]A border region is a cluster of geographically adjacent counties spanning across both sides of a DMA border.

[18]To be more precise, to allow for decreasing marginal returns to advertising, we use the logarithm of total advertising spending per household.

ads were placed.

To code the content of these creatives, we hired a team of 15 student research assistants. These research assistants were trained to code whether a creative (i) talked about prices/rates/discounts, (ii) conveyed (non-price) product feature information, (iii) focused on the brand name, and/or (iv) was humorous/funny/entertaining.[19] The training was conducted as follows:[20] research assistants first received a document containing a written description of each content type and a set of 20 creatives that they coded on their own. Then they met with one of the authors to discuss their coding decisions and to resolve other uncertainties. After this meeting, research assistants started coding creatives.

Creatives can contain more than one type of content. Each creative was independently coded by at least three research assistants and we use the average coding across the three research assistants for each creative in the analyses.[21] Fleiss' kappa is a measure of inter-rater agreement in coding. Figure 1 shows a histogram of Fleiss' kappas for the coded creatives. The average value is .64 with a median of .63 indicating substantial agreement.

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Insert Figure 1 about here

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3.2 Data Description

3.2.1 Consumer Shopping Behavior

We start by discussing consumer characteristics and consumer shopping behavior. In Table 1, we compare descriptive statistics for all consumers (column (i)), non-shoppers (column (ii)), and shoppers (column (iii)) separately.[22] Among all consumers, about 80% of respondents

[19] A detailed description of each content type with examples is shown in Appendix A.

[20] Research assistants were screened for language skills (English and Spanish) and basic knowledge of the auto insurance market before employment.

[21] Robustness checks with majority coding are shown in Tables C-1 and C-2 in Appendix C.

[22] Recall that we only include respondents living in border counties of the top 130 DMAs in our final samples. Descriptive statistics comparing the original and final data sets are shown in Appendix B. The distributions of demographic and insurance-related variables are largely similar.

are between 25 and 65 years old, 40% are male, and 54% are married. 59% of respondents have a college degree and 23% of respondents have an annual income of more than $100k. Comparing the two subgroups of shoppers and non-shoppers (columns (ii) and (iii) in Table 1), we find shoppers to be more likely male, married, and to belong to a racial minority than non-shoppers. For shoppers (only), we have additional information on insurance-related variables: 37% of shoppers were also shopping for homeowner's or renter's insurance and 6% of shoppers indicated having a poor credit history. Further, 3% and 4% of shoppers reported having had two or more accidents and tickets, respectively, during the last three years.

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Insert Table 1 about here

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Next, we discuss consumer shopping behavior. In our data, 32% of consumers are shoppers and the remaining 68% of consumers are non-shoppers.[23] While the proportion of shoppers might appear high, it is consistent with proportions reported by other sources: 46% of consumers reported having shopped for auto insurance during the past 12 months according to a 2015 comScore survey,[24] 25% of consumers reported having shopped for auto insurance during the past 12 months according to a 2017 Princeton Research Survey Associates International survey,[25] and 33% of consumers reported having shopped for auto insurance during the past 12 months according to the 2012 McKinsey Auto Insurance Customer Insights Research report.[26] Further, note that the proportion of consumers who switch their auto insurance provider is much smaller than the proportion of consumers who shop.

Among shoppers, 43% of consumers switch their auto insurance provider after the shopping occasion under study and the remaining 57% of consumers remain with their previous insurance

[23]The percentage of shoppers slightly increased from 32% in 2008 - 2010 to 33% in 2014 - 2016.

[24]https:www.comscore.comInsightsPress-Releases201511comScore-Releases-2015-US-Online-Auto-Insurance-Shopping-Report

[25]https:www.huffingtonpost.comentrypaying-too-much-for-auto-insurance-many-consumers_us_58c2dbede4b070e55af9ee2b

[26]https:www.mckinsey.com mediamckinseydotcomclient_serviceFinancial%20ServicesLatest%20thinkingInsurance Winning_share_and_customer_loyalty_in_auto_insurance.ashx

provider.[27] Projecting to the whole population, we find that 17% of all consumers switch their auto insurance provider in a year. The 2012 McKinsey Auto Insurance Customer Insights Research similarly report found about 1/3 of shoppers or 13% of the total population to switch insurance providers.

In Figure 2, we show the distributions of awareness set sizes for all consumers, shoppers, and non-shoppers separately. The left panel shows the distributions of unaided awareness set sizes and the right panel shows the distributions of aided awareness set sizes. Across the three groups of consumers, the distributions have similar shapes. However, the right tail of the unaided awareness set size distribution for shoppers has more mass than the right tail of the unaided awareness set size distribution for non-shoppers pointing to shoppers being aware of more brands. The average number of auto insurance brands consumers are aware of is 4.15 for unaided awareness and 12.02 for aided awareness. As expected, non-shoppers are aware of fewer brands than shoppers: 3.64 vs. 4.91 (difference statistically significant at $p < 0.001$) for unaided awareness and 11.94 vs. 12.12 (difference statistically insignificant) for aided awareness.

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Insert Figure 2 about here

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Figure 3 visualizes the relationship between unaided and aided awareness set sizes for all consumers. The Pearson correlation coefficient between consumers' unaided and aided awareness set sizes is 0.39 ($p < .001$), i.e. there is a relatively consistent though far from perfect relationship between unaided and aided awareness set sizes. Between 2008 and 2016, average unaided awareness set sizes increased from 3.73 to 4.16 (increase of 12%), while aided awareness set sizes decreased from 13.17 to 11.00 (decrease of 16%). This latter decrease is likely due to several companies either exiting the auto insurance market (e.g. AIG), being acquired by another auto insurance company and stopping to sell insurance under its old brand name (e.g. 21st Century) or re-branding (GMAC is now National General).

[27] The percentage of switchers among shoppers increased from 40% in 2008 - 2010 to 44% in 2014 - 2016.

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Insert Figure 3 about here

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We next turn to the brands that consumers are aware of (see Table 2). The probability that a consumer is aware of any brand is 23% (unaided) and 67% (aided) (columns (i) to (ii) in Table 2). Across all consumers, the brand-specific awareness probabilities range from 2% (GMAC) to 70% (State Farm) for unaided awareness and 15% (Amica Mutual) to 97% (State Farm) for aided awareness. Next, we compare the brand-specific awareness probabilities for shoppers and non-shoppers (columns (iii) to (vi) in Table 2). Not surprisingly, shoppers have, on average, a higher probability of being aware of any brand than non-shoppers. Looking at the top 4 insurance brands (Allstate, Geico, Progressive, State Farm), we find that the differences in unaided awareness probabilities between shoppers and non-shoppers can be substantial: while the differences in awareness probabilities for Allstate and State Farm are 10% and 7%, respectively, they are 16% and 23% for Geico and Progressive, respectively. To put it differently, shoppers have much higher unaided awareness probabilities for brands that have an image of being inexpensive.

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Insert Table 2 about here

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In the following, we focus on shoppers and their consideration and purchase decisions. The top half of Figure 4 visualizes the relationship between unaided awareness and consideration set sizes and the bottom half of Figure 4 visualizes the relationship between aided awareness and consideration set sizes. Recall that shoppers are, on average, aware of 4.91 brands (unaided) and 12.12 brands (aided). On average, they consider 3.12 brands which includes their previous insurance provider.[28] The Pearson correlation coefficient between consumers' unaided awareness and consideration set sizes is 0.73 ($p < .001$) and the Pearson correlation coefficient between

[28] Average consideration set sizes increased from 2.92 in 2008 - 2010 to 3.14 in 2014 - 2016.

consumers' aided awareness and consideration set sizes is 0.19 ($p < .001$), i.e. the relationship between consumers' unaided awareness and consideration set sizes is much closer than the relationship between consumers' aided awareness and consideration set sizes.

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Insert Figure 4 about here

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Table 3 contains consideration and purchase shares for all brands as well as conversion rates for consideration, i.e. conditional on being aware of a brand the proportion of consumers that consider the brand, and for purchase, i.e. conditional on considering a brand the proportion of consumers that choose the brand. Conditional on unaided awareness, the conversion rates to consideration vary from 48% (State Farm) to 94% (GMAC) with an average of 63%. Conditional on aided awareness, the conversion rates to consideration vary from 10% (Metlife) to 41% (Erie) with an average of 25%. And lastly, conditional on consideration, the conversion rates to purchase range from 14% (Geico) to 68% (Erie) with an average of 29%. To summarize, there is substantial variation within a purchase stage and across purchase stages both in shares and in conversion rates across brands.

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Insert Table 3 about here

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3.2.2 Advertising Quantity

Insurance companies can advertise nationally and locally, i.e. at the DMA-level. On average, insurance brands spend $75 million annually on national advertising placing around 49,000 ads. There is large variation in national advertising spending ranging from $59,000 (Erie) to $487 million (Geico) per year. At the DMA-level, insurance brands spend, on average, $88,000 per DMA placing about 650 ads. While national advertising has increased during the observation period, DMA-level advertising has decreased. In Figure 5, we plot total, i.e. national and

DMA-level, advertising spending by channel (TV, Internet, radio, magazines, newspapers, and outdoor) for all brands. Across the different channels, 80% of the total advertising budget is spent on TV, 7% on the Internet, 6% on the radio, 7% on print, and less than 1% on outdoor advertising.[29]

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Insert Figure 5 about here

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There is substantial variation in advertising quantities at the DMA-level. This geographic variation in advertising levels (together with variation over time) is essential for identifying the effects of advertising. Figure 6 depicts the geographic variation in average advertising spending per household in the top 130 DMAs. Moreover, there is also variation in local advertising spending across brands. Figure 7 depicts DMA-level advertising spending per household for the largest four auto insurance brands in the top 130 DMAs. Again, we find substantial geographic variation in advertising spending. For example, Geico has the largest ad expenditure per capita in Miami-Ft. Lauderdale and San Francisco-Oakland-San Jose, while Houston, Chicago, and Salt Lake City are the top DMAs for State Farm.

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Insert Figures 6 and 7 about here

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Focusing on the top 130 DMAs, average total, i.e. national and DMA-level, advertising spending per household was \$0.79 (0.0013 units) with brands such as Erie, GMAC, and Safeco spending \$0 (0 units; after rounding) and brands such as Progressive and Geico spending \$2.78 (0.0042 units) and \$5.15 (0.0058 units), respectively, per household (see columns (i) and (ii) in Table 4). Following Shapiro (2018), we will use total advertising spending per household as our measure of advertising intensity in the empirical analyses. As robustness checks of our

[29] At the national level, 84% of the national advertising budget is spent on TV, 8% on the Internet, 2% on radio, and 6% on print. At the DMA-level, 62% of the DMA-level advertising budget is spent on TV, 2% on the Internet, 25% on radio, 8% on print, and 2% on outdoor.

advertising measure, we also use total advertising units per household and local ad expenditure per household in \$ as measures of advertising. Descriptive statistics of these two variables are shown in columns (ii) and (iii) in Table 4.

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Insert Table 4 about here

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3.2.3 Advertising Content

Table 5 depicts the percentages of ads (weighted by spending) for each brand that contain a specific type of content.[30] Recall that ads containing cues about price and non-price product features are marked as having informational content and ads that are brand name focused and/or funny/entertaining are marked as having non-informational content. Note that an ad can have both informational and non-informational content. On average, 10% of ads are only informational, 30% of ads are only non-informational, and 60% of ads are both informational and non-informational.

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Insert Table 5 about here

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There is a large amount of variation in ad content across brands. The percentage of only informational ads varies from 0% (AIG, GMAC, Safeco) to 47% (Erie), the percentage of only non-informational ads ranges from 0% (21st Century) to 100% (GMAC), and the percentage of ads that include both informational and non-informational content varies from 0% (Safeco) to 100% (GMAC). Brands communicate different mixes of ad content to consumers: some brands mostly focus on one mix – non-informational only for Auto Owners, Safeco, and USAA and both informational and non-informational for 21st Century, AIG, Amica Mutual, Geico, GMAC, and Mercury. We do not observe brands that only focus on informational content. And some

[30]Recall that the content of each ad is determined by the average coding across the research assistants who coded a specific ad. Robustness checks with majority coding are shown in Tables C-1 and C-2 in Appendix C.

brands employ a rather balanced blend of mixes. For example, 32% of Allstate's ads are only informational, 21% of Allstate's ads are only non-informational, and the remaining 47% are both informational and non-informational. A similar pattern can be observed for Erie, Nationwide, and State Farm. And lastly, some brands such as American Family, Metlife or Travelers employ a mix of non-informational only content and informational and non-informational content when communicating with consumers.

In the following, we show empirical evidence for geographic variation in advertising content and variation in advertising content across brands and time. These two types of variation are essential to identifying the effects of informational and non-informational ad content. In Figure 8, we present the average difference in local advertising spending per household between informational and non-informational content by DMA. The red color represents DMAs in which brands spend more money on non-informational than informational content and the blue color represents DMAs in which brands spend more money on informational than non-informational content. The darker the color, the larger is the difference in the amounts of these two types of content. The map shows substantial variation in the relative amounts of informational and non-informational content shown to consumers in different parts of the U.S. For example, brands spend more money on ads that convey rather informational content to consumers in Florida and New Mexico. The opposite is true for consumers living in, for example, Illinois, Indiana or Michigan.

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Insert Figure 8 about here

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In Figure 9, we repeat the same type of maps as in Figure 8, but show the difference in local ad spending per household between informational and non-informational content for each of the four largest auto insurance brands. We show substantial variation in ad content within each brand across geographies as well as across brands within the same DMA.

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Insert Figure 9 about here

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And lastly, in Figure 10, we present DMA-level advertising spending per household on advertisements containing informational and non-informational cues for the four largest auto insurance brands. The four graphs show that, both within a brand across time and across brands within a year, there is substantial variation in the relative spending on informational and non-informational advertising content. For example, State Farm spent more or equally on informational and non-informational content up to 2011. Starting in 2012, State Farm started spending significantly more on non-informational than informational content. However, it is not a general trend that auto insurance brands have been spending more on non-informational than informational content in recent years. Geico, for example, has been spending more on informational content.

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Insert Figure 10 about here

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4 Model and Estimation

We quantify the effects of advertising on consumers' purchases, consideration and awareness sets using a set of linear probability models. We account for the potential endogeneity of the advertising decision using the regression discontinuity approach suggested by Shapiro (2018). Advertising endogeneity is a concern for all three stages of consumers' purchase process. Its cause are omitted variables or, more specifically, time-varying local "events" which we do not observe in the data, but which might be correlated with brands' advertising decisions. Such time-varying local "events" include sponsorships of local sports teams or festivals and changes in the focal brand's or competitive brands' local agent network (i.e. openings and closings of agencies).

In the following, we briefly describe the main idea of the regression discontinuity approach. Figure 11 shows an example of a border of two DMAs – Austin and San Antonio. Note that the DMA borders do not – as they do not for most DMAs – coincide with state borders. Rather, historically, DMAs are centered around a large city or metropolitan area. The border strategy to deal with advertising endogeneity considers the 12 counties along the border of the two DMAs (i.e., the dark blue and dark red ones in Figure 11) as two treatment groups in every year. While consumers living on different sides of the DMA border are similar, they are being treated with different advertising (amounts and content). The advertising effect can be identified by comparing how consumers living in the two groups of border counties react differently to differences in advertising. Moreover, due to the geographical adjacency, these 12 counties also constitute a "market" facing similar demand shocks at the market level. We include border-specific fixed effects to capture these demand shocks.

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Insert Figure 11 about here

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Using a set of linear probability models, we estimate the effect of adverting quantities on consumers' awareness and consideration as follows: let Y_{ibt} be the binary dependent variable of interest, i.e. (unaided or aided) awareness or consideration for consumer i, brand b, and year t. Then

$$Y_{ibt} = \beta A_{bdt} + \tau_i + \varrho_{bt}^{D_i} + \varphi_{bt}^{D_i}\mathbb{I}_i^o + \nu_{bdr} + \eta_{brt} + \zeta_{bst} + \epsilon_{ibt} \tag{1}$$

where A_{bdt} captures advertising intensity, i.e. the logarithm of total advertising spending in dollars per household, by brand b in DMA d in year t. Moreover, we include a large set of fixed effects:[31] first, τ_i are individual-specific fixed effects. Second, we include brand-demographic-group-year fixed effects, $\varrho_{bt}^{D_i}$.[32] While we do not observe other potentially targeted offline

[31]To give the interested reader a better idea of "large," we include about 420,000 fixed effects in the estimation of the unaided awareness model (some of which are dropped due to collinearity).

[32]The demographic groups for which we estimate fixed effects are as follows: age < 25 years, age between

marketing activities such as direct mail, as long as the targeting is based on demographics, our brand-demographic-group-year fixed effects control for it. Third, we include online-brand-demographic-group-year-fixed effects, $\varphi_{bt}^{D_i}$. The dummy variable $\mathbb{I}_i^o$ is individual-specific and indicates whether a consumer spends more than the median amount of hours per week online (14 hours). While we do not observe online search advertising in our data, these fixed effects control for the amount of exposure to targeted online advertising. Fourth, brand-border-DMA fixed effects, ν_{bdr}, capture persistent differences across different markets. Fifth, brand-border-year fixed effects, η_{brt}, capture unobserved market-specific trends. And sixth, brand-state-year fixed effects, ζ_{bst}, capture changes at the state level such as changes in insurance rates, i.e. premium levels, or regulations over time. ϵ_{ibt} is a standard normally distributed error term and $\theta = \left\{\beta, \tau_i, \varrho_{bt}^{D_i}, \varphi_{bt}^{D_i}, \nu_{bdr}, \eta_{brt}, \zeta_{bst}\right\}$ is the vector of parameters to be estimated.

Note that we condition on consumers' awareness sets when estimating the effects of advertising on consumers' consideration decisions, i.e. we only include the set of brands for each consumer that the consumer is aware of. We do so once using consumers' unaided and once consumers' aided awareness sets. Similarly, in the following model describing the effects of advertising quantity on purchases, we condition on individual consumer's consideration set.

We quantify the effects of advertising quantities on consumers' purchase decision as follows: Let $Y_{ibt} = 1$ if consumer i purchases an insurance policy from brand b in year t and $Y_{ibt} = 0$ otherwise. Then

$$Y_{ibt} = \beta A_{bdt} + \delta_1 \mathbb{I}_{Y_{ib,t-1}} + \delta_2 \mathbb{I}_{ibt}^p + \tau_i + \varrho_{bt}^{D_i} + \varphi_{bt}^{D_i} \mathbb{I}_i^o + \nu_{bdr} + \eta_{brt} + \zeta_{bst} + \epsilon_{ibt} \tag{2}$$

where $\mathbb{I}_{Y_{ib,t-1}}$ captures state dependence and is operationalized as a dummy variable indicating whether brand b chosen in time period t is the same brand that consumer i chose in time period $t-1$. The variable $\mathbb{I}_{ibt}^p$ is also a dummy variable that indicates whether brand b offered the lowest premium for consumer i in time period t among the brands consumer i

25 and 45 years, age between 45 and 65 years, male, driver under 25 years on policy, shopped for homeowner insurance, more than one accident in last 3 years, has college degree, income of more than $100k.

considered and is a self-reported variable. Thus, while the brand-state-year fixed effects ζ_{bst} capture average premium changes across all consumers in a state (for a company and year), the dummy variable $\mathbb{I}^{p}_{ibt}$ is specific to each consumer and his consideration set. The remaining variables are defined as in Equation (1). ϵ_{ibt} is a standard normally distributed error term and $\theta = \left\{\beta, \delta_1, \delta_2, \tau_i, \varrho^{D_i}_{bt}, \varphi^{D_i}_{bt}, \nu_{bdr}, \eta_{brt}, \zeta_{bst}\right\}$ is the vector of parameters to be estimated.

In the next two equations, we describe how we jointly study the effects of advertising quantity and advertising content on consumers' awareness, consideration, and purchase. Equation (3) is our specification for (unaided and aided) awareness and conditional consideration and Equation (4) depicts our conditional purchase model:[33]

$$Y_{ibt} = \beta_1 A^{f}_{bdt} + \beta_2 A^{nf}_{bdt} + \tau_i + \varrho^{D_i}_{bt} + \varphi^{D_i}_{bt}\mathbb{I}^{o}_{i} + \nu_{bdr} + \eta_{brt} + \zeta_{bst} + \epsilon_{ibt} \tag{3}$$

$$Y_{ibt} = \beta_1 A^{f}_{bdt} + \beta_2 A^{nf}_{bdt} + \delta_1 \mathbb{I}_{Y_{ib,t-1}} + \delta_2 \mathbb{I}^{p}_{ibt} + \tau_i + \varrho^{D_i}_{bt} + \varphi^{D_i}_{bt}\mathbb{I}^{o}_{i} + \nu_{bdr} + \eta_{brt} + \zeta_{bst} + \epsilon_{ibt} \tag{4}$$

where A^{f}_{bdt} and A^{nf}_{bdt} capture the logarithm of total spending in dollar per household on informational and non-informational ads, respectively. The remaining variables are defined the same way as in Equations (1) and (2).

5 Results and Discussion

5.1 Advertising Intensity

The results for advertising intensity are shown in Table 6: the top half of the table shows the model estimates using the border strategy and the bottom half of the table shows the model estimates without the border strategy. Note that all standard errors are clustered at the DMA-level. With and without the border strategy, we find advertising intensity, i.e. advertising spending per household, to significantly affect consumers' unaided and aided awareness (see columns (i) and (ii) in Table 6).

[33]Here, again, we condition on consumers' awareness sets when modeling consideration and on consumers' consideration sets when modeling purchase.

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Insert Table 6 about here

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To understand the magnitudes of these advertising effects, we calculate average advertising elasticities. Using the border strategy, the average advertising elasticities for unaided and aided awareness are 0.0289 and 0.0107, respectively.[34] In columns (i) and (ii) in Table 7, we show the average brand-specific advertising elasticities for unaided and aided awareness from our main models using the border strategy. Esurance, Liberty Mutual, Nationwide, and Progressive have the largest average advertising elasticities for unaided awareness ranging from 0.08 to 0.06, while Esurance, Allstate, Geico, and Progressive have the largest average advertising elasticities for aided awareness ranging from 0.03 to 0.02. When it comes to the brands with the smallest average advertising elasticities for unaided and aided awareness, they contain the same sets of brands: Auto Owners, Erie, GMAC, Metlife, and Safeco. We conclude that the two alternative operationalizations of consumer awareness, i.e. whether consumers' unaided or aided awareness is measured, lead to similar results in terms of the brands whose advertising has the smallest or largest effects.

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Insert Table 7 about here

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We now describe the effects of advertising intensity on the other stages of the purchase process. Recall that to do so we use data on shoppers only since non-shoppers do not shop and thus do not form consideration sets. In columns (iii) and (iv) in Table 6, we show the results for consideration conditional on unaided and aided awareness, respectively. In both cases, advertising does not have a significant effect on consideration. Turning to the purchase stage, we find advertising spending per household to have an insignificant effect on conditional choice

[34]Without the border strategy, the average advertising elasticities for unaided and aided awareness are 0.0337 and 0.0110 (not tabulated), respectively, i.e. advertising elasticities are overestimated by 17% and 3%, respectively.

(column (v) in Table 6). Compared to the awareness and conditional consideration regressions, we include two additional variables in the conditional choice regression (column (v) in Table 6): a dummy variable indicating whether a brand is a consumer's previous insurance provider and a dummy variable indicating whether a brand offered a consumer the lowest premium. The parameter estimates for both variables are significant and have the expected signs: consumers are more likely to purchase an insurance policy from their previous insurance provider and are also more likely to pick the insurance brand that offers them the lowest premium.

Lastly, in column (vi) in Table 6, we compare our results to those from a model under full information, i.e. a model in which consumers are aware of and consider all companies in the market. We find advertising to have a small, but significant positive effect on choice with an elasticity of 0.0110. This result stands in contrast to the result from the conditional choice model in column (v) in Table 6 where advertising does not have a significant effect. Further, under full information, the effect of the previous insurer dummy is overestimated and the effect of the best price dummy is underestimated. Not accounting for consumers' limited information leads to quantitatively and qualitatively different results.

To recap, we find that advertising intensity has significant positive effects on consumers' (unaided and aided) awareness, but no effects on conditional consideration and conditional choice. These findings are consistent with those in Honka, Hortaçsu, and Vitorino (2017) in the context of retail banks and suggest that advertising predominantly affects consumer awareness. Further, these results are also consistent with advertising professionals' recent demands for companies to focus on consumer awareness rather than consumer engagement.[35]

[35]See e.g. http://www.adweek.com/brand-marketing/advertisers-need-to-stop-chasing-engagement-and-get-back-to-focusing-on-awareness/?utm_content=buffer42f1f&utm_medium=social&utm_source=facebook.com&utm_campaign=buffer

5.2 Advertising Content

We now discuss our results on the effects of advertising content.[36] Recall that we operationalize our advertising content variables as total spending per household on informational and non-informational content. Columns (i) and (ii) in Table 8 show the parameter estimates for consumer awareness. Our results reveal that advertising spending per household on non-informational ads has a positive and significant effect on unaided awareness and an insignificant effect on aided awareness, while advertising spending per household on informational ads has insignificant effects on both unaided and aided awareness.[37] Given that unaided awareness is the type of awareness consumers utilize when shopping for auto insurance and given the closer descriptive relationship between unaided awareness and consideration (see Section 3.2), we conclude that non-informational advertising increases consumer awareness for a brand.[38] The resulting average elasticity of non-informational advertising content on unaided awareness is 0.0320.

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Insert Table 8 about here

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In columns (iii) and (iv) in Table 8, we show the results for consideration conditional on unaided and aided awareness and the results for conditional choice in column (v). Neither type of advertising has a significant effect on consideration or choice. Further, in the conditional choice regression (column (v) in Table 8), the coefficient estimates for the previous insurer and lowest price dummies are very similar to those in Table 6 (column (v)) where we showed results from modeling the effects of advertising intensity.

[36]Note that the results currently shown in Tables 8 and 10 are preliminary: they do not include the content of Internet ads yet. Incorporating them is work-in-progress. However, insurers spend 11 times more on TV than Internet ads making us confident that our results will hold after the inclusion of Internet ad content.

[37]This result is not driven by collinearity between both types of advertising. We estimated the same regressions as in Table 8 only including one type of ad content and found the same patterns in terms of direction and significance. The results are available from the authors upon request.

[38]Further note that, using two alternative operationalizations of the ad content variables, we find non-informational advertising to have positive significant effects on both unaided and aided awareness (see Appendix C).

Recall that informative advertising informs consumers about product existence and (price and non-price) product features, while persuasive advertising alters consumers' tastes and creates spurious product differentiation (Bagwell 2007). *Any* type of advertising that conveys the existence of a product to consumers, i.e. makes consumers aware of a product, has an informative effect. To put it differently, the effect of *both* informational and non-informational advertising content on consumer awareness is informative. In our empirical application, we find non-informational advertising to increase consumer awareness, i.e. to have an informative effect. To understand whether advertising has an informative and/or persuasive effect in the consideration and choice stages of the purchase process, the content of ads has to be observed. If non-informational ad content were to affect conditional consideration and/or conditional choice, the effect of advertising could be interpreted as persuasive. If informational ad content were to affect conditional consideration and/or choice, the effect of advertising could be interpreted as informative. In our empirical application, we find neither informational nor non-informational ad content to affect conditional consideration and/or choice. Thus the only effect that advertising has in the auto insurance industry is informative: it increases consumer awareness for auto insurance companies.

To recap, only non-informational but not informational content has a significant positive effect on consumer awareness.[39] These results are consistent with Cronqvist (2006) and Bertrand et al. (2010) who find non-informational content to influence consumers' decision-making for financial services. An explanation consistent with this pattern of results is that non-informational ads lead to consumers recalling the brand name better. The influence and importance of memory on brand recall and through brand recall subsequently on brand choice has long been acknowledged. Nedungadi (1990) highlights the role of memory in brand retrieval and thus consumer

[39]In the main analysis, we operationalize the ad content variables as dummy variables capturing the presence or absence of non-informational or informational content. In Appendix C, we test the robustness of our results with respect to alternative operationalizations of the ad content variables. More specifically, we test two alternatives: (i) two count variables for the number of non-informational and informational cues, respectively, and (ii) difference in the number of non-informational and informational cues. Our results are qualitatively robust to these alternative operationalizations.

awareness of a brand.[40] Mitra and Lynch (1995) present a framework that incorporates the effect of advertising on both brand recall and on preferences. They show that advertising – no matter its type – increases brand recall; however, the effect on brand recall is larger.

If non-informational content leads to consumers remembering and recalling brand names better than informational content, an important question is as to why this is the case. Recall that non-informational ads are brand name focused and/or fun/humorous/entertaining ads. Brand name focused ads are creatives that either dominantly and/or frequently show the brand name or contain no information on car insurance but that mention the brand name (e.g. TV program sponsorships, public service messages). It is well-known that repetition enhances memory (e.g. Ebbinghaus 1885, Hintzman 1976). Funny/humorous/entertaining creatives contain an emotional appeal to the consumer, a story, and often an unexpected event (Heath and Heath 2008). Emotional messages make people care and develop empathy for the main character. Consequently, emotional events and messages are better remembered and recalled (Reisberg and Hertel 2004). Funny/humorous/entertaining ads often contain a story that allows for imagination and inspiration and increases memory (Zwaan and Radvansky 1998). And lastly, funny and humorous ads often contain an element of surprise that catches and increases the consumer's attention (Pieters, Warlop, and Wedel 2002). Through the increase in attention, unexpected events then turn into memories.

To summarize, we find that advertising affects consumer awareness for a company. This finding can be interpreted as advertising playing an informative role in the U.S. auto insurance industry as it informs consumers about the existence of a brand. Further, we find that it is non-informational content that increases consumer awareness pointing to differential effects of different types of advertising content and memory playing an important role in consumers' formation of awareness sets.

[40]Note that Nedungadi (1990) uses the terms "awareness" and "consideration" interchangeably to refer to brand retrieval or brand accessibility.

5.3 Vulnerable Consumers

Next, we investigate whether vulnerable consumers are differently affected by advertising than the remainder of the population. Potentially adverse effects of advertising are concerning from an ethical, legal, and a public policy perspective. The 2016 FTC Report on Big Data raises concerns about companies using big data to target vulnerable consumer groups with misleading offers.[41] Previous empirical literature on financial services (e.g. Gurun, Matvos, and Seru 2016 for mortgages) has found some evidence that vulnerable consumers might be adversely affected by advertising. Other previous work has argued it is not in insurance companies' self-interest to discriminate (e.g. Block, Snow, and Stringham 2008). However, to the best of our knowledge, no previous work has empirically investigated this question for the property and casualty insurance sector.

We define vulnerable consumers the same way as previous literature (e.g. Gurun, Matvos, and Seru 2016): racial minorities (Asian, Black, Hispanic, Native American), low income (less than $50k), and low education (high school degree or less) consumers. Using these three criteria, 14% of consumers in our data are classified as vulnerable.

In Table 9, we show our results for advertising quantity. Looking at the awareness results in columns (i) and (ii), we find four significant interaction effects for the low income dummy, the low education dummy, and the racial minority dummy. While the interaction effects with low education and low income have positive signs, the interaction effect with the racial minority dummy has a negative sign. To judge the magnitudes of the effects of advertising on vulnerable consumers compared to the remainder of the population, we calculate advertising elasticities. The advertising elasticities for vulnerable consumers are 0.0332 and 0.0130 for unaided and aided awareness, respectively, and the advertising elasticities for the remainder of the population are 0.0263 and 0.0099, respectively. Both differences in elasticities for unaided and for aided awareness are statistically significant at $p < .001$, i.e. vulnerable consumers are affected

[41] https:www.ftc.govsystemfilesdocumentsreportsbig-data-tool-inclusion-or-exclusion-understanding-issues160106big-data-rpt.pdf

by advertising to a larger degree than the remainder of the population. To put it differently, advertising to vulnerable consumers is more effective in increasing their awareness than advertising to the remainder of the population. Consumers benefit from higher awareness levels by being able to consider from a larger set of brands that they are aware of. Thus the informative effect of advertising is stronger for vulnerable consumers, i.e. they are favorably affected by advertising.

Columns (iii) - (v) in Table 9 show the results for conditional consideration and conditional choice. Vulnerable consumers are not affected by advertising (just like the remaining population) when making these two types of decisions.[42] After investigating the effects of advertising quantities along consumers' purchase process, we conclude that advertising affects vulnerable consumers the same way or more favorably than the remainder of the population.

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Insert Table 9 about here

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In Table 10, we show our results for advertising content.[43] We find all six interaction terms between non-informational advertising and the low income dummy, the low education dummy, and the racial minority dummy to be statistically significant. Since two of the effects are negative and four are positive, we again calculate elasticities to be able to compare the magnitudes of the advertising effects. For unaided awareness, the advertising elasticities for vulnerable consumers and the remainder of the population are 0.0511 and 0.0190, respectively. The difference in elasticities is statistically significant at $p < .001$. Similar to the results for advertising quantity, our results for non-informational ad content point to it being more effective in increasing awareness of vulnerable consumers than the remainder of the population. Given that consumers benefit from higher awareness levels, this represents a favorable effect for vulnerable consumers. Columns (iii) - (v) in Table 10 show the results for conditional consideration and conditional choice. Vulnerable consumers are neither affected by informational

[42]While the interaction effects with the low income dummy are significant, the resulting advertising elasticities are not significantly different.

[43]Note that our data contain ads both in English and in Spanish.

nor non-informational advertising (just like the remaining population) when making these two types of decisions.[44]

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Insert Table 10 about here

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To summarize, we find no evidence that advertising – whether containing informational or non-informational content – adversely affects vulnerable consumers' shopping and purchase decisions compared to the remaining population.

6 Robustness Checks

We evaluate the robustness of our results using several checks. The results from all robustness checks are shown in Appendix C. First, we evaluate the robustness of our results with respect to our decision to use the average coding across the research assistants when deciding on the presence or absence of informational and non-informational content. To do so, we instead use the majority coding by the research assistants. Table C-1 replicates Table 5 using majority coding. We find quantitatively very similar patterns in terms of advertising content. Then, we re-estimate our main models for advertising content using majority coding. The results are shown in the top half of Table C-2 in Appendix C and confirm that our results are robust to this alternative operationalization of the advertising content variables.

Second, we investigate the robustness of our results with respect to an alternative approach of modeling the effects of advertising content. Instead of operationalizing advertising content as the spending (in $) on informational or non-informational ads, we include three advertising variables: the logarithm of total advertising spending per household, the percentage of spending per household on informational ads, and the percentage of spending per household on non-informational ads. The results are shown in the bottom half of Table C-2 in Appendix

[44] While two of the interaction effects are significant, the resulting advertising elasticities are not significantly different for vulnerable consumers and the remainder of the population.

C. Overall, our results are qualitatively robust to this alternative operationalization. Third, we investigate the robustness of our results with respect to alternative ad content measurements. More specifically, we re-estimate our models using the following two ad content variables: (i) two count variables for the number of non-informational and informational cues, respectively, ranging from 0 to 2 for each count variable and (ii) differences in the number of non-informational and informational cues ranging from -2 to $+2$. The results are shown in Table C-3 in Appendix C. Overall, our results are qualitatively robust to these alternative ad content measurements.

Fourth, we evaluate the robustness of our results with respect to an alternative operationalization of the advertising quantity variable. Here, we re-estimate our models using the logarithm of total advertising *units* per household as our measure of advertising intensity. The results are shown in the top half of Table C-4 in Appendix C and confirm that our results are qualitatively robust to this alternative operationalization. And lastly, we investigate the robustness of our results with respect to our use of total advertising spending. Here, we re-estimate our models using the logarithm of DMA-level advertising spending per household as our measure of advertising intensity. The results are shown in the bottom half of Table C-4 in Appendix C. Overall, our results are qualitatively robust to this alternative operationalization. We conclude that our results are robust to a number of alternative specifications of the advertising quantity and advertising content variables.

7 Conclusion

Understanding how advertising influences consumers' decision-making is crucial for companies. In this paper, we quantify the effects of advertising quantities and advertising content in the context of the U.S. auto insurance industry. We find that advertising primarily affects awareness and has no discernible effect on consideration and choice. This finding is consistent with an informative role of advertising in this industry as it informs consumers about the existence of a brand. Interestingly, the advertising content that leads to consumers' increased awareness is non-informational implying that the effect on awareness derives from non-informational content leading to better brand recall. And lastly, our results show no evidence of vulnerable consumers being adversely affected by advertising.

There are several limitations to our work and opportunities for future research. First, our results are based on data from one industry. While previous research (e.g. Honka, Hortaçsu, and Vitorino 2017) has found results that are consistent with ours for other financial services, it is likely that the generalizability of our results decreases the further one moves away from the financial services sector. Second, we have information on four types of ad content in this paper: price and non-price product features, brand name focus, and fun/humor/entertainment. Exploring how other types of ad content such as the mention of competitors or quality information affect consumers' decision-making is left for future research.

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Tables and Figures

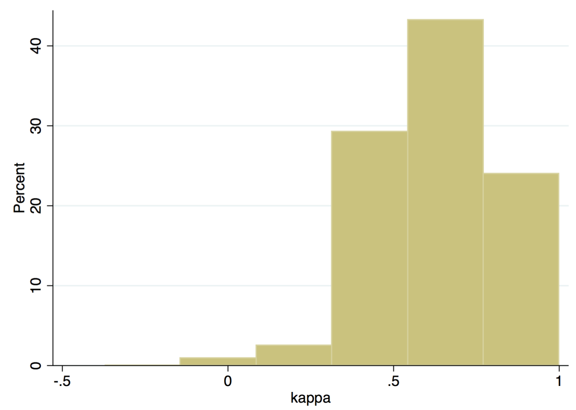

Figure 1: Histogram of Fleiss' Kappas
(Median = 0.63 and Mean = 0.64)

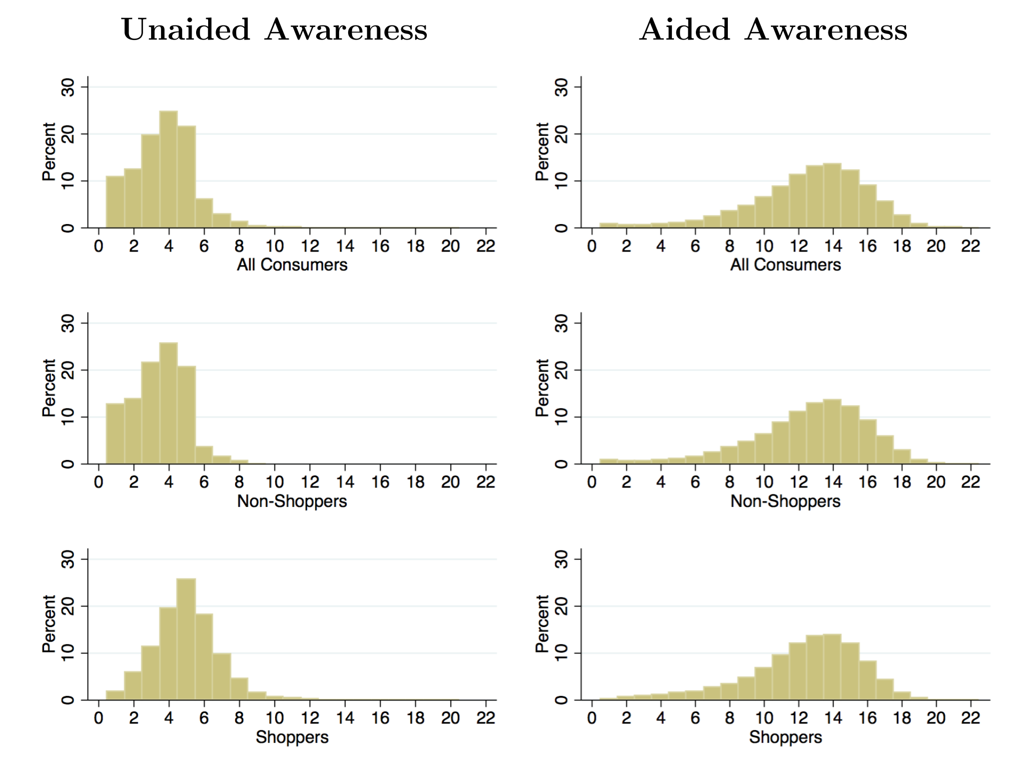

Figure 2: Awareness Set Sizes

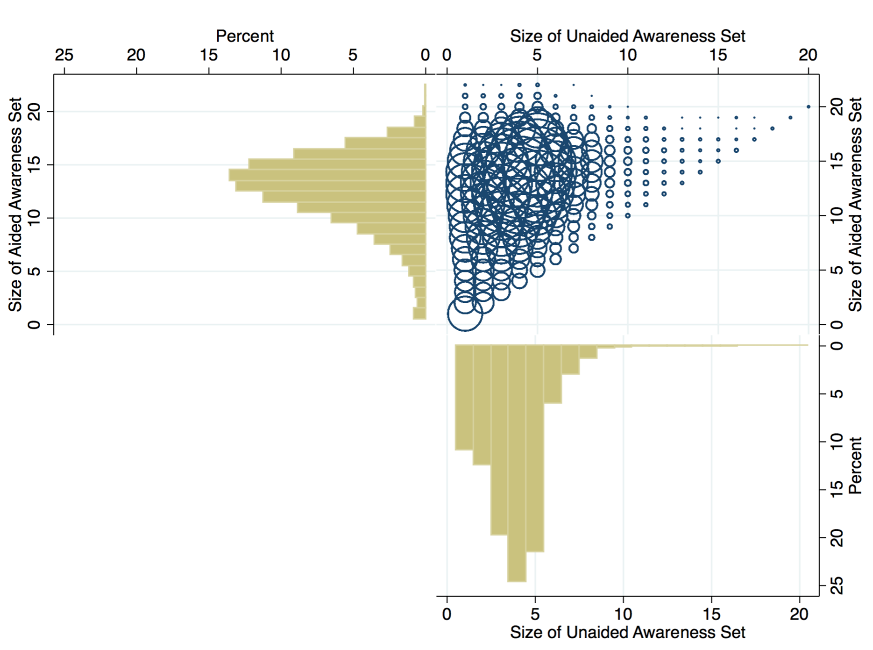

Figure 3: Aided and Unaided Awareness Set Sizes

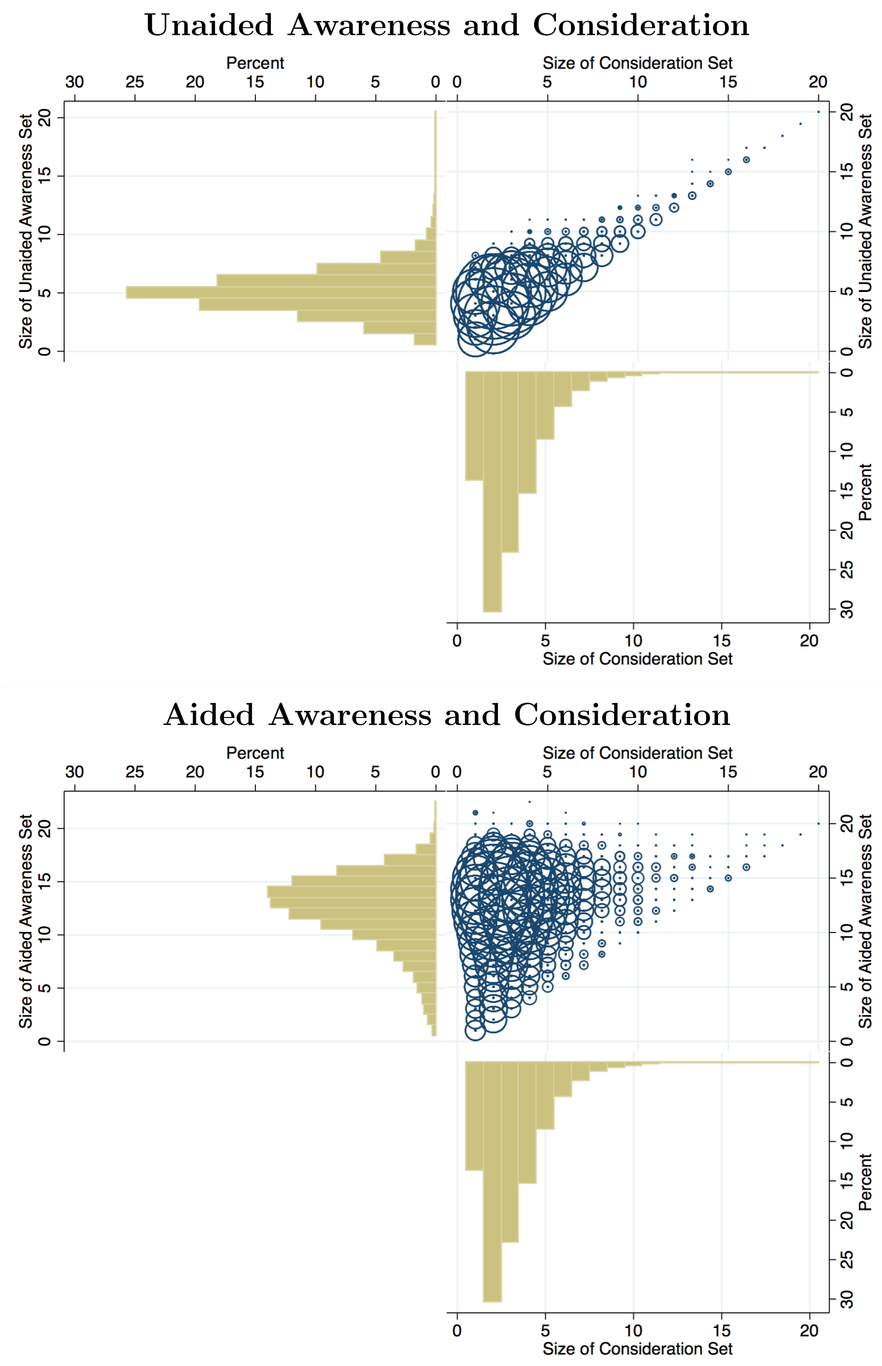

Figure 4: Awareness and Consideration Set Sizes (Shoppers Only)

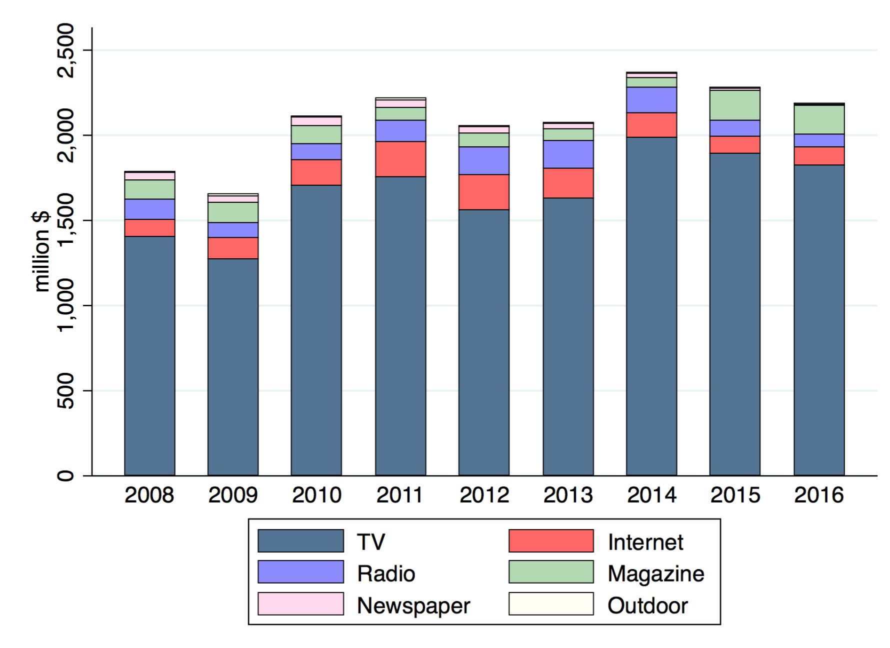

Figure 5: Advertising Spending by Media Type

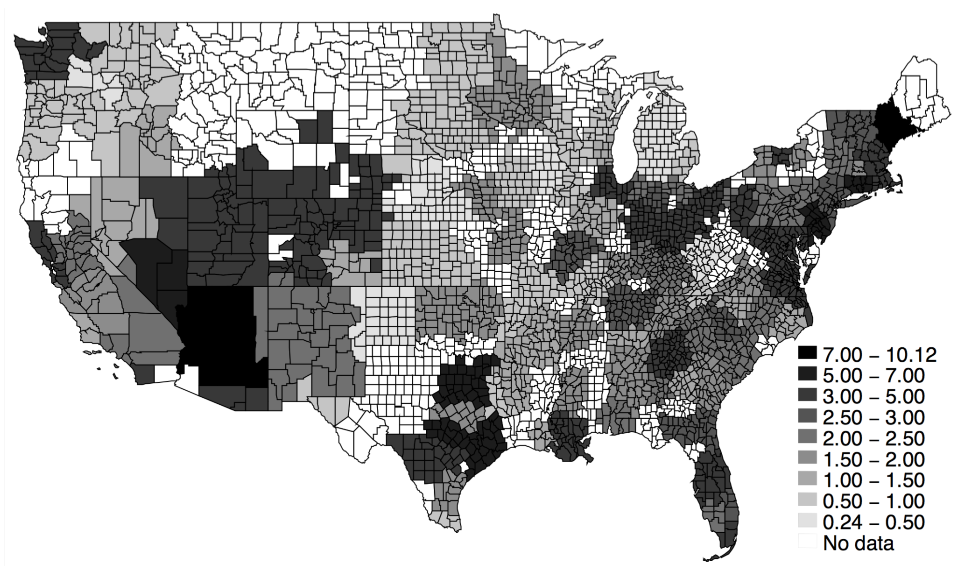

Figure 6: Local Advertising Expenditure ($) per Household by DMA

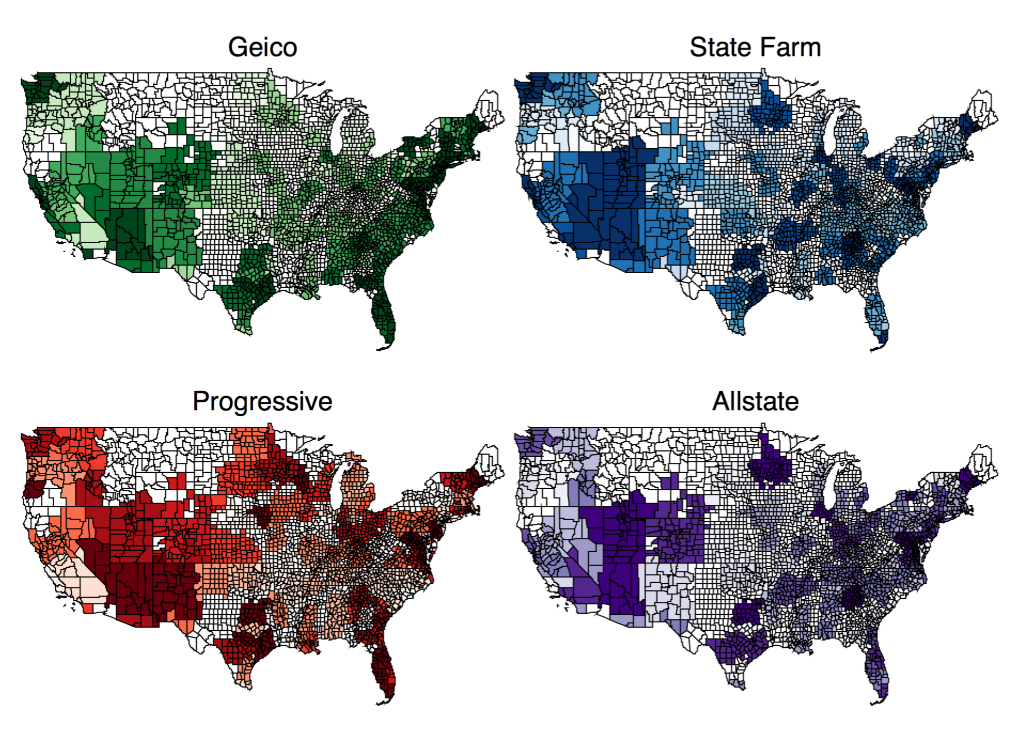

Figure 7: Local Advertising Expenditure ($) per Household for the 4 Largest Auto Insurance Brands

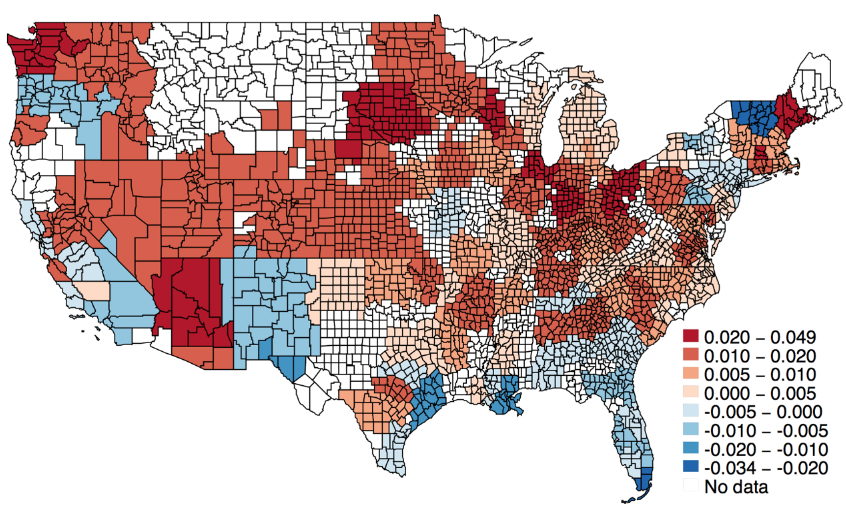

Figure 8: Difference in Local Advertising Content Expenditure ($) per Household by DMA (Red color means there are more non-informational ads)

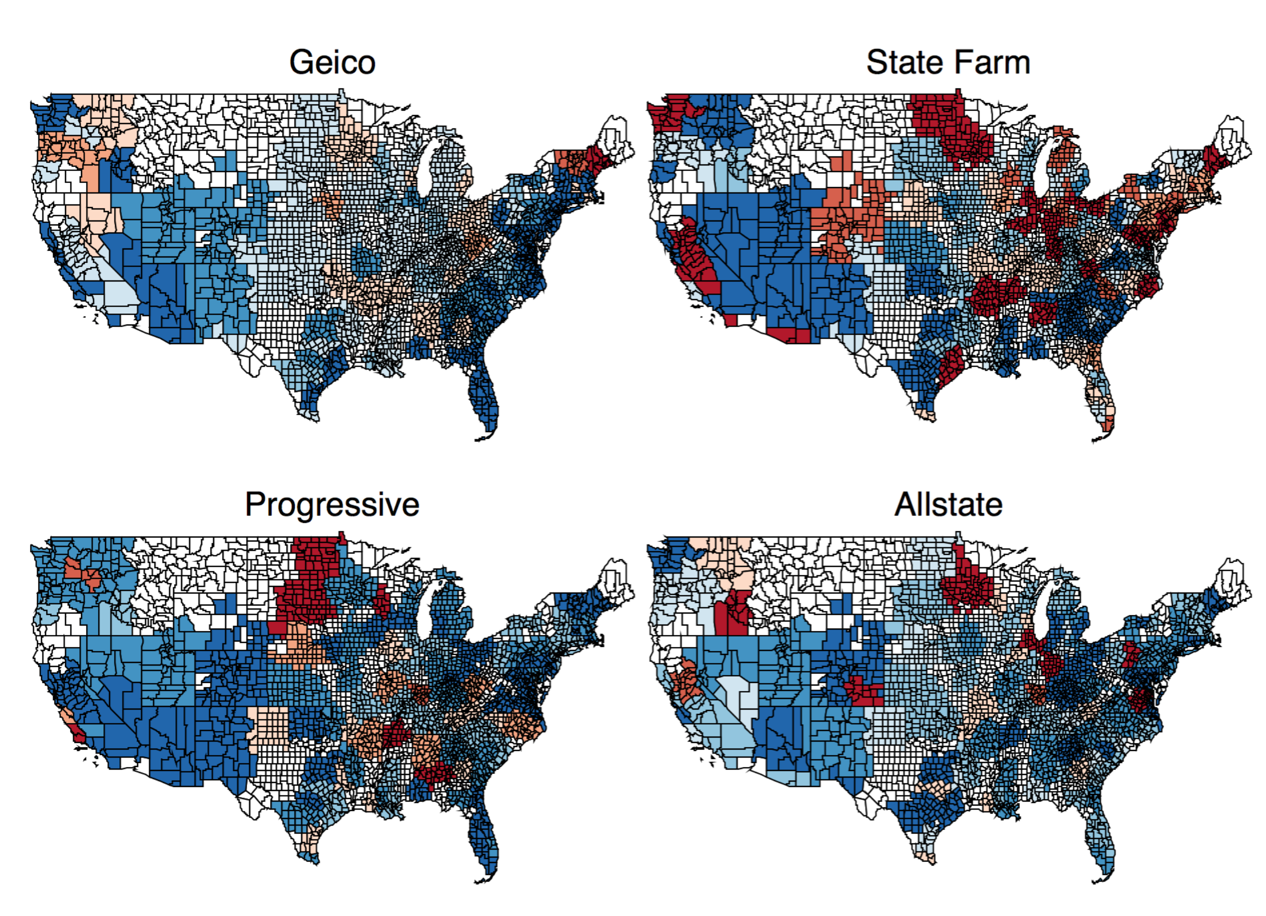

Figure 9: Difference in Local Advertising Content Expenditure ($) per Household for the 4 Largest Auto Insurance Brands

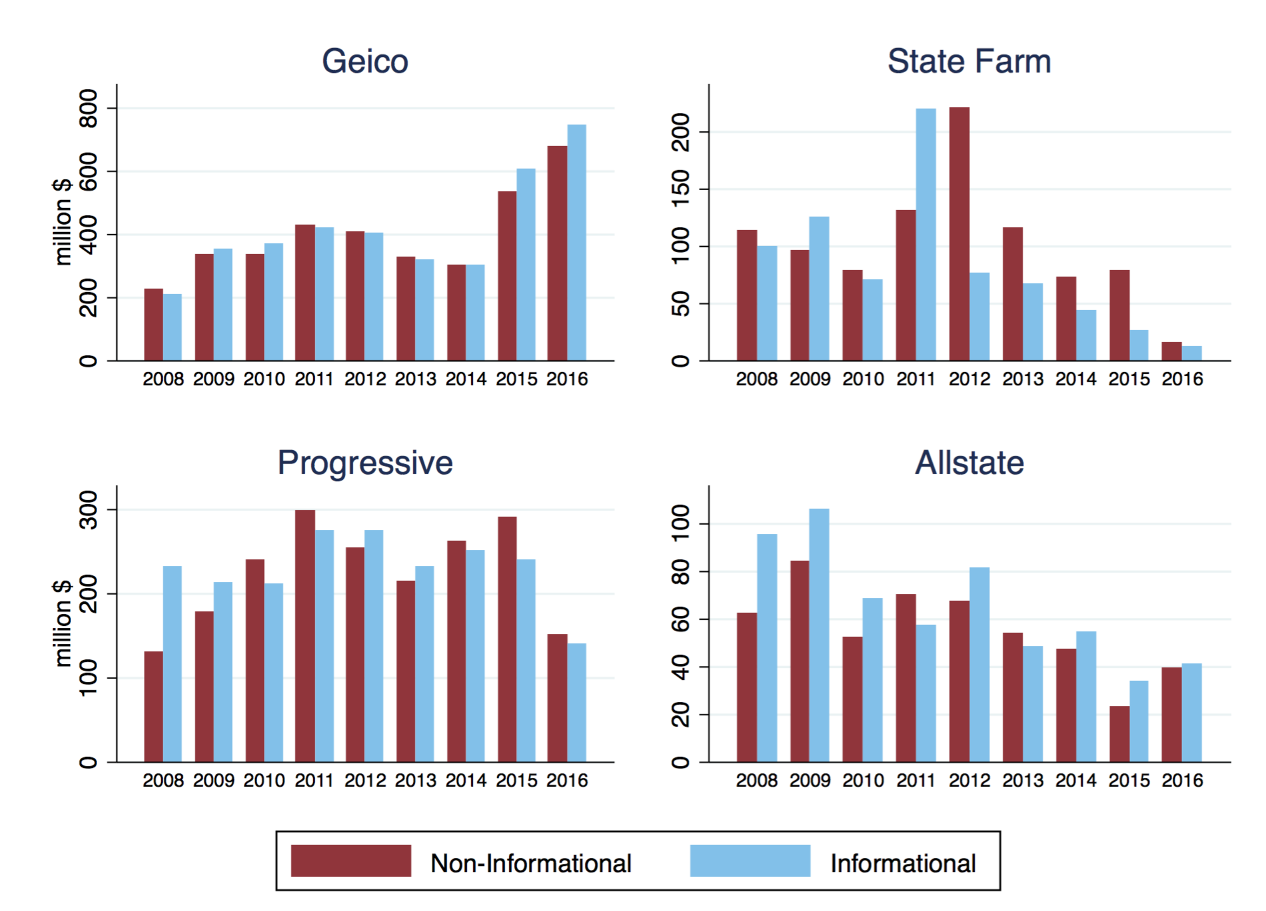

Figure 10: Local Advertising Content Expenditure ($) per Household for the 4 Largest Auto Insurance Brands

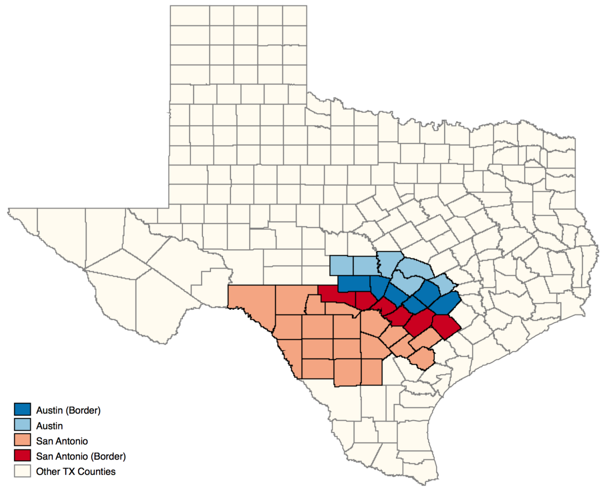

Figure 11: Example of Border Strategy: Austin and San Antonio DMAs

Demographics	(i) All Consumers	(ii) Non-Shoppers	(iii) Shoppers
Age $\leq$ 25 Years	0.0569	0.0608	0.0511
26 Years $<$ Age $\leq$ 45 Years	0.3825	0.3806	0.3855
46 Years $<$ Age $\leq$ 65 Years	0.4148	0.4121	0.4188
Age $>$ 65 Years	0.1458	0.1465	0.1446
Male	0.4003	0.3701	0.4461
Black	0.0387	0.0344	0.0451
Hispanic	0.0372	0.0201	0.0623
Asian	0.0723	0.0829	0.0567
Married	0.5371	0.5136	0.5691
College Degree	0.5928	0.6235	0.5471
Income Greater than $100k	0.2292	0.2332	0.2231
Lived in Urban Area			0.1786
Someone under 25 Years Insured under the Policy			0.1388
Shopped for Homeowner's Insurance			0.3658
Shopped for Renter's Insurance			0.1043
Shopped for Life Insurance			0.0433
Shopped for Personal Umbrella Insurance			0.0633
Two or More Accident(s) in the Last 3 Years			0.0302
Two or More Ticket(s) in the Last 3 Years			0.0384
Poor Credit History			0.0594
Same Insurer as in Previous Year			0.5033

Table 1: Descriptive Statistics

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	All Consumers		Non-Shoppers		Shoppers	
Brand	Unaided	Aided	Unaided	Aided	Unaided	Aided
21st Century	0.1011	0.5462	0.0720	0.5495	0.1449	0.5415
AAA	0.2963	0.8231	0.2851	0.8045	0.3130	0.8478
AIG	0.0715	0.8328	0.0427	0.8177	0.1575	0.8623
Allstate	0.6475	0.9584	0.6091	0.9552	0.7053	0.9626
American Family	0.2310	0.8305	0.1969	0.8415	0.2745	0.8188
Amica Mutual	0.0291	0.1483	0.0157	0.0943	0.0493	0.2195
Auto Owners	0.0467	0.1892	0.0366	0.1863	0.0567	0.1915
Erie	0.1176	0.3305	0.0905	0.2735	0.1594	0.4052
Esurance	0.0758	0.5623	0.0414	0.5134	0.1580	0.6487
Farmers	0.4389	0.8965	0.4233	0.8994	0.4662	0.8920
Geico	0.6171	0.9572	0.5550	0.9506	0.7105	0.9659
GMAC	0.0151	0.3415	0.0056	0.3414	0.0296	0.3415
Hartford	0.0978	0.6788	0.0630	0.6603	0.1506	0.7034
LibertyMutual	0.1279	0.8117	0.0778	0.7973	0.2033	0.8307
Mercury	0.1329	0.4825	0.1314	0.5372	0.1357	0.3960
Metlife	0.0524	0.7910	0.0330	0.7901	0.0815	0.7921
Nationwide	0.1927	0.8120	0.1456	0.7964	0.2625	0.8323
Progressive	0.4340	0.9122	0.3426	0.8932	0.5714	0.9372
Safeco	0.0456	0.3630	0.0302	0.3519	0.0688	0.3776
State Farm	0.6909	0.9662	0.6687	0.9652	0.7243	0.9676
Travelers	0.1008	0.7341	0.0678	0.7130	0.1504	0.7621
USAA	0.1011	0.4301	0.0980	0.3995	0.1058	0.4706
Average	0.2310	0.6736	0.2013	0.6647	0.2765	0.6855

Table 2: Awareness Probabilities

Brand	Considered	Chosen	Aware (unaided) → Considered	Aware (aided) → Considered	Considered → Chosen
21st Century	0.1423	0.0397	0.8464	0.2549	0.2998
AAA	0.2968	0.1214	0.8163	0.3434	0.4147
AIG	0.1175	0.0198	0.7282	0.1368	0.2766
Allstate	0.3179	0.0512	0.4675	0.3309	0.1609
American Family	0.2139	0.0947	0.7058	0.2580	0.4428
Amica	0.0481	0.0233	0.8006	0.2166	0.4850
Auto Owners	0.0698	0.0462	0.8434	0.3231	0.6626
Erie	0.1800	0.1229	0.8297	0.4068	0.6824
Esurance	0.1324	0.0363	0.8319	0.2081	0.2744
Farmers	0.2299	0.0573	0.4897	0.2568	0.2491
Geico	0.3891	0.0529	0.5796	0.4047	0.1358
GMAC	0.0362	0.0164	0.9370	0.1015	0.4520
Hartford	0.1303	0.0523	0.7667	0.1818	0.4014
Liberty Mutual	0.1455	0.0469	0.7273	0.1753	0.3222
Mercury	0.1368	0.0724	0.7930	0.3144	0.5288
Metlife	0.0765	0.0373	0.7838	0.0958	0.4876
Nationwide	0.1533	0.0466	0.5889	0.1841	0.3069
Progressive	0.3548	0.0528	0.6635	0.3804	0.1489
Safeco	0.0728	0.0396	0.8347	0.1818	0.5442
State Farm	0.3369	0.0496	0.4835	0.3488	0.1473
Travelers	0.1101	0.0437	0.6976	0.1432	0.3965
USAA	0.0840	0.0447	0.7858	0.1787	0.5318
Average	0.1768	0.0501	0.6277	0.2548	0.2870

Table 3: Consideration, Purchase, and Conversion Probabilities (Shoppers Only)

Brand	(i) Total Ad Expenditure Per Household in $	(ii) Total Ad Units Per Household	(iii) Local Ad Expenditure Per Household in $
21st Century	0.20	0.0005	0.01
AAA	0.16	0.0011	0.14
AIG	0.22	0.0003	0.05
Allstate	1.86	0.0032	0.10
American Family	0.09	0.0005	0.07
Amica	0.21	0.0010	0.18
Auto Owners	0.01	0.0000	0.00
Erie	0.00	0.0001	0.00
Esurance	1.20	0.0012	0.03
Farmers	0.13	0.0006	0.02
Geico	5.15	0.0058	0.90
GMAC	0.00	0.0000	0.00
Hartford	0.44	0.0003	0.21
Liberty Mutual	1.20	0.0012	0.04
Mecury	0.04	0.0001	0.03
Metlife	0.02	0.0001	0.00
Nationwide	0.76	0.0009	0.11
Progressive	2.78	0.0042	0.26
Safeco	0.00	0.0000	0.00
State Farm	1.96	0.0048	0.17
Travelers	0.16	0.0004	0.01
USAA	0.44	0.0008	0.08
Average	0.79	0.0013	0.11

Table 4: Advertising Quantities

Brand	Informational Only	Non-Informational Only	Both Informational and Non-Informational
21st Century	5.04	0.00	94.96
AAA	17.29	14.70	68.00
AIG	0.00	0.00	100.00
Allstate	32.47	20.98	46.55
American Family	7.44	60.60	31.96
Amica Mutual	0.02	9.11	90.87
Auto Owners	6.53	82.18	11.29
Erie	47.32	14.81	37.86
Esurance	4.89	18.82	76.29
Farmers	3.52	73.83	22.65
Geico	5.53	3.02	91.45
GMAC	0.00	0.00	100.00
Hartford	7.28	9.02	83.70
Liberty Mutual	2.16	16.42	81.42
Mercury	2.35	2.41	95.24
Metlife	8.13	37.57	54.30
Nationwide	22.48	27.49	50.03
Progressive	12.24	9.86	77.89
Safeco	0.00	100.00	0.00
State Farm	13.60	34.92	51.48
Travelers	5.60	39.27	55.13
USAA	2.30	83.19	14.52
Average	10.12	29.83	60.05

Table 5: Percentage of Ads (Weighted by Spending) Containing Informational and Non-Informational Content

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	Unaided Awareness	Aided Awareness	Consideration		Choice	Choice
Conditional on			Unaided Awareness	Aided Awareness	Consideration	
Border Strategy						
Advertising Spending	0.0304^a	0.0294^a	-0.0389	0.0112	-0.0313	0.0049^c
per Household in $ *	(0.0054)	(0.0047)	(0.0282)	(0.0162)	(0.0196)	(0.0025)
Same Insurer as in Previous Year					0.1842^a	0.8202^a
(Yes = 1)					(0.0092)	(0.0011)
Insurer Provided the Best Price					0.7709^a	0.4263^a
(Yes = 1)					(0.0099)	(0.0026)
Individual FEs	yes	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes	yes
Without Border Strategy						
Advertising Spending	0.0352^a	0.0270^b	-0.0012	0.0334^c	-0.0029	0.0058^a
per Household in $ *	(0.0068)	(0.0086)	(0.0204)	(0.0148)	(0.0131)	(0.0015)
Same Insurer as in Previous Year					0.1845^a	0.8166^a
(Yes = 1)					(0.0080)	(0.0011)
Insurer Provided the Best Price					0.7723^a	0.4278^a
(Yes = 1)					(0.0086)	(0.0027)
Individual FEs	yes	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes	yes
Brand-DMA FEs	yes	yes	yes	yes	yes	yes
Number of Observations	7,278,626	6,384,462	328,801	821,178	184,764	5,613,571

Table 6: Results for Advertising Quantity

a: <.001, b: <.01, c: < .05.

Standard errors in parentheses (clustered at the DMA level).

* Measured on a logarithmic scale.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	All Consumers		Non-Shoppers		Shoppers	
Brand	Unaided	Aided	Unaided	Aided	Unaided	Aided
21st Century	0.0239	0.0078	0.0255	0.0084	0.0207	0.0066
AAA	0.0088	0.0031	0.0079	0.0029	0.0105	0.0034
AIG	0.0396	0.0094	0.0333	0.0096	0.0585	0.0089
Allstate	0.0311	0.0200	0.0324	0.0203	0.0283	0.0195
American Family	0.0279	0.0059	0.0298	0.0057	0.0247	0.0063
Amica Mutual	0.0106	0.0051	0.0087	0.0045	0.0144	0.0063
Auto Owners	0.0016	0.0015	0.0013	0.0010	0.0019	0.0021
Erie	0.0006	0.0005	0.0004	0.0004	0.0010	0.0007
Esurance	0.0798	0.0254	0.0748	0.0262	0.0890	0.0239
Farmers	0.0094	0.0043	0.0089	0.0043	0.0104	0.0044
Geico	0.0410	0.0240	0.0441	0.0242	0.0347	0.0237
GMAC	0.0002	0.0001	0.0001	0.0001	0.0003	0.0001
Hartford	0.0433	0.0129	0.0429	0.0131	0.0442	0.0126
Liberty Mutual	0.0629	0.0148	0.0597	0.0146	0.0690	0.0151
Mercury	0.0124	0.0042	0.0137	0.0046	0.0095	0.0033
Metlife	0.0030	0.0010	0.0028	0.0010	0.0034	0.0010
Nationwide	0.0677	0.0153	0.0682	0.0156	0.0667	0.0149
Progressive	0.0637	0.0227	0.0744	0.0231	0.0422	0.0219
Safeco	0.0005	0.0003	0.0007	0.0003	0.0003	0.0002
State Farm	0.0275	0.0184	0.0284	0.0188	0.0256	0.0177
Travelers	0.0185	0.0047	0.0192	0.0052	0.0172	0.0037
USAA	0.0332	0.0128	0.0272	0.0119	0.0453	0.0143
Average	0.0289	0.0107	0.0289	0.0108	0.0288	0.0105

Table 7: Average Advertising Elasticities

	(i)	(ii)	(iii)	(iv)	(v)
	Unaided Awareness	Aided Awareness	Consideration		Choice
Conditional on			Unaided Awareness	Aided Awareness	Consideration
Border Strategy					
Spending per Household in $ on...					
... Informational Ads *	-0.0304	0.0107	0.0210	-0.0358	-0.0231
	(0.0202)	(0.0148)	(0.0625)	(0.0648)	(0.0852)
... Non-Informational Ads *	0.0667^b	0.0139	-0.0502	0.0768	-0.0094
	(0.0220)	(0.0150)	(0.0620)	(0.0564)	(0.0698)
Same Insurer as in Previous Year					0.1838^a
(Yes = 1)					(0.0093)
Insurer Provided the Best Price					0.7710^a
(Yes = 1)					(0.0100)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Without Border Strategy					
Spending per Household in $ on...					
... Informational Ads *	-0.0001	-0.0240	-0.0166	-0.0192	-0.0447
	(0.0192)	(0.0334)	(0.0656)	(0.0473)	(0.0667)
... Non-Informational Ads *	0.0579^b	0.0602^c	-0.0065	0.0708	0.0368
	(0.0211)	(0.0233)	(0.0668)	(0.0464)	(0.0598)
Same Insurer as in Previous Year					0.1842^a
(Yes = 1)					(0.0081)
Insurer Provided the Best Price					0.7723^a
(Yes = 1)					(0.0087)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Brand-DMA FEs	yes	yes	yes	yes	yes
Number of Observations	7,278,626	6,384,462	328,801	821,178	184,764

Table 8: Results for Advertising Content

a: <.001, b: <.01, c: < .05.

Standard errors in parentheses (clustered at the DMA level).

* Measured on a logarithmic scale.

	(i) Unaided Awareness	(ii) Aided Awareness	(iii) Consideration	(iv) Consideration	(v) Choice
Conditional on			Unaided Awareness	Aided Awareness	Consideration
Border Strategy					
Advertising Spending	0.0418^a	0.0386^a	-0.0433	-0.0351	-0.0317
per Household in $ *	(0.0108)	(0.0079)	(0.0290)	(0.0255)	(0.0198)
Interaction between Advertising Spending					
per Household in $ * and ...					
... Minority	-0.0189^a	0.0038	-0.0053	-0.0070	-0.0069
	(0.0047)	(0.0023)	(0.0067)	(0.0072)	(0.0044)
... Low Education	-0.0211	0.0332^b	-0.0161	-0.0164	0.0049
	(0.0136)	(0.0108)	(0.0353)	(0.0359)	(0.0197)
... Low Income	0.0200^a	0.0072^b	0.0169^c	0.0176^c	0.0042
	(0.0033)	(0.0026)	(0.0077)	(0.0084)	(0.0047)
Same Insurer as in Previous Year					0.1842^a
(Yes = 1)					(0.0093)
Insurer Provided the Best Price					0.7709^a
(Yes = 1)					(0.0099)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Number of Observations	7,278,626	6,384,462	328,801	821,178	184,764

Table 9: Results for Advertising Quantity – Vulnerability Analysis

a: <.001, b: <.01, c: < .05.

Standard errors in parentheses (clustered at the DMA level).

* Measured on a logarithmic scale.

	(i) Unaided Awareness	(ii) Aided Awareness	(iii) Consideration	(iv) Consideration	(v) Choice
Conditional on			Unaided Awareness	Aided Awareness	Consideration
Border Strategy					
Spending per Household in $ * on ...					
... Informational Advertising	-0.0323	-0.0302	0.0192	-0.0355	-0.0236
	(0.0379)	(0.0252)	(0.0624)	(0.0647)	(0.0853)
... Non-Informational Advertising	0.0751[c]	0.0403	-0.0513	0.0700	-0.0091
	(0.0350)	(0.0246)	(0.0934)	(0.0566)	(0.0700)
Interaction between Spending on Non-Informational Ads per Household in $ * and ...					
... Minority	-0.0199[b]	0.0062[c]	-0.0115	-0.0182	-0.0102[c]
	(0.0066)	(0.0026)	(0.0077)	(0.0095)	(0.0048)
... Low Education	-0.0334[c]	0.0240[c]	-0.0771	-0.0772	0.0293
	(0.0156)	(0.0116)	(0.0559)	(0.0436)	(0.0239)
... Low Income	0.0235[a]	0.0095[a]	0.0147	0.0279[a]	0.0064
	(0.0038)	(0.0026)	(0.0084)	(0.0064)	(0.0054)
Same Insurer as in Previous Year					0.1838[a]
(Yes = 1)					(0.0093)
Insurer Provided the Best Price					0.7710[a]
(Yes = 1)					(0.0100)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Number of Observations	7,278,626	6,384,462	328,801	821,178	184,764

Table 10: Results for Advertising Content – Vulnerability Analysis

a: <.001, b: <.01, c: < .05.

Standard errors in parentheses (clustered at the DMA level).

* Measured on a logarithmic scale.

Appendix A: Advertising Content Classifications

Coders were provided with the following set of instructions to classify advertising content into categories:

- Price / Rate / Discount

  Does the ad mention any price-related information? For example: competitive rate, low-cost, premium, discount, budget, saving you money, save 28% on your premium.

- (Non-Price) Product Features

  Does the ad talk about (new) non-price characteristics of the insurance product? For example: accident forgiveness, safe driver discount, getting competitive quotes on its website.

- Brand Name Focus

  Is the focus of the ad the name of the insurance brand? Ads with brand name focus can usually be found in “holiday wishes”, “thank you to the customers”, or it could be that mentioning the company name is the biggest part of the ad.

- Humor / Fun / Entertainment

  Is the ad funny/entertaining? For example: it’s a cartoon or cars do weird things or damage from a superhero fight is covered. Note: about humor/entertainment and fear/safety concerns of an ad. Please pick one (dominant) emotion for the ad coding. For example, Allstate has ads with a guy causing crazy mischief – that falls under humor as these ads are intended to be fun/enjoyed by consumers. Fear/safety concerns means that the ad is trying to instill serious (not funny) concerns into the consumer.

Appendix B: Descriptive Statistics for Original Data Set

In this appendix, we compare descriptive statistics from the final (border) samples to those from the original data sets. Table B-1 shows the statistics for all consumers (columns (i) and (ii)), non-shoppers (columns (iii) and (iv)), and shoppers (columns (v) and (vi)). Comparing all consumers who belong to the original and final samples, we find few differences among the demographics. Consumers from the final sample who live in border regions (column (i)) are less likely to be male (40.03% vs. 42.04%) compared to consumers from the original sample (column (ii)). The differences for the other demographic variables are all smaller than 2%.

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Insert Table B-1 about here

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Comparing non-shoppers from the final and original data samples (columns (iii) and (iv)), we find non-shoppers from the final sample to be less likely above 65 years old (14.65% vs. 17.23%) and less likely to be married (51.36% vs. 53.55%) compared to non-shoppers from the original sample. Among the remaining demographics, the differences are smaller than 2%.

Comparing shoppers from the original and final samples (columns (v) and (vi) in Table B-1), we find shoppers from the final sample to be less likely between 25 and 45 years old (38.55% vs. 40.80%) and less likely to have a college degree (54.71% vs. 56.87%) compared to shoppers from the original sample. The differences for the other demographic variables are all smaller than 2%. For shoppers only, we have access to more information on insurance-related consumer characteristics such as other insurance products the consumer shopped for or past accidents and tickets. Among these variables, we find – not surprisingly – that shoppers from the final sample are less likely to live in an urban area than shoppers from the original sample (17.86% vs. 20.11%). Two other differences are that shoppers from the final sample are less likely to also have been shopping for homeowner (36.58% vs. 38.59%) and less likely to stay with their previous insurance provider (50.33% vs. 54.78%) compared to shoppers from the original sample. The differences for the other insurance-related variables are all smaller than 2%.

We conclude that the distributions of demographic and insurance-related variables for all consumers and the subgroups of shoppers and non-shoppers are similar when the original and final data samples are compared.

	(i)	(ii)	(iii)	(iv)	(v)	(vi)
	All Consumers		Non-Shoppers		Shoppers	
Demographics	Final	Original	Final	Original	Final	Original
Age $\leq$ 25 Years	0.0569	0.0556	0.0608	0.0603	0.0511	0.0519
25 Years $<$ Age $\leq$ 45 Years	0.3825	0.3904	0.3806	0.3680	0.3855	0.4080
45 Years $<$ Age $\leq$ 65 Years	0.4148	0.4054	0.4121	0.3994	0.4188	0.4100
Age $>$ 65 Years	0.1458	0.1487	0.1465	0.1723	0.1446	0.1301
Male	0.4003	0.4204	0.3701	0.3892	0.4461	0.4451
Black	0.0387	0.0514	0.0344	0.0436	0.0451	0.0573
Hispanic	0.0372	0.0375	0.0201	0.0190	0.0623	0.0515
Asian	0.0723	0.0624	0.0829	0.0784	0.0567	0.0503
Married	0.5371	0.5548	0.5136	0.5355	0.5691	0.5678
College Degree	0.5928	0.5997	0.6235	0.6396	0.5471	0.5687
Income Greater than $100k	0.2292	0.2381	0.2332	0.2526	0.2231	0.2266
Lived in Urban Area					0.1786	0.2011
Someone under 25 Years Insured under the Policy					0.1388	0.1457
Shopped for Homeowner Insurance					0.3658	0.3859
Shopped for Renters Insurance					0.1043	0.1122
Shopped for Life Insurance					0.0433	0.0440
Shopped for Personal Umbrella Insurance					0.0633	0.0673
Two or More Accident(s) in the Last 3 Years					0.0302	0.0315
Two or More Ticket(s) in the Last 3 Years					0.0384	0.0412
Poor Credit History					0.0594	0.0587
Same Insurer as in Previous Year					0.5033	0.5478

Table B-1: Descriptive Statistics

Appendix C: Robustness Checks

In this appendix, we present the results from several robustness checks. First, we evaluate the robustness of our results with respect to our decision to use the average coding across research assistants when deciding on the presence of absence of informational and non-informational content. To do so, we use majority instead of average coding. Table C-1 replicates Table 5 from the paper using majority coding. We find very similar data patterns compared to those from Table 5.

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Insert Table C-1 about here

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Next, we re-estimate our main models for advertising content using majority coding and the border strategy. The results are shown in the top half of Table C-2. Our results are qualitatively robust: non-informational advertising has a significant effect on unaided and aided awareness (though the effect on unaided awareness is only significant at $p < .10$) and insignificant effects on conditional consideration and choice. Informational advertising does not have any significant effects.

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Insert Table C-2 about here

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In a second robustness check, we investigate the robustness of our results with respect to an alternative approach of modeling the effects of advertising content. Instead of operationalizing advertising content as the total spending per household (in \$) on informational and non-informational ads, we include three advertising variables: total advertising spending per household, percentage of spending per household on informational ads and percentage of spending per household on non-informational ads. The results are shown in the bottom half of Table C-2.

In a third robustness check, we investigate the robustness of our results with respect to alternative ad content measurements. More specifically, we re-estimate our models using the following two ad content variables: (i) two count variables for the number of non-informational and informational cues, respectively, ranging from 0 to 2 for each count variable and (ii) difference in the number of non-informational and informational cues ranging from -2 to $+2$. To do so, we calculate non-informational ad scores for each ad by taking the difference between the number of non-informational and the number informational content elements in an ad. For example, an ad containing two non-informational pieces of content and zero informational pieces of content would have a non-informational ad content score of $+2$. An ad containing one non-informational piece of content and two informational pieces of content would have a non-informational ad content score of -1.

Using these alternative ad content measurements, we re-run our main models from Table 8. The results are shown in Table C-3. For both alternative ad content measurements, we find the same pattern of results as in our main model: Non-informational content has significant effects on awareness and insignificant effects on conditional consideration and choice. All effects of informational ad content are insignificant. These robustness checks also show that the more non-informational content an ad contains, the more likely it is that consumers will remember and be aware of the company.

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Insert Table C-3 about here

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In a fourth robustness check, we evaluate the robustness of our results with respect to an alternative operationalization of the advertising quantity variable. In the paper, we use the logarithm of total advertising spending per household as our measure of advertising intensity. Here, we re-estimate our models using the logarithm of total advertising *units* per household as our measure of advertising intensity. The results are shown in the top half of Table C-4. While the advertising coefficients for awareness are insignificant, they are directionally consistent with the results from Table 6 in the paper. The advertising coefficients for conditional consideration and choice are, as in our main model, insignificant.

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Insert Table C-4 about here

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And lastly, we investigate the robustness of our results with respect to our use of total advertising spending. Here, we re-estimate our models using the logarithm of DMA-level advertising spending per household as our measure of advertising intensity. The results are shown in the bottom half of Table C-4. Consistent with the results from Table 6 in the paper, we find positive significant effects of advertising on consumers' awareness and insignificant effects for consideration and choice.

We conclude that our results are robust to a number of alternative specifications of the advertising quantity and advertising content variables.

Brand	Informational Only	Non-Informational Only	Both Informational and Non-Informational
21st Century	2.90	0.00	97.10
AAA	0.21	15.16	84.63
AIG	0.00	0.00	100.00
Allstate	30.56	21.89	47.55
American Family	2.76	67.40	29.84
Amica Mutual	0.00	10.02	89.98
Auto Owners	4.08	82.18	13.74
Erie	58.64	14.81	26.55
Esurance	0.00	19.15	80.85
Farmers	1.47	77.48	21.05
Geico	0.30	2.60	97.10
GMAC	0.00	0.00	100.00
Hartford	6.69	9.23	84.08
Liberty Mutual	1.55	18.38	80.07
Mercury	0.00	0.20	99.80
Metlife	11.13	35.47	53.40
Nationwide	16.81	27.71	55.48
Progressive	10.70	9.26	80.04
Safeco	0.00	100.00	0.00
State Farm	11.31	34.74	53.95
Travelers	0.00	39.27	60.73
USAA	0.00	83.19	16.81
Average	7.51	30.37	62.12

Table C-1: Percentage of Ads (Weighted by Spending) Containing Informational and Non-Informational Content Using Majority Coding

	(i)	(ii)	(iii)	(iv)	(v)
	Unaided Awareness	Aided Awareness	Consideration		Choice
Conditional on			Unaided Awareness	Aided Awareness	Consideration
Majority Coding					
Spending per Household in $ on...					
... Informational Ads *	-0.0215	0.0095	0.0094	-0.0288	-0.0861
	(0.0203)	(0.0150)	(0.0601)	(0.0583)	(0.0846)
... Non-Informational Ads *	0.0567^c	0.0138	-0.0430	0.0670	0.0515
	(0.0227)	(0.0141)	(0.0597)	(0.0509)	(0.0681)
Same Insurer as in Previous Year					0.1838^a
(Yes = 1)					(0.0093)
Insurer Provided the Best Price					0.7710^a
(Yes = 1)					(0.0100)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Percentage Specification					
Advertising Spending	0.0305^a	0.0283^a	-0.0359	0.0081	-0.0289
per Household in $ *	(0.0048)	(0.0048)	(0.0280)	(0.0143)	(0.0204)
% of Spending per Household in $ on...					
... Informational Ads *	-0.0045	0.0154	-0.0027	-0.0531^c	0.0091
	(0.0075)	(0.0079)	(0.0325)	(0.0224)	(0.0231)
... Non-Informational Ads *	0.0049	-0.0040	-0.0396	0.0452^c	0.0013
	(0.0074)	(0.0076)	(0.0341)	(0.0219)	(0.0243)
Same Insurer as in Previous Year					0.1788^a
(Yes = 1)					(0.0094)
Insurer Provided the Best Price					0.7742^a
(Yes = 1)					(0.0100)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Number of Observations	7,278,626	6,384,462	328,801	821,178	184,764

Table C-2: Robustness Checks – Results for Advertising Content

a: <.001, b: <.01, c: < .05.

Standard errors in parentheses (clustered at the DMA level).

* Measured on a logarithmic scale.

	(i)	(ii)	(iii)	(iv)	(v)
	Unaided Awareness	Aided Awareness	Consideration		Choice
Conditional on			Unaided Awareness	Aided Awareness	Consideration
Count Variable					
Informational Cues Count	-0.0032	-0.0077	0.0324	-0.0088	0.0290
	(0.0053)	(0.0032)	(0.0243)	(0.0159)	(0.0243)
Non-Informational Cues Count	0.0124[c]	0.0105[a]	-0.0333	0.0161	-0.0253
	(0.0051)	(0.0026)	(0.0210)	(0.0135)	(0.0197)
Same Insurer as in Previous Year					0.1838[a]
(Yes = 1)					(0.0093)
Insurer Provided the Best Price					0.7710[a]
(Yes = 1)					(0.0100)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Ad Score					
Non-Informational Ad Score	0.0117[c]	0.0104[a]	-0.0335	0.0155	-0.0250
	(0.0050)	(0.0026)	(0.0212)	(0.0136)	(0.0195)
Same Insurer as in Previous Year					0.1838[a]
(Yes = 1)					(0.0093)
Insurer Provided the Best Price					0.7710[a]
(Yes = 1)					(0.0100)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Number of Observations	7,278,626	6,384,462	328,801	821,178	184,764

Table C-3: Robustness Checks – Advertising Content

a: <.001, b: <.01, c: < .05.

Standard errors in parentheses (clustered at the DMA level).

* Measured on a logarithmic scale.

	(i)	(ii)	(iii)	(iv)	(v)
	Unaided Awareness	Aided Awareness	Consideration		Choice
Conditional on			Unaided Awareness	Aided Awareness	Consideration
Unit Coding					
Advertising Units per Household *	0.1961	0.1112	-1.3538	-1.2195	0.4420
	(0.2287)	(0.1144)	(0.9086)	(0.6198)	(0.4921)
Same Insurer as in Previous Year					0.1839^a
(Yes = 1)					(0.0095)
Insurer Provided the Best Price					0.7701^a
(Yes = 1)					(0.0101)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
DMA-Level Advertising Only					
Advertising Spending in $	0.0079^a	0.0048^a	-0.0154	-0.0052	-0.0063
per Household *	(0.0021)	(0.0011)	(0.0082)	(0.0066)	(0.0062)
Same Insurer as in Previous Year					0.1839^a
(Yes = 1)					(0.0095)
Insurer Provided the Best Price					0.7702^a
(Yes = 1)					(0.0101)
Individual FEs	yes	yes	yes	yes	yes
Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Online-Brand-Demographics-Year FEs	yes	yes	yes	yes	yes
Brand-Border-DMA FEs	yes	yes	yes	yes	yes
Brand-Border-Year FEs	yes	yes	yes	yes	yes
Brand-State-Year FEs	yes	yes	yes	yes	yes
Number of Observations	7,278,626	6,384,462	328,801	821,178	184,764

Table C-4: Robustness Check – Results for Advertising Quantity

a: <.001, b: <.01, c: < .05.

Standard errors in parentheses (clustered at the DMA level).

* Measured on a logarithmic scale.