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Market Segmentation Revisited: The Predictive Utility of Demographics

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Abstract

This paper compares the predictive power of demographic variables to that of other, more complex segmentation variables. To achieve this objective, the mean R-square of 20 demographic models obtained from a representative survey was judged against mean R-square of 34 non-demographic models drawn from existing published studies. The result indicates that demographics have significantly higher explanatory power than some well-established theories. Thus, our finding strongly refutes the proposition advanced by a number of prominent market segmentation researchers that the relationships between demographic segments and marketing variables are too weak to be of any practical value. Based on the result of this analysis, and given the fact that only five variables were used in the demographic models, it is concluded that demographics are, at least as useful as other segmentation bases.

Introduction

The concern of this research is the usefulness of demographic variables as market segmentation bases. Generally, to be considered as a valid market segmentation bases, a given variable needs to satisfy certain criteria: *responsiveness*, *accessibility*, *substantiality*, *identifiability*, *stability* and *actionability* (Engel, Fiorillo and Cayley, 1972; Wedel and Kamakura, 2000). Demographics are frequently dismissed for lacking responsiveness or predictive power. Earlier studies indicate that members of different demographic segments do not exhibit differential buying behavior (Frank, Massy and Wind, 1972). In a recent investigation, Wedel and Kamakura (2000) evaluated the different segmentation bases in terms of the above six criteria observing that demographics were superior to non-demographics in all aspects except responsiveness criterion. As a result, they concluded that the relationships between demographic segments and purchase behavior/marketing variables are often too weak to be of any practical value.

Despite these criticisms of demographics, there is a reasonable amount of supporting evidence which warrants further investigation of the matter. In particular, the study conducted by Novak and MacEvoy (1990) is notable due to the objective research methodology employed. Using a sample of 1,406 randomly selected individuals, Novak and MacEvoy (1990) examined the impact of VALS type, LOV values and a set of seven demographics (*i.e.*, age. education, marital status, ethnicity, conservatism, social class and income) on 64 behaviors which included items such as product ownership and media usage. Originally, their intention was to replicate Kahle, Beatty and Homer’s (1986) finding that LOV outperforms VALS in predicting 73 behavioral items such as frequency of watching types of television shows, media readership, engaging in various sports and using various products. Novak and MacEvoy (1990) found that median R-square for 64 demographic models (*i.e.*, 0.04) was greater than both of LOV (*i.e.*, 0.011) and VALS (*i.e.*, 0.026) models pointing to the better predictive power of demographics compared to the more recent segmentation variables. Further, the number of significant R-squares in the result table provided by Novak and MacEvoy (1990) showed that 89.1 percent of demographic models (57 out of 64 models) were significant whereas comparable figures for LOV and VALS models were 69.9 and 82.8

percent, respectively. Novak and MacEvoy (1990) also looked at explanatory power of LOV and VALS after controlling for the effect of demographics. Interestingly, they found that only 16 out of 64 or 25 percent of the LOV models were significant after accounting for demographic variables. The comparable figure for VALS models was 24 out of 64 or 37.5 percent. These findings indicate that first, a relatively small number of demographic variables illustrate greater predictive power compared to more complex models such as LOV and VALS. Second, significant portion of LOV and VALS explanatory power is already embedded in demographic variables. Baumann, Burton and Elliott (2005) and Sharp, Romaniuk and Cierpicki (1998) have also investigated predictive power of demographics and reported similar findings.

Though these findings appear to be compelling, they fall short of decisively challenging the strong argument put forward by Frank, Massy and Wind (1972) and Wedel and Kamakura (2000) in relation to inferiority of demographics. Clearly, more empirical evidence is required to resolve this question.

Objective of the Study

The purpose of the current study is to use a sound and objective methodology to compare the predictive utility of demographics with that of other market segmentation variables. To achieve this objective, the mean R-square of 20 demographic models obtained from a representative survey was judged against mean R-square of 34 non-demographic market segmentation models drawn from the extant literature. Our findings should contribute to the literature by clarifying the status and importance of demographic variables in discriminating consumers' behavior and their utility as segmentation bases. If found superior and given that demographics are easy to measure and collect (Mitchell, 1996), the theoretical and managerial implications would be of paramount significance.

Methodology

As pointed out earlier, this study compares two sets of R-squares. The first set which measures the predictive power of demographic variables is produced by using data from the General Social Survey 2002 (ABS, 2003). The dataset contains information on 15510 individuals' actual e-shopping (reported in 14 separate categories), e-government, e-banking and finally e-share trading adoption. Respondents were asked to report their online activities during the 12 months immediately before the survey. All dependent variables (20 in total) were measured as nominal variables (adopted=1, not adopted=0). The dataset also contains respondents' selected demographic characteristics. After reviewing the literature a set of five demographic indicators was selected as the independent variables. All independent variables were treated as categorical variables.

The second set of R-squares comes from the literature. A total of 30 published papers were selected as the unit of analysis. The procedure for selecting these papers was as follows. First and as a matter of practicality, only one online database service provider (*i.e.*, Emerald) was selected. This particular database was chosen because it contains large number of full text marketing, management and business related journals. Next, the Emerald was searched using "online shopping" as key words. This has yielded 1420 hits. The first 500 papers were thoroughly investigated to identify those papers which examined actual adoption, intention to adopt, or attitudes towards online shopping, e-government, e-banking and e-share trading and reported the corresponding R-squares. The remaining 920 papers were not reviewed in depth as they showed little or no relevance to the topic (Emerald ranks papers according to their relevance). In total 30 relevant papers were selected however due to the fact that some papers reported more than one R-square we identified 34 R-squares which were subsequently subjected to meta analysis.

Findings

Table 1 presents the adoption rates for 20 types of consumer e-commerce activities. The rates vary dramatically from 0.6 percent (online purchase of alcohol) to 23.1 percent (e-banking). In accordance with the theory of Diffusion of Innovations (Rogers, 2003) one might identify these adopters as “innovators” and “early adopters”. The research problem we face here requires classifying the respondents into two segments: (i) the adopters segment which encompasses both innovators and early adopters and (ii) non-adopters segment. A problem of this nature is better handled via logistic regression than discriminant analysis, as the former imposes less restrictive assumptions (Agresti and Finlay, 1999; Norušis, 1997; Press and Wilson, 1987). Thus, logistic regression was adopted for further data analysis.

In selecting demographic predictors, a conservative approach was adopted limiting their number to only five variables (age, sex, education, income and occupation). This is consistent with the implicit assumption of this research that only limited demographics are required to achieve predictive power comparable to other, more complex models. After all, most of the popularity of demographics has been due to difficulties associated with identifying, collecting and measuring non-demographic variables (Mitchell, 1996). Using a large number of demographics would undermine those advantages. We were also concerned about inherent multicollinearity among demographics.

The results of the logistic regression analysis are presented in Table 1. The models’ Chi-squares are all significant suggesting reasonable fit to the data. Further evidence of fit is given by models’ Hosmer & Lemeshow test. This test essentially assesses how closely the observed and predicted probabilities match (Norušis, 1997). As expected the Chi-square values are not significant except for one model (*i.e.*, computer software) pointing to a good fit to the data. The models have respectable R-square and hit ratio values which range from 0.19 to 0.46 and 65.4 percent to 78.7 percent, respectively. Note that to avoid unequal cell size problem we have created 20 sub-samples with equal number of adopters and non-adopters (selected randomly from corresponding non-adopter respondents) in each sample. This procedure resulted in Maximum Chance Criterion (MCC) of about 50 percent for all samples which can be readily used as a point of reference when evaluating the hit ratios. A number of authors have used Proportional Chance Criterion (PCC) advocated by Morrison (1969) in this situation. However, reconstructing equal cell size sample appears to provide results which are straightforward and easy to understand (Berry and Linoff, 1997).

Table 2 depicts the results of the meta analysis. In total, 34 R-squares were collected from the extant literature which draws upon a number of well established theories or conceptual frameworks including the Technology Acceptance Model (Davis, 1989; Davis, Bagozzi and Warshaw, 1989; McKechnie, Winklhofer and Ennew, 2006), Theory of Planned Behavior (Ajzen, 1985; George, 2004) Diffusion of Innovation Theory (Rogers, 2003), general and

Table 1 Results of Logistic Regression Analysis for Demographic Models

Ref	Dependent Variables	Percentage adopted	R^2	Hit ratio	Hosmer & Lemeshow test	n
1	e-banking	23.1	29.2**	69.3	ns	7124
2	e-share trading	3.2	36.7**	73.2	ns	988
3	Food and groceries	1.9	35.7**	73.0	ns	575
4	Alcohol	0.6	46.2**	78.7	ns	188
5	Toys	0.8	38.8**	71.5	ns	253
6	Videos or DVDs	1.8	38.3**	72.8	ns	547
7	Music or Cds	2.5	33.5**	71.8	ns	786
8	Books or magazines	4.6	30.0**	68.9	ns	1445
9	Financial services	2.2	37.5**	73.5	ns	678
10	Computer hardware or peripherals	1.4	40.4**	74.9	ns	446
11	Computer software	3.2	31.5**	67.6	.012	997
12	Clothing or shoes etc.	2.2	38.6**	71.3	ns	675
13	Sporting equipment	0.9	35.8**	71.8	ns	277
14	Travel or accommodation	7.8	34.3**	72.0	ns	2412
15	Tickets to entertainment or the cinema	3.9	38.0**	72.8	ns	1217
16	Other goods or services	3.0	18.5**	65.4	ns	937
17	Electronic lodgment of tax returns	4.2	23.2**	68.1	ns	1320
18	Electronic lodgment of applications or claims for benefits	1.0	36.2**	73.2	ns	310
19	Electronic lodgment of applications for permits etc.	1.8	32.4**	70.4	ns	554
20	Electronic lodgment of bill payments (e.g. rates and car registration)	11.2	29.0**	68.7	ns	3499

*** $p<0.01$*
ns: not significant

Table 2 Descriptive Analysis of Published R-squares for Non-demographic Models

	N	Mean	Std. Deviation	range
Meta analysis				
Actual adoption of e-commerce	25	.18	.158	0.00 - 0.62
Attitudes & intention to adopt e-commerce	9	.33	.256	0.05 - 0.77
Total	34	.22	.197	0.00 - 0.77
Logistic Analysis	20	.34	.062	0.19 - 0.46

Table 3 Results of ANOVA Analysis

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.187	1	.187	7.205	.010
Within Groups	1.349	52	.026		
Total	1.535	53			

domain-specific innovativeness (Goldsmith 2001; Goldsmith and Goldsmith, 2002), shopping orientation (Brown, Pope and Voges, 2003; Fenech and O'Cass, 2001), consumers' perceptions of online risk (Gefen, Karahanna and Straub, 2003; Liebermann and Stashevsky, 2002) and website design (Kim and Eom, 2002). The R-squares of these 34 studies averaged 0.22.

We conclude therefore that the mean R-square for non-demographics obtained from our meta-analysis was found to be smaller than the average of 20 R-square values (*i.e.,* 0.34) for demographic models. Further analysis using ANOVA indicates that the observed difference is statistically significant (Table 3).

Discussion

Consistent with observations reported by Novak and MacEvoy (1990), Baumann, Burton and Elliott (2005) and Sharp, Romaniuk and Cierpicki (1998) our findings indicate that demographics outperform other variables in terms of explanatory power. This may be considered as a fresh challenge to the view put forward by a number of prominent authors and recently was re-emphasized by Wedel and Kamakura (2000) suggesting inferiority of demographics in discriminating consumer behaviors. The findings of this study fundamentally challenge this view. Our results strongly support the use by practitioners of demographics as a primary basis of market segmentation. Demographics are, of course, cost effective and widely available, and, as such, can be particularly important for direct marketing campaigns where models built on small sample can be used in conjunction with populations' demographic characteristics to target potential consumers. Moreover, the application of demographics requires less investigation, knowledge and skills than more complex segmentation bases. This would facilitate application of market segmentation in smaller organisations.

Beyond the simple economic and pragmatic empirical arguments, the results of this study highlight an immediate need for developing theories or conceptual frameworks capable of explaining demographics' impact on consumer behavior. It may be argued that demographics have no intrinsic value; that is, while they can predict they do not provide explanation. This shortcoming needs to be addressed by marketing researchers. Indeed, there are a number of theories scattered in the literature which can be used as a starting point. For example, the New Theory of Consumer Behaviour (Michael and Becker, 1973; Pollak and Wachter, 1975) has been used to rationalize the relationship between income and consumers' shopping behaviour. Adapting this theory to the consumer e-commerce context, one may argue that when the cost of non-market time (*i.e.,* income) is high a rational consumer would use the least time-intensive channel of shopping (i.e., non-store shopping environments such as the internet) to reduce the overall cost of shopping. In the context of credit card, Kinsey (1981) noted as the value of time increases, households tend to use the least time-intensive medium of exchange (*i.e.,* credit cards) in order to minimize the household's cost of producing a given level of shopping services. Similarly, differential risk perception seems to be useful framework to describe gender differences in e-commerce adoption (Garbarion and Strahilevitz, 2002) or self-efficacy has been used to connect education and adoption of online shopping (Burroughs and Sabherwal, 2002; Eastin, 2002). Needless to say that building a comprehensive demographical theory is a daunting task. Notwithstanding, the results of this study suggest that demographics provide a powerful predictive tool for market segmentation and, as such, should provide the starting point for the development of explanatory theory.

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