BUILDING CROSS-MEDIA NORMS

OPTIMISING COMMUNICATION CHANNELS AGAINST MARKETING OBJECTIVES

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BACKGROUND

Research on the comparative effects of advertising media has focused historically on the persuasiveness of traditional media, particularly in isolation (Wright, 1974; Liu and Stout, 1987[1]; Stafford and Day[2]). Advertising as a marketing tool has evolved from mass media communication vehicles, such as TV, print, and radio, that were expected to "build and maintain awareness of a brand or product in the consumer's mind, communicate product benefits, and reflect positioning strategy". With the proliferation of new media choices and consumer centric models of media consumption, the objectives of advertising have gone beyond these traditional isolated media metrics. The marketing communication function has moved from mass media advertising to an "integrated marketing communications management approach" (Chiagouris and Perrell, 1989).

Given consumers' active avoidance of advertising, an escalating number of advertiser messages, the technological advancements in media options, and shifts in media consumption patterns, more effective and efficient marketing communications planning is required. "Examining media choice and selection is important for identifying current patterns in social interaction" (Land, 2007)[3] and linking these interactions to changes in brand predisposition is becoming necessary. When building normative benchmarks, the media effects "should be evaluated according to the objective of the advertisement presented in the media" (Berthon et al, 1996;[4] Harvey, 1997[5]). While some media may be effective for generating attention towards a product, others may be more effective for persuasion (Fill 1995).

The proposed method for benchmarking media effects and their interactions could be a valuable asset to the marketing and research industry. Understanding media synergy is critical in the current media landscape, where accountability is essential, and "the demand for faster, more decision-relevant information and for ROMI based measures is even greater" (Cooke and Talluri, 2004)[6]. It is our belief that the practical use of performance-based benchmarks as a planning tool in the media selection process is more likely to lead to greater payoff in terms of campaign outcomes.

The concept of leveraging media interactions (synergy) as a means to improve communication and build brand equity (share, awareness, intention, etc.) needs to be integrated in the strategic selection of media channels. Research has shown that "when print and TV are used synergistically, print can lead people to see the TV commercial in new ways, encourage more response, reinforce the TV message, and create a more positive feeling towards the brand" (Cooke and Talluri, 1997)[7]. Many practitioners call this "the multiplier effect," where mixed TV and print exposure opportunities can transfer credibility and can improve the learning effect (Speetzen, 2001).

Most studies that have generalized the effects of media advertising (in isolation or combination) have been constrained by the number of campaigns aggregated per category, considerations of the target audience definition, brand tenure, and loyalty. It has also been argued that norms in some sense are bad, "and need to be related to similar brands in similar situations in the market" (Baxter, 1999).

The goal of this research is to identify a source of data for marketing communication planning that recognizes the added value of media synergy. The impact of the media mix consists not only of each medium's contribution as a separate entity, but also in the joint impact of multiple activities. "Despite synergy's importance, its role in the multimedia communications is not well understood" (Naik, 2003)[8]. The fundamental question that this analysis sets out to answer is how to provide further support for the manager's decision process regarding size and allocation of a media budget when media synergy may be present. From a management perspective, it is important to access planning tools that incorporate the necessary inputs to evaluate alternative scenarios and optimize potential outcomes. One of "the benefits of optimizing ROMI (is to) analyze the potential outcomes across a variety of circumstances. By creating what-if scenarios, marketers can evaluate more quickly and efficiently a wide range of alternative strategic and tactical options" (Cook and Talluri, 2004)[9]. As reported in other research, the "lack of benchmarks [applied] within the framework of current media planning software is often difficult to implement" (Gugel and Deniz, 2004). The ability to establish continuously managed multivariate normative benchmarks can help marketers and planners alike predict consumer response to a given media plan.

RESEARCH

CrossMedia Research conducted by Dynamic Logic and Millward Brown examines the branding impact of advertising campaigns that utilize a multiple media strategy. The fundamental methodology and measures used to capture media exposure and brand attitudes *in situ* are consistent over time. Attitudinal measures are an important component of models of buyer behavior and an understanding of the influence of attitudes is necessary when organizations seek to develop effective marketing strategies (Mitchell and Olson, 1981). Among advertising theories, variations of the hierarchy-of-effects model have been commonly used to understand the variety of consequences produced by marketing communications. The model developed by Lavidge and Steiner, 1961[10] illustrates the process by which advertising commonly works and portrays consumers passing through a series of sequential phases starting from brand or advertising awareness (cognitive stage), to favorability or preference (affective stage) and finally to actual purchase (behavioral stage). Among other versions of the hierarchy-of-effects model are the Attention, Interest, Desire, and Action model (Strong, 1925) and "Defining Advertising Goals for Measured Advertising Results" (Colley, 1961). The model shows clear steps of how advertising works, even though it has been criticized for simplifying the sequence of steps that people follow.

The research presented in this paper is based on a sample of fifty CrossMedia Research studies conducted by Dynamic Logic and Millward Brown between 2004 and 2008. These studies were selected based on the presence of three media – television, magazines, and online – with similar campaign timing and media weight. In order to assess each medium's role within the hierarchy of advertising effects, five widely recognized branding metrics were used in the studies (see figure 1). Minor variation in question wording exists due to the specific requirements of individual brand categories across the 50 cross media campaign evaluations.

The focus of the analysis is on developing averages or norms for media contribution to campaign impact, both individually and in combination. Normative databases of advertising effectiveness are becoming more important "as a baseline for evaluating performance within different vertical markets to make go/no go decisions about advertising" allocations (Hollier and Remington, 2001)[11].

FIGURE 1
STANDARD METRICS USED IN QUESTIONNAIRE

Key Metrics	Definition
Aided Brand Awareness	Measures the level of familiarity respondents have with the brand listed.
Aided Advertising Awareness	Measures the level of claimed awareness respondents have with any brand-related marketing communications
Message Association	Measures the extent to which respondents can match the campaign messaging with the sponsor or brand.
Brand Favorability	Measures the extent to which respondents have a positive or favorable opinion of the brand.
Purchase Intent	Measures the likelihood of respondents to make a purchase

Each of the cross media studies was a live, in-market test that measured a campaign's impact on the audience to which the campaign was targeted, both online and offline. Respondents for CrossMedia Research are usually sampled by using a combination of Dynamic Logic's proprietary AdScout tracking system and from a nationally representative online panel to account for audiences that are not reached by the online media. Using an online survey instrument, the research relates advertising "opportunity to see" (OTS) to brand attitudes, utilizing a control/exposed research design. The analysis is based on comparisons of respondent groups that have exposure opportunity to different combinations of media, where each of these groups is compared against a baseline control group. Each study was conducted on a custom basis with standardized branding metrics employed. Each study represents the effects of a planned media effort and is not designed with the objective of predicting or measuring audience size, which would require sampling techniques similar to the industry standard for audience measurement for each medium.

To determine exposure to or opportunity to see (OTS) online display advertising, the studies utilize AdScout, a patent-pending cookie technology that is part of Dynamic Logic's AdIndex system. When respondents enter the survey, the system recognizes whether or not they have been served any online ads in a given campaign. Television advertising OTS is survey-based and measured by self-reported media usage and compared with syndicated audience measurement data. The offline media schedule is reconciled with media usage reported by the respondent to determine if they had an opportunity to see the advertisement. Print OTS is determined either by specific-issue level reading or by frequency of reading.

Out of over 200 cross media campaigns that have been measured, 47 that had a combination of television, magazine and online (display) with similar media allocation and duplication levels were aggregated to better understand how these media work together at building or shifting specific brand attitudes through the traditional hierarchy of advertising effects model.

Benchmarking the distribution of media impact allows the researcher or marketer to assess the relative return on marketing objectives over time. Past attempts at developing these normative measures have examined the incremental effects of multimedia advertising with television as the base medium and other media added to the effect of television. The current research takes these analyses further by quantifying the synergistic effects as well as the isolated effects among a large-scale dataset, using regression techniques at the respondent level.

ANALYSIS

The analysis of media effectiveness across campaigns employs a basic regression model in which media opportunity to see (OTS) variables collected throughout the campaign measurement period are used as predictors of change in marketing metrics. Using binary logistic regression, a model used for prediction of the probability of the occurrence of an event, we use the binary OTS variables to predict binary outcomes (e.g., aware/unaware, favorable/unfavorable, likely to purchase/not likely to purchase). Using the backwards elimination approach based on log-likelihood, all the variables are entered into the model together and are tested for removal one by one. The removal of a variable from the model is based on the significance of the change in the log-likelihood. The likelihood-ratio statistic provides the best criterion for deciding which variables are to be removed (Agresti, 2002).

It has been at length discussed that logistic regression on pure single-source data (Birch, 2002) or time-series panel data (Tjur, 2002) may not be the most appropriate model to measure advertising effects. However, in the current case of attitudinal response comparison, respondents were sampled in live "in-market" conditions, where brand survey questions were blinded and advertising recall is not used to assess opportunities for exposure. That is, respondents were asked to participate in the "footprint" of the media plan from a nationally representative sample frame.

The function *f(x)* represents the probability of metric change (coded as 0 or 1), given the media exposure level. This variable, also known as the logit, is a measure of the total contribution of all the media exposures used in the model. For the purpose of this analysis, the metric (dependent) is usually defined as:

$$\mathbf{logit}\left[\theta(\mathbf{x})\right] = \mathbf{log}\left[\frac{\theta(x)}{1-\theta(x)}\right] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i$$

Where β = the coefficient of the predictor variables and

x_1 = TV opportunity to see
x_2 = Print opportunity to see
x_3 = Online opportunity to see
α_0 = a constant indicating the metric level if no media advertisements are seen

Each of the regression coefficients describes the size of the contribution of that medium or media combination. A positive regression coefficient means that exposure increases the probability of a positive branding effect, where the size of the coefficient is proportional to the size of the metric difference. As in OLS regression, the addition of interaction terms was used in the model (e.g., print*online).

In almost all campaign studies, the non-exposure group to each medium was sampled in a short time interval before the campaign started. Comparing the control sample, where media consumption habits and brand predispositions are matched to the in-market sample, is a critical step of the design (given potential brand loyalty biases between the groups). Past research has compared fractional OTS definitions with advertising effectiveness scores and have recommended that there is "little or no evidence that fractional OTS is related to brand choice" (Birch, 2002). If the design is quasi-experimental, controlling for predisposition toward the brand, the loyalty parameter should become constant, thus isolating the effect of advertising.

To develop a database that compares the relative contribution of media exposure, the data were coded at the respondent level, where respondents were given values to assess their opportunity to see each medium or media combination. A total of n=154,383 respondents were identified as taking part of a cross media advertising effectiveness study, where at least print, online and television were included in the media plan. A weighting scheme was employed to account for disproportionate campaign sample sizes within each category to equalize the contribution of each campaign to the category averages. Please refer to the appendix for a total listing of campaigns by category and respective sample sizes.

In order to make improved generalized comparisons of media effects on marketing investment, individual models where developed within the database for each product category. In the aggregate, as it has been well acknowledged, different media generate different effects at the category level. The sample distribution per category permitted this research to assess relative contributions per medium or media combination for consumer packaged goods and technology-related campaigns. Multi-collinearity diagnostics were examined at the onset of the analysis using simple linear regression models. Tests for significance were done at the 95% confidence level for entry and retention within the metric-level model.

The data values for each media combination provided below represent Exp(B), which is the predicted change in odds for a unit increase in the predictor, a measure of relative strengths among the independent variables. If a non-significant relationship exists resulting in an independent variable being excluded from the stepwise model), the corresponding cell is left blank. For each of the models below, the Wald statistic was used to assess whether an effect exists or not at a 95% confidence level. In all cases an omnibus test of model coefficients was done to report significance levels by the traditional chi-square method. This statistic tests if the model with the predictors is significantly different from the model with only the intercept. The omnibus test may be interpreted as a test of the capability of all predictors in the model jointly to predict the response (dependent) variable. A finding of significance, as in the illustration below, corresponds to the a research conclusion that there is adequate fit of the data to the model, meaning that at least one of the predictors is significantly related to the response variable. An example of the test for the purchase intent analysis within the technology category appears in table 1.

ANALYTICAL CASE 1: CONSUMER PACKAGE GOODS (CPG)

The category with the largest number of campaigns in the database was Consumer Package Goods (CPG), or Fast Moving Consumer Goods (FMCG), with 13 studies. The summarized results for the analysis on the five branding metrics appear in table 2.

Among the 13 campaigns tested, the strongest effect size (measured as the odds ratio) is seen for "online and television" or "online and print advertising". Given the nature of most consumer package brands, they have a well established position in the market and likely have a consumer base of repeat purchasers; therefore a large contribution from the "constant" (in the absence of advertising) is noted for brand awareness. This is most likely a function of sustained brand equity over time. However, when "TV and online" are evaluated as complementary media, they provide a strong contribution into brand and advertising awareness. More interestingly, the effects of TV advertising are strong contributors to the persuasion metrics, either in isolation or with online advertising. As seen from previous campaign-

TABLE 1
OMNIBUS TESTS OF MODEL COEFFICIENTS FOR PURCHASE INTENT, TECHNOLOGY

	Chi-square	df	Sig.
Step 1	1442.018	7	.000
Block 1	1442.018	7	.000
Model 1	1442.018	7	.000
Step 2	-.627	1	.429
Block 2	1441.391	6	.000
Model 2	1441.391	6	.000

Note: negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

TABLE 2
CONSUMER PACKAGED GOODS (EXP(B))

	-2 log likelihood	Constant	TV	Print	Online	TV & Print	TV & Online	Online & Print	TV & Print & Online
Aided Brand Awareness	43772	5.60		1.22	.54	1.42	2.63	1.59	.70
Aided Ad Awareness	74543	.61	1.84	1.45		1.14	1.20	1.12	
Message Association	49176	.33		.71	.66		2.84	2.07	.56
Brand Favorability	76120	.93	1.08	1.89	.84	.77	1.33	1.21	.781
Purchase Intent	75874	.74	1.14	2.58	.93	.57	1.12		.83

N=13 campaigns (n=55,541 respondents)

*Note: variable(s) entered on step 1: TV, Online, Print, Online*TV, Print*TV, Online* Print, Online*Print*TV*

specific case studies, print advertising does tend to have the strongest effect on purchase intention, as in the above model. Active attention and reader control to this advertising medium may have a role in these results.

Generally speaking, the combined paired media combinations were effective, particularly TV and online overall. However, the interaction of the three media exposures did not yield a strong contribution to the category advertising effect. From a planning perspective, these coefficient weights could be used in combination with reach and frequency estimates to produce a strategic response among the target audience.

PREDICTED PROBABILITIES OF IMPROVEMENT

Evaluation of pure exposure effects in terms of predicted probabilities of metric improvement supports television's contribution to advertising awareness. However, television's strongest effect is seen when held in combination of print and online advertising. (See table 3.)

Table 3 illustrates the impact of online advertising, where the probability of improvement is relatively large when paired with another medium. Print advertising exposure, as consistent with the model coefficients presented in table 2, yields relatively large probabilities of improvement for both brand favorability and purchase intent. This suggests when marketing objectives for this category require higher product or brand consideration, strategic channel placement using print (magazines) could be evaluated on a basis of reach, frequency, predicted impact (as seen above), and cost. One area for further development of this analysis would be to analyze the sequential effects of media advertising. In addition, more research is needed on how magazines interact with different digital components of the media mix as more media options become available. In particular, research could examine how much overlap is seen on a campaign basis between specific media companies, and how they can leverage a clear narrative among their audience. As magazine publishers move into other media platforms, understanding how these platforms work together can provide useful insights to optimize cross media campaigns.

ANALYTICAL CASE 2: TECHNOLOGY-RELATED BUSINESS TO BUSINESS CAMPAIGNS

Twelve business-to-business campaigns were analyzed within the technology category. The results are summarized in table 4.

TABLE 3
CONSUMER PACKAGED GOODS (PREDICTED PROBABILITIES OF IMPROVEMENT)

Category Consumer Packaged Goods: Predicted Probabilities of Improvement								
	Control	TV	Online	Print	TV & Online	TV & Print	Print & Online	TV & Print & Online
	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Aided Brand Awareness	.84843	.84843	.75012	.87230	.88776	.90670	.85380	.93834
Aided Ad Awareness	.37874	.52922	.37874	.46887	.57519	.65003	.49815	.71555
Message Association	.24662	.24662	.17758	.20206	.38043	.20206	.25693	.35510
Brand Favorability	.48178	.50187	.43900	.63751	.52974	.59600	.64091	.60839
Purchase Intent	.42502	.45749	.40798	.65602	.46887	.55220	.64003	.51779

TABLE 4
TECHNOLOGY (EXP(B))

	-2 log likelihood	Constant	TV	Print	Online	TV & Print	TV & Online	Online & Print	TV & Print & Online
Aided Brand Awareness	33172	1.92	9.41	1.85	.86	0.31	.28	1.36	2.89
Aided Ad Awareness	45057		5.12	1.43	.72	.622		1.77	.381
Message Association	13479	0.58	3.26	.763	1.33	1.60	.775	.728	
Brand Favorability	46195	.535	4.11	1.51	.768		.824	1.36	.387
Purchase Intent	44767	.415	3.83	1.47	.858		.696	1.12	.518

N=12 campaigns (n=35,182 respondents)

*Note: variable(s) entered on step 1: TV, ONLINE, PRINT, ONLINE*TV, PRINT*TV, ONLINE* PRINT, ONLINE*PRINT*TV*

For technology campaigns, television advertising made the largest contribution to increases in all brand metrics. Given that these campaigns span over a four-year period, it is likely that a longitudinal analyses would warrant more explanation into televisions large effects; however, sample sizes are insufficient for years 2006 and 2008 (in 2006 and 2008, contributions due to online and print far exceed television).

While all media have a role within the hierarchy of effects, media synergy is most prevalent between online and print, a combination that is commonly used within this product category. Closer attention to the interaction effects appears important to this category in particular, given recent news according to the TV & Technology Survey, produced by the Association of National Advertisers and Forrester Research, that "62%

of marketers believe that TV advertising has become less effective in the past two years" (BrandWeek 2008).

DISCUSSION

Practical use of cross media normative data can help advertisers strategically define media placement beyond demographic targeting using attitudinal objectives; although media ratings systems do not typically ask the required questions to accomplish this (Walsh, 2007). Our proposition is continued development of a cross media advertising effectiveness database, coupled with reach and spend information, which ultimately can be used to optimize a planning strategy on both marketing objectives and on reach and frequency parameters. However, there are many considerations one must take into account in the continual development of a multimedia effectiveness database: the introduction of other media, creative quality, brand tenure, the potential to include frequency of exposure per medium, past brand usage, target market characteristics, and, naturally, more robust samples to represent a given product category. One of our general findings is that using a multivariate approach provides a better understanding into complementary effects of media synergy. For example, when evaluating the consumer package goods industry, our data suggest print advertising alone may produce a greater effect in purchase intent than opportunity to see three media. However, when building awareness, such as launching a new product line or repositioning a brand, the combination of all three media exhibits the largest probability for an improved awareness measure.

Another consideration in the development of cross media comparisons is to match control samples more rigorously; thus reliance on post stratification sample weighting should be minimal. Although matching control sample with exposure groups does hold many brand-related parameters constant, perhaps introducing more personal parameters to the model may account for potential differences not explained by advertising effects.

The results suggest that further research in media sequencing is warranted. The results of previous cross media aggregate analysis show that magazines have a higher level of influence on purchase intent when used incrementally to television advertising. However, the previous analysis does not address issues of scheduling and sequencing of exposure. Future research could examine differences in magazine advertising effectiveness due to timing of exposure.

Footnotes

1. Liu and Stout, 1987 p. 192-205.
2. Stafford and Day, 1995 p. 57-71.
3. Land, 2007, p. 1.
4. Berthon et al, 1996, p. 43-54.
5. Harvey, 1997, p. 11-20.
6. Cooke and Talluri, 2004, p. 245.
7. Ibid., p. 244-254.
8. Naik, 2003, p. 375-388.
9. Cook and Talluri, 2004, p. 244-254.
10. Lavidge and Steiner, 1961, p. 59-62.
11. Hollier and Remington, 2001, p. 253-265.

References

Agresti, A. (2002). Categorical Data Analysis, 2nd ed. New York: John Wiley and Sons.

Baxter, Marilyn. (1999). "How to use targets and norms in advertising tracking," Admap Magazine.

Birch, Kristina. (2002). "Analyzing Effects of Advertising Using Conditional Logistic Regression," Copenhagen Business School

Berthon, P., Pitt, L.F. and Watson, R.T. (1996). The World Wide Web as an Advertising medium. Toward an understanding of conversion efficiency. *Journal of Advertising Research,* January/February, p. 43– 54.

BrandWeek Magazine. (2008). Study: Marketers Think TV Less Effective, issued February 20, accessed at: http://www.brandweek.com/bw/news/recent_display.jsp?vnu_content_id=1003712790

Chiagouris L., Perrell L. (1989). "Asking the Right Questions", Review of Business, Vol. 11.

Colley, H. (1961). Defining Advertising Goals for Measured Advertising Results. New York: Association of National Advertisers.

Cooke, Barbara (1997). "Advertising in Magazines is Different. Or, How to Tap Into the Power of Magazines," *Publishing Research,* Lisbon, November 1997, Brussels: ESOMAR.

Fill, C. (1995). Marketing Communication. Frameworks, Theories and Applications. London: Prentice Hall.

Gugel. C. and Deniz, T. (2004), "Multimedia Exposure and Variations in Consumer Response," *Proceedings of ESOMAR Cross Media Conference, Geneva.*

Harvey, B. (1997). The expanded ARF model: bridge to the accountable advertising future. *Journal of Advertising Research,* March/April, p. 11– 20.

Hollier, A. and Remington, K. (2001). "Advertising research in the 21st century," *proceedings of ESOMAR, Latin America, Mexico City, p. 253-265*

Land, V, Frohlich, D.M. and Lumkin, M. (2007). Cross-media communication patterns. Proceedings of ECSCW 2007.

Lavidge, Robert J. and Gary A. Steiner. (1961). "A Model of Predictive Measurements of Advertising Effectiveness," *Journal of Marketing,* vol. 25 (6), 59-62.

Liu, S.S., and Stout, P.A. (1987). Effects of Message Modality and Appeal on Advertising Acceptance, *Psychology & Marketing,* vol. 4, no. 3, p. 167-187.

Mitchell, A. and Olson, J. (2000). "Are Product Attribute Beliefs the Only Mediator of Advertising Effects on Brand Attitude?" *Advertising & Society Review,* Vol. 1, No. 1.

Naik, P. and Raman, K. (2003). Understanding the impact of synergy in multimedia communications. J. Marketing Res., v 40, pp. 375-388.

Speetzen, Rolf. (2001). "The Multiplier Effect," *Print Brands and Multi-Media,* Paris, Brussels: ESOMAR.

Stafford, M.R. and Day, E. (1995). Retail Services Advertising: The Effects of Appeal, Medium, and Service, *Journal of Advertising,* vol. XXIV, no. 1, p. 57-71.

Strong, E.K. (1925). "The Psychology of Selling," McGraw-Hill: New York.

Talluri, Vijay S. and Cook, William A. (2004). "How the pursuit of ROMI is changing marketing management," Journal of Advertising Research, Vol. 44, No. 3, pp.244-254 .

Tjur, T. (2002). Logistic regression models for single-source data – a simulation study. Dept. of Management Science and Statistics, Copenhagen Business School.

Walsh, P. (2007). "Market research data integration: Coming to intersections from two directions" International Journal of Market Research, v.49, No. 4, pp. 471-488.

Wright, P.L. (1974). Analyzing Media Effects on Advertising Responses, *Public Opinion Quarterly,* vol. 38, no. 2, p. 192-205.

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APPENDIX
WEIGHTED AND UN-WEIGHTED SAMPLE SIZES PER CATEGORY

	Unique Campaign Number	Weighted Count n=	Unweighted Count n=
Alcohol	00001	3842	3842
Automotive	00002	3252	3267
	00003	3252	2283
	00004	3252	4259
	00005	3252	3199
Consumer Packaged Goods	00006	4272	7407
	00007	4272	3265
	00008	4272	11867
	00009	4272	1186
	00010	4272	5631
	00011	4272	3158
	00012	4272	4956
	00013	4272	3054
	00014	4272	2825
	00015	4272	3528
	00016	4272	3350
	00017	4272	4980
	00018	4272	335
Electronics	00019	2420	3659
	00020	2420	1182
Entertainment	00021	3961	3961
Financial Services	00022	2326	2329
	00023	2326	1249
	00024	2326	4958
	00025	2326	2562
	00026	2326	533
Professional Services	00027	2170	1628
	00028	2170	2712
Restaurant	00029	3445	2628
	00030	3445	1665
	00031	3445	5994
	00032	3445	2831
	00033	3445	4106
Technology	00034	2927	1392
	00035	2927	7541
	00036	2927	1222
	00037	2927	1023
	00038	2927	3440
	00039	2927	1022
	00040	2927	2565
	00041	2927	1344
	00042	2927	6056
	00043	2927	2906
	00044	2927	5354
	00045	2927	1263
Telco	00046	4192	4192
Travel	00047	674	674