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The Economic Value of Meta-Report Cards: The Case of Automobiles

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Report Summary

Meta-report cards are product report cards that aggregate information from multiple public sources with the goal of easing consumer decision making. It is not apparent whether and how meta-report cards influence consumer decisions and market demand.

On one hand, because meta-report cards do not introduce proprietary information or sell products and simply synthesize existing information, one could question their potential to influence consumer decisions. On the other hand, synthesis of information could potentially aid in consumer search and product ratings could be a signal of quality offering.

To better understand the economic value of meta-report cards, Guneet Kaur Nagpal and Rajdeep Grewal use a revealed preferences approach with data from the U.S. automobile industry.

In 2007, U.S. News & World Report (USNWR) introduced a meta-report card (www.cars.usnews.com) that synthesized information from multiple public sources, including J.D. Power and Kelly Blue Book, among others. This offered a natural experiment, with a pre-post (before 2007 and after 2006), treatment-control (brands rated and brands not rated) design. Complementing the USNWR ratings with data from multiple other sources, the authors estimate a nested logit demand model for brand choice with aggregate data and include the USNWR rating as an endogenous product characteristic.

They show that meta-report cards offer economic value for consumer and marketers through the mechanisms of search cost reduction and quality assurance.

- The presence of brands on USNWR meta-report card translates to societal benefit of $10.53 for an average consumer (with this value ranging from $2.90 to $16.89 between 2007 and 2012).
- On average, one standard deviation improvement on USNWR ratings (measured on a 10-point scale with standard deviation of .58) enables a brand to charge $3560 more or save around $12 million on advertising.

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1. Introduction

Product report cards, in the form of third party reviews, ratings, and rankings by experts, are an important source of information for consumer purchase decisions; thus, these report cards form the basis of many scholarly endeavors.[1] With proliferation of report cards, we are witnessing the genesis of meta-report cards – the report cards that synthesize information from incumbent report cards. The prime example of meta-report cards is the automobiles ratings launched in 2007 by the U.S. News & World Report (USNWR). Brian Kelly, the editor and chief content officer at USNWR described the report card as a 'review of reviews' to label it a meta-report card that would serve as a one stop shop for information seekers in the automobiles category. At the time of the launch of USNWR automobile report card, there were multiple incumbent automobile report cards in the marketplace, such as Consumer Reports, J.D. Power, Kelly Blue Book, and Edmunds, which had sizeable reach and credibility among consumers. Unlike these incumbent report cards, which create new information through original research (e.g., crash tests), USNWR gathers and evaluates public information to synthesize it in a form it believes would be useful for consumers (see www.usnwr.com and Figure 1).

It is not apparent whether such meta-report cards would influence consumer decisions and therefore market demand. On one hand, because meta-report cards do not introduce proprietary information or sell products and simply synthesize existing information,[2] one could question their potential to influence consumer decisions (Marshall et al. 2000). Such an argument

[1] For example, see the work of Ursu (2017) on hotels, Luca and Smith (2013) and Monks and Ehrenberg (1999) on colleges, Reinstein and Snyder (2000) on movies, Schiefer and Fischer (2008) and Friberg and Gronqvist (2012) on wine, Sorensen (2007) on books, and Pope (2009) on hospitals.
[2] As we discuss in the final section, endeavors similar to USNWR meta-report card are emerging in other industries, such as Techbargains for technology gadgets and Zillow for real estate.

would rest on the premise that the value of information source depends on the new and novel insight it provides to reduce information uncertainty (Hilton 1977). For durables, such as automobiles, where typical consumer decision making lasts for 2-3 months (e.g., Google 2011) and consumer prefers to look at opaque product details and avoid cognitive shortcuts (e.g., Chetty, Looney, and Kroft 2009), meta-report cards may not be valuable. On the other hand, synthesis of information could potentially aid in consumer search (e.g. Ghose, Ipeirotis, and Li 2014) and product ratings could be a signal of quality offering (e.g., Jin and Leslie 2003). These gains concerning the ease of search and quality signals would suggest that meta-report cards would influence consumer decisions and market demand. Thus, we seek to study whether and how meta-report cards influence market demand. For the purpose, we conceptualize the introduction of USNWR meta-report card to the United States market in 2007 as a natural experiment (see Figure 2) with a pre-post and treatment-control design.[3] As brands (make-model) rated by USNWR belong to the treatment group and those not rated define the control group, we use the year 2007 as a cutoff for pre-post periods (pre 2007 and post 2006). USNWR rated 83 brands in 2007 with the number rising to 179 by 2012 (from a total of 447 automobile brands; once a brand is rated, it is rated every subsequent year). With this setting, we collate a multi-source dataset on unit sales, marketing mix, and product features of automobiles at the make-model level (e.g., Toyota Camry) from 2004 to 2012. We augment the dataset with automobile ratings from three frequently used ratings report cards: Consumer Reports, Kelly Blue Book, and J.D. Power (according to J.D. Power 2014).

[3] The USNWR report card appears as one of the top links in the Google search results for “automobile” keyword search, and may in fact be one of the first few information sources consumers may use to search for automobiles. We used spyfu.com website to provide empirical evidence for this claim. For example, for the keywords such as – car rank, car rating, best car, best sedan, best SUV, best sports car, best pickup truck, make-model price (e.g., Honda Accord price), USNWR link appears among the top 5-7 links.

With this aggregate data around the introduction of USNWR ratings, we estimate a demand model to assess the influence of USNWR meta-report card on demand. We utilize a nested logit model that allows correlations among consumer tastes across ‘competing’ brands (e.g., Berry 1994). Specifically, we examine two model configurations; first where we code treatment and control as a dummy variable and second where we model the influence of ratings for the rated (treated) brands. As USNWR is unlikely to select brands to rate randomly (see Doherty, Kartasheva, and Phillips (2012) for similar situation in the context of credit rating agencies), our primary identification challenge concerns strategic allocation of brands to treatment (i.e., rated) and control (i.e., not rated) conditions. We address this challenge by using a mix of control variables, fixed effects, and instruments.

Overall, we find the USNWR ratings influence demand with evidence suggesting search cost reductions and quality signaling are the two underlying mechanisms. Our economic value calculations suggest that the presence of USNWR meta-report card adds $10.53 per customer on an average with this value ranging from $2.90 to $16.89 between 2007 and 2012. This average value of $10.53 per customer is also suggestive of the price that USNWR could charge for Best Cars Guidebook (currently it is free and relies on advertising for revenue), which is consistent with price of USNWR ratings in other domains (USNWR charges $9.95, $11.95, and $6.99 for Best Business Schools, Best Colleges, and Best Hospitals Guidebooks respectively; www.usnews.com). The effect size for actual rating (as opposed to whether one is rated or not) is economically meaningful as well. One standard deviation increase in rating (the standard deviation is .58 for USNWR ratings on a 10-point scale) amounts to $3560 more in price and savings of around $12 Million on advertising. A comparison with other ratings suggests that

USNWR coefficient is 1.13 and 1.18 times higher than Consumer Reports and JD Power respectively, which one should expect for a meta-report card.

Our research closely relates to the literature on product report cards and metasearch portals. Scholars have studied product report cards, which represent credible third party performance disclosures, in diverse contexts such as healthcare plans (Wedig and Tai-Seale 2002), real estate (Figlio and Lucas 2004), and restaurants (Jin and Leslie 2003), among others. Unlike product report cards that create and introduce information to reduce uncertainty, meta-report card synthesize existing information. Recognizing that the value of information increases when information is organized, synthesized, and judged (Taylor 1982), we add to the literature on product report cards by investigating the value of a meta-report card. Similar to meta-report cards, metasearch portals (e.g., Expedia) synthesize information but also facilitate sales (unlike meta-report cards). Thus, research on metasearch portals relies on linking search results to consumer behavior (e.g., clicks/purchases; Ursu 2017) and explores search cost reduction as the underlying mechanism (e.g., Chen and Yao 2016). We build on this metasearch literature in three ways. First, we study automobile purchases as opposed to travel purchases, where the search process is more time consuming and costly (few weeks compared to a few hours). Second, we use aggregate data as opposed to individual data and model other rating sources (e.g., Kelly Blue Book) in addition to the meta-report card. Third, we explore quality signal mechanism in addition to search cost reduction mechanism.

We organize the remainder of this manuscript as follows. In section 2, we discuss the relevant literature and juxtapose our contributions to the literature. In section 3, we describe data and in section 4, we elaborate on model specification and identification strategy. In section 5, we present model free evidence and model-based results. We conclude with section 6 by discussing the contributions and limitations of our research.

2. Related Literature

From our perspective, meta-report cards should meet two conditions: synthesize (as opposed to create) information and should not sell products to consumers directly. We know of no existing studies of meta-report cards, so we turn to related literature on product report cards and metasearch portals.

2.1. Product Report Cards

Product report cards refer to the credible third party performance disclosure in the form of ratings/rankings/reviews of alternatives in a product category. The value of product report card lies in the reduction of the information uncertainty by providing heretofore unavailable information to consumers, a precondition to accommodate the use of any new piece of information (e.g., Lawrence 2012). For example, in his study on determinants of information value, Hilton (1981) argues for a decision maker with a given wealth, risk aversion, and situation flexibility, uncertainty is the key determinant of the value of information.

There is already a rich and growing research regarding the value of information imparted by product report cards, especially in the service industry and for experiential goods. For example, in the healthcare industry, several studies examine health plan choices when healthcare plan report cards were introduced to federal employees (Wedig and Tai-Seale 2002), General Motor employees (Scanlon et al. 2002), and Harvard employees (Beaulieu 2002); common finding suggests that better rated plans enjoy higher demand. In real estate, Figlio and Lucas (2004) find that real estate values improve when the school report card rating improves. For restaurants, Jin and Leslie (2003) find that hospitalizations from food-borne diseases declined by

20 percent after Los Angeles County posted restaurant hygiene report card ratings in 1998 as consumers started choosing restaurants that are more hygienic. For movies, Reinstein and Snyder (2005) exploit the timing of movie critics to identify the impact on box office sales and find that narrowly released movies benefit the most from positive ratings from critics.

We contribute to the literature on product report cards by studying the value of meta-report cards. While product report cards reduce information uncertainty by providing information heretofore unavailable to consumers, meta-report cards reduce the uncertainty by synthesizing information from multiple sources, including incumbent report cards. Thus, we build on Taylor's (1982) premise that information becomes more valuable when it is organized, synthesized, and judged. For example, in academia, information synthesis done usually in the form of a domain meta-analysis is considered to be one of the most valuable contributions a researcher can make (Goldschmidt 1986). Notably, most of the extant literature on information synthesis is conceptual in nature with little empirical scrutiny; we provide this scrutiny.

2.2. Metasearch Portals

Metasearch portals are web portals, such as, Expedia and Travelocity, which gather information from multiple sources (like meta-report cards) and allow consumers to make purchase on these portals (unlike meta-report cards). There are a handful of articles on these portals, mostly in the travel industry (e.g., Chen and Yao 2016; Koulayev 2014; Ursu 2017), where the key research objective is to estimate the effect of the rank order of brands on consumer clicks and/or purchases. For example, Chen and Yao (2016) find that refinement of options based on product attributes significantly influences consumer welfare by facilitating matching. Similarly, De los Santos and Koulayev (2017), Ghose, Ipeirotis, and Li (2014), and Ursu (2017) find that information portals, such as Travelocity and Expedia, influence consumer clicks and transactions through their ranking mechanisms.

As metasearch portals sell products, typical research on these portals uses individual level data to link search results to consumer behavior (e.g., clicks); in contrast, we rely on aggregate market level data and model information from rating sources (such as consumer reports) other than the meta-report card. We also study a higher involvement product category (i.e., automobiles as opposed to hotels and airline tickets), where the search process is likely to be more time consuming and costly (e.g., hours as opposed to a weeks). We build on the literature on metasearch portals that examines search cost reduction as a mechanism to explore search costs mechanism. Further, as ratings signal quality beyond objective product quality, we study quality signal as a potential mechanism for the influence of meta-report card on demand.

3. Data Description

To collate a comprehensive dataset, we gathered data from diverse sources on automobile price, advertising spends, automobile features, automobile ratings, and USNWR meta-report card. As a result, we gathered a panel data on 447 automobile brands (where a brand is at the make-model level, e.g., Ford Taurus, Honda Civic) from 2004 to 2012; our dataset includes 85% to 90% of the automobile brands (in terms of share and number of registrations) sold in the United States during this time period. In Table 1a and 1b we provide a breakdown of the observations at the make (manufacturer) as well as type level respectively. In Table 2, we detail the data sources and present descriptive statistics in Table 3.

3.1. Marketing-Mix

We obtain manufacturer suggested retail pricing (MSRP) information from four sources: Polk, Consumer Reports, Autoevolution.com, and Autotrader.com. For every brand (e.g., Honda Accord), there are multiple alternatives available every year (e.g., Honda Accord LX and Honda Accord EX). We collect price of the most basic alternative for each brand. We accessed the information on advertising spending from Kantar Group's Ad$pender database, which includes information on aggregate dollar spending on TV, magazines, newspapers, radio, and internet. The annual information is available at the make-model (i.e., Honda Accord) level.

3.2. Automobile Features

We access data on a comprehensive set of automobile features (29 features)[4] from Pluup.com to control for factors that can possibly influence demand. For every automobile model, there are multiple alternatives available in the market, such as LX and EX models for Honda Accord; thus, to be consistent, we collect features data of the most basic model for each brand. Typically, the empirical literature on demand estimation in automobile category includes three key automobile characteristics: price, fuel efficiency, and some measure of size such as height or width (e.g., Lave and Bradley 1980; Sudhir 2001). Along with these three basic characteristics, some researchers have expanded the list to incorporate, horsepower or acceleration-time along with the weight of vehicle (Lave and Train 1979; Goldberg 1998) as a proxy for power of the vehicle. Berry, Levinsohn, and Pakes (1995) and a series of other papers, such as Goldberg (1995), and Petrin (2002), also included information on wheelbase, automatic

[4] We have automobile feature data on: engine cc, engine type, engine position, valves, horsepower, torque, compression, top-speed, acceleration, country of origin, tire types, CO_2 emission, brakes type, seats, doors, turn-circle, weight, length, width, cargo-space, fuel efficiency, tank capacity, fuel type, transmission, rear/front drive, tire dimensions, chassis, luxury/non-luxury and towing weight.

transmission, front-wheel drive vs. all-wheel drive, and air conditioning using indicator variables. Although we have access to an extensive list of 29 automobile brand features, there is high collinearity among the features (e.g. power, torque, and acceleration). Thus, consistent with extant research (e.g., Thatchenkary 2008), we only use a subset of these features: horsepower, weight, and height that capture "performance" (speed and acceleration), width and weight variables that capture "safety," and width and height that capture "size and comfort." Other than these, we have indicator variable for luxury/non-luxury automobile brands, i.e., 0 for luxury brand and 1 for non-luxury brand. We also have a variable for generation change, with value 0 if the generation of a brand in a year is same as the one in previous year, 1 otherwise; and we also include a variable indicating age of the brand in terms of number of years since its initial launch year in the U.S. market.

As an additional measure of quality, we use annual recalls data obtained from NHTSA, i.e., national highway traffic safety administration. A recall is described as: "When a manufacturer or the National Highway Traffic Safety Administration determines that a car or item of motor vehicle equipment creates an unreasonable risk to safety or fails to meet minimum safety standards, the manufacturer is required to fix that car or equipment." A manufacturer will have to rectify or replace parts, if the recall is a safety recall, and to inform the vehicle owner of the recall. We use data on the potential number of affected vehicles as the measure of recalls for a make-model-year.

3.3. Ratings Data

As mentioned earlier, we are exploiting the launch of the USNWR automobiles meta-report card on the backdrop of incumbent ratings in the market. According to a study by J.D.

Power (2014),[5] J.D. Power, Kelly Blue Book, and Consumer Reports, are the three most important information resources consumers consider when researching the quality of automobile brands. We include data on these automobile performance disclosure sources. Most of the automobile manufacturer websites and offline dealer stores advertise the performance of their brands on Kelly Blue Book yearly awards and J.D. Power reliability studies. We use the initial quality score/predicted reliability score from J.D. Power (1-5 score), and the best cars awards (1/0 code for award/no award) in various automobile segments from Kelly Blue Book. We also use the overall road test rating (0-100 score) from Consumer Reports, which is a surrogate for the 'existing consumer voice' on the automobile brands in market (www.consumerreports.org). The correlation between the incumbent ratings from J.D. Power and Consumer Reports is .30, an evidence of variation in performance scores across brands and hence an opportunity for information synthesis. We also include the automobile ratings of our focal interest, i.e., ratings on USNWR automobile meta-report card about overall performance of automobile brands on 1-10 score (correlation of USNWR ratings is .36, .47, and .21 with Consumer Reports, J.D. Power, and Kelly Blue Book respectively). In Figure 3, we show the density plot of ratings, while in Figure 4, we present the screenshot of the USNWR report card on usnwr.com (assessed December 2017).

[5] See http://www.jdpower.com/press-releases/2014-new-autoshopper-study, assessed April 2018.

4. Model Specification

In this section, we specify the econometric model to estimate the economic value of meta-report cards in section 4.1, followed by discussion on identification challenges and strategy in section 4.2.

4.1. Consumer Demand and the Value of Meta-Report Cards

We specify an aggregate nested-logit model of demand, akin to model by Berry (1994), and use this model to estimate the economic value of the meta-report card (Train 2009).

4.1.1. Demand Model

For a market with $b = 1, \ldots, B$ automobile brands (where we represent year as $t = 1, \ldots, T$), we conceptualize the mean utility level for brand b as the ratio of log of the brand share s_{bt} to the share of outside alternative s_{0t} at time t (Berry 1994). As Berry (1994) discusses, when consumer tastes are identically and independently distributed, only mean utility differentiates the brands. The mean utility is specified as a function of observed automobile brand features (x_{bt}), price (p_{bt}), and unobserved brand attributes (ξ_{bt}; i.e., brand specific information uncertainty). As is often the case (e.g., Honka 2014; Sudhir 2001), we augment this specification by including other demand influencers, i.e., advertising spending (a_{bt}), incumbent ranking (w_{bt}; i.e., Consumer Reports, J.D. Power Ratings, and Kelly Blue Book), and indicator variable takes the value 1 for brands rated in USNWR (USN_{bt}).

(1) $$\ln(s_{bt}/s_{0t}) = \beta_x x_{bt} + \beta_p p_{bt} + \beta_a a_{bt} + \beta_w w_{bt} + \beta_u USN_{bt} + \xi_{bt}.$$

where, the β coefficients represent the influence of the respective variables; our interest is in β_u, which if positive and statistically significant implies value of meta-report card to consumers. The market shares s_{bt} and s_{0t} are defined by using number of households in the U.S. in a given year as market size (e.g., Gordon 2009).

In the above model specification, distributional assumption on the error term ξ_{bt} enables one to estimate the model. As the substitution patterns for logit errors suffer from independence of irrelevant alternatives issues (e.g., Train 2009), we use the nested logit specification, which allows correlations among consumer tastes across 'competing' brands (e.g., Berry 1994). Under this specification, the decision process that generates demand follows a nested structure, i.e., consumers choose an automobile type first (sedan, compact cars, sports car, SUV, pick-up trucks etc.) followed by the brand (Highlander, CR-V, R8). Thus, we divide the brands into $g = 0,1,2 \dots G$ groups (see Table 2) with $g = 0$ being the outside alternative.[6] Following Berry (1994, p. 253) one can transform the logit equation (1) into a nested logit equation by adding a term $\ln(\bar{q}_{b|g})$, the log of within group share where group is defined based on the automobile segment.

(2) $$\ln(s_{bt}/s_{0t}) = \beta_x x_{bt} + \beta_p p_{bt} + \beta_a a_{bt} + \beta_w w_{bt} + \beta_u USN_{bt} + \sigma \ln\left(\bar{q}_{b|g}\right) + \xi_{bt}$$

The model in equation (2) represents a linear demand equation that accommodates the pre-launch and post-launch period of USNWR to estimate the effect of meta-report card on consumer demand. Thus far, we only model whether a brand is rated or not. To assess the impact of ratings, only for brands that the meta-report card rates, we specify a similar model, where we model the ratio of log of shares but only for the rated brands. Thus, this model estimates the effect of unit change in rating for the rated brands. Specifically:

(3) $$\ln(s_{bt}/s_{0t}) = \gamma_x x_{bt} + \gamma_p p_{bt} + \gamma_a a_{bt} + \gamma_w w_{bt} + \gamma_r R_{bt} + \eta \ln\left(\bar{q}_{b|g}\right) + \mu_{rbt}, if\ USN = 1$$

[6] For specificity, if we use i to represent a utility maximizing consumer, then, similar to Cardell (1997), we can represent the consumer-brand-time level error term as: $\zeta_{igt} + (1-\sigma)\, \epsilon_{igbt}$. Here, ζ_{igt} is the shock common to all brands in group g, σ is the similarity coefficient (which ranges between 0 and 1, where values closer to 1 suggest that shocks consumers receive are similar within a group), and ϵ_{igbt} is the idiosyncratic consumer-brand-time specific shock, which for nested logit model comes from type I extreme value distribution.

where, R_{bt} denotes the USNWR meta-report ratings (1-10 scale), with γ_r as the corresponding coefficient and μ_{rbt} is the nested logit error term.

4.1.2. Value of Information Synthesis

The primary benefit that USNWR meta-report card offers to consumers is the synthesis of multi-source information, i.e., the systematic aggregation, evaluation, and presentation of information in a form useful to consumers (Repo 1989). To evaluate the value of this information synthesis, we use the "willingness to pay" definition of consumer surplus offered by Marshall (1920), i.e., the excess monetary amount the consumers are willing to pay for meta-report card given access to other information sources.

The automobiles market has multiple product report cards; for example, Consumer Reports and J.D. Power that both publish new car quality scores (called Road Test Score and Initial Quality Score respectively). Often these multiple report cards offer divergent information that leads to an information uncertainty (e.g., in 2011, Toyota FJ Cruiser has 5 points (1-5 scale) on J.D. Power Initial Quality Score and 36 points (0-100 scale) on the Consumer Reports Road Test Score). The information synthesis offered by meta-report card holds the potential of reducing information uncertainty, thereby enhancing consumer utility (Repo 1989).

We base our argument for the benefit of information synthesis on the assumption that consumers are aware of the USNWR website for automobile meta-report card. Similar to Armstrong and Zhou (2009), we offer two points of defense for this assumption. First, rational consumers would access the USNWR meta-report card before approaching other information sources, which are likely to be the inputs to meta-report card. Second, bounded rational consumers should be susceptible to information presentation formats (e.g., Dranove and Jin 2010). During online search for automobiles, as USNWR appears among the top results, these consumers are likely to view the meta-report card and thereby rely on the synthesized information.

Formally, the economic value of information synthesis represents the money that a consumer may be willing to pay to obtain the USNWR meta-report card. It is the incremental utility, in dollar terms that a consumer receives due to change in choice situation in a regime where USNWR meta-report card exists. Alternatively**,** from USNWR's perspective, economic value is the price-point that USNWR might want to choose if it plans to sell its automobile ratings. For our nested-logit model specification, we represent the expected value of economic value of information synthesis (EVI) as (e.g., Small and Rosen 1981):

(4) $$E(EVI) = \left(1/\beta_p\right) * [ln\,(\textstyle\sum_{j=0}^{J} \exp(V_{USNWR=1}) \;-\; ln\,(\sum_{j=0}^{J} \exp(V_{USNWR=0})]\,,$$

where the utility is linear in price (income) coefficient β_p , the term $V_{USNWR=1}$ refers to the measurable portion of utility derived from the brands when USNWR meta-report is available, and $V_{USNWR=0}$ refers to the measurable portion of utility derived from brands when the report card is unavailable. The division by the marginal utility of price, i.e., β_p , translates it into dollars. Since only a part of utility is measured/observed, i.e., V, we are able to calculate the expected value of information, where the expectation is over all possible values of ξ_{bt}.

4.2. Identification Challenges and Strategy

In equations (2) and (3), there could be omitted variables that correlate with critical independent variables that result in identification challenges. These challenges fall under four categories: (1) endogeneity of treatment (brand being rated vs. not-rated) that concerns β_u coefficient, (2) endogeneity of the brand rating that concerns γ_r coefficient, (3) endogeneity of marketing mix variables that concerns β_p (and γ_p) for price and β_a(and γ_a) for advertising, and

(4) endogeneity of nested-logit term. For each of these variables, we first discuss the potential reasons that could lead to endogeneity concern followed by our identification strategy.

4.2.1. Endogeneity of Treatment

USNWR's decision on which brands to rate (i.e., treat) is unlikely to be random or non-strategic as USNWR has a profit motive. Based on our understanding of the research context, we believe that there are three rules USNWR likely uses to decide which brands to rate. First, USNWR might rate brands in a specific segment in order to provide comprehensive ratings within segments. The choice of segment is likely to be strategic such that USNWR might choose popular segments to rate in order to garner higher traffic for its website. Empirical evidence points to such selection, where, for example, we find that the luxury automobiles brands are less likely to be rated. Likewise, we find that the average price of rated brands is lower than the not-rated brands (Figure 5). Second, as USNWR meta-report card relies on information existing in the market (e.g., incumbent report cards), as information on a brand increases, the likelihood of the brand being rated should also increase. Thus, brands that are newly launched and brands that see a generational changes (which happen every 4-7 years for most brands) should be less likely to be rated. Third is the brand popularity, i.e., USNWR could rate popular automobile brands, as customers are more likely to seek these brands and therefore more likely to rely on USNWR ratings (see Doherty, Kartasheva, and Phillips (2012) for similar issue concerning credit rating agencies).

We use control variables to correct for the first two rules. First, for USNWR tendency to rate specific segments, we include segment-specific fixed effects and luxury/non-luxury indicator variable in the demand model (equation 2). Likewise, for information available in the market, we include covariates for generation change variable and age of the brand since launch in the demand model. For the third rule that concerns brand popularity, we use an instrumental variable approach wherein we use the lagged sales of the brand as the excluded variable. The lagged sales (z_i) satisfies the exclusion restriction criteria because the utility derived from a brand depends on its characteristics and not on the past sales per say.

Since treatment is a binary endogenous variable, 2SLS instrument variable approach used for linear model becomes a 'forbidden regression' (Angrist and Pischke 2009, p. 190). Consequently, we use the three-step approach instrumental variable that Wooldridge (2002, p. 623-625) and Angrist and Pischke (2009, p. 191) advocate. In the first step, we estimate a probit regression of the endogenous treatment variable on the exogenous variables in equation (2)[7] and lagged sales, our instrumental variable. In the second step, we estimate a least squares regression of the endogenous treatment variable on the exogenous variables in equation (2) and the predicted probabilities from first step. In the final step, the outcome variable $\ln(s_{bt}/s_{0t})$ is regressed on the exogenous variables and the predicted values from second step – as is typical final step for instrumental variable regression. The intermediate step in this approach allows us to employ a non-linear probability for the assignment of the treatment but does not impose distributional assumption for the probability model (Basinger and Ensley 2010).

As a robustness check, we also use the Heckman (1979) style approach for treatment endogeneity correction, which is a two-step approach. The first stage is a probit model, similar to previous approach. We use the result from first stage regression to compute the inverse Mills

[7] Exogenous variables are automobile features (height, width, horsepower/weight, length, efficiency, and cargo space), and incumbent ratings (JD Power, Kelly Blue Book, and Consumer Reports). Since there are multiple endogenous variables in the demand equation for treatment model (equation 2), we perform the general IV regression model (Angrist and Pischke 2009, p. 176), wherein for each of the first stage regressions for three endogenous variables, we include the instrument variables for all the endogenous variables.

ratio (λ), which we include in the demand model as a covariate. As we elaborate subsequently, our results are consistent across the instrumental variable and Heckman style approaches.

4.2.2. Endogeneity of Brand Rating

For the brand rating model (equation 3), omitted time varying brand-specific variables could result in correlation between brand rating R_{bt} and the error term. We use a combination of fixed effects and time varying covariates to proxy such omitted variables. First, we use a comprehensive set of automobile features and incumbent brand ratings. In an alternate model, we also use number of brand recalls to further proxy any quality related time varying omitted variable. Second, we include 'make' fixed effects (e.g., Ford, Honda, Acura, etc.), to account for make level time invariant quality and year fixed effects to account for time trends, including change in rating policy.

4.2.3. Endogeneity of Marketing Mix

USNWR might choose the brands to rate based on their marketing mix variables, i.e., price (p_{bt}) and advertising spends (a_{bt}). The primary goal of USNWR is to generate viewership for the meta-report card. As more individuals buy lower priced and more advertised brands (e.g., Iizuka and Jin 2005; Manchanda, Rossi, and Chintagunta 2005), USNWR viewership should be higher if lower priced and more advertised bards are rated. We propose to correct for the price and advertising endogeneity using an instrumental variable approach.

Following Berry, Levinsohn, and Pakes (1995), for price we use average of the characteristics of other brands in the nest as the focal brand as the instruments. The instrument meets the relevance condition because the characteristics of brands in a particular automobile segment should correlate with its price. The instrument meets the exclusion restriction because characteristics of brand $k \neq j$ do not influence the utility of brand j. Consistent with

Chintagunta, Gopinath, and Venkataraman (2010), for advertising spends we use future advertising spends as the instrument. Consistent with the instrument relevance condition, current advertising spends should correlate with advertising spends in future. However, since the utility for consumers at time t should not be influenced by advertising spends at time $t+1$ or later; the instrument meets the exclusion restriction. Further, as we include covariates for a rich set of brand attributes and fixed effects (make and time fixed effects), in conjunction with the instruments, endogeneity of price and advertising spends should be obviated.

4.2.4. Endogeneity of Nested Logit Term

In equations (2) and (3), the nest term i.e., $\sigma \ln\left(\bar{q}_{b|g}\right)$ or ($\eta \ln\left(\bar{q}_{b|g}\right)$) term is endogenous because any unobserved variable that impacts demand of a brand also impacts the within nest share of that brand (Berry 1994). We use the log of price and non-price automobile attributes of other brands within the group as instruments to correct for this potential endogeneity issue (as in Berry 1994). Incorporating all changes discussed, leads to rewriting equations (2) and (3) as:

(5) $\ln(s_{bt}/s_{0t}) = \beta_x x_{bt} + \beta_p p_{bt} + \beta_a a_{bt} + \beta_w w_{bt} + \beta_u USN_{bt} + \sigma \ln\left(\bar{q}_{b|g}\right) + \omega_t + m_b + \xi_{bt}$

(6) $\ln(s_{bt}/s_{0t}) = \gamma_x x_{bt} + \gamma_p p_{bt} + \gamma_a a_{bt} + \gamma_w w_{bt} + \gamma_r R_{bt} + \eta \ln\left(\bar{q}_{b|g}\right) + \varpi_t + \mathcal{M}_b + + \mu_{rbt}, if\ USN = 1.$

where, ω_t and ϖ_t are time fixed effects and m_b and $\mathcal{M}_b$ are make fixed-effects for treatment and rating models respectively.

5. Results

5.1. Model Free Evidence

To provide the model free evidence we explore the relationship between sales (and sales growth) for brands that are rated/not-rated brands and correlation of sales (and sales growth) with the rating score itself. First, across the years since the launch of USNWR meta-report card, automobile brands that are rated in the meta-report card, on average have significantly higher sales than the brands which are not rated in that year (Figure 6 and Table 4 Column 1: $\beta_u = .388, p < .01$). Similar findings emerge for sales growth in a comparison of rated brands with not-rated brands (Table 4 Column 2: $\beta_u = .295, p < .01$). Second, as we see from Figure 7 (also see Table 4 Column 3: $\gamma_r = .324, p < .01$), brands with higher ratings do have higher sales associated with them; further, ratings also positively correlate with change in sales (Table 4, Column 4: $\gamma_r = .003, p < .10$).[8]

5.2. Model Based Evidence

In Table 5, we present the findings from the nested logit model (equation 5), where log of the ratio of brand share to share of the outside option is the dependent variable. Results show that the availability of the USNWR report card is associated with higher brand share ($\beta_u = .354, p < .01$). This association exists for automobile quality information in the form of performance disclosure from Consumer Reports, Kelly Blue Book, and J.D. Power, which accounts for the performance, safety, comfort, reliability, and awards conferred to automobiles, and automobile

[8] To examine how UNSWR meta-ratings relate to incumbent ratings (JD Power, Consumer Reports, and Kelly Blue Book), we ran a regression of USNWR meta- ratings on these incumbent ratings. The r-square of .47 for this regression suggests that USNWR meta-ratings capture more than just the incumbent ratings.

features. As expected, the price coefficient is negative and significant ($\beta_p = -.029, p < .10$), while advertising spends coefficient is positive and significant ($\beta_m = .001, p < .10$). JD Power dependability/reliability ratings are significant ($\beta_{w=JDP} = .146, p < .01$), and so are the Consumer Reports ratings ($\beta_{w=CR} = .006, p < .01$). In addition, the term pertinent to nested logit model group-share is also positive and significant ($\sigma = .124, p < .01$) implying that there are interactions between consumer choices and product characteristics.[9]

To get closer to causality, we first correct for the possible endogeneity owing to the selective and staggered inclusion of brands in USNWR automobile ratings. Specifically, as we discussed earlier, we use the three-step IV approach in the nested logit specification. In the three step approach, we first estimate a first stage probit model with treatment dummy variable as the dependent variable and lagged log-sales ($\beta = .180, p < .01$) probabilities as excluded variable followed by a linear regression with predicted probabilities ($\beta = .323, p < .05$) from fist stage and the excluded variable ($\beta = .008, p < .10$). In the third step, we include the fitted values of the endogenous variable (instead of endogenous variable itself) in the demand equation. This correction reduces the magnitude of USN coefficient, but it is still statistically significant ($\beta_u = .305, p < .01$). We also did the robustness check, wherein we used the Heckman correction for treatment endogeneity correction. We find the treatment coefficient to be positive and significant ($\beta_u = .721, p < .05$).

[9] The coefficients for most of the automobile features are not statistically significant. Since we are using a fixed effects model (manufacturer level and time fixed effects) along with various performance disclosure measures from Consumer Reports, J.D. Power, Kelly Blue Book, and USNWR automobile report card, perhaps there is little variation left for the automobile features to explain. In absence of fixed effects and report cards information, automobile features do have statistically significant coefficients in the expected direction.

We also correct for endogeneity of price and advertising spends and the nested-logit term using established instrumental variable approaches. As we see from Table 5 Column 3, the USN coefficient reduces in magnitude but it is still statistically significant ($\beta_u = .282, p < .01$). In contrast, the coefficients for advertising spends ($\beta_a = .007, p < .01$) and price ($\beta_p = -.037, p < .01$)[10] increase in magnitude. These parameter estimates are mostly consistent across all the models and past studies for automobiles.[11]

5.2.1. Value of Information Synthesis

Using the estimates in the nested-logit demand estimation given in Table 5, Column 3, we estimate the value of information synthesis associated with introduction of USNWR meta-report card; specifically, we obtain the value of the measurable utility terms $V_{treat=1}$ and $V_{treat=0}$. We find that introduction of meta-report card leads to the consumer gain of $10.53 (average over years 2007-2012).

We calculate value of information synthesis (using equation 4) for all years 2007-2012, and quantified value ranges from $2.90 to $16.89, with the average value (over years) narrowing to $10.53. A potential reason for value to increase over years is that the number of brands that are 'treated' increase over years, which makes the additive term $ln\ (\sum_{j=0}^{J} \exp(V_{USNWR=1})$ larger and the term $ln\ (\sum_{j=0}^{J} \exp(V_{USNWR=0})$ smaller.

[10] Whenever there is a positive demand shock (i.e., demand shifts outward), price goes up. This shift should lead to upward bias for the price coefficient. Thus, after the endogeneity correction, as expected, the coefficient of price has become more negative. Since, likelihood of treatment (i.e., brands be rated) declines with increase in price (see Figure 5.) the direction of bias for treatment dummy (i.e., USN for brands rated/not-rated) should be in opposite direction to that of price. Consistently, the coefficient for USN drops to .282 from .305.

[11] In the meta-analysis on advertising elasticities, Henningsen, Heuke, and Clement (2011) present average coefficient of all studies to be .09. In the meta-analysis on price elasticities, Bijmolt, Heerde, and Pieters (2005) find that for 81% of the studies, coefficient lies between -4 and 0.

5.2.3. Ratings and Demand

The alternatives rated higher are more attention catching and connote higher quality than lower rated brands (Armstrong et al. 2009). In this section, we estimate demand equation (6), for brands that are rated, i.e., $USN = 1$. For these rated brands we find that one unit increase in ratings (where ratings range from 1 to 10) is associated with .329 ($\gamma_r = .329, p < .01$) increase in mean utility of brand (Table 8, Column 1). The size of this effect reduces to .254 ($\gamma_r = .254, p < .01$) in Table 8 Column 3, after we correct for selection bias and endogeneity of marketing mix variables is addressed. On an average, one standard deviation (where SD = .58) improvement on USNWR ratings enables a brand to charge $3560 more or save around $12 million on advertising. Compared to other product report cards, the effect of USNWR has 1.13 and 1.18 times more pronounced than Consumer Reports and J.D. Power respectively.

5.3. Behavioral Mechanisms

To explore the mechanism underlying the effect of ratings on demand, we study the search cost reduction mechanism and quality assurance mechanism. As we do not observe individual level search behavior and only observe the aggregate sales and other aggregate measures at the brand level (e.g., price, marketing spends etc.), we identify search cost reduction by examining situations when search costs are likely to change. Specifically, search costs should increase as information from other sources decline. As advertising is an important source of information, search efforts should decrease as advertising spends increase. Anecdotal evidence seems to suggest this possibility. For example, according to the Statista Database (2017), Subaru, Chevrolet, Infiniti, and Volkswagen are the four largest automobile T.V. advertising spenders ensuring sizeable reach among consumers; in contrast, Ford, Lexus, Kia, and Toyota are the four most searched brands online – these brands spend relatively less on advertising. Thus, we expect that coefficient for *USN* (i.e., whether a brand is rated/not-rated) to be higher as advertising spends decline. To test this assertion, we introduce an interaction term between *USN* and advertising spends (where the coefficients of interest is β_{ua}):

(7) $\ln(s_{bt}/s_{0t}) = \beta_x x_{bt} + \beta_p p_{bt} + \beta_a a_{bt} + \beta_w w_{bt} + \beta_u USN_{bt} + \beta_{ua}(USN_{bt} * a_{bt}) + \sigma \ln\left(\bar{q}_{b|g}\right) + \omega_t + m_b + \xi_{bt},$

We find support for our assertion as β_{ua} is negative (Table 9, Column 1, $\beta_{ua} = -.038, p < .01$); thus, the value of a brand being rated decreases as advertising spends increase, thereby supporting the search cost reduction mechanism.

As additional evidence for search cost reduction mechanism, we explore information uncertainty among incumbent report cards as indicated by the standard deviation (Ω_{bt}) between the scores of incumbent product report cards. The value of meta-report card should increase with increase in uncertainty, i.e., standard deviation increases. Thus, we estimate the following specification:

(8) $\ln(s_{bt}/s_{0t}) = \beta_x x_{bt} + \beta_p p_{bt} + \beta_a a_{bt} + \beta_w w_{bt} + \beta_u USN_{bt} + \beta_{u\Omega}(USN_{bt} * \Omega_{bt}) + \sigma \ln\left(\bar{q}_{b|g}\right) + \beta_\Omega \Omega_{bt} + \varpi_t + \mathcal{M}_b + \xi_{bt}$

Here again, we find support for search cost reduction mechanism. Specifically, as the uncertainty increases, the value of the meta-report card increases (Table 9, Column 2 $\beta_{u\Omega} = .225, p < .01$).

To explore the quality assurance mechanism, we argue that if the effect of ratings (on 1-10 scale) exists even if the objective quality of the automobile does not change, the positive effect of ratings suggests the presence of quality assurance mechanism. We use two model specifications, to establish quality assurance mechanism for ratings model: single generation model and the recalls model.

First, we estimate the model in equation 6 using a subset of data containing only one generation of each make-model. A generation of an automobile brand refers to the number of years for an automobile brand during which there are no substantial changes in its features. Typically, a generation of an automobile brand lasts for 4-7 years, where during this period observable (e.g., weight) and unobservable (e.g., design) brand characteristics do not change substantially. For example, for Acura MDX, there are three generations in the time-period 2004 to 2012; however, there is not a major change in brand features over the three generations 2004-2005, 2006-2007, and 2008-2012. To exploit this constancy in objective quality of automobiles, we only include data for the longest period where we do not observe a substantial change in its features. For relatively newer brands (e.g., Honda Fit) in the market, we include observations for later generations than the initial ones, because in the initial years more changes are likely.[12] We find that the effect of ratings still exit (Table 10, Column 1, $\gamma_r = .362, p < .05$).

Second, in the recalls model, we use the number of make-model recalls in a particular year as an additional controller of quality of the automobile. Here again, we find that the effect of ratings is positive and statistically significant (Table 10, Column 2, $\gamma_r = .132, p < .05$).

[12] In the demand equations 5-6, we include two types of fixed effects – manufacturer level fixed effects to control for the time-invariant omitted quality variables, and time fixed effects to control for industry specific time shocks. The key identifying assumptions underlying a fixed effects model are that (1) the omitted variable(s) are invariant over the time period of study, and (2) there is enough cross-sectional variation in the variables of interest and sales of automobiles to be able to estimate the effect. Typically, when the time dimension is short, the identifying assumption of time-invariance of omitted variables is easier to justify. However, this assumption can be questioned in our case because the sample period runs over eight years. One cannot expect the omitted quality/imagery variables to be static for so long. Thus, having a single generation model observations (only) in the estimation mollifies the issue of issue of invariance of omitted variables over time (Table 9).

6. Discussion

We begin by summarizing the insights of our research, followed by discussion on the limitations, contributions, and conclusion. Given inundation of information sources these days, the important empirical question regarding meta-report cards concerns their value to consumers and marketers, i.e., whether consumers benefit from meta-report card in presence of other information sources, and whether marketers benefit from having their brands rated by the report card.

Recognizing that value of information lies in uncertainty reduction, which a meta-report card accomplishes by information synthesis, we empirically estimate the monetary value of USNWR automobile meta-report card to consumers as $10.53 (ranging from $2.90 to $16.89 depending upon the year 2007-2012). For marketers, one standard deviation improvement in USNWR rating is equivalent to $3560 in price charged and around $12 million advertising spends. We establish the same by using a natural experiment generated by the introduction of USNWR automobile meta-report card in the automobile market, and isolate the causal effect of USNWR ratings of brands on consumer demand. We find that the value of meta-report card manifests through search cost reduction and quality assurance mechanisms.

6.1. Limitations

It is important we recognize a couple of limitations. First, it is likely that some consumers might not even visit the USNWR meta-report card website while searching for automobiles, while others might rely heavily on the report card. Although our effects are at the aggregate level, this phenomenon may play a nontrivial role in amplifying the effect of rating because we assume that all automobile shoppers access the report card. Nevertheless, there is anecdotal evidence in favor of this assumption. Foremost, the USNWR ratings seem to be an important information source online as the website is one of the top links in google search results for automobile keyword search. We used spyfu.com website for empirical evidence of this claim.[13] For example, for the keywords such as – car rank, car rating, best car, best sedan, best SUV, best sports car, best pickup truck, make model price (e.g. Honda Accord price), USNWR link is mostly at the top or amongst the top 5-7 links. Further, USNWR is a free source for automobile performance reporting, unlike, for example, Consumer Reports, and due to its existing equity in college rankings it is a credible source of information for consumers.

Second limitation concerns the supply side perspective to the meta-report card. Foremost, as the value of meta-report card ratings lies in affecting demand, in the long run, manufacturers may have incentives to allocate resources to improve ratings without changing product characteristics. Further, we assume that incumbent report cards, such as J.D. Power or Consumer Reports, do not change their rating strategy after the launch USNWR meta-report card. We abstract away from this supply-side view in this research. Despite these limitations, we believe that our research makes important contributions towards understanding the role of meta-report card for big-ticket products such as automobiles.

6.2. Contributions

By empirically estimating the value of automobile meta-report card USNWR, we add to the literature on product report cards and metasearch portals. In doing so, we build on the existing literature on product report cards in two ways. First, most of the existing scrutiny on product report cards is in the experiential goods or service category (e.g., Jin and Leslie 2003;

[13] The spyfu.com website that provides a keyword research tool that allows one to get the rank order of websites for the keyword combination put by the user.

Luca and Smith 2013); we extend the context of investigation to durable goods category. Second, while product report cards reduce information uncertainty by providing new information to consumers, meta-report cards do so by synthesizing information from multiple sources, including incumbent report cards. Second, most of the extant literature on information synthesis is largely conceptual in nature with little empirical scrutiny (e.g., Taylor's 1982; Goldschmidt 1986); we provide this scrutiny.

We also contribute to the literature on metasearch portals (e.g., De los Santos and Koulayev 2017; Ghose, Ipeirotis, and Li 2014), which unlike meta-report cards, also sell products. Most of the existing work has been about the metasearch portals in travel industry, where the consumers make decisions in a matter of hours or days. We study a relatively higher involvement category of automobiles with an extended decision-making period. Due to this more extensive decision-making period and, consecutively, deeper and wider search the influence of synthesized information is less apparent (e.g., Chetty, Looney, and Kroft 2009). Further, the existing research on metasearch portals uses individual level data to link search results to consumer behavior (e.g., clicks; De los Santos and Koulayev 2017) and examines search cost reduction as the mechanism underlying effect of metasearch portals (e.g., Ursu 2017). In contrast, we rely on the aggregate market level data and include information from rating sources (such as consumer reports) other than the meta-report card. We explore the search cost reduction and quality assurance as the potential mechanisms underlying influence of USNWR meta-report card.

6.3. Conclusion

It is reasonably facile to suggest that information available to consumer in the form of expert reviews and product report cards will swell. This trend across products and services should evince in the emergence of information synthesizers such as USNWR for the automobile sector. We show that such information synthesis is valuable for consumer and marketers where the underlying mechanisms concern search costs and quality assurance.

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Table 1a
Number of Models by Make (Total 447)

MAKE	N	MAKE	N
Acura	7	Land Rover	6
Aston Martin	4	Lexus	15
Audi	21	Lincoln	6
Bentley	6	Lotus	2
BMW	30	Maserati	2
Buick	4	Maybach	7
Cadillac	9	Mazda	11
Chevrolet	21	Mercedes-Benz	21
Chrysler	11	Mercury	7
Dodge	17	Mini	4
Ferrari	2	Mitsubishi	7
Ford	19	Nissan	19
Freightliner	2	Pontiac	11
Gem	9	Porsche	6
GMC	7	Rolls Royce	2
Honda	15	Saab	4
Hummer	4	Saturn	9
Hyundai	11	Smartcar	2
Infiniti	9	Subaru	9
Isuzu	4	Suzuki	4
Jaguar	11	Tesla	2
Jeep	9	Toyota	22
Kia	7	Volkswagen	11
Lamborghini	4	Volvo	15

Table 1b
Number of Make-Models by Automobile Type (N = 447)

TYPE	Total	Luxury	Non-Luxury
Compact SUV	40	7	33
Mid-size SUV	64	21	44
Full-size SUV	21	10	12
Traditional Compact	55	17	38
Traditional Subcompact	28	9	19
Traditional Full-size	38	18	20
Traditional Mid-size	48	24	24
Sports	60	39	21
Exotic/Prestige	34	34	0
Pickup	28	3	25
Van	30	0	30

Table 2: Information on Variables

Data Variable	Description	Source
Sales	Units at make-model level for each year	IHS Automotive/Polk
Price	Manufacturer suggested retail price for the most basic trim of make-model every year.	Polk, Consumer Reports, AutoTrader.com, autoevolution.com
Advertising Spends	TV, Internet, Radio, Newspapers, Magazines	Kantar Media Ad$pender
Automobile Features	Type (Table 1b), Engine cc, Engine type, Engine position, Valves, Horsepower, Torque, Compression, Top-speed, Acceleration, Country of origin, Tire types, CO_2 emission, Brakes type, Seats, doors, Turn-circle, Weight, Length, Width, Cargo-space, Fuel efficiency, Tank capacity, Fuel type, Transmission, Rear/front drive, Tire dimensions, Chassis, Luxury/non-luxury and Towing weight, Generation Change, Age of the Brand, Recalls	Pluup.com, NHSTA, Autoevolution.com
Report Cards	USNWR as well information from the popular incumbent report cards	USNWR, Consumer Reports, J.D. Power, Kelly Blue Book.

Table 3
Descriptive Statistics

Variable	N	Mean	Median	St. Dev
Sales Units	447	35711	15260	57164
Brand Share	447	.003	.001	.004
Brand Share in Nest	447	.33	.17	.35
Price(000'$)	447	52.97	31.71	73.41
Advertising Spend (000,000'$)	447	11.67	.304	25.68
USNWR Ratings (1-10 scale)	304	8.09	8.11	.59
J.D. Power Reliability (1-5 scale)	395	2.71	3.00	1.53
Consumer Reports Road Test Score (1-100 scale)	401	42.93	61.50	36.30
Kelly Blue Book (0-10, 1-10 awards, 0 no award)	354	6.21	4.30	0.46
Horsepower (HP)	447	240.30	210.30	126.30
Weight (kg)	447	1714.69	1675	433.13
Height (inch)	447	63.24	59.45	13.28
Width (inch)	447	73.31	73.00	7.02
Fuel Efficiency (mpg)	447	23.90	22.00	12.73
Cargo Space (liters)	447	700.30	464.01	847.55
Age of the Brand (No. of Years)	447	11.29	8.00	11.53
Generation Change	447	1.62	1	.74
Luxury/ Non-Luxury	447	0.41	0.00	0.49
Recalls (000,000s)	398	1.80	.45	2.83

Table 4
Model Free Evidence: Ordinary Least Squares

VARIABLES	(1) y = Sales	(2) y = Change in Sales	(3) y = Sales	(4) y = Change in Sales
Observations	1933	1728	894	821
USN (Rate = 1, Not Rate = 0)	.388***	.295***		
	(.123)	(.112)		
R_{bt}			.324***	.003*
			(0.09)	(.000)
Constant	8.817***	-.391***	7.331***	-.192
	(3.21))	(.022)	(1.34)	(.003)

Robust standard errors in parentheses
*** $p < .01$, ** $p < .05$, * $p < .10$

Table 5
Nested Logit Model

VARIABLES	(1) Base Model	(2) 3 Step IV for Treatment Endogeneity	(3) Final Model
Observations	1933	1933	1311
Number of Brands	447	447	377
p_{bt} (‘000s)	-.029*	-.035***	-.037***
	(.009)	(.011)	(.010)
a_{bt} (‘000 000s)	.001*	.004***	.007***
	(.000)	(.001)	(.005)
USN_{bt}	**.354*** **	**.305*** **	**.282*** **
	(.087)	**(.085)**	**(.098)**
σ_{bt}	.124***	.632***	3.34***
	(.032)	(.034)	(.046)
Horse Power/ Weight	-.519	-.588	.188**
	(.432)	(.432)	(.081)
Height	.001***	.007***	.005***
	(.000)	(.000)	(.000)
Width	.002	.012	-.003
	(.029)	(.030)	(.031)
Length	.004	.005	.104**
	(.004)	(.005)	(.004)
Fuel Efficiency	-.002	-.002	-.001
	(.011)	(.011)	(.012)
Cargo Space	.003	.006	.017
	(.001)	(.001)	(.001)
Age of the Brand	.011	.122	.121
	(.234)	(.321)	(.221)
Generation Change	-.103	-.333	-.133
	(.115)	(.225)	(.255)
JD	.146***	.120**	.145***
	(.029)	(.028)	(031)
CR	.006***	.007***	.003**
	(.002)	(.001)	(.001)
KBB	.0124	.0132	.0134*
	(.007)	(.006)	(.008)
Constant	19.49***	18.19***	18.694***
	(4.34)	(5.12)	(4.45)
Country of origin FE	YES	YES	YES
Year FE	YES	YES	YES
Make FE	YES	YES	YES
Automobile Type FE	YES	YES	YES

Robust standard errors in parentheses
*** $p < .01$, ** $p < .05$, * $p < .10$
Final model involves endogeneity correction of treatment variable, marketing mix and nested-logit term.

Table 6
3-Step IV Regression

Step 1 Results

VARIABLES	(1) Probit Model
Observations	1,894
Number of brands	435
Lagged Log-Sales)	.180***
	(.77)
Exogenous Variables (Table 5)	YES
Country of Origin FE	YES
Yea FE	YES
Make FE	YES
Automobile Type FE	YES

Standard errors in parentheses
*** p < .01, ** p < .05, * p < .10

Step 2 Results

VARIABLES	(1) Linear Model
Observations	1,894
Number of brands	435
Lagged Log- Sales	.008*
	(.00)
Predicted probability (Step 1)	.323**
	(.155)
Exogenous Variables (Table 5)	YES
Country of Origin FE	YES
Yea FE	YES
Make FE	YES
Automobile Type FE	YES

Standard errors in parentheses
*** p < .01, ** p < .05, * p < .10

Table 7
Nested Logit Model (Robustness Checks)

VARIABLES	(2) Heckman's Correction
Observations	1311
Number of Brands	377
p_{bt} ('000s)	-1.065***
	(.211)
a_{bt} ('000 000s)	.095**
	(.041)
USN_{bt}	**.721****
	(.111)
σ_{bt}	2.985***
	(1.034)
Horse Power/ Weight	-.488
	(.312)
Height	.005***
	(.000)
Width	-.003
	(.001)
Length	.104*
	(.030)
Fuel Efficiency	-.001
	(.021)
Cargo Space	.000
	(.001)
Age of the Brand	.011
	(.234)
Generation Change	-.103
	(.115)
JD	.048*
	(.011)
CR	.005***
	(.001)
KBB	.0134
	(.004)
λ_{bt}	-.303**
	(.004)
Constant	18.19**
	(6.66)
Country of origin FE	YES
Year FE	YES
Make FE	YES
Automobile Type FE	YES

Robust standard errors in parentheses
*** $p < .01$, ** $p < .05$, * $p < .10$

Table 8
Nested Logit Model for Rated Brands

VARIABLES	(1) Base Model	(2) Selection Bias Correction	(3) Final Model
Observations	643	643	453
Number of Brands	195	195	170
p_{bt} (‘000s)	-.008***	-.021***	-.032***
	(.008)	(.009)	(.011)
a_{bt} (‘000,000s)	.001	.008***	.011***
	(.002)	(.003)	(.004)
R_{bt}	**.329*** **	**.399*** **	**.254*** **
	(.088)	**(.098)**	**(.099)**
σ_{bt}	.423***	.406***	.374***
	(.021)	(.020)	(.051)
Horse Power/ Weight	-.336	-.289	-1.24*
	(.100)	(.100)	(.062)
Height	.007	.007	.009**
	(.011)	(.010)	(.000)
Width	.009	.080	.012
	(.013)	(.012)	(.011)
Length	.008	.008	.011**
	(.010)	(.003)	(.000)
Fuel Efficiency	-.002	-.002	.011
	(.012)	(.011)	(.060)
Cargo Space	.00014	.0002	.0009
	(.001)	(.001)	(.007)
Age of the Brand	.011	.031*	.211*
	(.014)	(.004)	(.014)
Generation Change	-.103	-.93	-.103
	(.512)	(.412)	(.441)
JD	.096***	.069**	.123**
	(.040)	(.020)	(.050)
CR	.005***	.009***	.004**
	(.001)	(.003)	(.000)
KBB	.009*	.011	.0121*
	(.050)	(.061)	(.050)
Constant	13.94***	13.81***	17.556***
	(5.331)	(4.173)	(4.321)
Country of origin FE	YES	YES	YES
Year FE	YES	YES	YES
Make FE	YES	YES	YES
Automobile Type FE	YES	YES	YES

Robust standard errors in parentheses
*** $p < .01$, ** $p < .05$, * $p < .10$
Final model involves endogeneity correction of marketing mix and nested-logit term

Table 9
Search Cost Reduction Mechanism

VARIABLES	(1) Advertising Spends	(2) Standard Deviation of Incumbent Ratings
Observations	1311	984
Number of Brands	377	322
p_{bt} (‘000s)	-.034***	-.029***
	(.012)	(.011)
a_{bt} (‘000,000s)	.011***	.003***
	(.005)	(.004)
USN	.414***	.247***
	(.010)	(.134)
USN * a_{bt}	-.038***	---
	(.009)	
USN* Ω_{bt}	---	.225***
		(.117)
Ω_{bt}	---	-0.03**
		(.001)
JD	.109***	.096**
	(.041)	(.044)
CR	.003***	.002***
	(.001)	(.000)
KBB	.013*	.019**
	(.005)	(.009)
Age of the Brand	.011	.210
	(.234)	(.331)
Generation Change	-.103	-.111
	()	(.)
Horse Power/ Weight	-1.114	-.212
	(.511)	(.111)
Height	.017***	.003***
	(.005)	(.001)
Width	.002***	.017***
	(.000)	(.008)
Fuel Efficiency	.0128	.006
	(.006)	(.005)
Cargo Space	.002	.003
	(.002)	(.001)
Constant	16.130***	21.632***
	(7.871)	(8.234)
Country of Origin FE	YES	YES
Year FE	YES	YES
Make FE	YES	YES
Automobile Type FE	YES	YES

Robust standard errors in parentheses
*** $p < .01$, ** $p < .05$, * $p < .10$

Table 10
Quality Assurance Mechanism

VARIABLES	(1) Single Generation Model	(2) Recalls Model
Observations	209	321
Number of Brands	93	131
p_{bt} ('000s)	-1.323***	-1.09***
	(.121)	(.011)
a_{bt} ('000,000s)	.051*	.077*
	(.006)	(.006)
R_{bt}	.365***	.132***
	(.123)	(.060)
Recalls		.034**
		(.016)
JD	.108**	.096**
	(.005)	(.044)
CR	.008***	.002***
	(.002)	(.000)
KBB	.017	.019**
	(.010)	(.009)
Age of the Brand	.011	.211
	(.234)	(0.221)
Generation Change	-.103	-.911
	(.12)	(.15)
Horse Power/ Weight	-.996	-.0697
	(.421)	(.127)
Height	.037***	.008***
	(.011)	(.001)
Width	.016**	.007
	(.008)	(.020)
Fuel Efficiency	.0211	.021*
	(.011)	(.017)
Cargo Space	.0048	.009**
	(.004)	(.004)
Constant	27.256 ***	21.201 ***
	(12.541)	(10.123)
Country of origin FE	YES	YES
Year FE	YES	YES
Make FE	YES	YES
Automobile Type FE	YES	YES

Robust standard errors in parentheses
*** p < .01, ** p < .05, * p < .10

Figure: 1

USNWR Automobile Rating

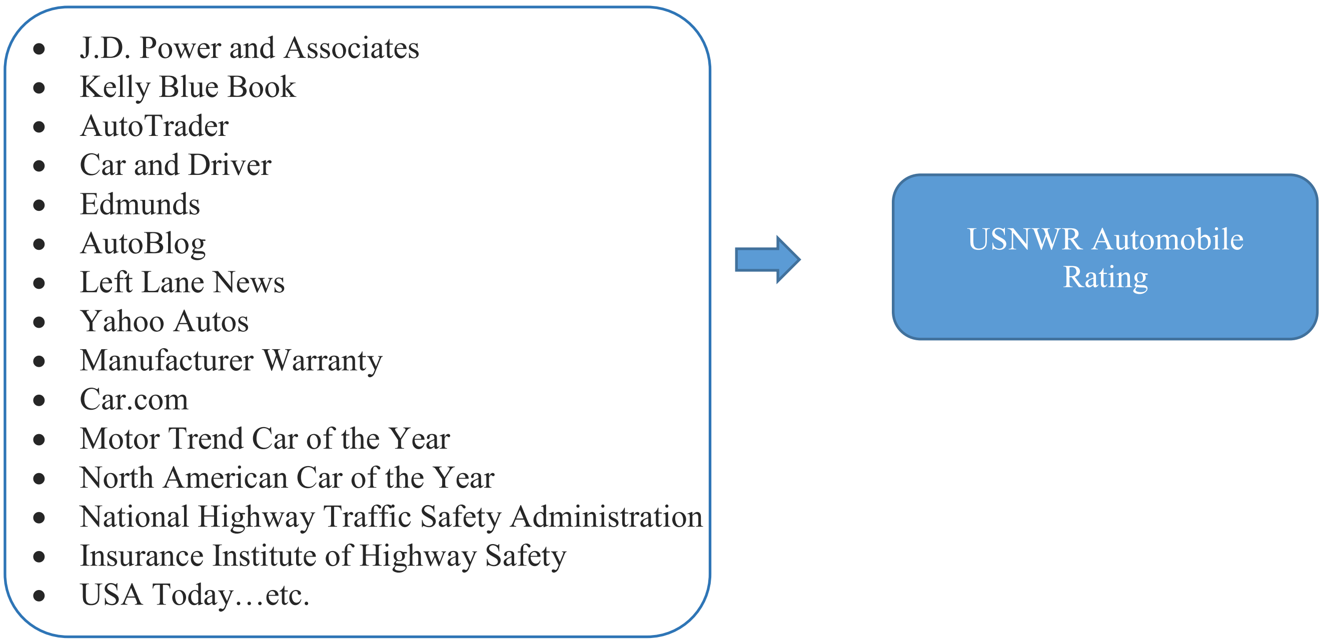


Figure: 2

Before/After Natural Experiment

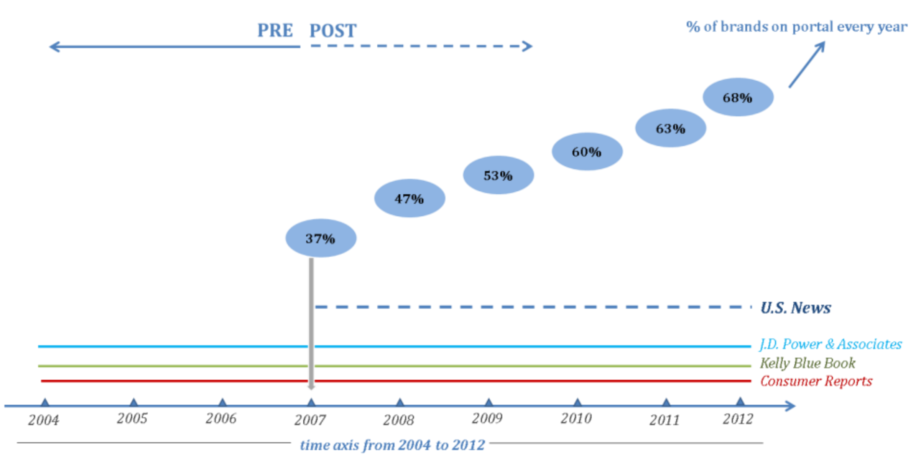


Figure: 3

Distribution of Ratings (1-10 score)

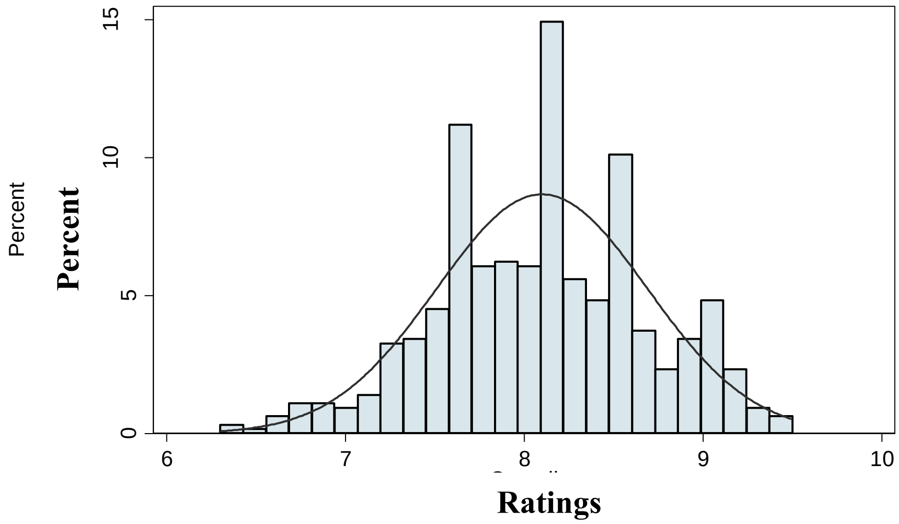
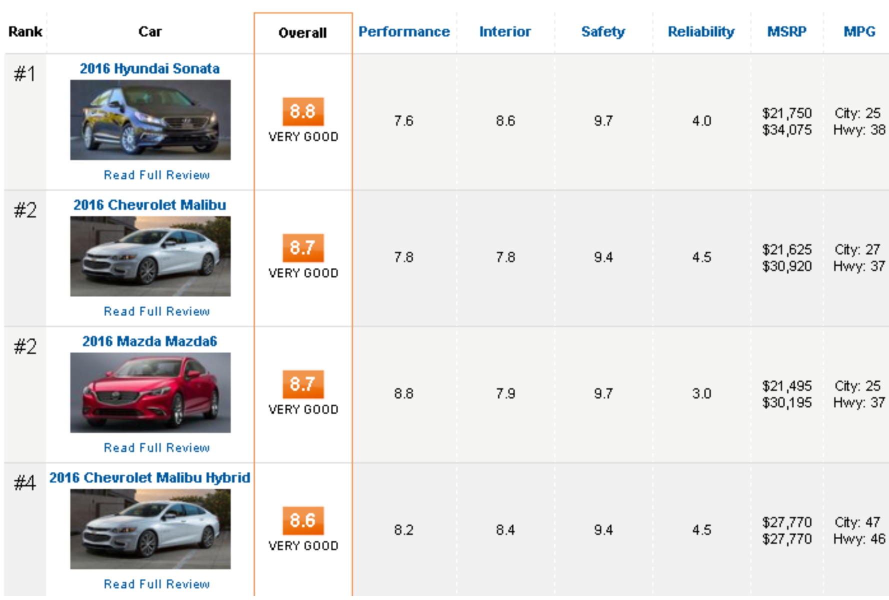


Figure: 4

Screenshot of the Automobile Ratings Mid-Size Sedans on USNWR



Rank	Car	Overall	Performance	Interior	Safety	Reliability	MSRP	MPG
#1	2016 Hyundai Sonata Read Full Review	8.8 VERY GOOD	7.6	8.6	9.7	4.0	$21,750 $34,075	City: 25 Hwy: 38
#2	2016 Chevrolet Malibu Read Full Review	8.7 VERY GOOD	7.8	7.8	9.4	4.5	$21,625 $30,920	City: 27 Hwy: 37
#2	2016 Mazda Mazda6 Read Full Review	8.7 VERY GOOD	8.8	7.9	9.7	3.0	$21,495 $30,195	City: 25 Hwy: 37
#4	2016 Chevrolet Malibu Hybrid Read Full Review	8.6 VERY GOOD	8.2	8.4	9.4	4.5	$27,770 $27,770	City: 47 Hwy: 46

Figure: 5

Average Price of Automobile Brands in the Treated and Non-Treated Group

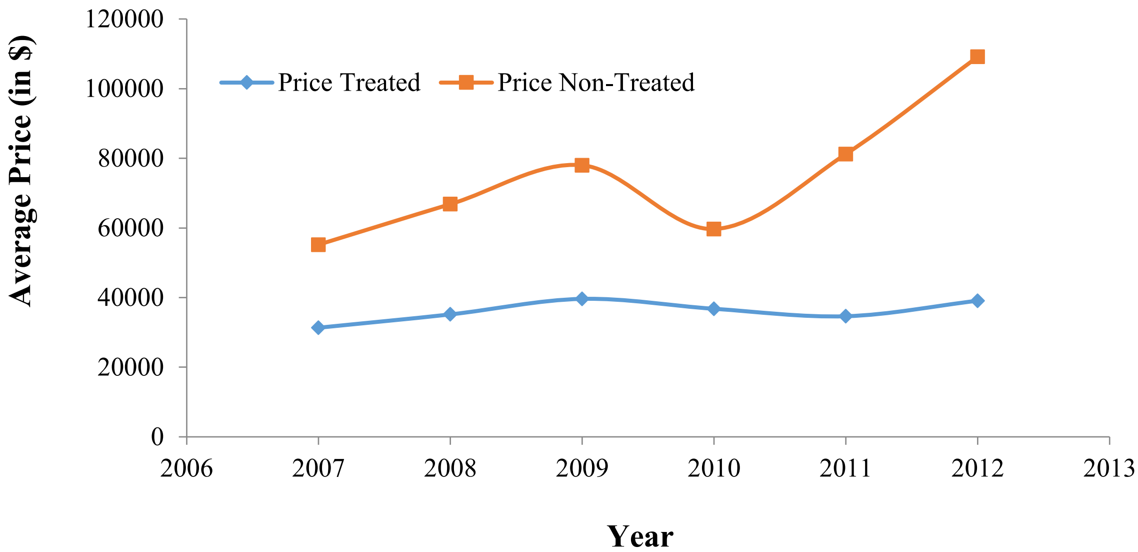


Figure: 6

Model Free Evidence: Average Sales of the Treated and Non-Treated Group

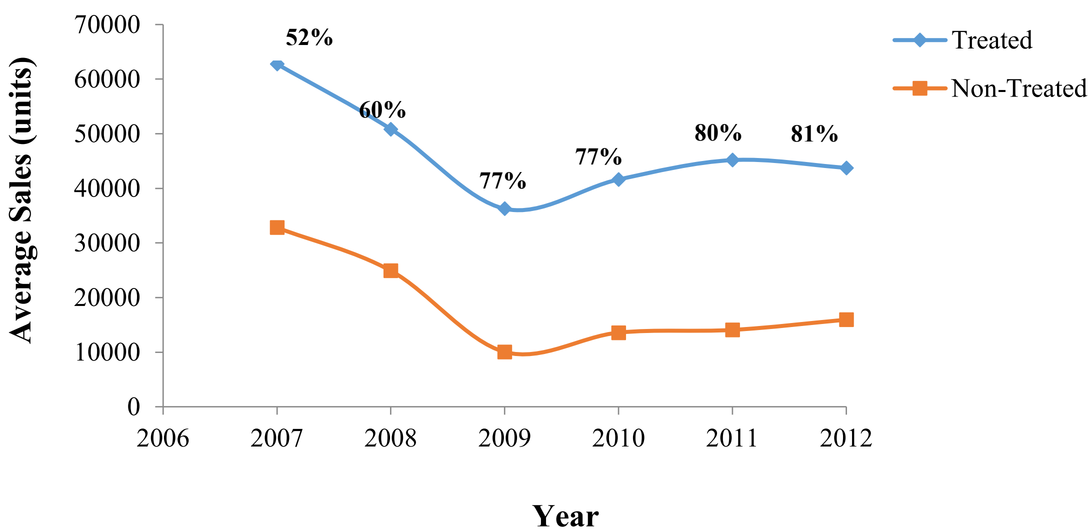


Figure: 7

Model Free Evidence: Sales vs. Ratings (1-10 Scale)