When it Rains They Respond: Understanding the Value of Exographics through Hierarchical Linear Models

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Abstract

Direct marketers and database marketers compile databases that often contain nested variables. Nested variables are data elements, which are geographically or logically nested within other data variables. For example, customer characteristics might be nested within postal carrier routes, which in turn are nested within ZIP codes, which are further nested in larger geographies such as Metropolitan Statistical Areas. The degree of nesting may be two, three or even more levels. In the social sciences the phenomena of nested variables is addressed with some form of multilevel analysis. Hierarchical Linear Modeling is the most popular technique for addressing the issue of nested variables; however it is not utilized in direct marketing. This is unexpected given that the occurrence of nested variables is quite frequent in direct marketing practice. Geodemographics are known to add value to customer response models, and recent developments (Greene and Milne 2004; Rust and Donthu 1995; Webber 2004) have shown that larger scale variables (exographics) may also be useful in traditional response models.

This paper demonstrates how HLM can be used to identify independent variables in a nested data environment, i.e., identify those variables which are most useful for building consumer response models. This is done by formulating hypotheses about the variables and then providing an appropriate procedure for testing the hypotheses. This paper posits that in addition to utilizing HLM as a modeling technique, the method is useful for data evaluation/variable selection. It is in this vein that the HLM method is investigated. Specifically, HLM is used in this paper to demonstrate the value of exographic data (large scale contextual variables) for direct marketers. This

demonstrates the utility of the HLM modeling technique in a direct marketing context for evaluating the relative contribution of predictor variables.

A two level response file representing auto insurance inquiries from a direct marketing campaign was analyzed. Significant effects were found at the micro (CART) level and the macro (MSA) level. Cross level interaction effects were also shown to be significant. The benefits of HLM analysis are demonstrated for testing theory, validating hypotheses and identifying significant variables in a nested data environment. This paper provides additional support to the claim made by Greene and Milne (2004) that exographics are useful in response model building.

Introduction

Direct marketers and database marketers compile databases that contain variables collected at multiple levels of scale, often times, one or more levels of nesting among the data elements occurs. Nested variables are data elements, which are geographically or logically nested within other data variables (Goldstein 2003; Raudenbush and Bryk 2002; Snijders and Bosker 1999). For example, individual customer behavior and household demographics are nested within larger scale geographies. Customer or household level characteristics are nested within postal carrier routes (CARTs), which in turn are nested within Postal ZIP codes, which are further nested within Metropolitan Statistical Areas (MSAs). The degree of nesting may be two, three or even more levels. Analysts may have variables on a data file that represent individual purchase behavior, neighborhood demographics, and larger scale characteristics that represent geographical counties, MSAs, or states. In other social sciences, specifically education, psychology and management, the phenomena of multiple levels of nested variables is addressed with some form of Multilevel Analysis (Snijders and Bosker 1999). The most popular technique is Hierarchical Linear Models (HLM) described in detail by Raudenbush and Bryk (2002). Although HLM has appeared in the preeminent Marketing journals (Anderson and Salisbury 2003; Baumbartner and Steenkamp 2001; Chatterjee et al. 2003; Steenkamp et al. 1999), it has not been popular in the direct marketing literature. This is unexpected given that nested variables occur frequently in database marketing practice. Popular texts suggest that geodemographics add value to customer response models (David Shepard Associates 1999; Nash 2000; Roberts and Berger 1999; Stone and Jacobs 2001). Greene and Milne (2004) suggest that even larger scale variables, referred to as exographics, are useful in traditional response models. Further support is provided by Reinartz and Kumar (2003) who utilize ZIP/02 level population density and Levin and Zahavy (2001) who use ZIP level demographics in their database marketing models. Several social scientists have argued that in a nested data environment HLM is a preferred modeling method (Brown, 2004; Goetz, 2004; Hofmann, 1997). We accept this claim and explore how HLM can be use to assess the contribution of different variables in a nested data environment.

The purpose of this paper is twofold; first to demonstrate the utility of the HLM method for direct marketing response models and second, to reinforce the potential value and importance of exographics in database or direct marketing. The remainder of this paper is organized as follows: the direct marketing environment and the nature of exographics and their relevance to direct marketing is discussed, the nature and benefit of the HLM method is addressed, third, hypotheses are formulated regarding the impact of demographics and exographics on a direct marketing response model, fourth, the HLM methodology is applied to a data file of automobile insurance inquiries and the results of the analysis are summarized, and finally, a brief discussion about additional exographic and HLM applications is presented.

Direct Mail Environment

A major channel in the direct marketing media mix is direct mail. This paper addresses a unique condition in direct mail for a large number of businesses that distribute mail throughout the country. Due to the complexity of delivering large volumes of mail the U.S. Postal service has granted substantial discounts to direct mailers who distribute mail according to postal geographies at saturated levels in carrier route walk sequence. That is, if the direct mailers can distribute the mail in carrier route walk sequence (the order in which the postal carrier actually delivers the mail) and if the postal geography is nearly saturated (90% of all households in the carrier route receive a piece of mail) (US Postal Service Publication 220, 2003), then a substantial cost saving is awarded to the direct mailer. The postal savings is approximately 40% ($0.15 vs. $0.25). Consequently, direct marketers interested in realizing the potential postal savings need to perform analyses and select clusters of households at the carrier route level (carrier routes typically vary between 50 and 300 households). This implies that predictor variables need to be compiled at the carrier route level. Census data (income, education, occupation, ethnic composition, home value, etc.) are available at the carrier route level from data vendors such as Claritas, Inc. and Scan US, Inc. Additionally, direct mailers can consider contextual variables at larger geographic units such as Postal ZIP codes, U.S. Counties, Metropolitan Statistical Areas or US states. There are a variety of sources which provide data at these larger geographic areas. Greene and Milne (2004) termed the word exographics to describe contextual variables outside the neighborhood level, typically geographies larger than ZIP codes. In their study they incorporated data at the CART and MSA levels to create direct mail response models. The data file that Greene and Milne used in their analysis clearly possesses the nesting attribute. This property is not unique to direct marketers. When data files contain multiple levels of aggregation, a substantial clustering problem occurs.

Direct marketers disaggregate their contextual data from the larger geographies and assign them to the smaller geographies. For example, a data file might contain a variable such as cost of living, at the MSA level. Every carrier route within the MSA is assigned the same cost of living value, producing a clustering effect. Then, the direct marketer applies ordinary least squares regression, ignoring the clustering of micro level variables within the macro level variables that has occurred. HLM proponents argue that this strategy is not appropriate (Goldstein 2003; Raudenbush and Bryk 2002; Snijders and Bosker 1999). This paper proposes that HLM analysis is a more appropriate methodology for direct mailers working with nested data elements. HLM can be used for testing hypothesized relationships, as well as identifying and choosing appropriate data variables for models while incorporating the systematic variance due to clustering.

Exographics

Direct marketers frequently incorporate Census data in their modeling efforts (David Shepard Associates 1999; Nash 2000) regardless of whether they are building response models at the individual or geographic level. One of the practical reasons is that Census data is readily available at multiple geographic levels and is recognized as the most comprehensive data source in the country. Although Census data is comprehensive in sample size (covering the entire U.S. population, or a very large sample) it is limited to a set of variables that represent demographic categories such as: age, income, education, occupation, automobiles, home value, housing stock, marital status, ethnicity and gender. As underscored by many empirical modelers, no model can succeed when predictor variables are inappropriate, inaccurate or invariant (David Shepard Associates 1999; Griffiths et al. 1993; Greene and Milne, 2004). Obviously there are other contextual characteristics that vary by geography which may influence consumer behavior. Going beyond the current direct marketing trend of using smaller geographical levels (e.g. ZIP+4) requires consideration of these contextual conditions, consideration that may require examining alternative data sources and measurement scales (Jackson and Wang 1996; Schmidt and Weber 1998). Moreover, Steenburgh, Ainslie, and Engbertson (2003) argue that massively categorical variables are useful to direct marketers. Boslaugh, et al. (2004) found that neighborhood characteristics and individual characteristics were both significant predictors, while (Brown et al. 2004) noted both individual and block level effects. Different contextual conditions have been noted in the marketing literature, which impact consumer behavior, for example: travel time (Hubbard 1978), retail atmospherics (Solberg and Wong 1992), minority status (Grier and Desphande 2001), and population density (Reinartz and Kumar 2003). Weather affects what we wear, culture affects what activities we engage in, topography and weather affect what sports and leisure activities we participate in, ethnic diversity affects what restaurants we frequent, local resources affect the style of our housing, and historical events affect what holidays we celebrate and how we celebrate them. In the next section we show how we can use HLM methods to evaluate the potential value of candidate exographic variables.

The Nature of Multilevel Analysis

Multilevel analysis is a combination of contextual analysis and mixed effects models. In the social sciences, contextual analysis refers to accounting for the social context which affects individual behavior. Mixed effects models in statistics assume that some of the beta coefficients in a regression model are random rather than fixed. This allows the researcher to account for variation between the subjects. Frequently, researchers collect data in multiple stages to facilitate the data collection process. An education researcher interested in studying student performance might first select appropriate schools within a school district, select classes within each of the schools and then select students within the classes (Goetz et al. 2004). In a business setting, a researcher might select specific industries, then companies within the industries and employees within the companies. Depending on the sampling process at each of the decision stages, systematic variation at some of the levels may be generated and must be controlled for in subsequent analyses (Maas and Hox 2004). The purpose of multilevel analysis is to create a methodology that can assess variation at each of the levels and describe the relative contribution of variables at different levels in terms of explained variance. The most popular multilevel analysis procedure is referred to as HLM, Hierarchical Linear Models. Although some researchers may argue that OLS regression may suffice with appropriate data aggregation or disaggregation, Snijders and Bosker (1999) argue against these approaches describing theoretical difficulties. In the case of aggregation of individual data points and averaging at the higher data level there may be a shift in meaning. Correlations between high level variables should not imply correlations with the original variables. Furthermore, variation between data points at the lower level is unavailable once the aggregated statistics replace the original variables. On the other hand, disaggregating data multiplies the number of units and causes samples to be exaggerated. One could simply ignore the higher order variables but this strategy would ignore systematic variation that may be theoretically intuitive and which has previously been shown to be significant. In effect, this would prevent explaining known systematic variation. Multilevel analysis was designed to avoid these limiting problems.

Benefits of HLM

HLM is the most widely used and best known method for addressing multilevel data. According to (Raudenbush and Bryk 2002), there are three major contributions of the Hierarchical Model over standard models. HLM allows improved estimation of individual effects by borrowing strength from the entire dataset to help estimate underrepresented groups. The HLM framework facilitates modeling the effects of variables across levels. Finally, HLM allows for partitioning of the variance and covariance components to identify within-group effects and between-group effects.

In terms of theory development, HLM techniques, similar to Structural Equation Modeling, can be used to evaluate relationships between multiple predictor variables, existing at multiple levels of context with a single response variable. One can not only determine if relationships between paths are significant but also the relative contribution of each variable. For the database marketer, HLM analysis can help determine which macro variables and in what arrangement they should be utilized in response models. Some scholars describe the strategy employed by direct marketing analysts as a fishing expedition, making no attempt to explain the cause and effect of a consumer behavior, but simply selecting variables to serve as model predictors based on their statistical significance. Additionally, relevant multilevel variable interactions are evaluated by forming the product of all possible contributions and evaluating which interactions yield the greatest correlations, however, this ignores the natural nesting of the data. HLM analysis can be used to improve this strategy with sound theoretical structure. Specifically, for a given set off micro and macro variables, one can establish which micro, macro, and micro-macro variables are the most promising for inclusion in response model building. Essentially, when evaluating the contribution of candidate variables for a response model, in a nested data environment, HLM is an appropriate technique.

Conceptual Framework

Research Hypotheses

Due to industry regulations and postal discounts, of particular interest to some direct mailers, is the response rate of a postal carrier route (Griffiths et al.) resulting from an advertising campaign. As a preliminary step in building response models it is necessary to select independent variables that are most useful for predicting response rate. Theoretically, consumers make inquiries (respond) regarding auto insurance when they need to purchase or plan to change their auto insurance policies. This occurs for a variety of reasons, but two of the more common ones are when changes in premium prices have occurred or changes in the driving characteristics of the household have occurred. These changes can be due to increases in the insurance premium, for example, a new driver is added or removed from the household policy, the driving status of a driver changes, a new vehicle is added to the household, etc. Changes in insurance premium price may occur for other reasons, state regulations, economic inflation adjustments, new policy terms, new assessments of automobile accidents, or recent motor vehicle violations. Marketing analysts often utilize U.S. Census demographic variables to predict customer response. Popular direct marketing texts suggest that geodemographics add value to customer response models (David Shepard Associates 1999; Roberts and Berger 1999; Stone and Jacobs 2001). In this study we demonstrate how hypotheses can be constructed and tested to assess the viability of different variables.

CART Level Effects

Income and age are two of the more commonly used demographic variables, occurring separately or together in a variety of studies (Gallo et al. 2005; Subramanian et al. 2005). People experience more changes when they are younger leading to the first hypothesis.

H_1: Response rate will be lower in carrier routes with a higher median age.

The effect of these changes is magnified when income is at a premium, this leads to the second hypothesis.

H_2: Response rate will be lower in carrier routes with a higher economic index.

Persons who rent, rather than own are more mobile and less stable. (Brown et al. 2004) found that renters exhibit less place attachment. Therefore, their propensity for change should be higher, leading to hypothesis three.

H_3: Response rate will be higher in carrier routes with a higher percentage of renters.

People who currently do not own a vehicle have no need for automobile insurance, this leads to hypothesis four.

H_4: Response rate should be lower in carrier routes with a high percentage of households with zero vehicles.

MSA Level Effects

At the metropolitan statistical area level, there are many factors that may affect automobile insurance rates. Geographies that have more traffic congestion are likely to have more traffic accidents. Individuals that have a traffic accident on their driving record are less likely to change auto insurance providers. This leads us to propose:

H_5: Response rate will be lower in MSAs with more traffic congestion.

In areas that have high rates of automobile theft policy holders will have more claims. Premiums will be adjusted more frequently, policy holders will be subjected to more volatile price fluctuations and will shop for insurance more frequently. The increase in claim frequency will result in more interaction between consumers and the company. Whether these interactions are positive or negative, they will influence the consumer's decision to respond to an automobile insurance advertisement.

H_6: Response rate will be affected by the amount of automobile theft in the MSA (note there is no hypothesized direction of the relationship).

Geographic areas with more hazardous weather have more traffic accidents. More traffic accidents yield more claims and increases insurance premiums. Thus, we propose:

> H_7: Response rate will be higher in MSAs with worse weather conditions.

At the MSA level, population growth is characterized by more dynamic life changes, new jobs, new homes, new cars, and more purchases. As previously noted, change is a harbinger of response, so we hypothesize:

> H_8: Response rate will be greater in MSAs with higher rates of population growth

Cross Level Effects

When looking at the impact of income on slope, there is reason to believe that the relationship would be partially mediated by larger scale effects. In congested areas automobile insurance tends to cost more, therefore it should affect CARTs with higher incomes. We propose:

> H_9: Traffic congestion will moderate the effect of income on response rate. Specifically, the negative effect of income on response rate will be less pronounced in MSAs with higher traffic congestion.

Moving or changing jobs causes people to contact their insurance company and reevaluate their insurance needs. This leads to the next three hypotheses.

> H_{10}: The rate of population growth will moderate the effect of income on response rate. The negative effect of income on response rate will be weaker in areas experiencing high population growth.
>
> H_{11}: The rate of population growth will moderate the effect of age on response rate. The negative effect of age on response rate will be weaker in areas experiencing high population growth.
>
> H_{12}: The rate of population growth will moderate the effect of percentage of renters on response rate. The positive effect of percentage of renters on response rate will be stronger in areas experiencing high population growth.

The following figure identifies the hypothesized relationships.

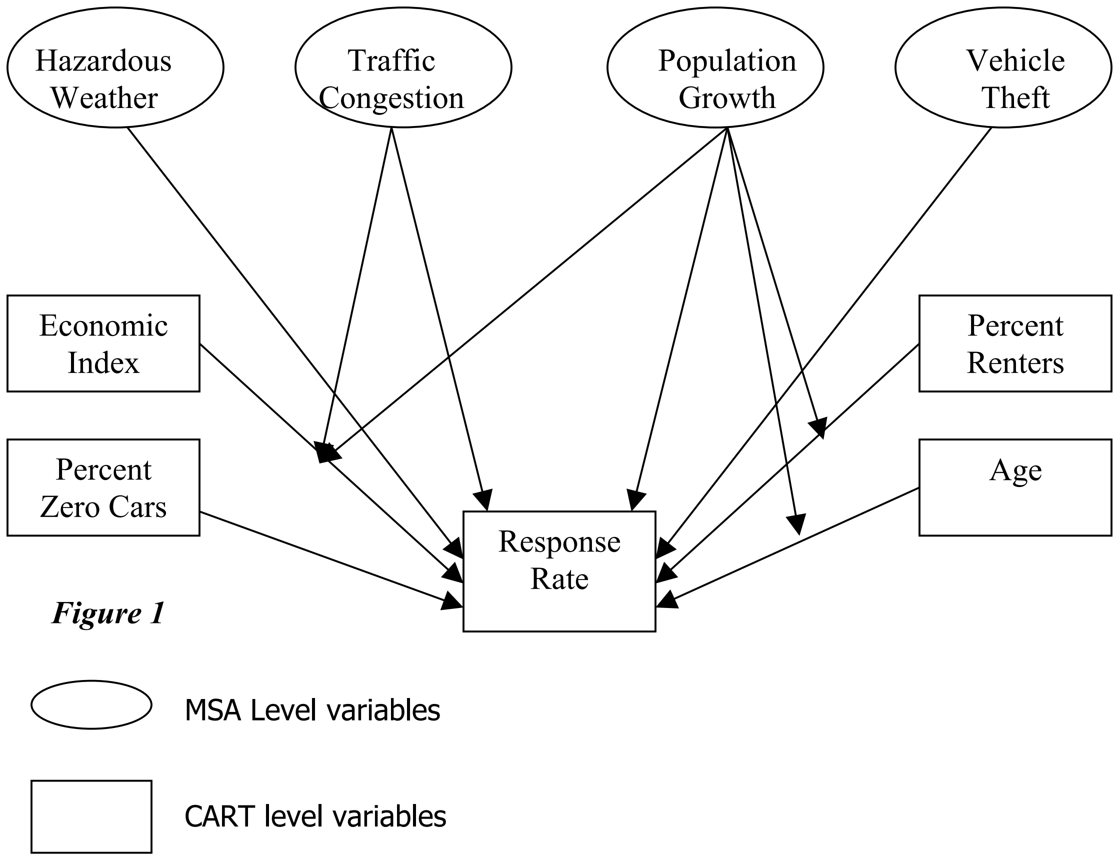


Figure 1

Methodology

Measures

A data file from a large automobile insurance carrier was obtained. The data file consisted of approximately 500,000 households from across the United States. Each carrier route represents 50-300 households. For each carrier route, the number of households that received an advertisement is known and the number of households that made subsequent inquiries was compiled. Response rate is calculated as the quotient of inquiries divided by households that received an advertisement. The carrier route response rates averaged 0.63% and varied from 0.02% to 100%. Census carrier route demographics were appended to the file. The variables appended were median age of the head of household (AGE), percent of households living in rental units (RENTERS), percent of households with zero vehicles (NOCAR), and an economic index (ECONI). The economic index is a standardized variable that combines household income, home value, and household wealth. Additional exographic variables, measured at the MSA level, were also available for appending. The MSA variables utilized were Population Growth Rate (GROWTH), Number of Automobile thefts (CARTHEFT), Hazardous weather score (HAZARD), and Daily Commute (COMMUTE). Hazardous weather score incorporates the amount of snow, and the frequency of strong winds and thunderstorms. Daily commute is measured in minutes and is our surrogate for measuring the amount of traffic congestion in an MSA.

The hypothesized model is conceptualized at 2 levels. Level 1 utilizes predictor variables at the carrier route (micro) level in an additive manner, similar to linear regression. However, unlike linear regression, the betas can represent complex relationships with variables at the next, larger (macro), scale (see equation 1). Three 2-level HLM models were built, the first to test our hypotheses, and the second and third as baseline models for comparative purposes. A standard HLM practice is to test hypothesized models against a random coefficients model to assess the magnitude of beta variation (model 2). Model 3 is a 'full model' which includes all variables and cross level interactions. This permits the researcher to assess the degree to which the hypothesized model fails to account for variation.

Our conceptual framework has four variables at the carrier route level and four variables at the MSA level, with CARTs nested within MSAs. HLM has been specifically developed to deal with this type of multilevel data, enabling the interactive effects of CART and MSA level variables. The equation that will be modeled is described below.

$$Equation\ 1$$

CART Level

$$RR_{ij} = \beta_{0j} + \beta_{1j} NOCAR_{ij} + \beta_{2j} ECONI_{ij} + \beta_{3j} AGE_{ij} + \beta_{4j} RENTERS_{ij} + r_{ij}$$

MSA Level

$$\beta_{0j} = \gamma_{00} + \gamma_{01} COMMUTE_j + \gamma_{02} HAZARD_j + \gamma_{03} CARTHEFT_j + \gamma_{04} GROWTH_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21} COMMUTE_j + \gamma_{22} GROWTH_j + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + \gamma_{31} GROWTH_j + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + \gamma_{41} GROWTH + u_{4j}$$

Results

The parameters, significance levels and variance estimates are detailed in Table 1.

Table 1.
Conditional Model with W1=GROWTH, W2=CARTHEFT, W3=COMMUTE, W4=HAZARD, (group-mean centering of NoCar, EconI, Age, Renters)

Fixed Effects	*Coefficient (SE)*	*t (df)*	*P*	*Reliability*
Model for mean **Response Rate** (β_0)				
Intercept (γ_{00})	2.408497 (0.069652)	34.579 (288)	0.000*	0.538
COMMUTE (γ_{01})	0.016795 (0.011434)	1.469 (288)	0.143	
HAZARD (γ_{02})	0.007999 (0.002611)	3.064 (288)	0.003*	
CARTHEFT (γ_{03})	-0.000295 (0.000257)	-1.147 (288)	0.253	
GROWTH(γ_{04})	0.027481 (0.018781)	1.463 (288)	0.144	
Model for ***No Vehicle*** Slopes (β_1)				
Intercept (γ_{10})	-0.029446 (0.005304)	-5.552 (292)	0.000*	0.049
Model for ***Economic Index*** Slopes (β_2)				
Intercept (γ_{20})	-0.185698 (0.025751)	-7.211 (290)	0.000*	0.051
COMMUTE (γ_{21})	0.004819 (0.001886)	2.556 (290)	0.011*	
GROWTH (γ_{22})	0.005179 (0.004648)	1.114 (290)	0.267	
Model for ***HH Age*** slopes (β_3)				
Intercept (γ_{30})	-0.034846 (0.006357)	-5.482 (291)	0.000*	0.015
GROWTH (γ_{31})	-0.004118 (0.001471)	-2.799 (291)	0.006*	
Model for ***Renter***s (β_4)				
Intercept (γ_{40})	0.000871 (0.002782)	0.313 (291)	0.754	0.053
GROWTH (γ_{41})	-0.001910 (0.000624)	-3.063 (291)	0.003*	

Random Effects (var. Components)	*Variance*	*Df*	*Chi-square*
Var. in mean response rate (τ_{00})	0.70437	278	1579.06238 (0.000)
Var. in NOCAR slopes (τ_{11})	0.00048	282	314.76577 (0.087)
Var. in Economic Index slopes (τ_{22})	0.00591	280	331.81190 (0.018)
Var. in HH Age slopes (τ_{33})	0.00019	281	238.77442 (>0.500)
Var. in RENTERS slopes (τ_{44})	0.00014	281	290.82291 (p=0.331)
Var. within MSAs (σ^2)	19.04408		

Deviance= 128565.699135 (parameters=29)
* indicates significance at the 0.05 level

Model Comparison and Interpretation

All of the models were built using Full Maximum Likelihood Estimation (FEML). The fitted model (1) was compared against a random effects model (see equation 2 and table 2). Comparing the deviances we find that model 1 is significantly different from the random coefficients model (χ^2=47.91752, df=8, p=0.000). The results indicate that there is a significant contribution of variables included in model 1 which were not included in model 2. Specifically, the second level variables explain a significant portion of variance in response. This reinforces the belief that exographics make a meaningful contribution above and beyond using demographics only. Compared to the random coefficients model, the addition of exographics (model 1) reduces the variance within mean response rate by 11.3%. Variance in the slopes has also been reduced. The variance of the slope for NOCAR has been reduced by 18.6%, the variance in the slope of ECONI has been reduced by 5.0%, the variance in the slope of AGE has been reduced by 48.6% and the variance in the slope of RENTERS has been reduced by 48.1%. Furthermore, the only slope with significant residual variation remaining is ECONI (τ_{22}=0.00591, p=0.018).

The next comparison involves model 1 and a model that contains all (given these variables) possible 2-level interaction effects (see equation 3, table 3). The deviances were compared and there was no statistically significant difference (χ^2= 20.31086, df=12, p= 0.061). A more complex model does not increase the explanatory power of the variables of interest.

Hypothesis Testing

With regard to the CART level hypotheses, we find support for H1 (γ_{30}=-0.035, p=0.000). As age increases average response rate decreases. We also find support for H2 (γ_{20}=-0.185698, p=0.000); as economic index increases mean response rate decreases. There was no support for H3, (γ_{40}=0.000871, p=0.754). While this relationship is in the direction that was proposed, it is not significant. The final CART level hypothesis, H4, is supported (γ_{30}=-0.034846, p=0.000), Carrier Routes with a high percentage of zero car owners have a lower mean response rate.

At the MSA level, we only find support for H7 (γ_{02}=0.007999, p=0.003) and we conclude that areas with more bad weather show higher mean response rates. H5 (γ_{01}=0.016795, p=0.143) and H8 (γ_{04}=0.027481, p=0.144) are directionally supported, although not statistically significant. Finally, H6 made no a priori conclusions about the direction of the relationship between vehicle theft and response rate, and no significant relationship was found (γ_{03}=-0.000295, p=0.253).

The first cross level effect that we discussed was the mediating effect of traffic congestion (COMMUTE) on the slope of ECONI. This hypothesis (H9) was supported (γ_{21}=0.004819, p=0.011). However, the mediating effect of GROWTH on the slope ECONI (H10) was only directionally supported (γ_{22}=0.005179, p=0.267). H11, the effect of GROWTH on the slope of AGE was not supported. The evidence points to a significant (γ_{31}=-0.004118, p=0.006) effect in the opposite direction. This result points towards the conclusion that experiencing a high rate of population growth enhances the negative effect of age on mean response rate. The final hypothesis, H12, proposed that the effect of renters would be strengthened by a high rate of population growth. This hypothesis was not supported (γ_{41}=-0.001910, p=0.003), and the opposing effect was found to be significant. High rates of GROWTH weakened the effect of renters on mean response rate. The hypotheses and the results of the modeling efforts are summarized in the table (4) below.

Table 4.

Hypothesis	*Description*	*Level*	*Supported*
H1	H_1: Response rate will be lower in carrier routes with a higher median age.	CART (1)	Yes
H2	H_2: Response rate will be lower in carrier routes with a higher economic index.	CART (1)	Yes
H3	H_3: Response rate will be higher in carrier routes with a higher percentage of renters.	CART (1)	No
H4	H_4: Response rate should be lower in carrier routes with a high percentage of households with zero vehicles.	CART (1)	Yes
H5	H_5: Response rate will be lower in MSAs with more traffic congestion.	MSA (2)	No
H6	H_6: Response rate will be affected by the amount of automobile theft in the MSA (note there is no hypothesized direction of the relationship).	MSA (2)	No
H7	H_7: Response rate will be higher in MSAs with worse weather conditions.	MSA (2)	Yes
H8	H_8: Response rate will be greater in MSAs with higher rates of population growth.	MSA (2)	No
H9	H_9: Traffic congestion will moderate the effect of the economic index on response rate. Specifically, the negative effect of economic index on response rate will be less pronounced in MSAs with higher traffic congestion.	Cross (1,2)	Yes
H10	H_{10}: The rate of population growth will moderate the effect of economic index on response rate. The negative effect of the economic index on response rate will be weaker in areas experiencing high population growth.	Cross (1,2)	No
H11	H_{11}: The rate of population growth will moderate the effect of age on response rate. The negative effect of age on response rate will be weaker in areas experiencing high population growth.	Cross (1,2)	YES
H12	H_{12}: The rate of population growth will moderate the effect of percentage of renters on response rate. The positive effect of percentage of renters on response rate will be stronger in areas experiencing high population growth.	Cross (1,2)	YES

We can now update figure 1 to show the statistically significant paths (the dashed lines are not significant).

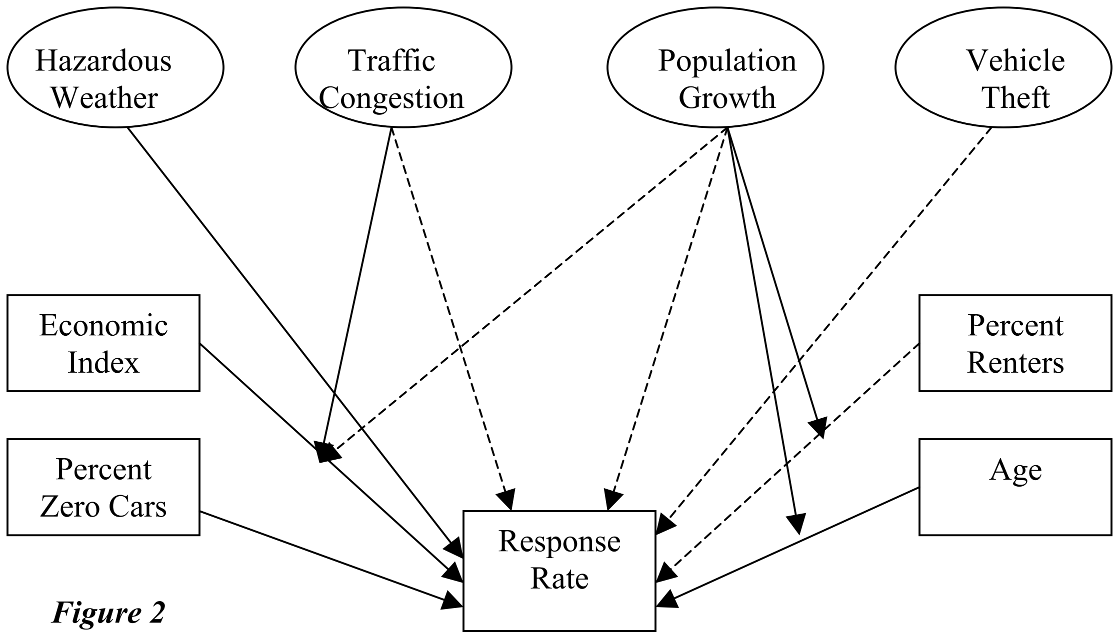


Figure 2

Graphs of the significant cross level effects can be found in the appendix (Graphs 1, 2, and 3). We have shown that HLM can be used to test hypotheses and identify predictor variables that are potentially meaningful in a response model. Specifically, we demonstrate with an empirical data set, the potential value of incorporating large scale contextual data (exographics) not typically discussed in the marketing literature.

Discussion

Limitations

This study investigated the use of exographics on response to automobile insurance direct mail advertising. In this regard the study is quite limited because we cannot generalize the results across industries or across advertising mediums. Another problem is the lack of literature in the direct marketing field addressing the use of multilevel data. The paucity of prior work made it particularly difficult to derive specific theory about expected effects and their direction. We were also limited to CART Census geodemographics and exographics at the MSA level. There are certainly other data sources available, some of which may contain significant explanatory variables. For example county level data may be available which more directly influences carrier routes than MSA level variables.

Conclusions and Future Research

We have discussed why HLM is an appropriate technique for direct marketers to utilize when developing and validating theory. More specifically, HLM can be used to properly assess the relative contribution of candidate predictor variables. In this study, we demonstrate that CART geodemographics significantly affect response rate to automobile insurance direct mail advertising. We also demonstrate that there are MSA level exographics that directly influence response rate. Furthermore, exographics played a significant role in the relationship between geodemographics and response rate, sometimes strengthening the relationship and at other times weakening it. We recommend future research to evaluate other response variables, such as closure rate (actual sales). We also suggest that research looks at alternative industries. The value of different exographics should be very sensitive to the type of product and industry. Researchers could also investigate the use of different geodemographics at the CART level. Perhaps, response rate is influenced by racial makeup, or by the presence of children in the household. Finally, researchers may want to investigate 3 level models, specifically to answer questions regarding where CARTs are most influential. CARTs are nested within counties (where insurance rates are often set), which are nested within MSAs (where there is traffic, different repair costs, etc.), and MSAs are nested within states (which regulate insurance practices). Any combination of these levels may yield important insights into the nature of consumer response.

Direct marketers should be encouraged to include exographics into their response models, and should utilize tools such as HLM to properly build and interpret those models. Given that direct marketers frequently operate in a nested data environment, HLM should be considered as a potential strategy for assessing and selecting independent variables. Applying the HLM strategy for assessing predictor variables, we concur with Greene and Milne (2004) that exographic variables have potential value in a direct marketing context. Finally, it seems reasonable to consider the HLM methodology for building response models. Comparing HLM model performance to OLS performance should be of interest to both academic and practitioners engaged in Direct Marketing.

Appendix

Equation 2: Random coefficients model

CART Level

$$RR_{ij} = \beta_{0j} + \beta_{1j}NOCAR_{ij} + \beta_{2j}ECONI_{ij} + \beta_{3j}AGE_{ij} + \beta_{4j}RENTERS_{ij} + r_{ij}$$

MSA Level

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + u_{4j}$$

Equation 3: All Cross level effects

CART Level

$$RR_{ij} = \beta_{0j} + \beta_{1j}NOCAR_{ij} + \beta_{2j}ECONI_{ij} + \beta_{3j}AGE_{ij} + \beta_{4j}RENTERS_{ij} + r_{ij}$$

MSA Level

$$\beta_{0j} = \gamma_{00} + \gamma_{01}COMMUTE_j + \gamma_{02}HAZARD_j + \gamma_{03}CARTHEFT_j + \gamma_{04}GROWTH_j + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}COMMUTE_j + \gamma_{12}HAZARD_j + \gamma_{13}CARTHEFT_j + \gamma_{14}GROWTH_j + u_{1j}$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21}COMMUTE_j + \gamma_{22}HAZARD_j + \gamma_{23}CARTHEFT + \gamma_{24}GROWTH_j + u_{2j}$$

$$\beta_{3j} = \gamma_{30} + \gamma_{31}COMMUTE_j + \gamma_{32}HAZARD_j + \gamma_{33}CARTHEFT + \gamma_{34}GROWTH_j + u_{3j}$$

$$\beta_{4j} = \gamma_{40} + \gamma_{41}COMMUTE_j + \gamma_{42}HAZARD_j + \gamma_{43}CARTHEFT + \gamma_{44}GROWTH + u_{4j}$$

Table 2.
Random Coefficients Model: group-mean centering of NoCar, EconI, Age, Renters

Fixed Effects	*Coefficient (SE)*	*t (df)*	*p*	*Reliability*
Model for mean Response Rate (β_0)				
Intercept (γ_{00})	2.430970 (0.070288)	34.586 (292)	0.000	0.562
Model for No Vehicle Slopes (β_1)				
Intercept (γ_{10})	-0.026469 (0.005275)	-5.018 (292)	0.000	0.057
Model for Economic Index Slopes (β_2)				
Intercept (γ_{20})	-0.128927 (0.018233)	-7.071 (292)	0.000	0.053
Model for HH Age slopes (β_3)				
Intercept (γ_{30})	-0.038874 (0.006424)	-6.051 (292)	0.000	0.027
Model for RENTERS (β_4)				
Intercept (γ_{40})	0.001438 (0.002844)	0.506 (292)	0.613	0.084

Random Effects (var. Components)	*Variance*	*Df*	*Chi-square*
Var. in mean response rate (τ_{00})	0.79409	282	1513.80656 (p=0.000)
Var. in NOCAR slopes (τ_{11})	0.00059	282	319.79344 (p=0.060)
Var. in Economic Index slopes (τ_{22})	0.00622	282	337.73069 (p=0.013)
Var. in HH Age slopes (τ_{33})	0.00037	282	248.22232 (p>0.500)
Var. in RENTERS slopes (τ_{44})	0.00027	282	305.46100 (p=0.161)
Var. within MSAs (σ^2)	19.04776		

Deviance=128613.616659 (parameters=21)

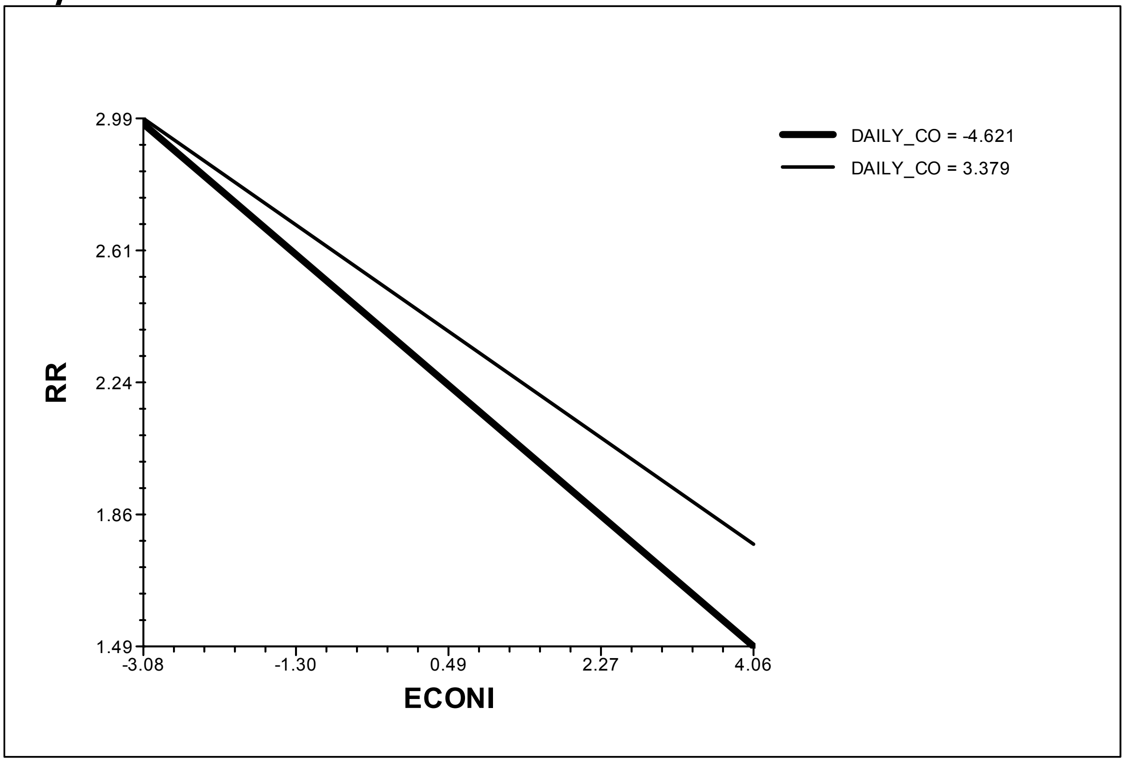
Table 3.
Conditional Model with W1=GROWTH, W2=CARTHEFT, W3=COMMUTE, W4=HAZARD, (group-mean centering of NoCar, EconI, Age, Renters)

Fixed Effects	*Coefficient (SE)*	*t (df)*	*p*	*Reliability*
Model for mean Response Rate (β_0)				
Intercept (γ_{00})	2.410276 (0.069729)	34.566 (288)	0.000	0.538
COMMUTE (γ_{01})	0.021638 (0.012196)	1.774 (288)	0.077	
HAZARD (γ_{02})	0.007294 (0.002818)	2.588 (288)	0.010	
CARTHEFT (γ_{03})	-0.000434 (0.000273	-1.590 (288)	0.113	
GROWTH(γ_{04})	0.036130 (0.019406)	1.862 (288)	0.063	
Model for No Vehicle Slopes (β_1)				
Intercept (γ_{10})	-0.021292 (0.007148)	-2.979 (288)	0.004	0.036
COMMUTE (γ_{11})	0.001085 (0.000669)	1.621 (288)	0.106	
HAZARD (γ_{12})	-0.000060 (0.000185)	-0.326 (288)	0.744	
CARTHEFT (γ_{13})	-0.000045 (0.000019)	-2.341 (288)	0.020	
GROWTH(γ_{14})	0.002972 (0.001461)	2.035 (288)	0.042	
Model for Economic Index Slopes (β_2)				
Intercept (γ_{21})	-0.17038 (0.028545)	-5.969 (288)	0.000	0.046
COMMUTE (γ_{21})	0.004992 (0.002661)	1.876 (288)	0.061	
HAZARD (γ_{22})	0.000399 (0.000670)	0.595 (288)	0.551	
CARTHEFT (γ_{23})	-0.000053 (0.000068)	-0.768 (288)	0.443	
GROWTH(γ_{24})	0.005873 (0.005013)	1.172 (288)	0.243	
Model for HH Age slopes (β_3)				
Intercept (γ_{30})	-0.045807 (0.008487)	-5.397 (288)	0.000	0.005
COMMUTE (γ_{31})	-0.000393 (0.000920)	-0.427 (288)	0.669	
HAZARD (γ_{32})	-0.000067 (0.000247)	-0.271 (288)	0.786	
CARTHEFT (γ_{33})	0.000051 (0.000024)	2.097 (288)	0.037	
GROWTH(γ_{34})	-0.005299 (0.001736)	-3.052 (288)	0.003	
Model for RENTERS (β_4)				
Intercept (γ_{40})	-0.000273 (0.003717)	-0.074 (288)	0.942	0.056
COMMUTE (γ_{41})	0.000019 (0.000441)	0.043 (288)	0.966	
HAZARD (γ_{42})	-0.000108 (0.000105)	-1.029 (288)	0.305	
CARTHEFT (γ_{43})	0.000003 (0.000011)	0.234 (288)	0.815	
GROWTH(γ_{44})	-0.002244 (0.000803)	-2.793 (288)	0.006	

Random Effects (var. Components)	*Variance*	*Df*	*Chi-square*
Var. in mean response rate (τ_{00})	0.70389	278	1547.65193 (p=0.000)
Var. in NOCAR slopes (τ_{11})	0.00032	278	293.29466 (p=0.253)
Var. in Economic Index slopes (τ_{22})	0.00517	278	332.48434 (p=0.014)
Var. in HH Age slopes (τ_{33})	0.00007	278	230.51221 (p>0.500)
Var. in RENTERS slopes (τ_{44})	0.00015	278	291.05268 (p=0.283)
Var. within MSAs (σ^2)	19.04457	278	

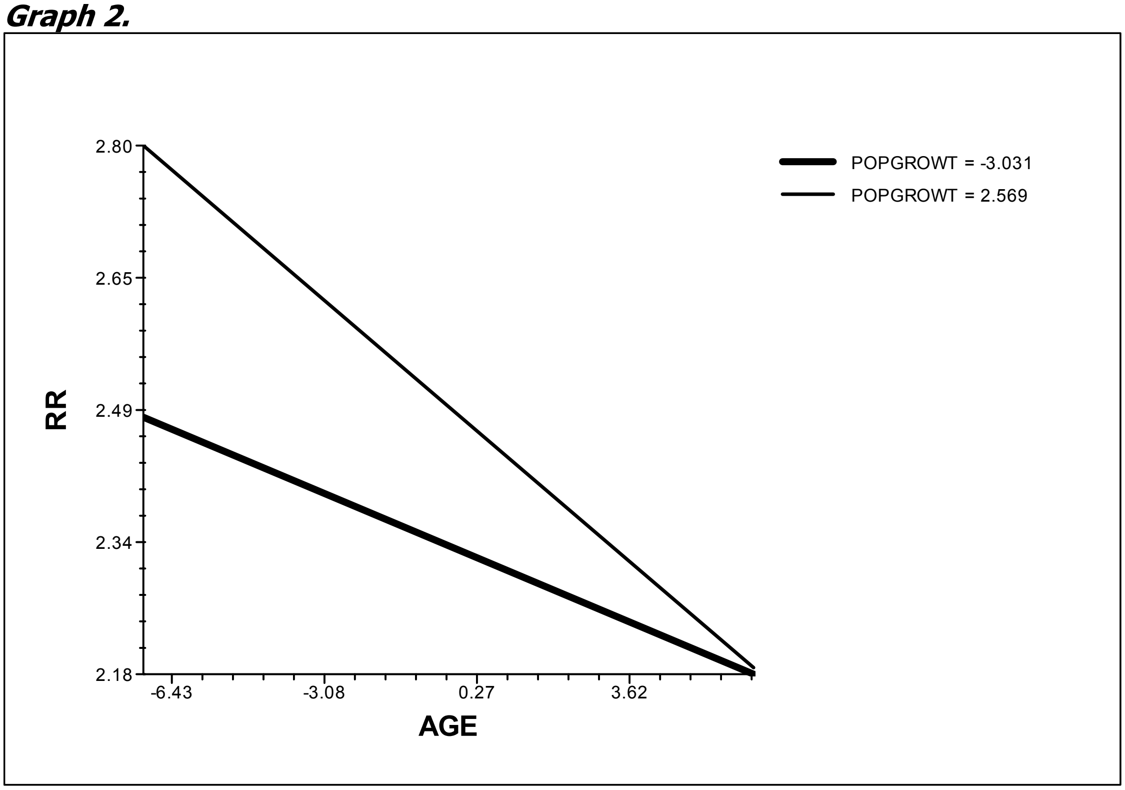
Deviance=128545.388276 (parameters=41)

Graph 1.



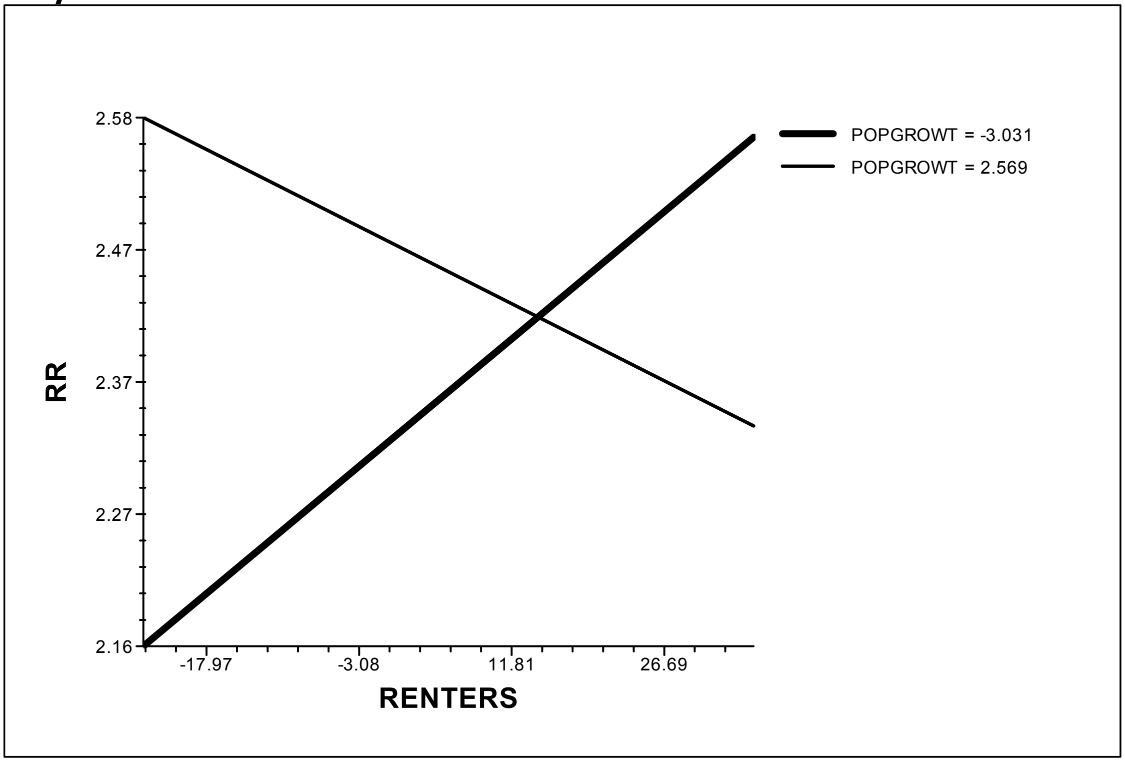
The effect of COMMUTE on the relationship between ECONI and response rate.

Graph 2.



The effect of GROWTH on the relationship between AGE and response rate.

Graph 3.



The effect of GROWTH on the relationship between RENTERS and response rate.

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