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Do Online Behavior Tracking or Attitude Survey Metrics Drive Brand Sales? An Integrative Model of Attitudes and Actions on the Consumer Boulevard

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Report Summary

Some marketers suggest that online behavior metrics have supplanted the classic purchase funnel and its attitudinal metrics. Both measures have advantages: online behavior metrics offer the benefits of timeliness and passive tracking, and classic attitude survey metrics use representative samples and have improved over decades of market research. Which metrics are best at explaining and predicting sales?

Koen Pauwels and Bernadette van Ewijk address this question for 36 brands over 15 categories, including services, durables, and fast-moving consumer goods in the Netherlands. They develop dynamic system models to capture interactions among metrics, between marketing and metrics, and between metrics and sales.

Their empirical analysis demonstrates that *both* attitude survey and online behavior metrics matter for sales explanation and prediction across a wide variety of (business-to-consumer) categories. Overall, online behavior metrics excel in sales explanation, while attitude survey metrics excel in sales prediction. This suggests that online behavior metrics are ideal for tactical planning, and attitude survey metrics are important in strategic planning.

Importantly, the authors find that online action does not simply follow from attitudes, it also drives them. New online metrics such as search, clicks, and website visits often Granger-cause attitude survey metrics. In other words, online activity substantially changes the decisions of at least some customers and can predict subsequent survey responses.

The authors propose an integrative model of consumer actions and attitudes as a “boulevard” of fast consumer actions (mostly online) and slower moving attitudes (mostly captured by surveys) and quantify how specific marketing actions can improve both types of metrics. Their model recognizes that consumers may go back and forth between search, awareness, website visits, consideration, and own loyalty and that consumers may be influenced by the expressed experience of others.

For managers, the consumer boulevard provides “toll booths” of online consumer behavior, which do show a funnel-like structure of shrinking elasticities. Quantifying these conversions for their own brand would enable managers to address weak links and take remedial action with both online and offline marketing instruments. For example, online marketing offers a high elasticity in changing both attitudes and actions, and TV advertising is a key driver of engagement metrics such as page views and social media conversations.

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When consumers hear about a product today, their first reaction is “Let me search online for it.” —Richard Tobaccowalla, Chief strategy & innovation office, Vivaki

Measuring brand effects on the basis of online behavior makes research less dependent on questionnaires and therefore more scalable at less cost. — Joris Merks, Google (2011)

As marketers we still need to effectively allocate dollars across multiple touchpoints as not everyone in every industry is living/engaging full in the digital space. —Camille (2011)

Introduction

The new reality of the connected consumer has inspired companies such as McKinsey and Google to promote the use of online behavior metrics, such as natural search, paid search clicks, website visits, and activity and social media activity. Marketers are catching on, with Coke’s marketing measurement shifting from impressions to consumer expressions (i.e., “a comment, a ‘like,’ uploading a photo or video or passing content onto ... networks”; Tripodi 2011). The mostly passive measurement of consumer online activity differs from solicited, mostly survey-based answers of consumers to attitude questions based on the classic purchase funnel (Lecinski 2011; Morwitz et al. 1993). Some proponents of online behavior tracking have declared the purchase funnel dead and claim that “the best marketers can hope to do in such an environment is to manage the process so that even though all roads may not lead to Rome, eventually all roads lead to, and through, digital ‘toll booths’ of content and information exchange” (Evans 2011).

However, online behavior metrics have also met with skepticism, as illustrated in the last opening quote. First, not everyone in every industry is online (Camille 2011, Macleod 2013). In other words, online behavior metrics do not cover the full (prospective) clientele of at least some brands in some industries. Second, even when online, consumers may not engage with brands. In particular, consumer packaged goods managers argue that their products are relatively low involvement and do not entice much online conversation (Lecinski 2011, p. 37). If only the most dedicated brand advocates and detractors are heard

online, metrics tracking their behavior may be unrepresentative of the average consumer.

Third, even if online behavior metrics in theory may have great predictive power, this does not necessarily mean that the currently used metrics in practice are superior to attitude survey metrics, which have been adjusted and refined through decades of marketing theory and practice (e.g., Ferris, Bendle, Pfeifer and Reibstein 2010, Pauwels et al. 2009). Last, and certainly not least for managers, the presumed importance of online behavior metrics does not necessarily mean marketing dollars need to shift online, as a majority of online consumers say TV ads influence their purchases (MarketingCharts 2012).

Given the controversy about the power of online behavior metrics over survey-based attitude metrics, our research questions are threefold:

- 1) How much do online behavior and attitude survey metrics *explain* sales?
- 2) How much do online behavior and attitude survey metrics *predict* sales?
- 3) How do online and offline marketing actions *drive* online behavior metrics?

Current academic literature is largely silent on the online versus offline path to purchase, which only recently made it to the top list of *Marketing Science Institute* research priorities (Marketing Science Institute 2012). Recent research has shown that attitude survey metrics help predict sales beyond the long-term effects of marketing actions (Srinivasan et al. 2010). Other researchers have demonstrated the predictive power of specific online behavior metrics, such as website visits (e.g., Biyalogorsky and Naik 2003), clicks and search activity (e.g., Ghose and Yang 2010), and positive, negative, and neutral social media conversations (e.g., Sonnier et al. 2011). Finally, Wiesel et al. (2011) consider the rather specific stages in an online and offline funnel for a business-to-business product, for which buyers formally ask for information, request a quote and then place an order. However, no one has combined comprehensive metrics of attitudes and online behavior attitude survey in the context of sales and marketing activity. This article does so for 36 brands in 15 categories, including services

(Internet, travel, insurance, energy, leisure parks), durables (cars), packaged food products (cheese, yellow fats, salty snacks, candy, beer, soft drinks), and packaged nonfood products (toilet tissue, sanitary napkins). Our variables include sales; offline and online marketing actions; attitude survey metrics of awareness, preference, intention, and loyalty; and online behavior metrics of paid, owned, and earned media. We apply vector autoregressive (VAR) models to capture the dynamic interdependencies among marketing, metrics, and sales. With this model, impulse response functions yield long-term elasticities, and variance decomposition shows which part of sales can be explained by baseline versus marketing, online behavior metrics and attitude survey metrics. We compare the in-sample explanation (adjusted R^2) and out-of-sample forecasting accuracy (Theil's inequality coefficient) of weekly sales.

Our contributions to literature are threefold. First, we compare the explanatory and predictive power of attitude survey and online behavior metrics across a wide variety of business-to-consumer industries. Second, we offer empirical generalizations on long-term sales and metric elasticities of offline and online marketing actions, thus pinpointing managerial levers to influence the new connected consumer. Third, we propose an integrative model of actions and attitudes on the consumer boulevard/funnel/journey/path to purchase. In doing so, we aim to contribute to the recent priority call “for rethinking the journey to purchase and beyond” and for “research that tests afresh models of the processes that precede and follow transactions and that measures the marketing actions and contextual factors that drive them” (Marketing Science Institute 2012, p. 3).

Research Background

In recent years, marketing modelers have begun combining behavioral and attitudinal data to predict brand sales, heeding the calls of Gupta and Zeithaml (2006, p. 734) and the Marketing Science Institute (2006). Attitudinal metrics have a long history in marketing, beginning with the DAGMAR model (Colley 1961) of communication-based objectives and measures and Lavidge and Steiner's (1961) model for the predictive measurement of advertising effectiveness. The concept of a purchase funnel of consumer attitudes became widely used in different variations. Among those, Vakratsas and Ambler (1999) showed the better fit is obtained in models that do not impose a hierarchy among cognition (think), affect (feel) and conations (do). Using such models, recent empirical studies have addressed the explanatory power of attitudinal metrics, demonstrating that they predict sales above and beyond long-term marketing effects (Hanssens et al. 2010; Srinivasan et al. 2010). These studies note, however, that it is costly to continuously track high-quality funnel metrics, which require representative sampling and survey procedures for hundreds of consumers. Therefore, they call for further research on the explanatory power of online behavior metrics relative to that of survey-based measures.

Proponents of online metrics have also made a case for their superiority over attitude survey metrics in the current reality of the connected consumer. McKinsey's study of "almost 20,000 consumers across five categories and three continents" finds that two-thirds of touchpoints during active product evaluation involve consumer-driven marketing activities, such as word of mouth and Internet information sites (Court et al. 2009, p. 2). Looking across the categories of fast-moving consumer goods, durables, and services, Google's Lecinski (2011) finds that many consumers search, access websites, and/or consult social media before making a purchase, with durable products showing more online activity than fast-moving consumer goods. He therefore proposes to add a "zero moment of truth" of consumer online

exposure before the first moment of truth of seeing a product at retail and the second moment of truth of experiencing its quality. Proclaiming the (classic) funnel dead, Evans (2011) notes the many potential entry points of prospective customers: “a billboard with a URL that they type into their smartphone’s mobile browser, or a click on a Facebook wall post from a friend's feed, or a search on Google. By setting up measurement beacons that customers interact with, marketers can understand what each digital customer narrative looks like.”

Despite the case for online behavior metrics, they also face several objections, especially as a replacement for attitude survey metrics (Camille 2011). First, they do not cover the full potential market for most products and services. Even in the highly connected US market, 39% of all consumers of food products do not consult any online or word-of-mouth sources (Lecinski 2011). Second, even when online, many consumers do not engage in much activity for low-involvement products, such as candy. Often, only the most dedicated brand advocates and detractors are heard online, making several online behavior metrics unrepresentative of the average (even online) consumer. Finally, even if online behavior metrics *in theory* may have great predictive power, this does not necessarily mean that the currently used metrics *in practice* are superior to attitude survey metrics, which have been adjusted and refined through decades of marketing research.

Conceptual Development

A priori Framework

As the starting point of our analysis, Figure 1 (following References) combines attitude survey and online behavior metrics with the online marketing and offline marketing actions marketers use to influence the purchase path. Our a priori framework generalizes the specific model for business-to-business company Inofec, whose offline and online funnel follow distinct stages of information requests, quotes and orders (Wiesel et al. 2011).

Marketing actions can both directly influence sales (e.g., Smith and Swinyard 1983; Srinivasan et al. 2010) and affect attitudes and online behavior. Among metrics, we allow for recursive effects (Aaker and Day 1971), multiple paths, and alternative hierarchies (Vakratsas and Ambler 1999). Moreover, effects are likely between attitudes and online behavior—for example, awareness may drive clicks on banner ads (paid media), which in turn may lead to website visits (owned media), developing brand affect (preference), which in turn may be verified in social media (earned media) before leading to purchase. Each of these metrics may feed back into marketing decisions by managers who track such metrics (Dekimpe and Hanssens 1999). Finally, a loyalty loop can shortcut the purchase path for a repeat customer (Court et al. 2009; Deighton et al. 1994) but also feed the purchase path for another (prospective) customer, influenced by the word-of-mouth narrative, whether digitally measurable or not (Godes and Mayzlin 2004).

Hypotheses

Both online behavior and attitude survey metrics have specific advantages that should help explain brand sales across categories. As to the former, the Internet has played a substantial role in lowering search costs (Ratchford et al. 2003) and enabling consumers to engage with brands and with each other about brands (Godes and Mayzlin 2004). Such empowered consumers are thought to move in a nonlinear manner through the buying decision journey, leaving measurable online tracks of the “research shopper” (Verhoef et al. 2007). A key advantage of online behavior metrics is that they are passive and unobtrusive; they do not require consumers to remember and explicitly formulate their opinions on consideration or preference for brands (Godes and Mayzlin 2004). Prior studies analyzing a single category have shown that online behavior metrics predict performance for products and services as diverse as TV shows (Godes and Mayzlin 2004), movies (Asur and Huberman 2010; Liu 2006), books (Chevalier and Mayzlin 2006), social networking sites

(Trusov et al. 2009), and office furniture (Wiesel et al. 2011). Online behavior metric proponents claim that fast-moving consumer goods manufacturers often underestimate online activity for their brands. A recent study found that the majority of consumers have consulted online sources for all analyzed categories, including food and nonfood grocery items (Lecinski 2011). In the words of Bob Thacker, chief marketing officer of OfficeMax (Lecinski 2011, p. 22): “Now, people engage in discovery before shopping on very small things. It crossed all categories of shopping behavior.”

Attitude survey metrics also possess key benefits over online behavior tracking. First, attitude survey metrics are designed to be representative of (prospective) category consumers, whether or not they engage with the category online. Attitude survey metrics thus have the advantage of coverage over online behavior metrics (Keller 2009), which may miss (the extent of) at least some change in a brand’s fortune. In each category studied Google’s research found that some consumers do not show any online activity (Lecinski 2011). Second, the key studies that induced McKinsey to propose the new online decision journey (Court et al. 2009) maintain that attitude survey metrics—namely, prepurchase awareness and postpurchase loyalty—remain important drivers of online behavior and sales. Third, companies have customized attitude survey metrics, often over decades of marketing research, to reflect what they believe are the key performance drivers in their industry and even for their specific brand (Pauwels et al. 2009). Such survey attitude metrics typically change slower than brand sales, thus reflecting deeper underlying forces as compared to short term, campaign-induced sales swings (Hanssens et al. 2010). Because of these distinct advantages of attitude survey metrics and online behavior metrics we propose that:

Hypothesis 1. The combination of Online Behavior and Attitude survey metrics explain sales more than either (a) Attitude Survey Metrics alone, or (b) Online Behavior Metrics alone.

Which attitude survey metrics should matter most in the context of online consumer behavior? Conventional wisdom holds that changes to upper-funnel metrics (e.g., awareness) have a lower sales impact than changes to lower-funnel metrics (e.g., consideration, liking, preference), which are closer to the action of purchase itself. Indeed, the few empirical findings on attitude metrics-to-sales elasticities report a three times higher elasticity for brand liking than for awareness in all four analyzed (grocery) product categories (Srinivasan et al. 2010). Could this ordering change for the new connected consumer?

We believe so. In the online world of easy information access, consumers start from an initial awareness/consideration set to explore their options in a nonlinear manner (Court et al. 2009). Therefore, upper-funnel metrics, such as awareness, should still play an important role. Likewise, postpurchase loyalty increases sales not just from the loyal consumers but also from the impact of their word of mouth on prospective buyers (Court et al. 2009). In contrast, we expect a lower explanatory power of “preference”, typically ascribed to one or two brands by each consumer in surveys. Before the advent of the Internet, consumers faced substantial search costs to overturn initial preference for a brand in a category (Ratchford et al. 2003). Instead, the new connected consumer is exposed to much more stimuli (e.g., user-generated content, social games) that may potentially alter his or her individual brand preference (Cooperstein 2011). Therefore, “shoppers don’t always move through a funnel, narrowing choices as they go ... they can actually widen their choices. The more they learn, the more choices they consider” (Lecinski 2011, p. 24). This implies that survey responses to “Which brand(s) do you prefer?” should be less predictive of sales in a connected world, while awareness continues to matter.

Hypothesis 2. In the context of the online behavior, attitude survey metric awareness is a more important sales driver than preference.

Important to brand managers is the difference between (in-sample) explanation and (out-of-sample) prediction (e.g., Neslin et al. 2006). Although online behavior metrics help explain sales in-sample, they may not do as well in forecasting future sales out-of-sample. The high over-time variation in online behavior metrics may be correlated strongly with current sales but yield too much noise for accurate predictions of future sales. Even if a brand's online ad gets clicked on a lot this week, a competitor's online activity may be more popular next week. In contrast, attitude survey metrics tend to move slowly and thus may reflect more fundamental attitude changes (Hanssens et al. 2010). If consumers' hearts do not change, future sales may not be affected by this week's competitor popularity. However, in the rare occasions that consumers' hearts do change, future sales are in jeopardy. Thus, although online behavior metrics may increase explanatory power in-sample, they may also add noise and reduce out-of-sample forecasting (Armstrong 2001). We investigate this important issue in an exploratory manner.

Managers are not just interested in tracking the best metrics to explain and predict brand sales but also in taking action to improve these metrics (Marketing Science Institute 2014). Recent research found substantial spillovers from online marketing to offline funnel metrics in the business-to-business context of office furniture (Wiesel et al. 2011). In business-to-consumer industries, much attention has been paid to the opposite behavior of offline marketing influence on online behavior (Verhoef and Neslin 2007, MarketingCharts 2012). We examine these potential effects in a flexible model that allows for both kinds of spillovers.

Methodology

The dynamic interactions, cross-metric effects, loyalty, and feedback effects in Figure 1 are captured in Vector Autoregressive (VAR) models (Dekimpe and Hanssens 1999). A key difference of this model vis-à-vis, for example, a recursive system of equations (e.g., Aaker and Day 1971; Ilfeld and Winer 2002) is that we do not need to specify a hierarchy among metrics (Vakratsas and Ambler 1999) or to assume that attitude survey and online behavior metrics precede purchase (Ray et al. 1973). Moreover, the VAR method offers a unified treatment of short- and long-term effects, allowing for wear-in, wear-out, and even permanent sales effects of marketing (Pauwels et al. 2002). By treating all variables in Figure 1 as endogenous (explained by the model), we capture the dynamic relationships among them without imposing a priori restrictions (Sims 1980).

Our empirical analysis involves six steps, detailed in Table 1 (following References). First, we test all variables for evolution and cointegration to identify the possibility for long-term (persistent) effects. We apply both the Augmented Dickey Fuller (ADF) and the KPSS tests for unit roots, and the Johansen et al. (2000) test for cointegration (see e.g. Trusov et al. 2009). Second, we establish the direction of temporal causality among the metrics in Granger (1969) causality tests. Third, from the test results, we specify the VAR models by using either the attitude survey or the online behavior metrics or by combining both in an “all metric” model. We perform these models for each brand (e.g. Pauwels and Hanssens 2007). Fourth, we estimate short- and long-term response elasticity of sales to each marketing action and funnel metric using generalized impulse response functions (GIRF). Fifth, we quantify the relative importance of changes in attitude survey versus online behavior metrics to explain changes in sales with generalized forecast error variance decomposition (GFEVD). Sixth, we provide the out-of-sample forecasting accuracy of the alternative models to compare the predictive sales power of the attitude survey versus the online behavior metrics.

In the first step, we test for the potential of permanent effects. No such effects are possible for series that are “stationary” (i.e., revert to a stable mean; e.g., Dekimpe and Hanssens 1999). Such mean reversion is shown through unit-root tests, such as the augmented Dickey–Fuller test and the KPSS test (Kwiatkowski et al. 1992). In contrast, an “evolving” series will not revert back to the mean after being shocked; the change will persist into the future. Some of these shocks may be due to the other variables in our dynamic system, as quantified in the estimation step. For model specification, evolving variables must be differenced to avoid “spurious relation” problems (Granger and Newbold 1986), unless they are tied to a long-term equilibrium. We test for such equilibrium with cointegration tests (Johansen et al. 2000).

In the second step, we test for Granger Causality (Granger 1969, Hanssens et al. 2001). Granger causality of a variable Y by a variable X means that we can predict Y substantially better by knowing the history of X than by only knowing the history of Y. This ‘temporal causality’ is the closest proxy for causality that can be gained from studying the time series of the variables (i.e., in the absence of manipulating causality in controlled experiments). We perform a series of Granger causality tests on each pair of variables, with special attention to the direction of causality between attitude survey and online behavior metrics. As in previous applications, we guard against lag misspecification by running the test for lags from 1 up to 13 (i.e. one quarter of 13 weeks) and report the results for the lag that has the highest significance for Granger causality (Trusov et al. 2009). Beyond the specific results, Granger causality tests also verify the data show a general pattern of dual causality and feedback loops, as implied in the framework of Figure 1 and the VAR model.

In the third step, we specify and estimate the VAR model for each brand. Because the exact definition and number of variables may vary across brands (see data description), we display the VAR model in matrix form in Equation (1):

$$Y_t = A + \sum_{i=1}^p \Phi_i Y_{t-i} + \Psi X_t + \Sigma_t, \quad t = 1, 2, \dots, T, \quad (1)$$

where Y_t is the vector of the endogenous variables, A is the vector of intercepts, p is the number of autoregressive lags, and X_t is a vector of exogenous control variables. The full residual variance–covariance matrix Σ contains the contemporaneous effect of each endogenous variable on the others, as interpreted in the third step. Each variable is included in logs, which accounts for diminishing returns and allows us to interpret the estimated effects as elasticities (Nijs et al. 2001). We estimate the model for each brand to maintain comparability with our benchmark for attitude survey metrics (Srinivasan et al 2010) – this choice is both typical for previous VAR-models in marketing (Pauwels et al. 2002, Srinivasan et al. 2004) and accommodates different variable operationalizations among brands (see data section).

For the all-metric full model, the vector of endogenous variables includes both attitude survey and online behavior metrics. In separate models, we leave out, respectively, the attitude survey metrics or the online behavior metrics to obtain the “online behavior model” and the “attitude survey model”. Finally, for comparison with Srinivasan et al. (2010), we leave out both attitude survey metrics and online behavior metrics to obtain the “marketing only model”. Volume sales and marketing actions are endogenous variables in each model.

In the fourth step, we derive the GIRFs from the VAR estimates (Dekimpe and Hanssens 1999). The VAR model in equation (1) captures both immediate and lagged and direct and indirect interactions among the endogenous variables. With these estimated reactions, the impulse response function calculates the net result of a “shock” to one variable (e.g., TV) on the other variables (e.g., paid clicks and sales) relative to their baselines (i.e., their expected values in the absence of the marketing shock). To tease out contemporaneous effects, we estimate GIRFs with the simultaneous-shocking approach (Pesaran and Shin

1998), in which we use the information in the residual variance–covariance matrix of Equation (1) to derive a vector of *expected* instantaneous shock values. The advantage of this approach is that it does not require selecting a causal ordering among the variables. We obtain short- and long-term elasticities by comparing each GIRF estimate with its standard error and only retaining those with a *t*-value higher than unity (Sims and Zha 1999). Following Pauwels’ (2004) most stringent criteria for significant differences between GIRFs, we combine the standard errors for each period’s estimate to evaluate whether e.g. the long-term sales elasticity of awareness is significantly different from that of preference (H2).

In the fifth step, we derive the GFEVD of sales to examine the relative importance of past changes in each variable in driving sales changes. Similar to a “dynamic R^2 ”, GFEVD provides a measure of the relative impact over time of shocks initiated by each of the individual endogenous variables in a VAR model, without the need for the researcher to specify a causal ordering among these variables (Nijs et al. 2007; Pesaran and Shin 1998). The GFEVD attributes 100% of the forecast error variance in sales to either (1) the past values of the other endogenous variables or (2) the past of sales itself, also known as “sales inertia” or “baseline.” Similar to Nijs et al. (2007) and Srinivasan et al. (2010), we assess the dynamic explanatory value of metrics by the extent to which they increase the sales GFEVD explained by the potential drivers of sales (i.e., the other endogenous variables in the model) and thus reduce the percentage attributed to past sales. The relative importance of the drivers is established from the GFEVD values at 26 weeks, which reduces sensitivity to short-term fluctuations. The standard errors obtained with Monte Carlo simulations allow us to evaluate statistical significance (Srinivasan et al. 2010) and thus to assess whether online behavior metrics add explanatory power to the attitude survey metrics (H1a) and vice versa (H1b).

In the sixth and final step, we assess out-of-sample forecasting performance of each VAR model. First, we estimate all VAR models on the first two-thirds of the sample (i.e., the

estimation sample). Second, we use the resulting estimated coefficients to make a static (i.e., one-step-ahead) forecast of sales performance in the last one-third of the data (i.e., the holdout sample). To compare models on out-of-sample forecasting accuracy, we calculate the mean absolute percentage error (MAPE) and Theil's Inequality coefficient (TIC), both of which are scale invariant (Theil 1966). One drawback of the MAPE is that though 0 means a perfect forecast, it is not bounded above, so it is difficult to interpret its value (Lindberg 1982). In contrast, TIC normalizes forecast error by that of a naive model (a random walk), so the TIC varies between 0 (perfect forecast) and 1 (if the model forecasts only as well as the naive model).

Data Description

To focus the scope of our study, we obtained data for the Netherlands. We contacted all Dutch clients of the metric providers GfK, Google, Metrix Lab, and Millward Brown with an invitation to participate in the study. If they were interested in participating, we checked with the brand managers whether data were available for both attitude survey and online behavior metrics for a sufficiently long period (eight months minimum for model estimation) in the last three years (to reflect the most current reality of the connected consumer). Given our purpose to generalize across industries, we gave priority to category and brand coverage over exact comparability of attitude survey metrics, which are often customized to the category and the brand in question. In other words, we include brands that differ among one another in the exact metrics covered in the classic purchase funnel. Of 79 brands contacted, 36 were able to deliver the needed time series (response rate = 46%). The average data period is 108 weeks, within the time frame of February 2008 to September 2011. We did not detect substantial differences between the responding and the non-responding brands in terms of market share (varying from largest to smallest player in our data), sales growth/decline (33% of studied brands show declining sales), or fraction of the marketing budget spent online

(varying between 0.5% and 84% in our sample, with an average of 30%). Although the included brands may differ in other dimensions from brands not participating in the study, our substantive findings are based on a broad sample in terms of online activity, market share, and sales growth.

Our sample of 36 brands covers 15 categories, including services (Internet, travel, insurance, energy, lodging), durables (automobile), packaged food products (cheese, yellow fats, salty snacks, candy, beer, soft drinks), and packaged nonfood products (toilet tissue, sanitary napkins). These categories differ on many dimensions, including consumer involvement, as Table 2 shows. We operationalize category involvement using expert judges from GfK on a 7-point scale. Durables (7 for automobile) and services (5–7, 4 for energy) obtain higher involvement scores than fast-moving consumer goods (2–3 of 7 and 4 for beer). Moreover, analyzed brands vary greatly in terms of the fraction of the marketing budget they spend online. The average is 30%, with a low of 0.5% (a salty snack brand) and a high of 84% (a soft drink brand). The variation across brands within a category is also substantial (e.g., travel agencies between 17% and 61%, soft drinks between 22% and 84%).

The data derive from several sources. First, the 36 brands provided us with volume sales¹, marketing communication expenditures by channel (e.g., TV, print, radio, Google display cost), and, for fast-moving consumer goods, price (average per volume unit), distribution (all commodity by value), and promotion pressure (% of unit sales sold on promotion). Second, the online behavior metrics consisted of (1) number of clicks on paid online ads, (2) number of website visits, (3) number of page views per visit, (4) positive and negative social media conversations, and (5) search (branded search and generic search). With permission from the brands, these data were provided through Alterian (now SDL) for earned media and through Google for other online information. As a key environmental

¹ New contracts for the insurance and Internet providers.

control variable, we used temperature for fast-moving consumer goods (obtained from GfK) and the Dutch Consumer Confidence Indicator for durables and services (obtained from the Dutch Centraal Bureau voor Statistiek). Finally, attitudes such as brand awareness (top-of-mind, spontaneous, aided), consideration and preference are measured by GfK with the scale in Table 2. Given the high correlation among the three versions of brand awareness, we select the operationalization that leads to the highest model fit for each brand.

While an awareness metric is available for all brands, the metrics of consideration and preference are available for respectively 17 and 21 out of 36 brands. Additionally, 16 brands collect post-purchase (loyalty) metrics. Such loyalty metrics differ per category, with classifications such as degree of closeness in beer (Flirt, Engaged, Married) or user status in soft drinks (Trial, Repeat, Stable user). Finally, 4 brands measure ‘intention’ and 2 brands measure ‘purchase intention. Given these low numbers, we focus our discussion on awareness, consideration, preference and loyalty. Table 3 lists the categories, brands and specific metrics.

Due to data confidentiality issues, we cannot provide brand-specific data descriptives. Across brands, Table 4 provides the correlations, means, standard deviation, and coefficient of variation for volume sales and the online behavior and attitude survey metrics available for the majority of brands.

Note that all metrics are positively correlated with sales but that the sales correlation of preference and online behavior metrics is higher than that of awareness and consideration. This is intuitive because online metrics represent actual behavior, and preference is closer to purchase than awareness and consideration in the classic funnel. Preference also mirrors sales in its dispersion over time, which we measure by the coefficient of variation (normalizing the standard deviation of each variable by its average). In contrast, awareness and consideration move slower than sales, and online behavior metrics move faster than sales.

Findings

VAR Model Specification and Fit

The unit-root tests showed that 2 of the 36 volume sales series were evolving but detected no cointegration for any brand. As a result, we include the evolving variables in first differences (i.e., sales growth instead of sales levels). First-differencing affects the interpretation of the explanatory and predictive power (e.g., the R^2 for sales growth is logically much lower than the R^2 for sales in levels). However, we can compare explanatory and predictive power across models because this first differencing is executed for each model of the brand in question. For the number of lags, one lag is indicated by the Bayesian information criterion for 50% of cases, with the remainder indicating between 2 and 4 lags.

The fit of the VAR models is adequate for sales, with the explanatory power significantly different from 0 in all cases (average F-statistic value = 4.44) and the R-square ranging from 0.10 (sales growth of the insurance provider) to 0.92 (sales of a fast-moving consumer good brand), with an average of 0.44. For prediction, the average MAPE is 350.2, and the average TIC is 0.32. Lindberg (1982) considers TIC values around 0.55 “very good”, and therefore we conclude that the models are usable for forecasting sales.

Table 5 shows the explanatory power (R^2) for each brand and each of the four alternative models. Figure 2 shows the average R^2 for respectively fast moving consumer goods (directly comparable with figure 3 in Srinivasan et al. 2010) and consumer durables and services. Adding attitude survey metrics to the marketing-only model increases the sales explanatory power (consistent with Srinivasan et al. 2010), but adding online behavior metrics does so as well. Note though that R^2 values (and its derivatives such as the adjusted R^2 , which adjusts for the number of explanatory variables) have no associated standard errors, and thus do not allow us to judge the statistical significance of any difference.

Finally, we calculate marketing–sales elasticities to verify that our sample of brands and categories reflects empirical generalizations based on prior research (Hanssens 2009). The average marketing-sales elasticities are -1.68 for price, 0.23 for in-store promotion (fast-moving consumer goods only), 0.05 for TV, 0.005 for radio, 0.01 for print, and 0.03 for online display, all well within range of historical averages (Bijmolt et al. 2005; Hanssens 2009; Tellis and Ambler 2007).

Attitude Survey and Online Behavior Metrics in Sales Explanation

We follow the order of our hypotheses to display the substantive results. Do online behavior metrics add explanatory sales power to a model that already includes marketing effects and attitude survey metrics (H1a)? Figure 3 shows how adding metrics reduces the sales GFEVD (“dynamic R^2 ”) attributed to sales’ own past (i.e., the contribution of the sales baseline) and thus increases the sales GFEVD attributed to the other variables in the model

Adding attitude survey metrics to marketing actions reduces the contribution of the sales baseline from 47% to 41%. However, adding online behavior metrics to the classic-funnel-only model further reduces the sales baseline’s contribution from 41% to 30%. These differences are statistically significant at the 5% level for all but four brands (three candy brands and one toilet tissue brand). For several categories, the improvement appears substantial. For lodging, sales baseline’s contribution drops from 55% to 6%, indicating that past changes in marketing and attitude survey and online behavior metrics almost fully capture current sales. Likewise, the sales baseline’s contribution for automobiles drops from 56% to 22% when we add attitude survey metrics and further to 14% when we add online behavior metrics. The likely reason is that consumers begin searching for lodging and cars weeks before purchase; the peak online search activity is two–three months before car purchase and one month before travel purchase (Lecinski 2011). In contrast, candy and toilet

tissue have only a 1% drop in the sales baseline's contribution when we add online behavior metrics. In Lecinski's (2011) study, such grocery products show minimal search activity, with a peak on the day of purchase.

Which online behavior metrics are most important in terms of explanatory power? We compute the average contribution to sales GFEVD for paid clicks, search (branded and generic), owned website (visits and page views per visitor), and earned social media (positive and negative web conversations). Paid clicks have the highest contribution (6.74%) to dynamic sales explanation, followed by search (4.99%), earned social media conversations (4.60%), and owned web visits (4.25%).

Do attitude survey metrics explain brand sales above and beyond online behavior metrics (H1b)? Yes, we find that adding attitude survey metrics to the online behavior-only model significantly increases the sales GFEVD (dynamic R^2) for 26 out of 36 brands. While significant, none of the sales GFEVD of any attitude survey metric exceed 3% on average, and thus are lower than the sales GFEVD of any online behavior metric. On average, the sales GFEVD of the combined attitude survey metrics is 9.73%, which is similar to the 8.4% for 'own mindset metrics' reported in Srinivasan et al. (2010). We also find a similar GFEVD contribution for the individual metrics that our data shares with theirs: 2.85% versus their 2.7% for Consideration, and 2.73% for our Preference versus 2.3% for their Liking metric. Thus, our new insight of the higher sales GFEVD of online behavior metrics is unlikely to be an artifact of the attitude metrics in the specific categories or country studied.

In sum, we find broad *support for Hypothesis 1* that the combination of online behavior and attitude survey metrics explains sales better than either metric type by itself.

Elasticities among Metrics, Sales, and Marketing Actions

Turning our attention to the sales effectiveness of changing metrics, which attitude survey metric has the highest sales elasticity (H2)? Figure 4 shows the average elasticities of attitude survey metrics: awareness (0.41), followed by preference (0.24), loyalty (0.17), and consideration (0.05). The sales elasticity difference between awareness and preference is statistically significant at the 5% level for all brands for which both variables are available. The three exceptions are the energy provider, a salty snack brand and a car brand.

Thus, we *find support for Hypothesis 2* and conclude that “upper-funnel” awareness metrics have a stronger sales elasticity than the “mid-funnel” metrics of consideration and preference. This reflects McKinsey’s finding that brand awareness matters (Court et al. 2009) but that offline surveys of consideration and preference have less power to predict sales in a world of connected consumers influenced online. We thus find aggregate-level support for anecdotal observations that brands that are not mentioned as considered or preferred in surveys, may still end up getting chosen by the new connected customer – a key insight of our study for brand managers.

The comparison with sales elasticities of online behavior metrics is insightful. As shown in Figure 5, owned website visits (0.26) has the highest sales elasticity, followed by search (0.20) and paid clicks (0.17). These elasticities are similar to that of preference and loyalty metrics, but lower than that for awareness. Finally, the low sales elasticity of the volume of social media conversations² is consistent with both company-specific reports at Coca-Cola and IBM (Malcolm 2012, Neff 2013) and academic research (e.g. Stephen and Galak 2012). As those authors note, the low sales impact per social media interaction does not account for its frequency. Indeed, our GFEVD estimates show that social media

² For the studied brands, we did not have information for the dispersion of social media conversations (Godes and Mayzlin 2004) nor for the specific topic of conversation (Stacey and Pauwels 2012)

interactions as a whole drive a higher part of business (4.60%) than owned web site interactions do (4.25%).

The elasticities within the online consumer journey are of particular interest to managers (Court et al. 2009). Logically, the Granger causality results support a hierarchy from (branded) search to paid search clicks to website visits to purchase, with elasticities of respectively 0.56, 0.41, 0.18 and 0.13. Thus, on average within our data, a doubling (100% increase) of online search leads to a 56% increase in paid clicks, which in turn leads to a 23% increase in visits, a 4% increase in brand sales and a 0.5% increase in social media conversations about the brand.

How do attitude survey and online behavior metrics drive each other? Our Granger Causality tests indicate interesting directional differences in pairs of attitude survey and online behavior metrics. First, consideration drives web visits, but not the other way around. In contrast, search drives preference, but the other way around. Awareness does show dual causality with web visits and paid clicks. In both cases, the majority of the Granger causality cases indicate that awareness follows from online behavior (76% of cases for web visits, 67% for paid clicks). In other words, *consumer online behavior is not simply a result of attitude survey metrics, it also drives them*. This is consistent with the notion that consumers may start with an initial consideration set, but change their minds and hearts to some extent during their decision journey (Court et al. 2009).

Finally, how can managers influence the important online behavior metrics? Figure 6 shows the average elasticities of online display and TV advertising (elasticities of the remaining marketing actions are below 0.01).

Although online marketing logically has the largest effect on most online behavior metrics, we note the large elasticities of TV on all online metrics: approximately 17% for search and paid clicks, 25% for owned website metrics, and 74% for positive social media

conversations. TV even outperforms online in increasing page views per website visitor and positive social media conversations. Downloading pages and social recommendations are consumer actions that indicate engagement (Calder et al. 2009). Thus, the importance of online behavior metrics does not mean that managers need to switch mostly to online marketing tools; offline TV is also a key driver of online consumer behavior. The opposite argument holds as well: online marketing activity has a larger elasticity than TV for all attitude survey metrics: on average 0.05 (versus 0.03) for brand awareness, 0.04 (versus 0.01) for consideration, 0.04 (versus 0.01) for preference and 0.06 (versus insignificant) for loyalty metrics. Thus, while attitude elasticity to online communication is in the .04-.06 range, attitude elasticity to TV advertising is lower, consistent with the 0.01-.02 range reported in Srinivasan et al. (2010). The relative high online impact on loyalty metrics highlights the role of the online channel to continue the relationship with consumers after purchase.

Attitude Survey and Online Behavior Metrics in Sales Prediction

Consistent with our conceptual argument, Table 3 shows that online behavior metrics are correlated highly with sales in the same week and have a similarly high variation over time. Does this also mean they can predict future sales? Table 6 shows the out-of-sample forecast error (TIC between 0 and 1) for sales of the model with attitude survey only, the model with online behavior only, and the all metric model.

We find that the all-metric model performs worst, with an average TIC (MAPE) of 32.19 (350.19) compared with 23.74 (54.58) for the attitude survey model and 28.68 (283.39) for the online behavior model. Moreover, the attitude survey model has the best TIC (MAPE) for 18 (23) of 36 brands and 12 (13) of 15 categories. Although the online behavior metrics thus perform better in-sample, the attitude survey metrics do better in forecasting out-of-sample. This is in line with our expectation that the online behavior metrics pick up short-term fluctuations, such that the slow-moving attitude survey metrics are better suited to capture the long-term trend in sales. Thus, we find some support for the reaction of managers that attitude survey metrics are crucial to forecasting sales (Camille 2011).

Towards an Integrative Model of Actions and Attitudes on the Consumer Boulevard

Our empirical analysis demonstrates that *both* attitude survey and online behavior metrics matter for sales explanation and prediction across a wide variety of (business-to-consumer) categories. Moreover, the causality among “classic funnel” attitudes and “new journey” online metrics goes *both ways*. Finally, while online behavior metrics tend to move at the same *speed* as sales and excel in explaining current sales, slower-moving attitude metrics excel at predicting future sales. What does this imply for “rethinking the journey to purchase and beyond (Marketing Science Institute 2012)? Instead of focusing either on online behavior metrics OR attitude survey metrics, we should integrate BOTH recognizing their relative

strengths and weakness. The traditional metaphor of a “funnel” is no longer appropriate, but likewise recent proposals such as the “consumer online decision journey” (Court et al. 2009), and the “measurable customer narrative” (Evans 2011) capture only part of this reality.

Figure 7 shows our proposed conceptualization integrating consumer attitudes and actions.

The “consumer boulevard” consists of slow lanes of consumer cognition (awareness, consideration) and affect (preference, love, loyalty), which are fed by the fast lanes of consumer actions – including (online) search, purchase, experience (consumption, use) and expressing this experience through (offline or online) word-of-mouth. All of these metrics may be affected by online and offline marketing actions and environmental factors (not shown in the figure). Note the dual causality among many aspects of ‘Know’, ‘Do’ and ‘Like’, many of which are empirically found in our data.

The proposed “consumer boulevard” integrates the ‘classic purchase funnel’ (e.g. Lavidge and Steiner 1961) with the “new online consumer journey” (Court et al. 2009). While recognizing the importance of attitudes, the boulevard does not maintain the idea of a ‘funnel’ in which consumers restrict choices as the move closer to purchase. Instead, it recognizes that consumers may go back and forth between search, awareness, website visits, consideration, own loyalty and being influenced by the expressed experience of others. For managers, the consumer boulevard provides ‘toll booths’ of online consumer behavior, which do show a funnel-like structure of shrinking elasticities. Quantifying these conversions for their own brand enables managers to address weak links and take remedial action with both online and offline marketing instruments. In sum, the consumer boulevard calls managerial attention to both online actions, which can be tracked unobtrusively and in real-time, and to slower-moving attitudes, which are often tracked in more representative survey of (prospective) customers. While online behavior metrics are ideal for tactical planning,

attitude survey metrics appear important in strategic planning – as we find the former perform better in explaining, but the latter perform better in predicting future sales.

Conclusion

In this paper, we set out to compare the sales explanatory and predictive power of both attitude survey metrics and new online decision journey metrics. We find that both metrics substantially add to sales explanation and prediction across a wide variety of categories. Online behavior metrics are important for durables and services but also matter for fast-moving consumer goods. Among attitude survey metrics, awareness has the highest sales impact, followed by the mid-funnel metrics of consideration and preference. Cross-funnel causality exists in both ways; as online behavior metrics often lead attitude survey metrics. Finally, TV advertising has a large impact on online behavior metrics and outperforms online display in increasing social media conversations and page views per website visitor.

Our first controversial finding is that online behavior metrics help explain sales of fast-moving consumer goods. How can this be when many consumers may not engage in online activity for such products (e.g., Lecinski 2011)? Even in so-called low-involvement categories, some consumers may be highly involved (e.g., Laurent and Kapferer 1985). These consumers can exert a strong influence, especially if their actions are covered by mainstream media. Moreover, online activity by these category mavens may act as a proxy of their offline word of mouth to the majority of less-involved consumers (Godes and Mayzlin 2004). Thus, online behavior metrics can quickly pick up on changes that currently used attitude survey metrics do not capture.

However, the attitude survey metrics still have explanatory sales power and show the best out-of-sample forecasting performance on average. Why is this the case? First, we observe less over-time variation in attitude survey than online behavior metrics, so attitude

survey metrics may better capture long-term movements that affect a brand's fortune. In other words, the frequent shifts in weekly online activity may fit sales well in-sample but contain a substantial amount of noise that masks the long-term signal. Second, attitude survey metrics have evolved over decades of marketing research and are often customized for specific brands in an iterative process (Pauwels et al. 2009). Third, many product categories are characterized by habitual and stable buying patterns (e.g., Ehrenberg 1974), which attitude survey metrics capture well (Srinivasan et al. 2010). In summary, changes to attitude survey metrics, while less frequent than changes in online behavior metrics, are likely leading indicators of future sales changes (Lautman and Pauwels 2009).

The dual causality of attitude survey and online behavior metrics came as a surprise to managers of several data providers, who believe that consumer online behavior merely reflects the classic funnel stages. From that perspective, online behavior follows from awareness, consideration, and so on, and simply performs well in sales prediction because, as behavior, it is closer to purchase action than survey responses are. In contrast, we find that new online behavior metrics such as search, clicks and website visits often Granger-cause attitude survey metrics. This result is consistent with Court et al.'s (2009) assertion that online activity substantially changes the decisions of at least some customers. We find online activity also predicts subsequent survey responses. Our data do not allow us to ascertain whether individual consumers indeed enlarge their consideration set through online activity, thus opening a promising area for further research.

Our finding that both attitude survey and new online metrics help explain sales is consistent with Lecinski's (2011) finding that consumers increase activity to accommodate new information rather than merely substitute old with new information source nodes. Such increased total search activity logically flows from a consumer model in which the online activity reduces search costs but consumers expect relatively high gains from additional

search (e.g., Ratchford et al. 2003). Even when the expected benefit from online activity is rather small (e.g., salty snacks), the low cost of online information gathering makes it worthwhile for at least some consumers to do so.

Limitations of our work include the aggregate and weekly nature of our data. The former is not atypical of studies on online activity, as privacy concerns limit access to individual-level information. Regarding the data interval, online metrics are typically available at finer frequencies than attitude survey metrics, which allows for faster assessment of the tactical successes of specific campaign executions. Our study does not consider this benefit of online behavior metrics and thus is likely to underestimate their value to managers who want real-time information on, for example, how much online behavior a specific TV campaign generates. Our methodology has the benefit of offering a dynamic and flexible description of data patterns and of forecasting the effect of marketing actions similar to those in the estimation period, but it does not allow a structural interpretation of the parameters or an optimization of the marketing effects. We also limited the scope of the study to the Netherlands, and so we invite further research in other countries and other categories.

In summary, we find that classic attitude survey metrics still have power in explaining and predicting sales across brands and categories. However, the midpoints of the classic funnel appear less important as consumers widen their search in their online decision journey. New metrics of online behavior are important for high-involvement goods and services, but they also matter for low-involvement categories. We propose the consumer boulevard to capture this new reality of fast consumer actions (mostly online) and slower moving attitudes (mostly captured by surveys) and quantify how specific marketing actions can improve both types of metrics. In particular, online marketing offers a high elasticity in changing both attitudes and actions. Within offline marketing actions, TV advertising a key driver of online

behavior metrics and even does a better job than online marketing in driving engagement metrics such as page views and social media conversations.

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Figure 1 Analysis Framework of Attitude survey and Online behavior Metrics

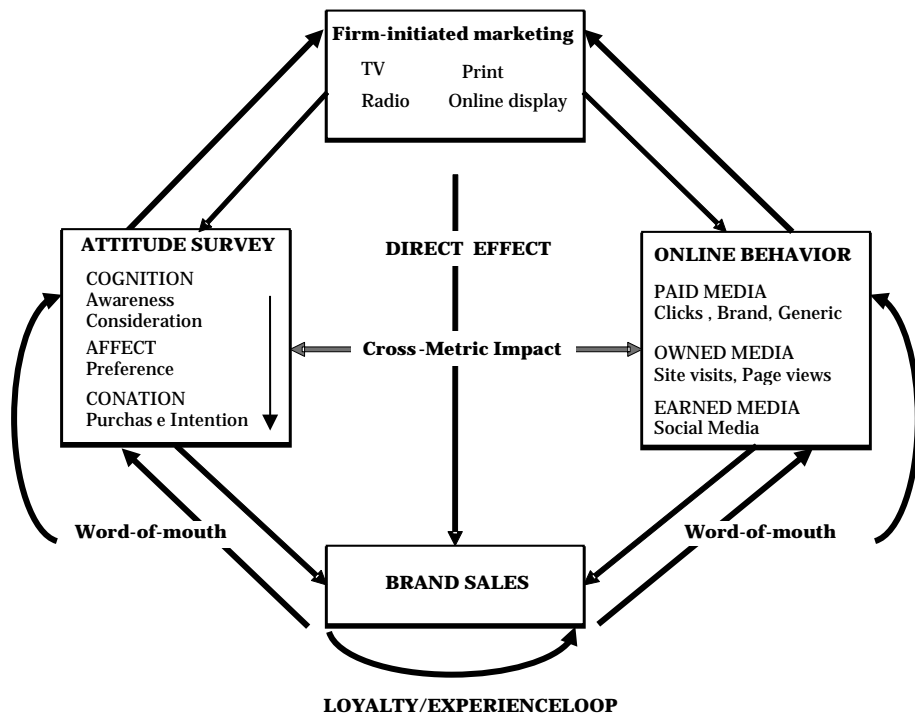


Figure 2: Each model's average R^2 for Fast moving consumer goods vs. durables & services

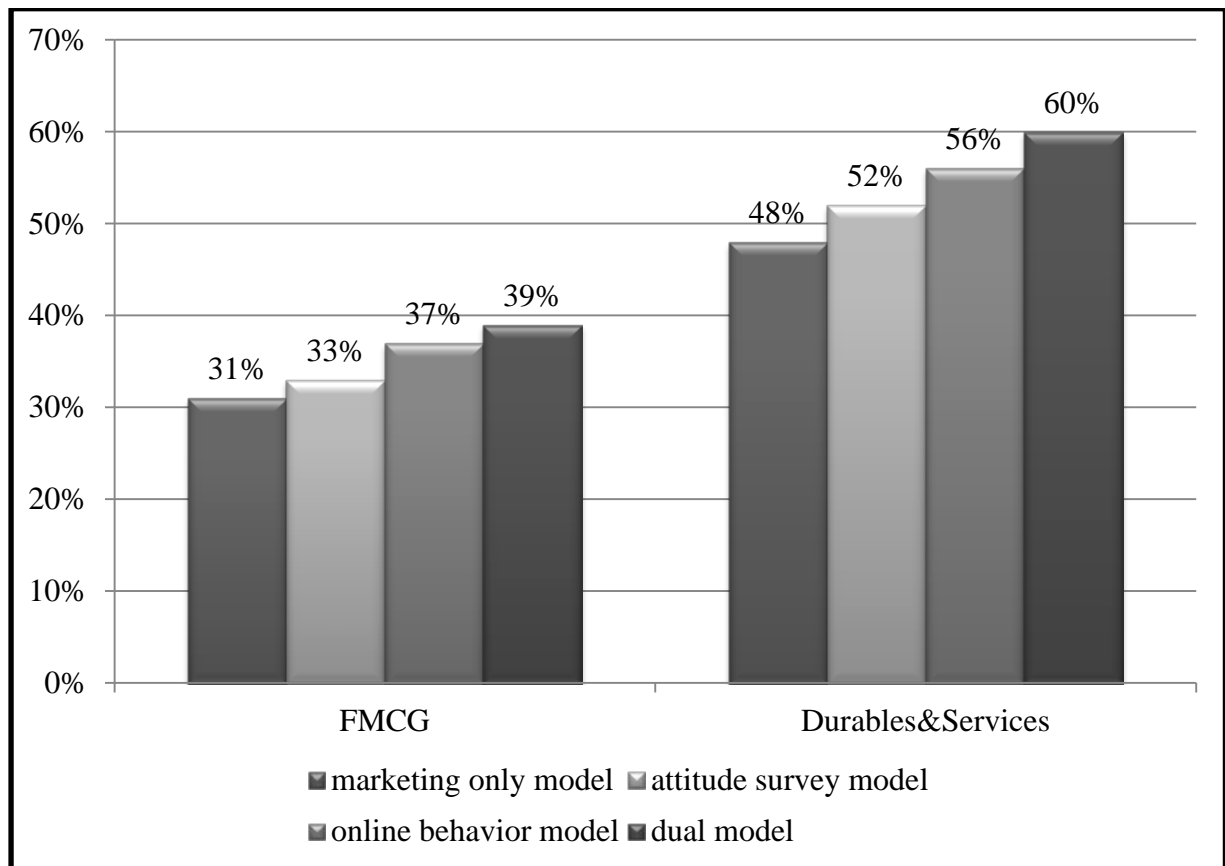
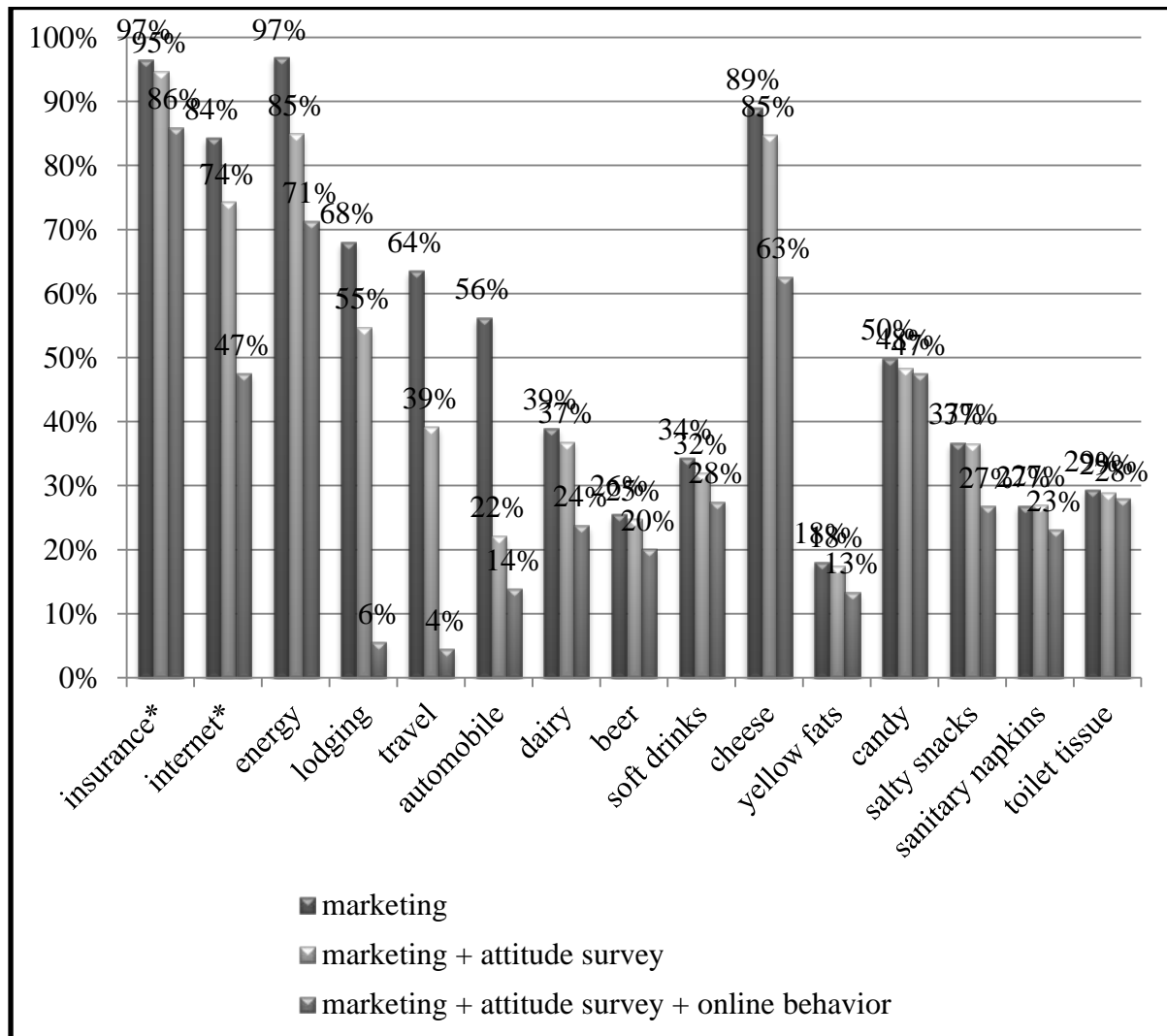


Figure 3 Sales Baseline (% Forecast Error Variance Explained by Own Sales Past)



* The dependent variable is sales changes because the sales variable is evolving.

Figure 4 Sales Elasticity of Attitude survey Metrics

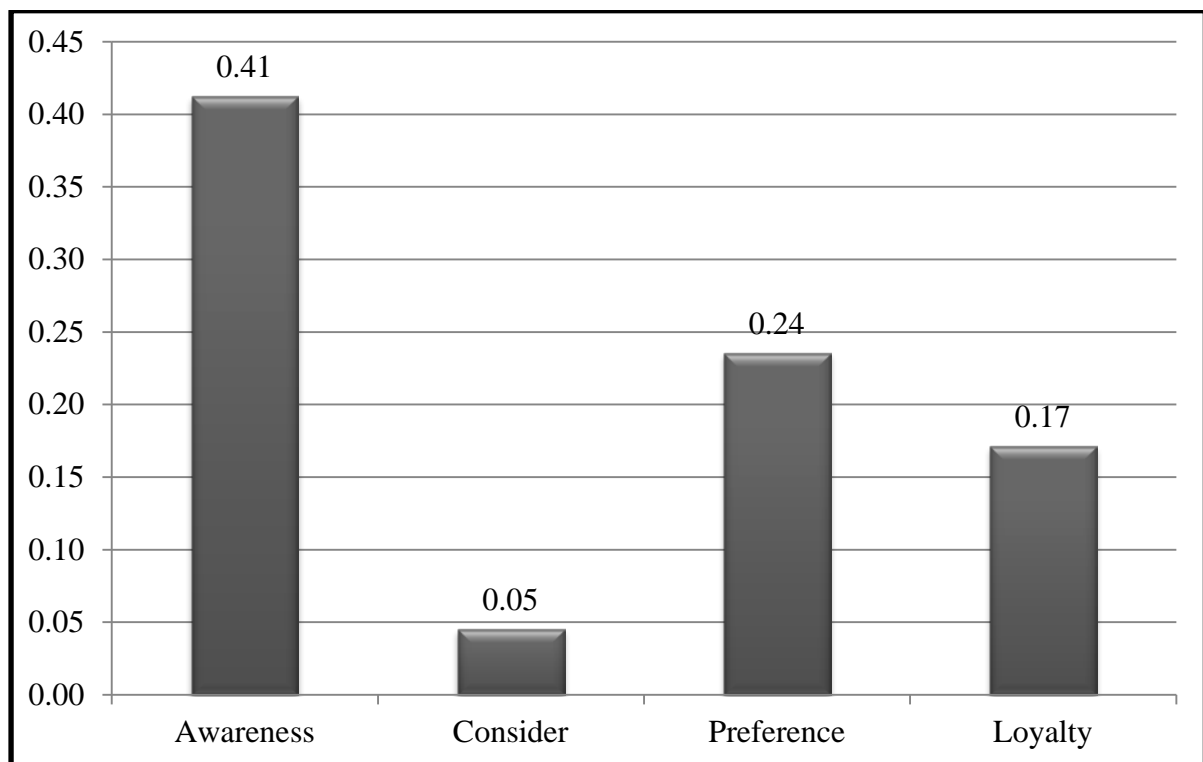


Figure 5 Sales Elasticity of Online Behavior Metrics

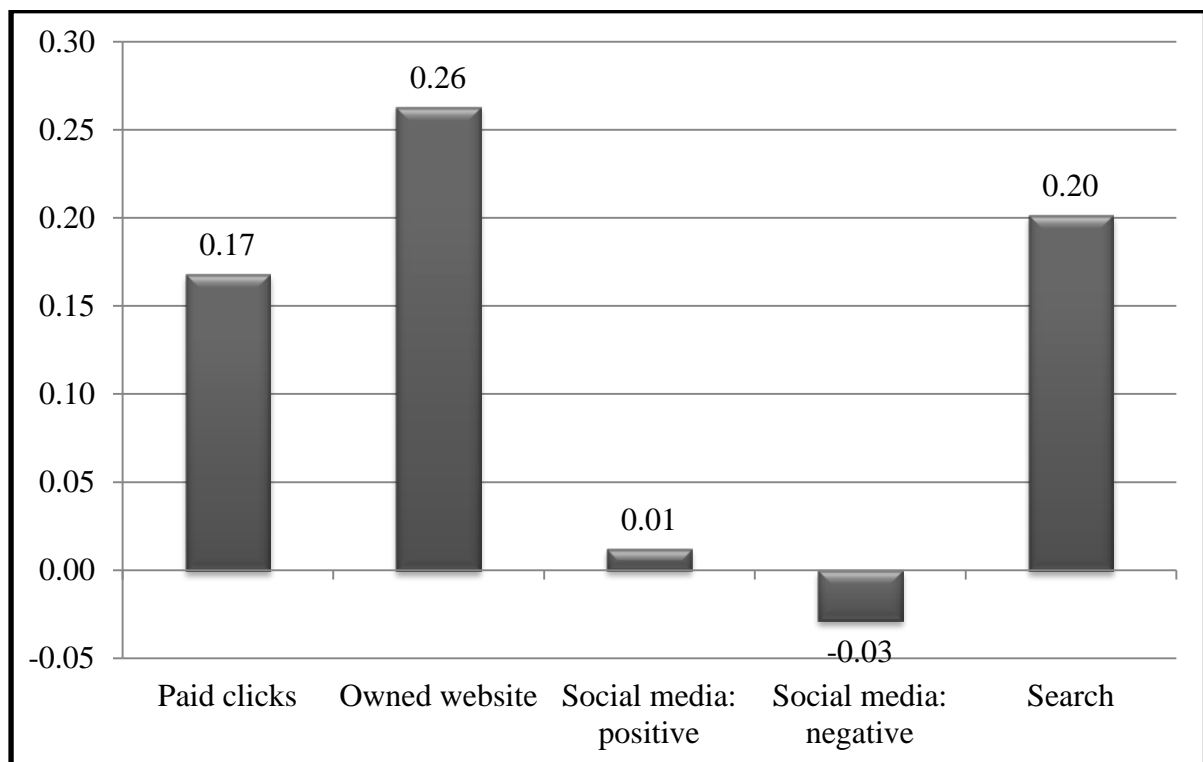


Figure 6 Online behavior Metric Elasticities to TV and Online Display Advertising

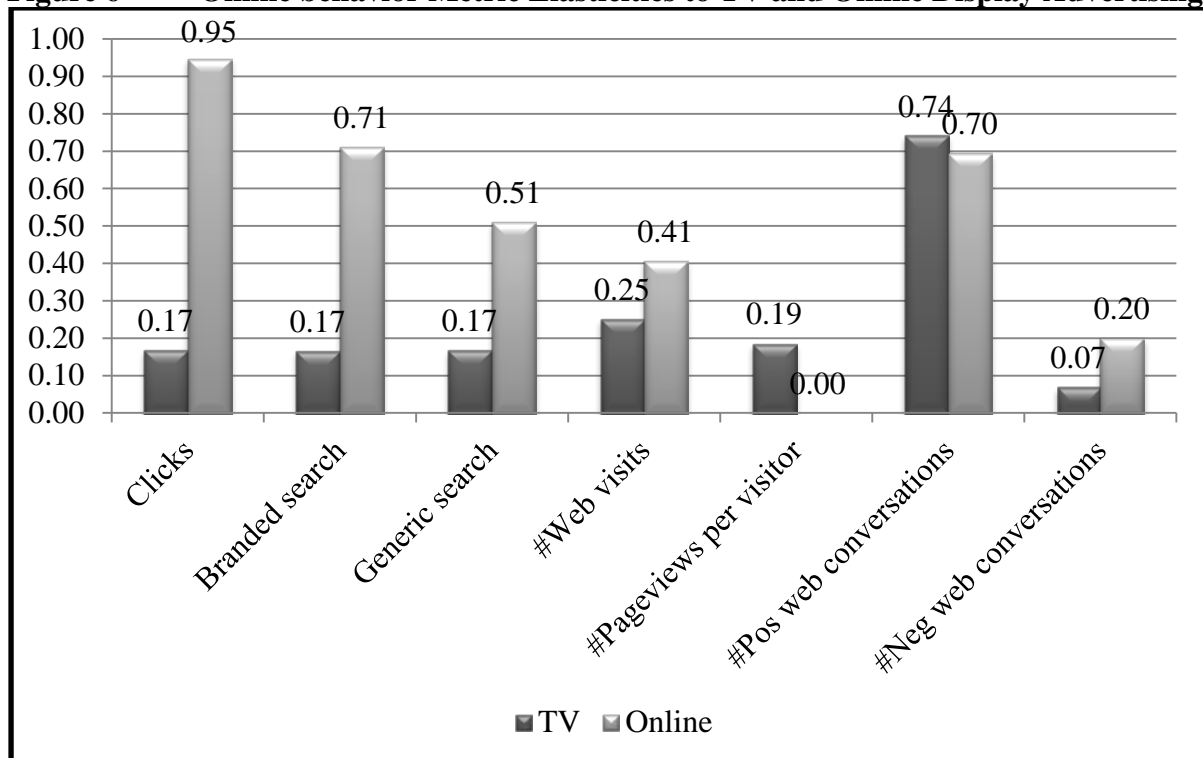


Figure 7 Integrative Model of Attitudes & Actions on the Consumer Boulevard

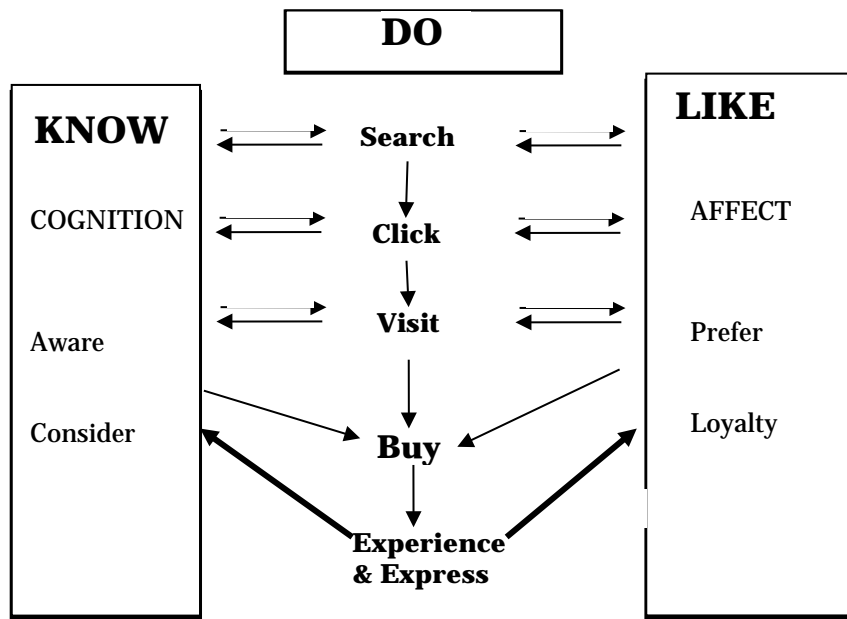


Table 1 Overview of the Methodological Steps

Methodological step	Relevant literature	Research question
<u>1. Unit root & cointegration</u> Unit-root test Cointegration test	Enders (2003) Johansen et al. (2000)	Are variables stationary or evolving? Are evolving variables in long-term equilibrium?
<u>2. Granger Causality</u>	Granger (1969) Trusov et al. (2009)	Which variable's changes precede another variable's changes over time?
<u>3. Model dynamic interactions</u> VAR model VAR in differences Vector error correction model	Sims (1980) Dekimpe and Hanssens (1999)	How do all endogenous variables interact over time, accounting for the unit-root and cointegration results?
<u>4. Policy simulation analysis</u> Impulse response function GIRF Long-term marketing elasticity	Srinivasan et al. (2004) Pesaran and Shin (1998) Pauwels et al. (2002)	What is the dynamic (performance) response to a (marketing) impulse? What is the immediate impulse effect, without imposing a causal ordering? What is the total, cumulative impact of a marketing impulse on performance?
<u>5. Sales driver importance</u> GFEVD	Nijs et al. (2007) Srinivasan et al. (2010)	What is the relative importance of each variable's past in driving sales?
<u>6. Forecasting accuracy</u> Out-of-sample forecast error	Theil (1966)	What is the forecasting error of the model compared to a naive model?

Table 2 Survey questions on attitude metrics awareness, consideration, preference, trial, repeat, stable, intention, usage and closeness

Top Of Mind brand awareness

If you think about <product category>, which brand first comes to mind?

1. ...

Spontaneous brand awareness

Which other brands of <product category> do you know?

Please write down all the brands you know.

2. ...
3. ...
4. ...
5. ...
6. ...
7. ...
8. ...
9. ...
10. ...

Aided brand awareness

Which of these brands of <product category> do you know, even if only by name?

Please also tick the brands you've written down earlier.

<show logo's>

1. <Brand>
2. ...
3. ...
4. none of these brands

Consideration

Which of the following brands of <product category> would you consider?

More answers possible

<Show logo's>

1. <Brand>
2. ...
3. ...
4. none of these brands

Preference

Which brands of <product category> would you prefer?

<Show logo's>

1. <Brand>
2. ...
3. ...
4. none of these brands
5. don't know

Trial, Repeat, Stable

<Randomize brands>

Below are some brands of <product category>.

Could you please indicate which of the following statements best applies to below mentioned brands?

<Brands, grid rows> <show logo's>

- <Brand>
- ...
- ...

<answers, grid columns>

1. never heard of
 2. only know the name
 3. I know this brand and would like to try it
 4. have used it, but not anymore
 5. use sometimes
 6. use regularly
 7. use most
- <solo>

Trial: % of respondents that answer '3', '4', '5' or '6'.

Repeat: % of respondents that answer '4', '5' or '6'.

Stable: % of respondents that answer '5' or '6'.

Intention

<Randomize brands>

Below are some brands of <product category>.

How likely would you buy <brand> in the future?

<Brands, grid rows> <show logo's>

- <Brand>
- ...
- ...

<answers, grid columns>

1. Would definitely buy
2. Would buy
3. Would not buy
4. Would definitely not buy
5. Don't know

Intention: % of respondents that answer '1' or '2'.

Usage

Which of the following brands of <product category> **have you ever eaten?**

More answers possible

<Show logo's>

5. <Brand>
6. ...
7. ...
8. none of these brands

Closeness

<Randomize brands>

Below are some brands of <product category>.

Could you please indicate which of the following statements best applies to below mentioned brands?

<Brands, grid rows> <show logo's>

- <Brand>
- ...
- ...

<answers, grid columns>

1. A brand where I feel comfortable with
2. I share interests, activities and style with this brand
3. This brand has high quality
4. This brand has good taste
5. ...

Closeness: % of respondents that answer '1' or '2'.

Table 3 Categories, Involvement, and Attitude survey Metrics* for Each Brand

Brand	Category	Involvement (1=low, 7=high)	Mind metrics
1	Insurance	5	Sp Aw, Cons, Pref
2	Internet	5	TOM Aw, Cons, Pref
3	Energy	4	Sp Aw, Cons, Pref
4	Lodging	7	Sp Aw, Cons, Pref
5,6,7	Travel	7	Sp Aw, Cons, Pref
8,9	Automobile	7	TOM Aw, Cons, Pref
10	Dairy	3	Sp Aw
11	Dairy	3	TOM Aw
12	Beer	4	TOM Aw, Cons, Pref
13,14,15	Beer	4	Sp Aw, Aided Aw, Closeness
16,17,18,19,20,21,22	Soft Drinks	2	Sp Aw, Trial, Repeat, Stable
23,24	Cheese	2	Aided Aw, Intention
25	Yellow Fats	2	Sp Aw
26,27,28,29	Candy	3	Sp Aw, Pref, Intention
30,31,32,33,34	Salty Snacks	3	Sp Aw, Cons, Pref, Usage
35	Sanitary Napkins	3	Aided Aw, Cons, Pref, Usage
36	Toilet Tissue	2	Aided Aw, Cons, Pref

*SpAw = spontaneous awareness, TOM = top-of-mind, Cons = consideration, Pref = preference.

Table 4 Correlation of Sales, Attitude Survey, and Online behavior metrics

Correlations	Paid clicks	Pageviews per visitor	Web visits	Spontaneous awareness	Consider	Preference	Sales
Page views per visitor	-0.17						
Web visits	0.48	-0.12					
Spontaneous awareness	0.07	-0.09	0.09				
Consider	0.11	-0.12	0.09	0.28			
Preference	0.08	-0.16	0.02	0.33	0.35		
Sales	0.19	0.12	0.16	0.09	0.02	0.15	
Average	55,462	4.98	259,833	36.91	50.21	13.46	109,049,738
Standard deviation	23,530	1.57	58,496	3.91	4.52	2.60	22,229,074
Coefficient of variation	0.42	0.31	0.23	0.11	0.09	0.19	0.20

Table 5 Sales Explanatory power across models: R^2 (adjusted R^2)

Brand	Category	Dual model	Online behavior model	Attitude survey model	Marketing only model
1	insurance	0.18 (0.11)	0.17 (0.12)	0.17 (0.12)	0.17 (0.13)
2	internet	0.42 (0.11)	0.42 (0.17)	0.35 (0.18)	0.34 (0.23)
3	energy	0.25 (0.15)	0.23 (0.14)	0.17 (0.11)	0.15 (0.10)
4	lodging	0.46 (0.07)	0.44 (0.14)	0.29 (0.05)	0.26 (0.09)
5	travel	0.78 (0.47)	0.73 (0.51)	0.71 (0.54)	0.69 (0.58)
6	travel	0.81 (0.47)	0.80 (0.51)	0.69 (0.59)	0.67 (0.58)
7	travel	0.88 (0.75)	0.74 (0.57)	0.85 (0.78)	0.70 (0.61)
8	automobile	0.89 (0.40)	0.88 (0.38)	0.85 (0.35)	0.84 (0.80)
9	automobile	0.73 (0.77)	0.65 (0.80)	0.57 (0.78)	0.48 (0.34)
10	dairy	0.15 (0.05)	0.15 (0.06)	0.13 (0.07)	0.13 (0.08)
11	dairy	0.71 (0.61)	0.70 (0.61)	0.68 (0.61)	0.67 (0.62)
12	beer	0.56 (0.22)	0.50 (0.22)	0.37 (0.13)	0.28 (0.09)
13	beer	0.20 (0.32)	0.18 (0.33)	0.18 (0.32)	0.16 (0.11)
14	beer	0.38 (0.32)	0.38 (0.33)	0.36 (0.32)	0.36 (0.33)
15	beer	0.35 (0.27)	0.32 (0.25)	0.29 (0.23)	0.27 (0.22)
16	soft drinks	0.39 (0.31)	0.38 (0.31)	0.36 (0.31)	0.35 (0.31)
17	soft drinks	0.35 (0.23)	0.33 (0.24)	0.24 (0.16)	0.23 (0.17)
18	soft drinks	0.45 (0.23)	0.39 (0.20)	0.28 (0.13)	0.23 (0.12)
19	soft drinks	0.26 (0.01)	0.26 (0.05)	0.21 (0.03)	0.20 (0.06)
20	soft drinks	0.84 (0.68)	0.83 (0.70)	0.82 (0.73)	0.81 (0.74)
21	soft drinks	0.17 (0.10)	0.11 (0.05)	0.15 (0.11)	0.09 (0.06)
22	soft drinks	0.74 (0.71)	0.72 (0.70)	0.72 (0.71)	0.71 (0.70)
23	cheese	0.39 (0.25)	0.37 (0.25)	0.31 (0.21)	0.29 (0.21)
24	cheese	0.46 (0.15)	0.46 (0.24)	0.30 (0.11)	0.30 (0.18)
25	yellow fats	0.33 (0.24)	0.31 (0.23)	0.31 (0.26)	0.31 (0.26)
26	candy	0.28 (0.22)	0.26 (0.21)	0.27 (0.23)	0.25 (0.22)
27	candy	0.48 (0.42)	0.48 (0.43)	0.48 (0.42)	0.47 (0.43)
28	candy	0.10 (0.02)	0.09 (0.02)	0.08 (0.02)	0.07 (0.03)
29	candy	0.25 (0.18)	0.25 (0.19)	0.24 (0.19)	0.24 (0.20)
30	salty snacks	0.16 (0.09)	0.16 (0.10)	0.09 (0.04)	0.08 (0.05)
31	salty snacks	0.17 (0.06)	0.15 (0.06)	0.15 (0.07)	0.15 (0.09)
32	salty snacks	0.77 (0.41)	0.69 (0.36)	0.56 (0.36)	0.43 (0.23)
33	salty snacks	0.20 (0.14)	0.18 (0.13)	0.17 (0.12)	0.15 (0.12)
34	salty snacks	0.71 (0.26)	0.68 (0.36)	0.64 (0.37)	0.58 (0.39)
35	sanitary napkins	0.33 (0.26)	0.32 (0.26)	0.31 (0.27)	0.30 (0.27)
36	toilet tissue	0.34 (0.26)	0.33 (0.27)	0.32 (0.26)	0.32 (0.27)

Table 6 Forecasting Error (Theil's Inequality Coefficient) across Models

Brand*	Category	Dual model	Online behavior model	Attitude survey model
1	insurance	0.07	0.06	0.06
2	internet	0.08	0.07	0.08
3	energy	0.15	0.14	0.13
4	lodging	0.87	0.18	0.84
5	travel	0.89	0.81	0.17
6	travel	0.11	0.14	0.13
7	travel	0.19	0.18	0.15
8	automobile	0.99	0.99	0.94
9	automobile	0.72	0.52	0.53
10	dairy	0.11	0.11	0.10
11	dairy	0.04	0.03	0.03
12	beer	0.28	0.26	0.30
13	beer	0.13	0.14	0.10
14	beer	0.32	0.32	0.26
15	beer	0.24	0.26	0.27
16	soft drinks	0.28	0.27	0.25
17	soft drinks	0.16	0.16	0.15
18	soft drinks	0.18	0.18	0.17
19	soft drinks	0.17	0.17	0.19
21	soft drinks	0.19	0.20	0.17
22	soft drinks	0.22	0.22	0.23
23	cheese	0.17	0.17	0.18
24	cheese	0.29	0.25	0.29
25	yellow fats	0.25	0.25	0.17
26	candy	0.17	0.16	0.16
28	candy	0.23	0.22	0.23
29	candy	0.19	0.18	0.22
30	salty snacks	0.19	0.19	0.19
31	salty snacks	0.15	0.13	0.13
32	salty snacks	0.86	0.76	0.28
33	salty snacks	0.82	0.91	0.17
34	salty snacks	0.38	0.31	0.36
35	sanitary napkins	0.25	0.24	0.09
36	toilet tissue	0.37	0.36	0.18

* Holdout samples are too small for brands 20 and 27.