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Media Multiplexing Behavior: Implications for Targeting and Media Planning

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There is a growing trend among consumers to serially consume small, incomplete “chunks” of multiple media types—television, radio, Internet, and print—within a short time period. We refer to this behavior as *media multiplexing* and note that key challenges for integrated marketing communications media planners are (1) predicting which media or combination of media their target audience is likely to consume at any given time and (2) understanding potential substitutions and complementarities in their joint consumption. We propose a forecasting model that incorporates media-multiplexing behavior of both traditional and new media, their interdependencies, and consumer heterogeneity, and we calibrate the model using a rich database of individual-specific media activity diaries. The results suggest that accounting for media synergies within a single utility specification significantly improves model forecasts. We also introduce a utility function that directly models cross-channel media complementarities via interactive effects of the satiation parameters of own and joint consumption of various media types. Finally, our individual-level analyses generate unique insights on consumer-level media switching, multiplexing, and individual heterogeneity often ignored in aggregate data.

Key words: integrated marketing communications (IMC); media planning; multichannel management; multimedia consumption; substitution and complementarities; interactive media; Internet advertising

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The challenging act of capturing the attention and emotional response of my target audience...[is] almost like going from shooting fish in a barrel to little minnows. The target has become faster, and the window of opportunity for capturing them has become smaller.

—Carl Marci, CEO of Innerscope Research (Steinberg 2012)

1. Introduction

Research from Nielsen in 4Q 2011 found that 45% of Americans who own tablets use them daily while watching television; in fact, 26% noted simultaneous use of both media forms throughout the day (Steinberg 2012). The habits of smartphone users are also similar. The emergence of such multimedia consumption paints a worrisome picture of consumers who are “snacking on short amounts of time with different types of media channels,” according to Unilever’s Global Director, Media Insights, Patti Wakeling (Steinberg 2012). Many companies such as

American Express and Coca-Cola are experimenting with cross-media advertising strategies, such as running a traditional print ad along with videos on the firm’s website or television ads. This is consistent with an integrated marketing communications (IMC) philosophy of a cohesive message across multichannel media forms. However, as consumers rapidly switch and simultaneously consume multiple media forms, the challenge for the advertising creative has never been higher. Moreover, although the success of IMC programs hinges on the ability to harness and leverage potential synergies—i.e., “the combined effect of multiple activities exceeds the sum of their individual effects” (e.g., Belch and Belch 1998, p. 11; Naik and Raman 2003)—there is little empirical guidance as to what combination of media forms and timing are best for tracking and targeting the “minnows” described above (Mantrala 2002, Danaher and Rossiter 2011).

Our goal is to help media planners better track and target consumers in today’s complex and rapidly changing media environment. The challenge is to

track *where* a target audience may be at any given point in time and predict *which* media or combination of media their target audience is likely to consume given potential intermedia synergies (Schultz 2002). To this end, we develop a predictive model of consumer choice of media in a multichannel context that can be applied within a product category or vertical. This represents a significant advancement over the literature on media choice modeling, because much of this work assumes that media are consumed one channel (or type) at a time; this implies a competitive model of time and attention exposure and is inconsistent with an IMC perspective.

We investigate the phenomenon of media multiplexing, whereby people serially (and potentially simultaneously) consume small, even incomplete “chunks” of media within a small period of time and may then switch to the consumption of programming/content on another media channel (Pilotta et al. 2004, Pilotta and Schultz 2005, Smith et al. 2006). The term “multiplexing” has its genesis in the telecommunications literature to describe signals or messages in a multichannel system. Our preference for this term rather than “coconsumption” is to allow for the possibility of simultaneous *multimedia* consumption, rather than the consumption of only two media forms. Pilotta and Schultz (2005) claim that the experience of media multiplexing is a shift in the logic of cultural perception and attunement from successive experience to simultaneity and synthesis of media that, in turn, restructures attention.

We calibrate a consumer-level demand model using a proprietary data set of individual-specific media consumption. To account for media multiplexing, we relax the discrete-choice assumption of commonly employed choice models, allowing for richer sources of intermedia dependencies, including (1) media switching and coconsumption, (2) potential complementarity and substitutability of the channels, (3) observed and unobserved consumer heterogeneity and process variation (e.g., satiation), and (4) day-, time-, and media-specific variables such as technology penetration and attention span. These factors rationalize consumers’ media choices, be they single media or multiplexing.

The IMC literature suggests that synergies across advertising and communication efforts exist and ought to be systematically leveraged. To this end, we introduce a utility function that directly models such cross-channel media complementarities through interactive effects of the satiation parameters of own and joint consumption of various media types. This allows us to quantify and evaluate the magnitude and direction of their combined usage. Although many suggest that multiplexing is valuable, there are neither theories nor evidence as to how various media forms should work together. We offer empirical findings to

inform this debate and use the models to address the following questions:

1. What is the improvement in predicting consumers’ media choices if we account for intermedia multiplexing? And what explains their media choice?

Using a data-driven approach, we examine controllable media-specific factors, attention and penetration, that impact substitution patterns across media alternatives. *Ceteris paribus*, the baseline utility for television is the highest relative to computer, radio, print, or any possible combination of these alternatives alone. However, the cross-media effect of attention on a media-specific baseline utility suggests interesting asymmetries across the media alternatives. For example, consumers with high attention for the computer are unlikely to multiplex traditional forms of media (radio, print, and television). In contrast, consumers with high attention for these traditional media options have higher utility for multiplexing all forms of media (including new and traditional).

2. For a given target audience, which media are substitutes and which are complements? What are the implications for old versus new media and combinations thereof?

We are also able to identify the consumer’s differential utility and marginal rate of substitution for each media and, hence, which media they are willing to give up. We find that print media is the form that is most easily switched away from, although this rate can be reduced if it is paired with other forms of media. We also find that all forms of old media—i.e., television, radio, and print—benefit when multiplexed with new media—i.e., the Internet.

Collectively, our findings identify viable old and new joint media combinations that could be exploited and underscore the need for multimedia channel collaboration over competition. Our research also serves as a critical first step toward a more detailed understanding of consumers’ media choices, taking into account media channel interdependencies and multiplexing behavior. For example, equipped with the proposed model, consumers’ media choices, and consumer-directed advertising schedules, one can extend the models proposed by Rust and Alpert (1984), Danaher and Rust (1996), and Wilbur (2008) to a multimedia channels setting. Although our data do not allow us to examine issues such as return on investment directly, they allow us to provide some insights that would move us toward that goal.

2. Literature Review

The IMC literature emphasizes effective interaction, integration, and deployment of various forms of media—for example, general advertising, direct response, sales promotion, and public relations—to clarify and make communications consistent.

However, the empirical IMC literature to date has focused on understanding a consumer's individual media choice such as television (Vakratsas and Ambler 1999), radio, and Internet (Manchanda et al. 1999). Within the focal media, these studies either measure the effectiveness of these individual channels for consumer-directed advertising or model the consumers' single-media choice problem such as the selection of television program channels (Rust and Alpert 1984, Shachar and Emerson 2000), thereby generating insights for the creation and scheduling of TV content. To the best of our knowledge, consumers' choice of multiple media (be it sequential or simultaneous) has received minimal, if any, attention in the current literature. One exception in this vein is Wendel and Dellaert (2005), who found that a media channel's perceived benefits and synergies across usage situations affect consumers' media channel consideration.

There is also a related stream of research examining firm-side media choice within an IMC setting. Naik and Raman (2003) demonstrate the sales gains from advertising across two media (i.e., television and print). Their study is the first to demonstrate the retail-level gains from honing media synergies. Our study also complements studies on aggregated synergies in marketing-mix elements (e.g., price and advertising combinations) such as Naik et al. (2005). However, they do not examine individual media choice decisions, and therefore, their ability to predict consumer sensitivity to media exposure is limited. Generally speaking, research on synergy focuses on the consequential impact of joint media consumption; we will focus on synergy as reduced satiation stemming from the complementarities that arise from multiplexed media consumption. In other words, if a consumer typically consumes one hour of radio and one hour of television, the multiplexed option might result in three hours of the complementary consumption of both.

There is little literature that aids the planning of communications strategies across multiple media using individual consumer preferences. An exception to this is Smith et al. (2006), who use individual-call-level data across print, direct mail, event sponsorships, radio, computer, and retail sources as inputs to the firm's lead generation process. Their descriptive model accommodates serial correlation across the media sources, carryover effects, and concave response functions but does not address potential substitution or complementary interdependencies; our approach does. We draw on recent advancements in the multicategory choice modeling literatures in marketing and economics to develop a *multivariate discrete/continuous choice* model that is utility-theory consistent so as to rationalize individual-specific

media multiplexing while accounting for unobserved heterogeneity and satiation.

Whereas research in the grocery retail context has increasingly examined the cross-category effects of marketing-mix activities (i.e., how consumers' purchases in one category are related to their purchase in another), the goal of this literature is to help firms better coordinate their marketing activities across categories and within each category so as to maximize profits. For example, Manchanda et al. (1999) and Chib et al. (2002) focus on recovering category interdependencies using household-level multicategory purchasing decisions and whether consumer preferences and sensitivity to marketing activities are household and/or category specific (Ainslie and Rossi 1998, Seetharaman et al. 1999, Mehta 2007). Cross-category (or product) interdependencies are accommodated in a variety of ways ranging from nonstructural specifications such as in Manchanda et al. (1999) and Edwards and Allenby (2003), to a more semistructural one such as in Dubé (2004), to a completely structural approach as undertaken in Kim et al. (2002) and Bhat (2005). Our approach is akin to Song and Chintagunta (2007) and Bhat (2005) in that multicategory interdependencies (i.e., media channels in our case) are accommodated via a behaviorally consistent utility-maximization framework while accounting for a mixture of discrete (e.g., which media to consume?) and continuous (e.g., how much to consume?) choices.

To summarize, we contribute to and advance the IMC and multicategory choice literature as follows:

(i) We complement Naik and Raman (2003) in that they utilize aggregate advertising data to speak to issues at the firm or market level, whereas we rely on individual-choice data across media and focus on predicting media choice(s) at the *individual* consumer level. Although we are also interested in synergies, our perspective focuses on media consumption, consistent with the firm's advertising challenge.

(ii) Methodologically speaking, our utility theory-consistent demand model incorporates the simultaneous consumption of different media, time effects, media technology penetration, and other exogenous factors. Instead of treating media choices as independent of each other, we explicitly model the determinants of a consumer's media choice and interdependencies between media within a *single* utility specification.

(iii) Further, we introduce a model form for assessing complementarity that expands on both Bhat (2005) and Kim et al. (2002). These papers represent the prevailing model form for discrete/continuous choice in the multicategory choice literature but do not model complementarity. Our innovation is to allow separate satiation parameters for such *joint* choices.

3. The Empirical Model

Consumer choice is characterized by the multiplexing of K media alternatives such as Internet, television, radio, and print media within a one-hour period. The choice of a one-hour period is largely a function of the data structure, which is collected via self-report diaries over half-hour increments. We develop the model along one-hour increments but note that there is no theoretical reason why the increment should be one hour, or more, or less. In the estimation section we also observe the model's flexibility to one-hour, half-hour, or even two-hour increments.

Our objective is to predict discrete incidences of individual i 's media consumption choice k (or multiple choices when consumer engages in multiplexing) and continuous quantities of media time allocations t_k while accounting for potential interdependencies across media alternatives. We employ a stochastic utility specification variant of Bhat (2005) that incorporates important media planning decisions such as a timing effect (including time of the day and day of the week), observed and unobserved consumer heterogeneity, attention span, and media penetration. We compare the proposed model with a single discrete/continuous model (Hanemann 1984) in later sections to show the improvement in model fit and prediction.

We specify the utility derived in a one-hour block. The functional form is a generalized variant of the translated consumer-expenditure-system function given by

$$U_i(\mathbf{t}) = \sum_{k=1}^K \frac{\gamma_k}{\alpha_k} \psi_{ik} \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\}, \quad (1)$$

where $U(\mathbf{t})$ is a quasi-concave, increasing, and continuously differentiable function with respect to the dependent variable of the continuous consumption quantity ($K \times 1$)-vector \mathbf{t} ($t_k \geq 0$ for all k), which is the time allocated to each media alternative. Multiplexing is accommodated by summing across K media alternatives, whereas ψ_k is the baseline utility for time invested in media activity k ; γ_k and α_k are translation parameters associated with good k .

A multiplicative random element is introduced to the baseline marginal utility of each media option as follows:

$$\psi_{ik} = \psi(z_{ik}, \varepsilon_{ik}) = \psi(z_{ik}) \cdot e^{\varepsilon_{ik}}, \quad (2)$$

where z_{ik} is a set of attributes characterizing media k and the decision maker, including baseline constants, time of the day, day of the week, demographics, attention levels, and media penetration, and ε_{ik} captures idiosyncratic (unobserved) characteristics that impact the baseline utility for media k for individual i . The term $\psi(z_{ik})$ is further parameterized as $\exp(\beta' z_{ik})$,

which then leads to the following form for the baseline random utility associated with media k :

$$\psi(z_{ik}, \varepsilon_{ik}) = \exp(\beta' z_{ik} + \varepsilon_{ik}). \quad (3)$$

The z_{ik} vector in the above equation includes a constant. The overall random utility function of Equation (1) then takes the following form, with the first good being the outside good:

$$U_i(\mathbf{t}) = \sum_k \frac{\gamma_k}{\alpha_k} [\exp(\beta' z_{ik} + \varepsilon_{ik})] \cdot \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\}. \quad (4)$$

From the econometrician's perspective, the individual is maximizing random utility subject to the binding linear budget constraint that $\sum_{k=1}^K t_k = T$, where T is a total budget of 60 minutes.

In our identification setting, α_k is further parameterized as $\exp(\beta' Z_k)/(1 + \exp(\beta' Z_k))$, and separate α values (rather, the corresponding functional forms) are estimated for all media alternatives including the outside good. The γ values for all media (except the outside good) are constrained to equal 1.

3.1. Optimal Time Allocations

Optimal time allocation occurs when an individual consumer i choose the media and quantities that maximize his or her utility within one-hour. This is achieved by forming the Lagrangian and applying the Kuhn–Tucker (KT) conditions. We derive the individual-specific consumption vector for the random utility-specification subject to the linear time constraint. For convenience, we drop the subscript i for now. The resulting Lagrangian is

$$L = \sum_k \frac{\gamma_k}{\alpha_k} [\exp(\beta' z_k + \varepsilon_k)] \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\} - \lambda \left[\sum_{k=1}^K t_k - T \right], \quad (5)$$

where λ is the multiplier associated with the constraint (i.e., the marginal utility of total time).

The first-order conditions for the optimal time allocations (the t_k^* values) are given by

$$\begin{aligned} [\exp(\beta' z_k + \varepsilon_k)] \left(\frac{t_k^*}{\gamma_k} + 1 \right)^{\alpha_k - 1} - \lambda &= 0, \\ &\text{if } t_k^* > 0, k = 1, 2, \dots, K, \\ [\exp(\beta' z_k + \varepsilon_k)] \left(\frac{t_k^*}{\gamma_k} + 1 \right)^{\alpha_k - 1} - \lambda &< 0, \\ &\text{if } t_k^* = 0, k = 1, 2, \dots, K. \end{aligned} \quad (6)$$

The optimal demand satisfies the conditions in Equation (6) plus the total time constraint $\sum_{k=1}^K t_k^* = T$. We specify an extreme value distribution for ε_k and assume its independence of z_k ($k = 1, 2, \dots, K$) and its independent distribution across media. Let V_k be

defined as follows:

$$V_k = \beta' z_k + (\alpha_k - 1) \ln(t_k^* + 1) \quad (k = 1, 2, 3, \dots, K). \quad (7)$$

Also, let $c_i = ((1 - \alpha_i)/(\gamma_i + t_i^*))$; following Bhat (2005), we obtain the following probability expression:

$$P(t_2^*, t_3^*, \dots, t_M^*, 0, 0, \dots, 0) \\ = \left[\prod_{i=1}^M c_i \right] \left[\sum_{i=1}^M \frac{1}{c_i} \right] \left[\frac{\prod_{i=1}^M e^{V_i}}{(\sum_{k=1}^K e^{V_k})^M} \right] (M-1)!. \quad (8)$$

When an outside good is present, for identification purposes, let $\psi(t_1, \varepsilon_1) = e^{\varepsilon_1}$. Then, the utility functional form is modified as follows:

$$U(\mathbf{t}) = \frac{1}{\alpha_1} \exp(\varepsilon_1) t_1^{\alpha_1} \\ + \sum_{k=2}^K \frac{\gamma_k}{\alpha_k} \exp(\beta' z_k + \varepsilon_k) \left\{ \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right\}. \quad (9)$$

There is no translation parameter γ_1 for the first good, because it is always consumed. This feature allows us to accommodate media consumption and other non-media activities.

3.2. Unobserved Heterogeneity

Examining the impact of consumer heterogeneity on a consumer's media choice gives insight into the competition between media and substitutability across consumers by examining unobserved heterogeneity in baseline utility as well as in the satiation parameters. We include random coefficients for each baseline preference constant and include one common error component among all media options to generate heteroscedasticity and covariance in unobserved factors across activity types. This means that consumers may follow a common mechanism in evaluating media options relative to the outside good. To achieve this, we need to partition the error term ε_j into two independent components, ζ_j and η_j . The first component, ζ_j , is assumed to be independently and identically standard Gumbel distributed across alternatives. The second component, η_j , allows the estimation of distinct scale (variance) parameters for the error terms across alternatives to reflect the fact that a consumer may evaluate certain media options in a similar fashion. Let $\boldsymbol{\eta} = (\eta_1, \eta_2, \dots, \eta_K)'$ and assume that $\boldsymbol{\eta}$ is distributed multivariate normal, $\boldsymbol{\eta} \sim N(0, \Omega)$. We considered other specifications such as a common error component for all traditional media choices or alternative combinations of the media choices. However, the results were not significantly different.

Therefore, Equation (8) can then be rewritten as

$$P(t_2^*, t_3^*, \dots, t_M^*, 0, 0, \dots, 0) \\ = \int_{\boldsymbol{\eta}} \left[\prod_{i=1}^M c_i \right] \left[\sum_{i=1}^M \frac{1}{c_i} \right] \left[\frac{\prod_{i=1}^M e^{(V_i + \eta_i)}}{(\sum_{k=1}^K e^{(V_k + \eta_k)})^M} \right] \\ \cdot (M-1)! dF(\boldsymbol{\eta}), \quad (10)$$

where F is the multivariate cumulative normal distribution. We extend Equation (10) to also include random coefficients on the independent variables z_k and random coefficients in the α_k satiation parameters.

4. Data

In this section, we describe the data set, the extent to which media multiplexing occurs (and related switching, time effects, and consumer heterogeneity), and current industry practice for targeting.

4.1. Media Consumption Data

The data are from the 2006 Universal McCann's Media in Minds Diary, spanning over 50 countries, including the United States. The survey highlights the multimedia pattern of adults and identifies when consumer segments best connect with old and new media forms; this study is the basis for the media plans for their global clients. The survey is continually adapted to reflect the changing landscape of all forms of communication and is the largest ongoing proprietary survey of its kind. Hence, it represents a generalizable sample of the population at large.

Our sample consists of a panel of 1,775 individuals in the United States who reported their media activities—i.e., computer (or Internet), television, radio, or print (newspapers and magazines) by checking a box indicating whether they had consumed a particular media channel in a specified half-hour block over a seven-consecutive-day period. Media consumption represented approximately 40.7% of this time. This is consistent with recent research commissioned by Time Warner's Time Inc. that suggests that consumers in their 20s switch media venues as much as 27 times per nonworking hour (Steinberg 2012). We refer to nonmedia consumption activities as the *outside* option, and this is substantial, representing 40% of all switching from one time interval to the next.

We use a randomly chosen set of 1,500 individuals for estimation and a holdout sample of the remaining 275 respondents. For each respondent, we have demographic information, including age, gender, household income, household size, and location (i.e., urban or rural); and adoption of new media technologies such as home computer ownership (83.7%), workplace computer availability (44.7%), and cable television subscription (64.9%). Adoption for television sets and radio are virtually 100% and not included.

Respondents report their activities and attention levels for each media channel for seven consecutive days, except for the time periods from 1–3 A.M. and 3–5 A.M., which are each recorded as two individual observations. We aggregate the data to the one-hour level for more flexible modeling of continuous components. Over the course of the week,

there are $22 \times 7 = 154$ time slots. The dependent variables are defined as the time spent on each media channel at each time slot, the total of which equals the time constraint. In the case of multiplexing, the total time will be treated as $t = 60$ minutes for each alternative chosen, because we do not observe the exact amount of time allocation to each media within the half-hour slot. Therefore, the complete data set contains $1,500 \times 154 = 231,000$ observations. Media multiplexing accounts for 8.7% of the observations ($n = 19,994$) and equivalently 21.4% of total media choices. A large share (40.2%) of this multiplexing occurs during the 7–9 A.M. and 7–9 P.M. time slots, prime advertising spots for television and radio. Whereas large segments engage in single-media consumption—i.e., computer (27.9%), radio (21.5%), and television (44.6%), nearly one out of five consumers in the sample are multiplexors.

4.2. Media Channel Switching

Table 1 displays the switching matrix for the average time movement across media. Each cell denotes the number and percentage share of occurrences of switching from the media channel in a row to the channel in the column in any consecutive time slot. For example, among those who used the computer in the past period, 18% remained with the computer channel in the next time period, whereas 8% switched to television, print, or an outside option and 7% switched to radio. In general, we observe that consumers are most likely to switch to television from radio (14%), print (16%), or an outside option (14%). The diagonal elements of these tables indicate the extent to which state dependence occurs; television exhibits the highest degree of state dependence (22%), followed by radio (21%), computer (18%), and print media (9%).

On weekends (Saturday and Sunday), 87% of the consumers in the sample are more likely to switch

away from media to an outside option, whereas during the week (Monday–Friday), only 56% of consumers will switch. Although we do not observe noticeable differences in state dependence and inter-media switching between males and females, we do observe that younger audiences (aged 18–34) have more state dependence for computers (20%) than older audiences (aged 65–75, 12%) and are more likely to switch to this medium from television, radio, print, or an outside option (9.25% on average) than older audiences (5.25% on average). Collectively, the data set suggests that multiplexing is prevalent, and a model that examines switching, time-varying properties, consumer heterogeneity, and media-specific factors is necessary for understanding this phenomenon. In the Web appendix (available at <http://dx.doi.org/10.1287/mksc.1120.0759>), we elaborate on these characteristics in further detail.

5. Results

We now describe the model covariates, compare goodness-of-fit measures, and assess the model's out-of-sample predictive ability.

5.1. Model Covariates and Constants

We included several variables to obtain a rich understanding of consumers' baseline marginal utility with respect to media choice, media-specific satiation, and time-usage behavior. One direction for future research would be to add the media content being consumed so as to decompose the content in the baseline utilities. Covariates include (1) time-of-day dummies (12 A.M. is the base time slot), (2) day-of-week dummies (Saturday is the base day of week), (3) sociodemographics (household size, age, income, gender, location of residence, etc.), (4) stated media attention level (where 1 = low, 2 = medium, and 3 = high attention), and (5) availability of media technologies: personal computer at home, computer at work, and cable television service. Together, these variables are stacked into the z_{ik} parameter.

We now contrast the results with an alternative demand specification—a single discrete/continuous demand model. This is our base specification, i.e., a Hanemann (1984) model. This model has been further developed by Chiang (1991) and Mehta et al. (2010). Specifically, we contrast results from the demand models using our parameterized form of the baseline marginal utility parameters, because this allows us to show the equivalence between models. For model selection, we examine both in-sample and out-of-sample statistical criteria.

5.2. Model Selection and Goodness-of-Fit Measures

The pseudo-log likelihood for the main model with the aforementioned covariates in the baseline utility

Table 1 Media Switching Matrix

	Computer	TV	Radio	Print	Outside
Computer	6,850 18%	5,274 14%	2,563 7%	1,260 3%	21,865 58%
TV	5,238 8%	15,009 22%	5,359 8%	2,521 4%	39,642 58%
Radio	2,674 7%	5,212 14%	7,749 21%	1,537 4%	20,451 54%
Print	1,265 8%	2,537 16%	1,499 9%	1,320 8%	9,600 59%
Outside	21,770 8%	39,750 14%	20,445 7%	9,597 3%	188,220 67%

Notes. Columns represent the media channel that consumers switch TO. Rows represent the media channel that consumers switch FROM. Cells indicate the number of consumers and their proportion in the sample. Diagonal elements (in bold) indicate state dependence (i.e., inertia).

Table 2 In-Sample Hit Rate Comparison

(A) Single-media consumption													
		Overall hit rate		Computer		TV		Radio		Print		Outside	
Media activities													
Hanemann model (%)		60.30		50.81		31.87		29.47		18.66		82.04	
Our model (%)		97.00		99.13		99.27		97.60		86.67		96.38	
(B) Multiplexing media consumption													
Media activities	Computer and TV	Computer and radio	Computer and print	TV and radio	TV and print	Radio and print	Computer and TV and radio	Computer and TV and print	Computer and radio and print	TV and radio and print	Computer and TV and radio and print		
Hanemann model	—	—	—	—	—	—	—	—	—	—	—		
Main model (%)	99.07	98.41	83.33	88.64	98.81	92.00	100.00	100.00	100.00	100.00	100.00		

Notes. The Hanemann (1984) model does not provide values for multiplexed combinations. Each cell contains the percent accuracy rate.

and the satiation/translation parameters as media-specific constants is $-4,564.68$. The log likelihood value at convergence of the Hanemann (1984) model with the main model's baseline utility covariates as explanatory variables is $-24,573.97$. The Bayesian information criterion (BIC) for our main model is 11,204.19 with 168 parameters. The BICs for the Hanemann model is 51,291.69 with the same number of parameters. Thus, our proposed model outperforms the Hanemann model, underscoring the importance of accounting for multiplexing media choice.

5.2.1. In-Sample Assessment. We contrast the in-sample hit rates for both models in Table 2, panel A. Interestingly, our model outperforms the benchmark model even when single media are consumed. The benchmark model predicts 50.8% for computer, 31.7% for television, 29.5% for radio, and 18.7% for print. In contrast, our single-media predictions are 99.1% for computer, 99.2% for television, 97.6% for radio, and 86.7% for print, underscoring the superiority of the proposed demand model from a goodness-of-fit standpoint. Table 2, panel B, displays the proposed model performance for all possible media interrelationships. Thus, our main model produces excellent predictive ability for multiplexing choices that would not be captured by a simple single discrete/continuous demand framework. To summarize, our model leads to a hit rate of 97.0% compared with 60.3% from a Hanemann model.

Several aspects are worth noting. First, although this hit rate is higher than previous research—(e.g., around 80% in Hansen et al. (2006), 89% in Mehta (2007), 78% in Ainslie and Rossi (1998), 77% in Chung and Rao (2003), and 84%–94% Schweidel et al. (2011)—it more closely approximates the rate observed in Manchanda et al. (1999) (i.e., 99%). However, Manchanda et al. (1999) took a model-fitting approach, whereas our structural approach provides some theoretical insight while still robustly achieving similar hit rates. Second, we reran the prediction model across three

subsamples of 5,000 randomly selected observations and observe consistently high hit rates (ranging from 95%–97%); more detail can be found in Table 3 of the Web appendix. Third, recall that 65% of the consumption choices involve an outside good, and these choices are accounted for, which might be driving up the hit rate to some extent.

5.2.2. Out-of-Sample Assessment. Two hundred and seventy-five individuals were held out and used for model validation; see Table 3, panels A and B. Again, the main model (95.9%) outperforms the benchmark models (60.1%) overall and for every possible single-media choice. Table 3, panel B, displays the proposed model performance for all possible media interrelationships.

Let us now examine the baseline-preference constants and satiation-parameter estimates. In the interest of space, we do not examine or contrast the parameter estimates for the benchmark model directly (these are provided in Table 2 of the Web appendix).

5.3. Robustness of the Time Period Specification

The data were collected in a half hour but could just as easily be aggregated to two-hour time periods (which is what we did between the hours of 1 A.M. to 5 A.M.). We estimated our model using half-hour time slots and observed that the parameter estimates are robust, both in direction and significance. For reason of space we did not include these estimates here; they are available from the authors upon request. Together, we conclude that our model is able to process and predict the continuous components of choice in a fairly flexible manner, more so than what is dictated by the data set structure.

5.4. Baseline-Preference Constants

The estimated baseline-preference constants and the corresponding t -statistics are presented in Table 4. Any activity that does not involve consumption of

Table 3 Out-of-Sample Hit Rate Comparison

		(A) Single-media consumption										
Media activities		Overall hit rate	Computer	TV	Radio	Print	Outside					
Hanemann model (%)		60.08	50.95	30.83	27.27	21.90	82.07					
Main model (%)		95.90	87.59	99.87	97.85	85.15	95.22					
(B) Multiplexing media consumption (continued from above)												
Media activities	Computer and TV	Computer and radio	Computer and print	TV and radio	TV and print	Radio and print	Computer and TV and radio	Computer and TV and print	Computer and radio and print	TV and radio and print	Computer and TV and radio and print	
Hanemann model	—	—	—	—	—	—	—	—	—	—	—	
Main model (%)	100.00	98.08	89.47	91.43	98.85	94.29	100.00	100.00	87.50	100.00	100.00	

Notes. The Haneman (1984) model does not provide values for multiplexed combinations. Each cell contains the percent accuracy rate.

any media is the base alternative. Because the outside alternative is considered more often than the inside alternatives, all the baseline-preference constants are negative. The baseline-preference constant for the print media option is more negative than other media, indicating the lower participation level of households in this media activity relative to the outside good. There are also significant baseline-utility differences across time of day and day of week and varying household and sociodemographic effects for each media. These specifics are of primary interest to media planners but, for reasons of space, are further described in Table 3 of the Web appendix. The Web appendix also contains additional details regarding unobserved heterogeneity in the baseline utilities.

5.5. Satiation Estimates

Recall that the role of α_k is to reduce the marginal utility with the increasing consumption of media k , hence its interpretation as a satiation parameter. The parameter estimates for our proposed model are displayed

in Table 4. High α_k values indicate low satiation. These parameters were introduced as a constant in our model specification for each media alternative. The satiation estimates and the corresponding t -statistics displayed in the last row of Table 4 suggest that significant differences exist in the time-investment patterns for each media. The alpha estimates suggest that utility for the computer is nearly linear in time spent (0.999). However, utility for all old media forms—television, radio, and print—have square-root diminishing returns to time spent (0.447–0.479). To the best of our knowledge, we are the first to provide such evidence regarding media consumption at the individual (versus aggregate) level.

5.6. Effects of Media Covariates and Cross-Media Effects

Fortunately, the data set contains information on media covariates such as attention and technology penetration. Not surprisingly, higher household attention for a focal media is associated with a higher level of utility for the same media. *Ceteris paribus*,

Table 4 Estimates for the Proposed Model

	Structural parameters: Coefficient (T -statistic)			
	Computer	TV	Radio	Print
Intercept	−8.47*** (−116.75)	−7.013*** (−146.6)	−8.153*** (−112.8)	−9.803*** (−77.31)
Attention levels for				
Computer	7.74*** (431.4)	−0.335*** (−14.6)	−0.421*** (−16.48)	−0.239*** (−6.45)
TV	−0.05*** (−4.35)	2.089*** (218.12)	−0.095*** (−6.64)	0.104*** (6.51)
Radio	−0.096*** (−9.37)	−0.044*** (−3.51)	2.212*** (139.43)	0.144*** (8.65)
Print	−1.41*** (−41.45)	0.469*** (26.33)	0.651*** (29.03)	3.599*** (151.34)
Media penetration				
Cable service	−0.063*** (−3.98)	0.078*** (5.8)	0.0036 (0.21)	0.07*** (2.8)
Computer at home	0.043** (1.94)	−0.084*** (−4.8)	−0.295*** (−13.61)	0.178*** (5.48)
Computer at work	0.132*** (7.72)	−0.099*** (−7.18)	−0.0041 (−0.23)	−0.051*** (−1.96)
Satiation parameters				
Alpha	0.999*** (4.66)	0.447*** (12.75)	0.479*** (2.95)	0.448*** (7.93)

Note. Alpha for the outside good is approximately 1 for all inside goods and 0 for the outside good.

** $p < 0.01$; *** $p < 0.001$.

holding the same attention level across media alternatives, the baseline utility for computer (7.740) is the highest relative to other media alternatives (2.089 for television, 2.212 for radio, and 3.599 for print). Whereas these attention levels would typically imply a 100% share of that media channel, by estimating the cross-media effects of attention on a media-specific baseline utility, we can infer whether attention levels enhance or weaken the utilities for alternative media. For example, although computer has the highest own-attention-level effect, the attention level for computer has a negative impact on the baseline utility for other media (e.g., -0.335 for television, -0.421 for radio, and -0.239 for print), suggesting that consumers who focus on computer media may be less likely to multiplex. In other words, for these consumers, non-computer media options might act as substitutes. In §6, we will examine the marginal rates of substitution to consider this possibility more rigorously. In contrast, consumers who have high levels of attention for television (2.089) are likely to multiplex print (0.104) but are unlikely to multiplex computer (-0.05) and radio (-0.095) media. Thus, for these consumers, utility for print and television is likely also increased.

Higher attention levels for all media alternatives negatively impact the baseline utility for computer, with the highest degradation from attention levels for print (-1.410). However, this substitution pattern is not found for the other three media alternatives. In fact, high attention levels for print media benefit the baseline utility for television (0.469) and radio (0.651). It is not uncommon for us to observe people reading newspapers while watching television or listening to radio. The allocation of attention suggests that consumer may intrinsically be attracted to multiple media channels, and the joint consumption is not necessarily as a result of satiation only.

We consider the role of media availability by examining media penetration in our sample. We acknowledge that this is a data-driven approach, and better data would be preferable. However, our approach is not inconsistent with the grocery choice literature (Manchanda et al. 1999, Kim and Allenby 2002), which also does not examine shelf availability directly. Respondents who have subscribed to cable television service derive more negative baseline utilities for computer consumption (-0.063) but positive utilities for television (0.078), radio (0.004), and print media (0.07). In contrast, consumers who own a personal computer have higher utilities for computer media (0.043) and print media consumption (0.178) but negative utilities for television (-0.084) and radio (0.295). In other words, consumers with a computer at home are more likely to have higher utility for print media. In addition, if respondents use computers at work, then they

experience more negative baseline utilities for all other media (e.g., -0.10 for television, -0.00 for radio, and -0.05 for print).

6. Media as Substitutes

The marginal rate of substitution for each media and cross-media alternative can give us insight into the nature of substitutability in joint media consumption. Specifically, it can enable the identification of which and what multiplexed options might be preferred to individual media options.

Recall from the discussions in §3 that ψ_k is the marginal utility at the point of zero consumption. It can be inferred by computing the marginal utility of consumption with respect to media k , which is

$$\frac{\partial U(t)}{\partial t_k} = \psi_k \left(\frac{t_k}{\gamma_k} + 1 \right)^{\alpha_k - 1}. \quad (11)$$

Alternatively, the marginal rate of substitution between any two media k and l at the point of zero consumption of both media is given by ψ_k/ψ_l . For two alternatives i and j , a higher baseline marginal utility for media i relative to media j implies that an individual will increase overall utility more by consuming media i rather than j at the point of no consumption of any media option. In other words, the consumer would be willing to give up media j in exchange for consuming more of media i . Thus, a higher baseline ψ_k implies a reduced likelihood of a corner solution for media k .

Using the recovered parameter estimates, we compute the own- and cross-marginal effects to examine individual media substitution patterns across the choice alternatives. These are presented in Table 5, which uses only media-specific intercepts in the baseline utilities of each media alternative; this represents consumers' intrinsic preference for switching from a media option in the column to an alternative on the row from the point of zero consumption. Hence, on average, consumers would gain more utility from the television than from the computer (4.289), radio (3.126), or print (16.268). In contrast, print media

Table 5 Marginal Rate of Substitution at the Point of Zero Consumption

	Computer	TV	Radio	Print
Computer	—	0.233	0.729	3.793
TV	4.289	—	3.126	16.268
Radio	1.372	0.320	—	5.204
Print	0.264	0.061	0.192	—

Notes. The column represents the media option that will be SUBSTITUTED FOR, and the row represents the media option that will be SUBSTITUTED TO. These effects are computed using only the media-specific intercepts in the baseline utilities.

are easily substituted for all other media (0.061 for TV, 0.264 for computer, and 0.192 for radio). These rates of substitution can be further generalized to a specific day of the week and time of the day, or to a specific demographic. For example, for a certain group of media enthusiasts, the substitution patterns between joint consumption and single consumption would show the incremental benefits of multiplexing over individual media, revealing potential synergies. It is worth noting that this is the conventional approach to understanding such interdependencies in the context of the Bhat (2005) model. Further, if we consider the full range of marginal rate of substitution patterns at the point of zero consumption for multiplexed options with respect to the baseline constants, we might conclude that there is little willingness to give up single-media consumption for multiplexed options. This is evidenced in the first five columns of Table 4 of the Web appendix.

However, one of the virtues of our data set is that it also contains additional information on media consumption, such as individual attention for each media form for each time period as well as the household penetration. Thus, we can further unpack the nature of substitution among single and multiplexed media options. A high marginal rate of substitution of a multiplexing media option (for example, media *AB*) with a single-media option (*A*) suggests that consumers are willing to give up more single consumption of *A* for joint consumption with *B*.

Specifically, we find that consumers with high attention to the computer are less willing to give up this media type for all forms of alternative single *and joint* media combination, including any consumption choice that involves the computer. In other words, consumers with high attention for new media are unlikely to multiplex old media forms (see Table 5A, column 2 of the Web appendix for detailed estimates). However, the reverse is not true; taking this same approach for each media form in turn, we find that those with high attention for old media are *more prone* to multiplex not only the consumption of new media such as the computer but also the consumption of all other forms of media (again, see the first five columns of Web Appendix Tables 5B–5D). Together, this suggests an interesting asymmetry in how prone consumers are to multiplex old and new media and gives insight into the nature of substitution patterns that exist in single versus multiplexed consumption.

In regard to computer penetration, we observe that individuals who own a computer are less likely to give up print media (see Table 5E, column 5 in the Web appendix) and that such owners are educated, with higher household incomes. In contrast, consumers who have cable television at home would easily give up computer media consumption relative

to all other forms of media (see the first two columns of Web Appendix Table 5F). These cable subscribers tend to have lower household incomes and less education. Collectively, these results are consistent with the media landscape in 2006, the time frame of our sample. Computer penetration was likely to be lower, and online news was not as plentiful as it currently is, which might explain this stickiness for the computer for those who owned computers and the lack of stickiness for those with cable subscriptions.

7. A Model of Complementarity

Although the Bhat (2005) and Kim et al. (2002) models are useful for better understanding the nature of substitution—i.e., whether a multiplexed option is preferred over a single-media option—it ignores complementarity between the choice options. We propose that the heart of the multiplexing phenomenon is the potential utility increase from joint consumption. We specify this mechanism as an interaction term among the media consumption options. This represents an important extension to the work of Bhat (2005) and Kim et al. (2002), which is primarily concerned with the main effects of choice options.

The closest research on complementarity in a multichoice context is Lee et al. (2011). They propose a direct utility model for asymmetric complements in a two-good case of milk and cereal. They use a simplified log form specification, i.e., restricting α to be 1 for all alternatives, γ to be 1 for all inside goods, and 0 for the outside option. However, we construct a more generalized direct utility model (i.e., with fewer restrictions and allowing for more choice alternatives). We allow for these possibilities via two-way interactions between all five media options. Note that our model can be applied and extended to solve for n -way complementarity, but we limit our analysis to two-way combinations for parsimony and interpretability concerns.

Specifically, the joint utility an individual consumer i derives from consuming time t over $j = 1, \dots, 5$ media activities can be written as¹

$$U(t) = \sum_{j=1}^5 \psi_j [(t_j + \gamma_j)^{\alpha_j}] + \sum_{k \neq j} \psi_j \psi_k [(t_j t_k + \gamma_{jk})^{\alpha_{jk}}], \quad (12)$$

where t is a vector of dimension 5. The first summation part is identical to Kim et al. (2002) and similar to Bhat (2005). The second part of the equation captures the additional utility gained from media multiplexing through interactive effects of the media options. Note that $\psi_{jk} = \psi_j \psi_k$ would introduce a multiplicative random element to the baseline marginal utility of each media option if we were to use the same

¹ We thank an anonymous reviewer for this utility form.

parameterization as before, such that $\psi_j = \psi(z_j, \varepsilon_j) = \psi(z_j) \exp(\varepsilon_j)$. This could raise identification concerns that we address later in this section. The terms α_{jk} and γ_{jk} reflect the differential satiation rates when consumers engage in media multiplexing as opposed to single-media consumption. Again, α and γ are not separately identifiable, so we fix γ to be 1 for all goods in our empirical estimation. Higher values of α are associated with more inertia of media consumption. The specific role of α_{jk} parameters in influencing the diminishing marginal returns is discussed and developed in detail in the paragraph below and graphed in Web Appendix 2. In short, α_{jk} represents the satiation effect of complementarity. If α_{jk} is greater than $\alpha_j + \alpha_k$, then consumers satiate less when multiplexing the two channels than consuming them independently. The marginal utility is obtained by

$$\frac{\partial}{\partial t_j} U(t) = \alpha_j \psi_j(t_j + \gamma_j)^{\alpha_j-1} + \sum_{k \neq j} \alpha_{jk} \psi_j \psi_k t_k (t_j t_k + \gamma_{jk})^{\alpha_{jk}-1}. \quad (13)$$

In previous models of cross-category choice, the marginal utility is usually defined to be *independent* of the levels of other goods. In contrast, our interaction specification more explicitly specifies the nature of complementarity between the two media options; this is the essence of the phenomenon of integrated marketing communications.

The second cross derivative of the marginal utility shows the decreasing impact of complementarity: as t_k increases, the impact of t_k on the marginal utility of t_j decreases as the complementarity effect satiates. We obtain

$$\frac{\partial^2}{\partial t_j \partial t_k} U(t) = \sum_{k \neq j} \alpha_{jk} \psi_j \psi_k ((t_j t_k + \gamma_{jk})^{\alpha_{jk}-1} + (\alpha_{jk} - 1) t_j t_k (t_j t_k + \gamma_{jk})^{\alpha_{jk}-2}). \quad (14)$$

Note that when $\alpha_{jk} = 0$, there is no complementarity effect, whereas when $\alpha_{jk} = 1$, there is no satiation of complementarity; i.e., the complementarity effect is linear. We take the log transformation of the error terms and obtain

$$\begin{aligned} \ln(U_j(t)) &= \ln\left(\frac{\partial}{\partial t_j} U_j(t)\right) + \varepsilon_j \\ &= \ln\left(\alpha_j \psi_j(t_j + \gamma_j)^{\alpha_j-1} + \sum_{k \neq j} \alpha_{jk} \psi_j \psi_k t_k (t_j t_k + \gamma_{jk})^{\alpha_{jk}-1}\right) + \varepsilon_j, \\ \varepsilon &\sim N(0, 1). \end{aligned} \quad (15)$$

However, this introduces nonadditive separable stochasticity, which is the same situation faced by Bhat

and Pinjari (2010). Like them, we assume that the analyst knows the parameters of the utility function to ensure identification. This approach does not allow the derivation of a random utility specification that is consistent with the additively separable stochastic specification of the baseline marginal utility in Equation (12). However, it is empirically indistinguishable (Bhat and Pinjari 2010) and computationally feasible to make assumptions that the analyst observes all factors relevant to utility formation, as specified in Equation (15).²

Given the time budget constraint $\sum_{j=1}^5 t_j = T$, the Lagrangian is given by $U(t) - \lambda(\sum_{j=1}^5 t_j - T)$. Then the Kuhn–Tucker problem reduces to the standard Lagrangian first-order conditions (there are five of them); note that we need to convert back from the log form because ε_j is assumed to be lognormal:

$$\begin{aligned} \frac{\partial}{\partial t_j} U(t) \exp(\varepsilon_j) - \lambda &= 0 \quad \text{if } t_j^* > 0, j = 1, \dots, 5, \\ \frac{\partial}{\partial t_j} U(t) \exp(\varepsilon_j) - \lambda &< 0 \quad \text{if } t_j^* = 0, j = 1, \dots, 5. \end{aligned} \quad (16)$$

Following Kim et al. (2002), we take logs, and for the optimal time allocation t_j^* , we have

$$\begin{aligned} V_j(t_j^*) + \varepsilon_j &= \ln \lambda \quad \text{if } t_j^* > 0, j = 1, \dots, 5, \\ V_j(t_j^*) + \varepsilon_j &< \ln \lambda \quad \text{if } t_j^* = 0, j = 1, \dots, 5, \end{aligned} \quad (17)$$

where

$$V_j(t_j^*) = \ln\left(\alpha_j \psi_j(t_j + \gamma_j)^{\alpha_j-1} + \sum_{k \neq j} \alpha_{jk} \psi_j \psi_k t_k (t_j t_k + \gamma_{jk})^{\alpha_{jk}-1}\right). \quad (18)$$

Again, assuming the first good is always consumed, we take the difference between error terms and obtain $\varepsilon_j - \varepsilon_1 = V_1(t_1^*) - V_j(t_j^*)$, $j = 2, 3, 4, 5$. We denote the left-hand side v_j and right-hand side $h_j(t_j^*)$. For the four conditions corresponding to the four media activities, we have the ij th element of the Jacobian term for $h(t_j^*)$:

$$J_{ij} = \frac{\partial}{\partial t_{j+1}} h_{i+1}(t_{i+1}^*), \quad i, j = 1, 2, 3, 4.$$

For simplicity of notation, we shall note the $(i-1, j)$ th element of the Jacobian, for $i, j = 2, 3, 4, 5$, instead:

$$\begin{aligned} J_{i-1,j} &= \frac{\partial}{\partial t_j} h_i(t_i^*) = \frac{\partial}{\partial t_j} (V_1(t_1^*) - V_j(t_j^*)) \\ &= \frac{\alpha_{1j} \psi_1 \psi_j t_1 (t_1 t_j + \gamma_{1j})^{\alpha_{1j}-2}}{\alpha_1 \psi_1 (t_1 + \gamma_1)^{\alpha_1-1} + \sum_{k \neq 1} \alpha_{1k} \psi_1 \psi_k t_k (t_1 t_k + \gamma_{1k})^{\alpha_{1k}-1}} \end{aligned}$$

² Research is currently underway to examine the additively separable stochasticity.

$$\begin{aligned}
& - \left(\alpha_j (\alpha_j - 1) \psi_j (t_j + \gamma_j)^{\alpha_j - 2} \right. \\
& \quad \left. + \sum_{k \neq j, k \neq 1} \alpha_{jk} (\alpha_{jk} - 1) \psi_j \psi_k t_k^2 (t_j t_k + \gamma_{jk})^{\alpha_{jk} - 2} \right) \\
& \cdot \left(\alpha_j \psi_j (t_j + \gamma_j)^{\alpha_j - 1} \right. \\
& \quad \left. + \sum_{k \neq j} \alpha_{jk} \psi_j \psi_k t_k (t_j t_k + \gamma_{jk})^{\alpha_{jk} - 1} \right)^{-1} \\
& \quad i, j = 2, 3, 4, 5.
\end{aligned}$$

Then the possibility that $n - 1$ of the m media activities are selected is simply equal to

$$\begin{aligned}
& \text{Prob}(t_i^* > 0, t_j^* = 0; i = 1, 2, 3, 4, j = 2, 3, 4, 5) \\
& = \int_{-\infty}^{h_5} \int_{-\infty}^{h_4} \int_{-\infty}^{h_3} \int_{-\infty}^{h_2} \Phi(h_2, h_3, h_4, h_5, V_2, V_3, V_4, V_5 | 0, \Omega) \\
& \quad \cdot |J| dV_2 dV_3 dV_4 dV_5, \quad (19)
\end{aligned}$$

where Φ is the probability density function of normal distribution of mean 0 and variance matrix Ω . We assume Ω to be the identity matrix for simplicity here.

Model scalability: The model is estimated by the Markov chain Monte Carlo method with the Metropolis–Hastings (M-H) algorithm and the GHK simulator as in Kim et al. (2002). These estimation methods are typically used in simulations or applied to small samples, as in Lee et al. (2011) and Kim et al. (2002), each of which contained sample sizes of $n = 78$ households and 332 households or $n = 2,380$ observations, respectively. This is because the model is difficult to “scale up”—i.e., to include all two-way, three-way, etc., interactions of j regressors.³ Hence, we apply our model to a randomly selected subsample (i.e., 1/10 of the entire sample of $n = 27,258$), or 177 respondents. We further assess the generalizability of our results in a specific geographical metro area, a sample of 177 households in New York City, and find no significant differences ($t_{26} = 0.19$, ns). Details are presented in the Web Appendix Table 6.

The implication of our approach is that we will focus on the interpretation of baseline constants and satiation parameters. Although our model is capable of accounting for heterogeneity and time/day differences, it leaves it to future research to more fully motivate the high-dimensional problem and investigate potential solutions. Hence, we restrict our focus here to the baseline constants, satiation parameters, and the interactions between them. Another advantage of this approach is that we stay away from identification issues resulting from multiplicative error

Table 6 Model of Complements Estimates

Satiation parameters	Coefficients	<i>T</i> -statistic	Baseline	Coefficients	<i>T</i> -statistic
α_{computer}	0.999	6.35	Φ_{computer}	0.988	9.76
α_{tv}	0.271	12.53	Φ_{tv}	0.653	14.32
α_{radio}	0.100	2.56	Φ_{radio}	0.600	3.56
α_{print}	0.111	7.78	Φ_{print}	0.779	7.37
$\alpha_{\text{computer-tv}}$	0.496	5.32	$\Phi_{\text{computer-tv}}$	0.421	—
$\alpha_{\text{computer-radio}}$	0.311	8.98	$\Phi_{\text{computer-radio}}$	0.593	—
$\alpha_{\text{computer-print}}$	0.902	1.67	$\Phi_{\text{computer-print}}$	0.769	—
$\alpha_{\text{tv-radio}}$	0.477	1.44	$\Phi_{\text{tv-radio}}$	0.392	—
$\alpha_{\text{tv-print}}$	0.224	3.89	$\Phi_{\text{tv-print}}$	0.508	—
$\alpha_{\text{radio-print}}$	0.903	1.77	$\Phi_{\text{radio-print}}$	0.467	—

Note. Log likelihood = $-5,290.21$.

terms when we keep the baseline utility ψ_j simple and unparameterized.⁴

Synergy is observed when the satiation parameter for the cross-media effect is greater than the satiation of the individual components (the satiation parameter is bounded between 0 and 1). Note that negative “synergies” are theoretically possible but are not observed in our results, which are reported in Table 6.

7.1. Results

Table 6 displays the coefficients for the individual and joint satiation parameters, which guide the insights regarding cross-media synergies.

7.1.1. Radio Synergies. We observe such synergistic effects for radio when it is multiplexed with television or print. The individual satiation rates for television, radio, and print are 0.271, 0.100, and 0.111, respectively. However, when radio is multiplexed with television, the satiation rate is 0.477, and when radio is multiplexed with print, the satiation rate is 0.903, evidencing cross-channel synergy. This suggests that radio media managers could benefit from campaigns that pair their media form with television or print forms.

7.1.2. Print’s Second Life. In 2008, of the \$141.7 billion spent on advertising in the United States, Internet advertising grew by 7.3%, whereas traditional print media advertising declined by 19.7% over 2009 (Kantar Media 2010). This has led some pundits to suggest that perhaps print media ought to be eliminated altogether, because the Internet and television are collectively able to completely reproduce its content (Isaacson 2009). However, our results suggest a very different story. We find that satiation for print is actually lowered when it is multiplexed with the computer (0.902), television (0.224), or radio (0.903), suggesting that the joint consumption of these media with

³ Advanced methodological theory in statistics is currently under-way to better resolve this issue; see Answani et al. (2011).

⁴ As a result, the estimates for the baselines will be different and noncomparable to those from our main model. We will focus our discussion on satiation parameters.

print is “stickier” than the consumption of print media (0.111) alone.

Whereas this bodes well for print media, the converse is not always true; consider the effects on the computer and television media. When these are multiplexed with print, the satiation parameter of each (Internet is 0.999 and television is 0.271) increases (compared to 0.902 for the Internet with print and 0.224 for television with print); this suggests that these media forms lose their stickiness when paired with print. Collectively, these results point to an intriguing irony: that print benefits when multiplexed with either old or new media forms but may undermine the stickiness of these individual alternatives.

7.1.3. The Internet and Old Media. A related concern regarding the elimination of print is the possibility that the Internet cannibalizes print media. We investigate this possibility by examining the satiation parameters for the joint consumption of the computer with any media form. We find that multiplexing the computer with any old media—i.e., television, radio, and print—lowers the satiation rate for each of these media forms—television is 0.496, radio is 0.311, and print is 0.902 versus 0.271, 0.100, and 0.111, respectively, for each medium individually. In other words, all old media forms *benefit* from being multiplexed with the Internet. This suggests a complementary versus a substitutionary role for new media, reviving and further enhancing the value of old media forms. This would suggest that the earlier statistic regarding increased multiplexing of television and tablets in 2012 leads consumers to consume more of both media than they would have in the absence of the other.

Conversely, we observe that *old media heightens satiation of new media*. In other words, although the multiplexing of television and the computer leads consumers to increase its consumption over the old media forms, the computer stickiness is degraded. This may also be because the data set reflects 2006 consumer habits, when multiplexing with the computer might have been less pervasive than today. Future research would be necessary to corroborate or disconfirm this finding.

8. Discussion

The goal of our research was to advance a model for predicting individual and multiplexed media choices while accounting for cross-channel synergies. The model performs well both in and out of sample and is robust to one-hour or half-hour time period specifications and differing metro areas. Although our model was developed at the individual consumer level, it can also be aggregated and cross-queried at the product

category or industry level to generate specific insights for brands and product verticals.

Our estimates suggest that consumers spend less time consuming computer or radio media on the weekend and more time watching television and reading print media instead. Additionally, we reveal interesting (and often asymmetric) interdependencies across media channels via their marginal rates of substitution. Attention spans, media adoption, and individual differences also play a role. We find that the cross-media effect of attention on a media-specific baseline utility suggests interesting asymmetries across the media alternatives. For example, consumers with high attention for the computer are unlikely to multiplex traditional forms of media (radio, print, and television). In contrast, consumers with high attention for these traditional media options have higher utility for multiplexing all forms of media (including new and traditional). We also show that failure to account for media multiplexing can significantly reduce the reliability of the media planner's audience predictions.

To this end, Bhat (2005) provides a robust model that is estimable on large data sets and can account for many independent variables, including media alternatives, heterogeneity, and time/day differences in helping to identify target segments. At a minimum, this enables IMC planners to better account for the media landscape when “targeting the minnows in the barrel.” However, although this is a useful first step, a shortcoming of this model is its inability to give insights into potential complementarities and synergies that are at the heart of the multiplexing phenomenon. The Kim et al. (2002) model provides the basis for specification of these complementary possibilities and identification of which media forms benefit and which are undermined, underscoring the nature and direction of asymmetries in multiplexed consumption vis-à-vis an individual consumption scenario.

Given a multiplexing perspective, we can identify synergies among old media types. For example, we find that the joint consumption of radio with television or print satiates at a lower rate. In other words, multiplexing radio media can result in greater stickiness for multichannel consumption of traditional forms of media. Interestingly, we also find that the diminishing share of print media consumption can be revived if print is multiplexed with old or new media, suggesting a potential “second life” for this media form. Finally, we find evidence that all forms of old media benefit from multiplexing with new media—i.e., the computer. In other words, the multiplexed consumption of media results in a lower satiation rate for print, television, and radio forms.

8.1. Limitations

This research is limited in its ability to explain *why* consumers multiplex their media choices. The Bhat (2005) model does not offer theory or a conceptual framework of what might account for these differences. However, Luo et al. (2012) are able to use the Bhat (2005) model to develop an explanation for how individuals allocate time across multiple leisure activities, because the composition of their data set better enable this.

From a methodological standpoint, we can identify a rank ordering among individual and joint consumption scenarios, but we cannot estimate the directional effects of each individual media on the other. In other words, although we can estimate the satiation of the joint effect of print and radio, we cannot isolate the effect of print on radio or radio on print. Fortunately, research in this vein is currently underway (see Lee et al. 2011).

And finally, the model of complementarity that we develop, although promising, remains a work in progress. Much is still to be done on its methodological development, such as scalability to higher-dimensional contexts and identification issues. As such, it is important that we temper our substantive conclusions regarding the intermedia synergies that we observed. In other words, these synergies are identified in the absence of media alternatives, heterogeneity, and time/day differences.

8.2. Implications for Management

Our research underscores the need for media planners to move away from single-media-focused choice models to the use of demand models that better incorporate and account for substitution and complementarities in multiplexing activities. Further, our study highlights the value of new individual-level (versus aggregated) media choice data. Market-level data can mask underlying consumer- and time-varying specific media choices and can limit our ability to identify media interdependencies. The demand model we introduce can be applied to other settings where consumers choose multiple alternatives and face some constraint that forces them to make appropriate trade-offs in the consumption of these alternatives.

Our findings also point to the need for multimedia partnerships and identify potential candidates. As an example, radio advertisements should be coordinated with print and television media. Print media should be partnered with radio and Internet media forms. In other words, successful media management strategies in today's marketplace require a collaborative (versus a competitive) mind-set—i.e., instead of viewing each media form as a substitute for another, potential complementarities should be exploited via joint media campaigns and simultaneous multimedia exposures. This also underscores the need to move away

from a competitive mind-set in media management (i.e., implied by a view of media consumption as being one at a time in sequence) to a multiplexed viewpoint in which consumers might serially “snack” on individual and simultaneous combinations of media forms. With this mind-set, the task of the media manager would be to empirically identify cross-channel media synergies and develop a strategy for its exploitation. Ultimately, we hope future research in this area will facilitate a better understanding of how firms can achieve higher levels of efficiency and effectiveness in their advertising resource-allocation efforts both within and across media.

Electronic Companion

An electronic companion to this paper is available as part of the online version at <http://dx.doi.org/10.1287/mksc.1120.0759>.

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