Received November 2009
Revised May 2010
Accepted July 2010

Interpreting interrelations across multiple levels in HGLM models

An application in international marketing research

Burcu Tasoluk
Faculty of Management, Sabanci University, Istanbul, Turkey, and
Cornelia Dröge and Roger J. Calantone
Department of Marketing, The Eli Broad Graduate School of Management, Michigan State University, East Lansing, Michigan, USA

Abstract

Purpose – Although the use of data from different levels is very common in international marketing research, the practice of employing multi-level analysis techniques is relatively new. The paper aims to provide an application of a specific case of multi-level modelling – where the dependent variable is dichotomous, which is often the case in marketing research (e.g. whether a consumer buys the brand or not, whether he/she is aware of the brand or not, etc.)

Design/methodology/approach – A hierarchical generalized linear model is employed.

Findings – Since this is a technical paper, the authors would like to emphasize the process rather than the empirical findings. In summary, the paper: provides a brief theoretical overview of Hierarchical Linear Modeling and Hierarchical Generalized Linear Modeling; illustrates the application of the method using the domains of consumers within countries and a dichotomous dependent variable; focuses on interpretation of log-odds results; and concludes with practical issues and research implications.

Originality/value – The main value of this research is to demonstrate how to employ multi-level models when the dependent variable is dichotomous. Multi-level techniques are quite new in international marketing research, although nested data structures are relatively common in our field. This is a technical paper that guides the researchers as to how to apply and interpret the results when modeling such data with a dichotomous dependent variable.

Keywords Multilevel marketing, Marketing models, International marketing

Paper type Technical paper

Introduction

International marketing research often involves models with variables that belong to different units of analysis, which themselves may form a hierarchical structure. For example, managers may be nested within companies, or consumers within countries.

Research studies, which influenced international marketing/international business researchers the most (i.e. cited the most), propose models/theories that are indeed suitable for multi-level modeling. A quick glance at the seven *JIBS* articles, which have been cited more than 200 times[1], illustrates situations where multi-level research would be beneficial (see Table I).

Hierarchical Linear Modeling (HLM, also known as multi-level modeling) was originally developed to deal with hierarchical (nested) data. A more generalized version of HLM called "Hierarchical Generalized Linear Modeling (HGLM)" (see Goldstein, 1991; Wong and Mason, 1985) is employed when the dependent variable is dichotomous, which is not seldom in marketing research. HGLM is ideally suited for research on international marketing, but has not been applied much in this literature.

International Marketing Review
Vol. 28 No. 1, 2011
pp. 34-56

0265-1335
DOI 10.1108/02651331111107099

Study and a brief summary (*JIBS*)	Related conceptual/operational levels for multi-level modeling
Johanson and Vahlne (1977): "The internationalization process of the firm – a model of knowledge development and increasing foreign market commitments" *Times Cited: 709* *Develops a model of the internationalization process of the firm that focuses on the development of the individual firm, and on its gradual acquisition, integration, and use of knowledge about foreign markets and operations, and on its successively increasing commitment to foreign markets*	The interplay between firm characteristics and foreign market characteristics; firms nested in markets
Kogut and Singh (1988): "The effect of national culture on the choice of entry mode" *Times Cited: 592* *Investigates whether characteristics of national cultures influence the selection of firms' entry modes*	The interplay between firm characteristics and cultural characteristics; company culture and country culture interface; firms nested in cultures
Kogut and Zander (1993): "Knowledge of the firm and the evolutionary theory of the multinational corporation" *Times Cited: 378* *Tests whether firms specialize in the internal transfer of tacit knowledge by examining the decision to transfer the capability to manufacture new products to wholly owned subsidiaries or to other parties. The notion of the firm as specializing in the transfer and recombination of knowledge is the foundation to an evolutionary theory of the multinational corporation*	Multi-national corporation (MNC) characteristics; Headquarters (HQ) home country characteristics; subsidiary characteristics; HQ and subsidiaries cross-nested in MNCs
Dunning (1988): "The eclectic paradigm of international production – a restatement and some possible extensions" *Times Cited: 311* *Reviews eclectic paradigm and extensions; eclectic paradigm as "A robust general framework for explaining and analyzing not only the economic rationale of economic production but many organizational and impact issues in relation to MNE activity."*	The interplay between firm, industry, and country variables. Firms/MNCs cross-nested in industries and countries
Anderson and Gatignon (1986): "Modes of foreign entry – a transaction cost analysis and propositions" *Times Cited: 259* *Offers a transaction cost framework for investigating the entry mode decision*	The interaction between transaction-specific investment (TSI), firms, and environmental uncertainty; TSI's nested in partner companies, which in turn nested in markets/environments
Hofstede (1983): "The cultural relativity of organizational practices and theories" *Times Cited: 217* *Summarizes findings about differences in people's work-related values among 50 countries. In view of these differences, ethnocentric management theories (those based on the value system of one particular country) have become untenable*	The interplay between organizations and cultures; company culture and country culture interface; firms nested in cultures
Oviatt and McDougall (1994): "Toward a theory of international new ventures" *Times Cited: 213* *A framework is presented that explains international new ventures by integrating international business, entrepreneurship, and strategic management theory*	The interaction of International New Ventures' characteristics and characteristics of the countries they operate; firms cross-nested in industries and countries

Table I.
Influential International Marketing/International Business (IM/IB) research topics and opportunities for multilevel research

In this research, we:

(1) provide a brief theoretical overview of HLM and HGLM;
(2) illustrate the application of the method using the domains of *consumers* within *countries* and a dichotomous dependent variable; and
(3) demonstrate the calculation and the interpretation of log-odds results.

The empirical tests are conducted using data from across 31 countries from more than 31,000 consumers.

Overview of HLM

Assume that we want to model consumer data from different countries. Two common traditional methods to deal with such nested data structures have been disaggregation and aggregation. The problem with the first approach is that the consumers in the same country will have the same value on each of the country variables. Therefore, the "independence of observations" assumption, which is basic for classical statistical techniques, does not hold (Raudenbush and Bryk, 2002). The second approach aggregates consumer characteristics over countries, and does a higher-level analysis. However, all the within-group information is lost, the relations between aggregated variables often seem to be much stronger than what they actually are, and the relations between the aggregate variables can be very different from the relations between the non-aggregate variables. Waste of information and distortion of interpretation are the downsides of this second approach (Raudenbush and Bryk, 2002).

Individuals in the same group are often closer or more similar than individuals in different groups. Consumers in different countries can be independent, but consumers in the same country share the same value on certain variables. If unaccounted for, these unobserved variables go into the error term of the linear model and cause correlation between disturbances. The disturbances have a group and an individual component. Group components are correlated within groups and independent between groups, whereas individual components are independent. In addition, some groups may be more homogeneous than other groups, thus the variance of the group components can differ (Raudenbush and Bryk, 2002). Therefore, combining all variables that belong to different levels of analysis into one regression equation undermines two basic assumptions of traditional linear model analysis: homoscedasticity and independence.

One approach to solve these problems is to include an effect in the model that corresponds to the grouping of the lower-level units, thus employing ANOVA or ANCOVA. However, there are a number of problems with this approach (Luke, 2004). As the number of groups increase, there are more parameters to estimate, and the model has less power and greater complexity. The treatment of group parameters as fixed effects ignores the random variability of the group characteristics. Furthermore, ANOVA methods are not very flexible in handling missing data or unbalanced designs (Luke, 2004).

HLM was developed to deal specifically with hierarchical (nested) data in education research (Bryk and Raudenbush, 1992; Raudenbush and Bryk, 2002). This method avoids the weaknesses outlined above. Each of the levels in the data structure has its own sub-model, which captures the relationships among variables within a given level and specifies how variables at one level influence relations occurring at another (Raudenbush and Bryk, 2002). Disciplines such as sociology, biometrics, econometrics, and statistics have all contributed to the development of such models for nested data structure. Although not very common, studies in organizational behavior (Hofmann, 1997; Hofmann and Gavin, 1998; Klein *et al.*, 1994) and strategic management research (Song *et al.*, 2002) also utilized this technique. Other names used in different literatures include multi-level linear models, mixed-effects models, random-effects models, random-coefficient regression models, covariance components models, etc. In marketing, multi-level modeling started to become popular as well (Bijmolt *et al.*, 2004).

A simple example of HLM follows for a two-level model, where there are individual- (level-1) and group-level (level-2) variables. To first isolate and then account for the effects of group-level variables, the individual-level variables are modeled as having a separate regression equation for each group. The parameters of these regression equations are then regressed on the group-level variables. This procedure lets group-level variables be used to explain variation in the individual-level parameters and allows testing for main effects, and interactions within and between levels.

Assume there are two level-1 variables (χ_1 and χ_2) and one level-2 variable (ω_1). The value of the dependent variable (Y_{ij}) can be predicted from the values of level-1 independent variables.

The regression equation is:

$$Y_{ij} = \beta_{0j} + \beta_{1j} * \chi_{1ij} + \beta_{2j} * \chi_{2ij} + r_{ij} \tag{1}$$

where "i" refers to the person number and "j" refers to the group number.

Each group will have a separate regression equation, and the coefficients β_0, β_1, and β_2 will be allowed to change from group to group. Further analyses can explain their variability. Thus, level-2 regression equations are formed to predict the value of the level-1 parameters using values of the level-2 independent variable:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} * \omega_{1j} + u_{0j} \tag{2}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} * \omega_{1j} + u_{1j} \tag{3}$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21} * \omega_{1j} + u_{2j} \tag{4}$$

Note that there is a separate equation for each parameter in Equation (1).

If the level-2 Equations (2)-(4) are substituted into the level-1's Equation (1), the combined model is:

$$\begin{aligned} Y_{ij} = {} & \gamma_{00} + \gamma_{01} * \omega_{1j} + u_{0j} \\ & + (\gamma_{10} + \gamma_{11} * w_{1j} + u_{1j}) * \chi_{1ij} \\ & + (\gamma_{20} + \gamma_{21} * w_{1j} + u_{2j}) * \chi_{2ij} + r_{ij} \end{aligned} \tag{5}$$

Coefficients that are allowed to vary from group to group, e.g. β_{0j}, β_{1j}, and β_{2j}, are referred to as "random" coefficients. Coefficients "γ" are not assumed to vary across groups (and hence they lack the subscript j); therefore, they are referred to as "fixed" coefficients (Hox, 1995). Standard OLS cannot be used to estimate this equation. As reviewed above, one necessary condition to conduct OLS is that the random errors are independent, normally distributed, and have constant variance. Note that the random error in Equation (5), which is $[u_{0j} + (u_{1j} * \chi_{1ij}) + (u_{2j} * \chi_{2ij}) + r_{ij}]$, is not independent across groups since the components u_{0j}, u_{1j}, and u_{2j} are common to every individual within group j. The errors do not have equal variances either, since u_{0j}, u_{1j}, and u_{2j} vary across groups and χ_{1ij} and χ_{2ij} vary across individuals. Although standard regression analysis is inappropriate, iterative maximum likelihood procedures can be used to estimate such models (Raudenbush and Bryk, 2002).

Note that if u_{0j}, u_{1j}, and u_{2j} were null for every j, Equation (5) would be equivalent to an OLS regression model.

Overview of hierarchical generalized linear models

When the dependent variable is dichotomous, linear regression methods should not be employed for two reasons (Snijders and Bosker, 1999). First, ordinary linear regression might give a fitted value that is outside the permitted range. For example, a dichotomous outcome variable Global Brand Ownership (GBO) may be 0 (failure; the consumer does not own the brand) or 1 (success; the consumer owns the brand). A fitted value of "0.80" can be interpreted as an 80 percent probability of owning the brand. A fitted value of "1.1" is meaningless, however.

The second reason against linear regression methods is that the mean and variance of a Bernoulli distribution are related (Snijders and Bosker, 1999). For a dichotomous variable Y with probability p for outcome 1 (success), the probability for outcome 0 (failure) is $1-p$. Then:

$$\begin{aligned} E(Y) &= p \text{ is the mean and} \\ \mathrm{Var}(Y) &= p(1-p) \text{ is the variance} \end{aligned} \tag{6}$$

The variance is not a free parameter because it depends on p (Raudenbush and Bryk, 2002).

Furthermore, ordinary HLM is inadequate because of two assumptions:

(1) linear relationships between the predictors and the dependent variable; and

(2) the normality of the random effects (Raudenbush and Bryk, 2002).

These assumptions are violated when the dependent variable is dichotomous. The level-1 random effect cannot be normally distributed, since it can take only two values. In a multi-level setting, the dichotomous outcome, Y_{ij} for level-1 unit i in group j, can be represented as the sum of the probability (average proportion of successes) in group j plus a residual for the individual i (assuming constant probability of success per group):

$$Y_{ij} = P_j + R_{ij} \tag{7}$$

The residual R_{ij} has a mean zero; however, it can have only the values P_j and $1-P_j$, since Y_{ij} must be 0 or 1. Given the value of the probability P_j, the variance of the residual is:

$$\mathrm{Var}(R_{ij}) = P_j(1 - P_j) \tag{8}$$

The linearity assumption does not hold either. GBO (our dependent variable) must lie in the $(0, 1)$ interval, requiring a nonlinear transformation of the predicted value.

The analysis of nonlinear structural models and non-normally distributed errors is accomplished by HGLMs, described below. The level-1 model consists of three parts: a sampling model, a link function, and a structural model.

Level-1 sampling model

Assume the level-1 outcome variable arises from a specific level-1 probability distribution, holding constant the level-1 expected value. Thus:

$$Y_{ij} | \varphi_{ij} \sim \mathrm{B}(m_{ij}, \varphi_{ij}) \tag{9}$$

where Y_{ij} is defined as the number of successes in m_{ij} trials, and φ_{ij} is the probability of success in each trial. Y_{ij} has a binomial Bernoulli distribution. When $m_{ij} = 1$, Y_{ij} can only be zero or one. The expected value and variance are:

$$\begin{aligned} E(Y_{ij} | \varphi_{ij}) &= m_{ij}\varphi_{ij}, \\ Var(Y_{ij} | \varphi_{ij}) &= m_{ij}\varphi_{ij}(1 - \varphi_{ij}) \end{aligned} \tag{10}$$

Level-1 link function

Instead of the probabilities, one can consider the odds (Snijders and Bosker, 1999). The odds of success are defined as the ratio of the probability of success (φ_{ij}) to the probability of failure ($1 - \varphi_{ij}$). Odds can take values from 0 to infinity (unlike probabilities):

$$Odds = \left(\frac{\varphi_{ij}}{1 - \varphi_{ij}} \right) \tag{11}$$

"Link function" is the general term for a transformation function and "Log-odds" is one of the most frequently used link function for probabilities. The logit function is an increasing function defined for numbers between 0 and 1, with range going from $-\infty$ to $+\infty$. The level-1 predicted value, φ_{ij}, is transformed via the following logit link function:

$$\eta_{ij} = \ln \left(\frac{\varphi_{ij}}{1 - \varphi_{ij}} \right) \tag{12}$$

where η_{ij} is the log-odds (natural logarithm) of the odds of success. When the probability of success $\varphi_{ij} = 0.5$, the odds of success are $\varphi_{ij}/(1 - \varphi_{ij}) = 0.5/0.5 = 1$ and the log-odds is 0. When $\varphi_{ij} < 0.5$, then odds < 1 and the logit is negative; when $\varphi_{ij} > 0.5$, then odds > 1 and the logit is positive. By forming Equation (12), φ_{ij} is constrained in the interval (0, 1), whereas η_{ij} can take any real value.

Level-1 structural model

The level-1 link function, η_{ij}, can be equated to a linear model having level-1 coefficients, i.e., to a level-1 structural model. A predicted log-odds is converted to odds by taking exp (η_{ij}); it is converted to a predicted probability by the logistic function in Equation (13). The logistic and logit functions are inverses, and φ_{ij} is in the interval (0, 1):

$$\varphi_{ij} = \frac{\exp(\eta_{ij})}{1 + \exp(\eta_{ij})} = \frac{1}{1 + \exp(-\eta_{ij})} \tag{13}$$

HLM can be viewed as a special case of HGLM where the sampling model is normal, the link function is the identity link, and the structural model is linear (Raudenbush and Bryk, 2002).

An application of HGLM in international marketing

In order to illustrate the unique interpretations available from the results of HGLM, we chose global branding as the context. Global brands are among the most important intangible assets a company can have. According to the Interbrand/BusinessWeek Study (2009), the financial value of the top 100 global brands exceeds $1 trillion. Many researchers have investigated different aspects of global branding, and *prestige* and *quality* are two associations commonly linked to global brands (Holt *et al.*, 2004a, b; Steenkamp *et al.*, 2003). However, research to date has not identified how these associations are related to overall global brand equity (GBE).

The model we test (Figure 1) rests on the contingency view, which states that the impact of a particular factor depends on other factors (Zeithaml *et al.*, 1988). We begin with the premise that, as identified by previous researchers, perceived brand *quality* and brand *prestige* drive "GBO". We also propose that the strengths of these relationships are contingent on overall GBE. Thus, the first important question concerns the impact of quality versus prestige on GBO, controlling for GBE. Second, are the strengths of the relationships between either quality or prestige and GBO contingent on GBE? If so, how do these interactions with GBE affect GBO?

In summary, our contingency model encompasses:

(1) the core relationships of equity, quality, and prestige to ownership (across 31 countries);

(2) the interaction effects, and also examines;

(3) the control variables of age and income; and

(4) country-level GDP per capita.

We examine whether the relationships among ownership, equity, quality, and prestige depend on age, income, and/or country-level GDP per capita. Figure 1's multi-level model enables us to scrutinize multiple core relationships because the interdependence

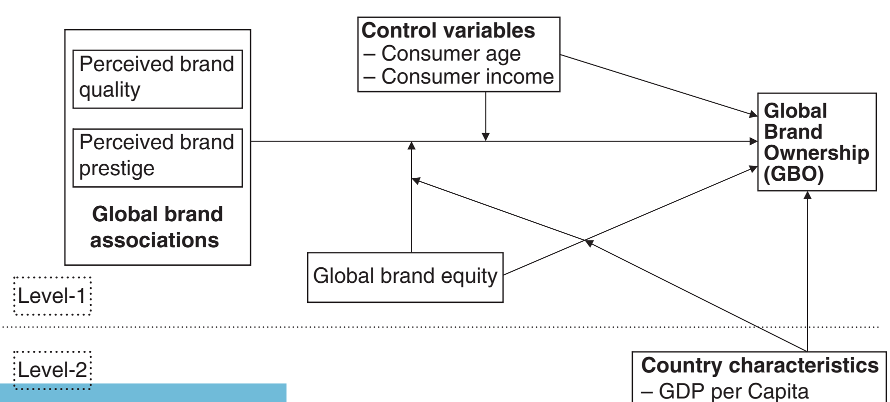


Figure 1.
The theoretical framework

of observations from consumers who are from the same country is explicitly incorporated into the analysis.

Model variables and their descriptions

For level-1 variables, proprietary data were obtained from a global marketing research company. The sample was designed to represent the national populations aged 13-65 years, and contained 31,397 respondents from 31 countries[2]. Public secondary data were used for the level-2 variable; GDP per capita values were taken from The World Factbook (2004) of the Central Intelligence Agency.

The names and descriptions of all variables are provided in Table II. While dichotomous variables were left uncentered, all continuous variables were grand-mean centered. Grand-mean centering was done by subtracting the grand mean of the predictor from the original predictor for each level-1 case. Grand-mean centering makes the interpretation of the intercept term meaningful (Raudenbush and Bryk, 2002): it is the expected value of the outcome variable when the values of explanatory variables are zero. For example, if AGE were left uncentered, the intercept would show the log-odds of GBO for a consumer who is zero years old; after grand-mean centering, the intercept is the expected value of GBO for an individual of "average" age. Previous research found that grand-mean centering also provides a computational advantage by reducing the correlation between the intercept and slope across groups, which in turn can help to mitigate potential level-2 estimation problems due to multicollinearity (Kreft *et al.*, 1995).

The GDPCAPITA variable used a purchasing power parity (PPP) basis instead of using official exchange rates[3]. The level-1 INCOME variable that was originally coded in local currency was also converted to its PPP[4] equivalent. This makes comparisons of income levels across different countries meaningful. Summary statistics for all variables are in Table III; Tetrachoric, Biserial, and Pearson correlations of the level-1 variables are in Table IV.

Level-1 variables	*Description (applies to individual consumers)*
Brand quality	QUALITY is a dichotomous, uncentered variable, coded 1 if the brand is perceived as high quality and 0 if it is not
Brand prestige	PRESTIGE is a dichotomous, uncentered variable, coded 1 if the brand is perceived as prestigious and 0 if it is not
Global brand equity	BEQUITY is a dichotomous, uncentered variable, coded 1 if the brand is perceived as being better and worth paying more for, 0 if it is not
Global brand ownership	GBO is a dichotomous, uncentered variable, coded 1 if the consumer owns the brand, 0 if s/he does not
Age	AGE is continuous, grand-mean centered, and expressed in tens
Income	INCOME is a continuous variable calculated by using Purchasing Power Parity (PPP). It is grand-mean centered and expressed in thousands.
Level-2 variable	*Description (applies to countries, not consumers)*
GDP per capita	GDPCAPITA is a continuous variable; it is GDP on a PPP basis divided by population. It is grand-mean centered and expressed in thousands.

Table II. Description of independent variables

Variable name	N	Mean	SD	Minimum	Maximum
Level-1 descriptive statistics					
QUALITY	31,337	0.35	0.48	0.00	1.00
PRESTIGE	31,337	0.24	0.43	0.00	1.00
BEQUITY	31,337	0.11	0.32	0.00	1.00
GBO	31,337	0.25	0.43	0.00	1.00
INCOME	26,863	−0.00	2.06	−2.34	17.00
AGE	31,329	0.00	1.45	−2.11	2.74
INCOME*QUALITY	29,772	0.02	1.20	−2.29	14.79
INCOME*PRESTIGE	30,294	0.01	1.00	−2.29	14.79
AGE*QUALITY	31,319	−0.01	0.85	−2.11	2.74
AGE*PRESTIGE	31,314	−0.01	0.70	−2.11	2.74
BEQUITY*QUALITY	31,337	0.06	0.23	0.00	1.00
BEQUITY*PRESTIGE	31,337	0.04	0.19	0.00	1.00
Level-2 descriptive statistics					
GDPCAPITA	31	16.63	10.34	2.90	37.80

Table III.
Descriptive statistics

	Quality	Prestige	Income	Age	GBE	GBO
Quality	1					
Prestige	0.28707**	1				
Income	0.02376**	0.01306	1			
Age	−0.02718**	−0.01117	−0.009	1		
GBE	0.24650**	0.16619**	−0.02041*	−0.02027*	1	
GBO	0.07629**	−0.08466**	0.07309**	−0.04849**	0.51085**	1

Note: $*p < 0.05$; $**p < 0.01$

Table IV.
Tetrachoric, Biserial, and Pearson correlations of model variables

Model specifications: level 1, level 2, and mixed

Level-1 conditional model. This model is formulated by using the log-odds of GBO as the outcome. The model is indicated below with $i = 1, 2, \ldots, n_{ij}$ consumers nested within each of $j = 1, 2, \ldots, j$ countries. η_{ij} is the log-odds of GBO for consumer i in country j:

$$\begin{aligned} \eta_{ij} = {} & \beta_{0j} + \beta_{1j} * (\text{QUALITY})_{ij} + \beta_{2j} * (\text{PRESTIGE})_{ij} \\ & + \beta_{3j} * (\text{BEQUITY})_{ij} + \beta_{4j} * (\text{INCOME})_{ij} \\ & + \beta_{5j} * (\text{AGE})_{ij} + \beta_{6j} * (\text{INCOME} * \text{QUALITY})_{ij} \\ & + \beta_{7j} * (\text{INCOME} * \text{PRESTIGE})_{ij} \\ & + \beta_{8j} * (\text{AGE} * \text{QUALITY})_{ij} \\ & + \beta_{9j} * (\text{AGE} * \text{PRESTIGE})_{ij} \\ & + \beta_{10j} * (\text{BEQUITY} * \text{QUALITY})_{ij} \\ & + \beta_{11j} * (\text{BEQUITY} * \text{PRESTIGE})_{ij} \end{aligned} \tag{14}$$

where the parameter β_{0j} is the intercept; β_{pj} are the slopes for the level-1 variables in country j.

Level-2 conditional model. The level-1 intercept and slope terms become outcome variables in the level-2 model in HGLM. We want to test whether the relationships between BEQUITY, BEQUITY*QUALITY, and BEQUITY*PRESTIGE with GBO, together with the average GBO, vary across countries as a function of the economic development level of the country. Thus, respective coefficients (i.e. β_{3j}, β_{10j}, and β_{11j}) and the intercept term (β_{0j}) are now modeled as random; and GDPCAPITA is included. This model is as follows:

$$\begin{aligned}\beta_{pj} &= \gamma_{p0} + \gamma_{p1} * (\mathrm{GDPCAPITA})_j + u_{pj} \\ &\text{if } p = 0, 3, 10, 11; \quad \beta_{pj} = \gamma_{p0} \\ &\text{otherwise}\end{aligned} \tag{15}$$

One caveat, though: If the purpose of the research is to find a model that has high predictive power, one may need to adapt a "step-by-step" model building approach (Raudenbush and Bryk, 2002). Relationships at the higher level can be modeled as random at first – with no explanatory variables – ($\beta_{pj} = \gamma_{p0} + u_{pj}$); and according to the significance levels of the variance components, subsequent models can be developed. Invariant relationships, which have insignificant variance components, are treated as fixed in these subsequent models (so there won't be a "u_{pj}" term in the equations). Adding a level-2 explanatory variable for these relationships is not preferred, unless one has strong theoretical reasons to do so. The rationale is that, if there is not enough variation in the relationships between certain level-1 variables across level-2, a level-2 explanatory variable won't be significant in explaining the already "non-existent" variation[5].

The mixed model. Substituting Equation (15) in Equation (14) gives the mixed HGLM model:

$$\begin{aligned}\eta_{ij} = \gamma_{00} &+ \gamma_{01} * (\mathrm{GDPCAPITA})_j + \gamma_{10} * (\mathrm{QUALITY})_{ij} \\ &+ \gamma_{20} * (\mathrm{PRESTIGE})_{ij} + \gamma_{30} * (\mathrm{BEQUITY})_{ij} \\ &+ \gamma_{31} * (\mathrm{GDPCAPITA})_j * (\mathrm{BEQUITY})_{ij} \\ &+ \gamma_{40} * (\mathrm{INCOME})_{ij} + \gamma_{50} * (\mathrm{AGE})_{ij} \\ &+ \gamma_{60} * (\mathrm{INCOME} * \mathrm{QUALITY})_{ij} \\ &+ \gamma_{70} * (\mathrm{INCOME} * \mathrm{PRESTIGE})_{ij} \\ &+ \gamma_{80} * (\mathrm{AGE} * \mathrm{QUALITY})_{ij} \\ &+ \gamma_{90} * (\mathrm{AGE} * \mathrm{PRESTIGE})_{ij} \\ &+ \gamma_{100} * (\mathrm{BEQUITY} * \mathrm{QUALITY})_{ij} \\ &+ \gamma_{111} * (\mathrm{GDPCAPITA})_j * (\mathrm{BEQUITY} * \mathrm{PRESTIGE})_{ij} \\ &+ u_{0j} + u_{3j} * (\mathrm{BEQUITY})_{ij} \\ &+ u_{10j} * (\mathrm{BEQUITY} * \mathrm{QUALITY})_{ij} \\ &+ u_{11j} * (\mathrm{BEQUITY} * \mathrm{PRESTIGE})_{ij}\end{aligned} \tag{16}$$

For the purposes of the analysis, HLM 6.03 software was utilized (Raudenbush *et al.*, 2000). The set of estimates for population average models was used[6].

The results and their interpretations

Random effects

Table V has the estimates of random effects (labeled "variance components"), the χ^2 tests and associated *p*-values. The results show that after GDP per capita is included, there is no significant variation across countries in:

(1) the direct effect of GBE on GBO;

(2) the interaction effect of quality*GBE on GBO; and

(3) prestige*GBE's effect on GBO.

This means that any variation across countries has been completely captured by inclusion of GDP per capita.

Fixed effects

Table VI shows the results for the fixed effects; we discuss *direct effects* first. Brand quality and GBE are positively related to GBO; but brand prestige is negatively related to GBO. As for consumer demographics, age is negatively related and income is positively related to GBO. The direct effect of GDP per capita on GBO is positive. Thus, on average, consumers in wealthier, more developed countries are more likely to buy global brands. Next, consider the *interaction effects*. As Table VI shows, age interacted with neither quality nor prestige, and income*quality was also nonsignificant. However, income*prestige was positive. Finally, one *cross-level interaction effect* with GDP per capita is significant, namely, GDP*equity*prestige.

The key issue is how to interpret these three types of fixed effects *together*. We use figures (discussed below), each containing a graph and an embedded table. First, for the graphs with continuous variables, 25th and 75th percentiles are used as the range of the *z*-axis. Second, for tables, we used Equation (16) (the mixed model) to obtain the probabilities from the estimated coefficients by first calculating the expected log-odds (η_{ij}) using the estimated coefficients (γ) in Table VI. Expected log-odds were then converted to expected probability using Equation (13).

Figure 2 shows the interaction effect of GBE – coded as BEQUITY – and quality on GBO. The graph and the table show the expected probabilities of GBO for four cases:

(1) 0.22 if quality = 0 and GBE = 0;

(2) 0.65 if quality = 0 and GBE = 1;

(3) 0.24 if quality = 1 and GBE = 0; and

(4) 0.62 if quality = 1 and GBE = 1.

Table V.
Random effects: variance components

Random effects	SD	Variance component	df	χ^2	*p*-value
Intercept, U0	0.22504	0.05064	29	210.42126	0.000
BEQUITY slope, U3	0.24081	0.05799	29	34.24163	0.230
BEQUITY*QUALITY slope, U10	0.18661	0.03482	29	26.52850	> 0.500
BEQUITY*PRESTIGE slope, U11	0.31225	0.09750	29	37.80512	0.127

(A) Direct effects	Notation	Coefficient	t-ratio	Relationship w/GBO
Intercept	γ_{00}	−1.284311	−29.804**	N/A
GDP per capita	γ_{01}	0.010057	2.056*	Positive
Brand quality	γ_{10}	0.117181	2.572**	Positive
Brand prestige	γ_{20}	−0.419560	−9.229**	Negative
Global brand equity	γ_{30}	1.914790	27.497**	Positive
Income	γ_{40}	0.044005	3.767**	Positive
Age	γ_{50}	−0.053155	−3.453**	Negative
(B) Interaction effects	*Notation*	*Coefficient*	*t-ratio*	*Relationship w/GBO*
Income*Quality	γ_{60}	−0.003327	−0.180	ns
Income*Prestige	γ_{70}	0.037175	1.939*	Positive
Age*Quality	γ_{80}	0.008591	0.401	ns
Age*Prestige	γ_{90}	−0.029912	−1.125	ns
GBE*Quality	γ_{100}	−0.254014	−3.104**	Negative
GBE*Prestige	γ_{110}	−0.227186	−2.478**	Negative
(C) Cross-level interactions	*Notation*	*Coefficient*	*t-ratio*	*Interaction w/GDP per Capita*
GDPCapita*GBE	γ_{31}	0.005163	0.903	ns
GDPCapita*GBE*Quality	γ_{101}	−0.006606	−0.948	ns
GDPCapita*GBE*Prestige	γ_{111}	−0.016908	−2.316*	Negative

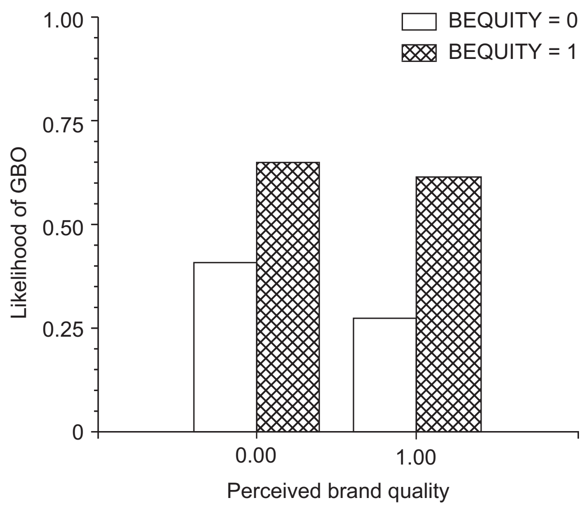
Note: * $p<0.05$; ** $p<0.01$; ns = nonsignificant

Table VI.
Fixed Effects

Clearly, *adding* GBE to either quality = 0 or quality = 1 has a huge impact (from 0.22 to 0.65 when quality = 0, and from 0.24 to 0.62 quality = 1). The increase from 0.22 to 0.65 means that the likelihood of GBO is much higher for high-equity brands when that brand is not perceived as having brand quality, but is lower when the low-quality brand is perceived as not having brand equity. But *adding quality* to either GBE = 0 or GBE = 1 has far less impact (0.22-0.24 and 0.65-0.62). In short, the *marginal impact* of adding quality to a given level of brand equity is far less than the *marginal impact* of adding brand equity to a given level of quality.

Figure 3 shows the interaction effect of GBE and prestige on GBO. In this case, as in the case for quality, the interaction effect was negative; however, the main effect of prestige on GBO was negative as well (unlike quality, which was positive). The negative effect of prestige can be seen when prestige is added to either GBE = 0 or GBE = 1: the probabilities *decrease* from 0.22 to 0.15 and from 0.65 to 0.50, respectively. The highest expected probability is achieved when the brand has equity but is not perceived as prestigious. Alternately, add GBE to either prestige = 0 or prestige = 1. Then the probabilities go from 0.22 to 0.65 (an increase of 0.43 when prestige = 0) and from 0.15 to 0.50, respectively (an increase of 0.35 when prestige = 1). The likelihood of GBO is lower for prestigious brands when the brand is not perceived as having brand equity, but is higher when the brand is perceived as having brand equity (the same is true for brands that don't have prestige). In summary, the *marginal impact* of adding prestige to a given level of brand equity is less than the *marginal impact* of adding brand equity to a given level of prestige.

Figure 4 shows the interaction of prestige (0, 1) and income (−1.468 = low and 0.906 = high). The main effects were negative and positive, respectively, and the interaction effect was positive. The negative effect of prestige can be seen in the



Brand quality	BEQUITY	η_{ij}	φ_{ij}
0	0	γ_{00}	0.22
0	1	$\gamma_{00} + \gamma_{30}$*(BEQUITY)$_{ij}$	0.65
1	0	$\gamma_{00} + \gamma_{10}$*(QUALITY)$_{ij}$	0.24
1	1	$\gamma_{00} + \gamma_{10}$*(QUALITY)$_{ij}$ + γ_{30}*(BEQUITY)$_{ij}$ + γ_{100}*(BEQUITY*QUALITY)$_{ij}$	0.62

Notes: Numerical demonstration – Case: Brand quality=1, Brand equity=1

$$\eta_{ij} = \gamma_{00} + \gamma_{10}\text{*(QUALITY)}_{ij} + \gamma_{30}\text{*(BEQUITY)}_{ij} + \gamma_{100}\text{*(BEQUITY*QUALITY)}_{ij}$$

$$\eta_{ij} = -1.284311 + 0.117181*1 + 1.914790*1 + (-0.254014)*1*1$$

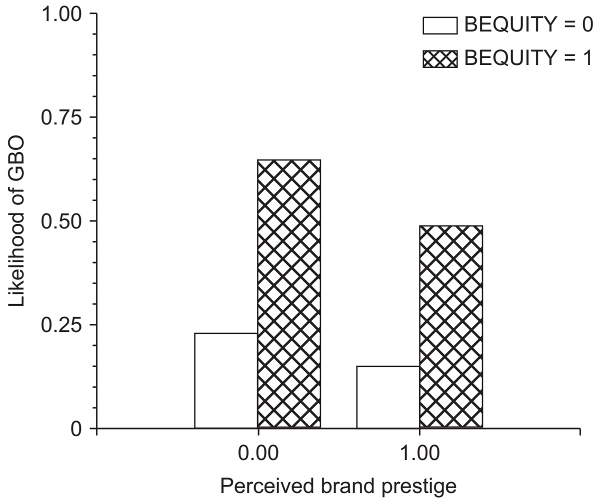
$$\eta_{ij} = 0.493646$$

$$\varphi_{ij} = \frac{1}{1+\exp(-\eta_{ij})} = \frac{1}{1+\exp(-0.493646)} = 0.62$$

Figure 2.
Interaction effects of GBE and brand quality

differences in the probabilities when prestige is added to *either* low or high income: the probabilities decrease from 0.21 to 0.14 and from 0.22 to 0.16, respectively. For prestigious brands, the likelihood of GBO is lower for lower-income consumers (0.14), but is higher for higher-income consumers (0.16).

Figure 5 shows the interaction effect of brand equity (0, 1), prestige (0, 1), and GDP per capita ("more-developed" is GDP per capita = 10.974 versus "less-developed" is GDP per capita = −9.226). In this case of cross-level interaction, there are eight groups to consider. The highest expected probability of GBO = 0.69 is achieved when equity = 1, but the brand is not perceived as particularly prestigious by consumers in more-developed countries; these brands, when evaluated by consumers in less-developed countries, had the second highest probability of GBO = 0.62. The next two highest probabilities of 0.50 and 0.49 were when consumers from less-developed versus more-developed countries (respectively) evaluated brands that they perceive as prestigious and having brand equity. Note that prestigious brands that were not



Brand prestige	BEQUITY	η_{ij}	φ_{ij}
0	0	γ_{00}	0.22
0	1	$\gamma_{00} + \gamma_{30}$*(BEQUITY)$_{ij}$	0.65
1	0	$\gamma_{00} + \gamma_{20}$*(PRESTIGE)$_{ij}$	0.15
1	1	$\gamma_{00} + \gamma_{20}$*(PRESTIGE)$_{ij}$ + γ_{30}*(BEQUITY)$_{ij}$ + γ_{110}*(BEQUITY*PRESTIGE)$_{ij}$	0.50

Notes: Numerical demonstration – Case: Brand prestige=0, Brand equity=1

$\eta_{ij} = \gamma_{00} + \gamma_{30}\text{*(BEQUITY)}_{ij}$

$\eta_{ij} = -1.284311 + 1.914790\text{*}1$

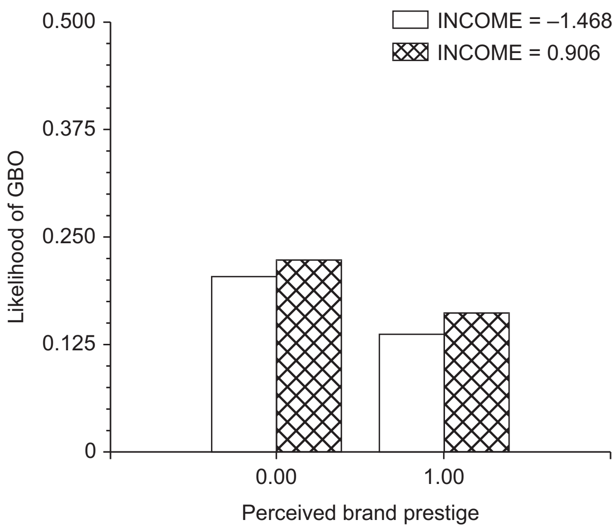
$\eta_{ij} = 0.630479$

$$\varphi_{ij} = \frac{1}{1+\exp(-\eta_{ij})} = \frac{1}{1+\exp(-0.630479)} = 0.65$$

Figure 3.
Interaction effects of GBE and brand prestige

perceived as having brand equity had probabilities of 0.14 and 0.17 for less-developed versus more-developed countries, respectively – these were the lowest probabilities in the table.

A second way to interpret these results in Figure 5 is to examine what happens when prestige goes from 0 to 1. First, *if equity* = *0*, then ownership probability drops from 0.20 to 0.14 for less-developed countries and from 0.24 to 0.17 for more-developed countries; i.e., adding prestige, given no equity, decreases ownership probabilities to almost the same extent in developed versus less-developed countries. Second, *if equity* = *1*, then ownership probability drops from 0.62 to 0.50 (12 points) for less-developed countries and from 0.69 to 0.49 (20 points) for more-developed countries; i.e., adding prestige, in the presence of GBE, decreases ownership probabilities, but to a lesser extent in less-developed countries. In summary, when prestige of 0 is compared to prestige of 1, the probability of GBO changes from between 0.06 to 0.20 probability points, where the exact change depends on levels of equity and GDP.



Brand prestige	Income	η_{ij}	φ_{ij}
0	−1.468	$\gamma_{00} + \gamma_{40}$*(INCOME)$_{ij}$	0.21
0	0.906	$\gamma_{00} + \gamma_{40}$*(INCOME)$_{ij}$	0.22
1	−1.468	$\gamma_{00} + \gamma_{20}$*(PRESTIGE)$_{ij}$ + γ_{40}*(INCOME)$_{ij}$ + γ_{70}*(INCOME*PRESTIGE)$_{ij}$	0.14
1	0.906	$\gamma_{00} + \gamma_{20}$*(PRESTIGE)$_{ij}$ + γ_{40}*(INCOME)$_{ij}$ + γ_{70}*(INCOME*PRESTIGE)$_{ij}$	0.16

Notes: Numerical demonstration – Case: Brand prestige=1, Income=0.906

$$\eta_{ij} = \gamma_{00} + \gamma_{20}*(\text{PRESTIGE})_{ij} + \gamma_{40}*(\text{INCOME})_{ij} + \gamma_{70}*(\text{INCOME*PRESTIGE})$$

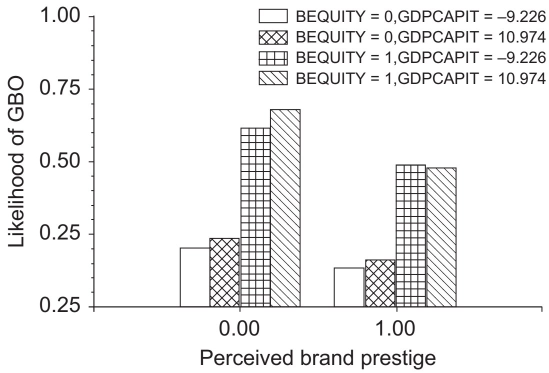
$$\eta_{ij} = -1.284311 + (-0.419560)*1 + 0.044005*0.906 + 0.037175*(0.906*1)$$

$$\eta_{ij} = -1.63032$$

$$\varphi_{ij} = \frac{1}{1+\exp(-\eta_{ij})} = \frac{1}{1+\exp(1.63032)} = 0.16$$

Figure 4.
Interaction effects of income and brand prestige

Finally, a third way to interpret the results in Figure 5 is to examine what happens when equity goes from 0 to 1. First, *if prestige* = *0*, then ownership probability rises from 0.20 to 0.62 for less-developed countries (0.42 points) and from 0.24 to 0.69 for more-developed countries (0.45 points); i.e., adding equity, given no prestige, increases ownership probabilities dramatically in both less and more developed countries. Second, *if prestige* = *1*, then ownership probability increases from 0.14 to 0.50 (0.36 points) for less-developed countries and from 0.17 to 0.49 (0.32 points) for more-developed countries; i.e., adding equity, given the presence of prestige, increases ownership probabilities, but to a somewhat greater extent in less-developed countries. In summary, when equity of 0 is compared to equity of 1, the probability of GBO changes from 0.32 to 0.45 probability points, where the exact change depends on levels of prestige and GDP. Overall, the *marginal impact* of adding



Brand prestige	EQUITY	GDPCAPITA	η_{ij}	φ_{ij}
0	0	–9.226	$\gamma_{00} + \gamma_{01}$*(GDPCAPITA)$_j$	0.20
0	0	10.974	$\gamma_{00} + \gamma_{01}$*(GDPCAPITA)$_j$	0.24
0	1	–9.226	$\gamma_{00} + \gamma_{01}$*(GDPCAPITA)$_j$ + γ_{30}*(BEQUITY)$_{ij}$ + γ_{31} *(GDPCAPITA)$_j$*(BEQUITY)$_{ij}$	0.62
0	1	10.974	$\gamma_{00} + \gamma_{01}$*(GDPCAPITA)$_j$ + γ_{30}*(BEQUITY)$_{ij}$ + γ_{31} *(GDPCAPITA)$_j$*(BEQUITY)$_{ij}$	0.69
1	0	–9.226	$\gamma_{00} + \gamma_{01}$*(GDPCAPITA)$_j$ + γ_{20}*(PRESTIGE)$_{ij}$	0.14
1	0	10.974	$\gamma_{00} + \gamma_{01}$*(GDPCAPITA)$_j$ + γ_{20}*(PRESTIGE)$_{ij}$	0.17
1	1	–9.226	$\gamma_{00} + \gamma_{01}$*(GDPCAPITA)$_j$ + γ_{20}*(PRESTIGE)$_{ij}$ + γ_{30}*(BEQUITY)$_{ij}$ + γ_{31}*(GDPCAPITA)$_j$*(BEQUITY)$_{ij}$ + γ_{110}*(BEQUITY*PRESTIGE)$_{ij}$ + γ_{111}*(GDPCAPITA)$_j$*(BEQUITY*PRESTIGE)$_{ij}$	0.50
1	1	10.974	$\gamma_{00} + \gamma_{01}$*(GDPCAPITA)$_j$ + γ_{20}*(PRESTIGE)$_{ij}$ + γ_{30}*(BEQUITY)$_{ij}$ + γ_{31}*(GDPCAPITA)$_j$*(BEQUITY)$_{ij}$ + γ_{110}*(BEQUITY*PRESTIGE)$_{ij}$ + γ_{111}*(GDPCAPITA)$_j$*(BEQUITY*PRESTIGE)$_{ij}$	0.49

Notes: Numerical demonstration – Case: Brand prestige=0, Brand equity=1, GDP per capita=–9.226

$$\eta_{ij} = \gamma_{00} + \gamma_{01}*(\mathrm{GDPCAPITA})_j + \gamma_{30}*(\mathrm{BEQUITY})_{ij} + \gamma_{31}*(\mathrm{GDPCAPITA})_j*(\mathrm{BEQUITY})_{ij}$$

$$\eta_{ij} = -1.284311 + 0.010057*(-9.226) + 1.914790*1 + 0.005163*(-9.226*1)$$

$$\eta_{ij} = 0.49$$

$$\varphi_{ij} = \frac{1}{1+\exp(-\eta_{ij})} = \frac{1}{1+\exp(-0.49)} = 0.62$$

Figure 5.
Cross-level HGLM interaction effects

prestige to given brand equity and development levels (0.06 to 0.20 probability points) is less than the *marginal impact* of adding brand equity to given prestige and development levels (0.32 to 0.45 probability points).

"Log-odds" interpretation of the estimated coefficients

In HGLM, the effects of independent variables on the outcome are usually interpreted using the odds ratio: log-odds (η_{ij}). Predicted log-odds are converted to odds ratio by taking the exp (η_{ij}) and/or converted to a predicted probability using Equation (13) (as already explained above). The logit model is linear and additive for the log-odds, but multiplicative for the odds. For example, a 1 unit increase in AGE changes the logit by β_5 and multiplies the odds by $e^{\beta 5}$. The interpretation for AGE, a continuous variable, is as follows: when AGE is increased by c units, the odds of GBO increase by a factor of $e^{c\beta 5}$, controlling for other model predictors. If β_5 is 2, increasing AGE by 1 unit increases the odds by a factor of e^2. The interpretation of the effects of a dummy variable is different. For example, the effect of QUALITY can be interpreted as the odds of GBO for a quality brand are $e^{\beta 1}$ times greater than the odds for a non-quality brand, where β_1 is the estimate for QUALITY.

We follow the ANOVA-like procedure suggested by Subedi (2005). The main effects are calculated by taking the exponential of the estimated parameter coefficients after multiplying it by a constant "c" = two standard deviations of the continuous variable (e.g. AGE); "c" is 1 for dichotomous variables.

$$\text{Main effect}_{\text{AGE}} = \exp(c_{\text{AGE}} * \gamma_{50}) \tag{17}$$

Cross-level interaction effects are calculated by taking the exponential of the estimated parameter coefficients after multiplying with two constants, where the c's are associated with the respective variables. Again, the constant "c" is 1 for dichotomous variables.

$$\text{Interaction effect}_{\text{BEQUITY}*\text{GDP}} = \exp(c_{\text{BEQUITY}} * c_{\text{GDP}} * \gamma_{31}) \tag{18}$$

The results for the significant model coefficients are provided in Table VII and VIII, which lists the log-odds, the p-values, and the interpretations. Note the "reference brand" is an attribute-free global brand having a value of zero on each of the brand-level variables; a "reference consumer" has average age and income; and a "reference country" has average GDP per capita.

For the direct effects, the coefficients show the change in odds of brand ownership when the brand is perceived to have the associated attribute *versus* when it is perceived not to have it, all else being equal. For example, for "quality," the log-odds of 0.117 in Table VII translates into an odds ratio of exp (0.117) = 1.124, meaning the expected odds of ownership of a high quality global brand are 1.124 times the odds of ownership of similar brand but not as high quality. The interaction effects (calculated as per Equation 18) can be interpreted similarly. For example, consider the income*prestige interaction in Table VIII: the effect of prestige for a consumer who has two standard deviations, higher income is a factor increase of exp (4.12*1*0.037) = 1.165 in the odds ratio. This means that the odds of ownership are 1.165 times higher for consumers with two standard deviations above-average income, when the brand is prestigious than the base-line case where a reference consumer and a reference brand are considered.

Main effects	η (log-odds)	p-value	Interpretation
Intercept	−1.284311	0.000	Expected odds of global brand ownership for a reference brand, reference consumer and a reference country are exp(−0.128) = 0.28
GDP per capita	0.010057	0.025	Country GDP per capita is associated with higher log-odds of ownership, *ceteris paribus*. Two standard deviations difference in GDP per capita is associated with a difference in the log-odds of ownership of 20.68*0.01 = 0.208 or a relative odds of exp(0.208) = 1.23
Quality	0.117181	0.005	Quality is associated with higher log-odds of ownership, all else constant. The expected odds of ownership of a high quality global brand are exp(0.117) = 1.124 times the odds of ownership of an otherwise-similar global brand which is not perceived as high quality
Prestige	−0.419560	0.000	Prestige is associated with lower log-odds of ownership, holding constant all else. The expected odds of ownership of a prestigious are exp(−0.419) = 0.657 times the odds of ownership of an otherwise-similar global brand which does not have prestige
GBE	1.914790	0.000	GBE is associated with higher log-odds of ownership, holding constant the other predictors in the model. The expected odds of ownership of a high-equity global brand are exp(1.915) = 6.79 times the odds of an otherwise-similar brand which is not high-equity
Income	0.044005	0.000	Income is associated with higher log-odds of global brand ownership, *ceteris paribus*. Two standard deviations difference in income is associated with a difference in the log-odds of ownership of 4.12*0.044 = 0.181 or a relative odds of exp(0.181) = 1.20
Age	−0.053155	0.001	Age is associated with lower log-odds of global brand ownership, *ceteris paribus*. Two standard deviations difference in age is associated with a difference in the log-odds of ownership of 2.9*(−0.05) = 0.15 or a relative odds of exp(−0.15) = 0.86

Table VII.
Significant model coefficients and their interpretations: main effects

Other practical considerations when designing and analyzing international multi-level studies

There are certain issues needed to be taken into account while conducting multi-level studies. Although these issues are very broad and cannot be explained thoroughly in

Interaction effect	η (log-odds)	p-value	Interpretation
Income* Prestige	0.037175	0.026	The effect of perceived "prestige" of a global brand for a consumer who has two standard deviations higher income is a factor increase of exp(4.12*1*0.037) = 1.165 in the odds ratio
GBE* Quality	−0.254014	0.003	The effect of GBE and perceived "quality" association of a global brand to co-exist is a factor decrease of exp(1*1*−0.254) = 0.776 in the odds ratio
GBE* Prestige	−0.227186	0.010	The effect of GBE and perceived "prestige" association of a global brand to co-exist is a factor decrease of exp(1*1*−0.227) = 0.797 in the odds ratio
GBE* Prestige* GDPCapita	−0.016908	0.014	The effect of GBE and perceived "prestige" association of a global brand to co-exist in a country with two standard deviations higher GDP per capita is a factor decrease of exp(1*1*20.68*−0.017) = 0.705 in the odds ratio

Table VIII. Significant interaction effects and their interpretations

this article, below, we try to provide the main sources to consult when designing and analyzing multi-level studies.

Level-1 and level-2 sample size

Determining the optimal sample size is not so straightforward in multi-level modeling, since it changes according to research objectives. Snijders and Bosker (1999, p. 140) state that the sample size at the highest level is usually the most restrictive element in the design, and requirements on the sample size at the highest level – with q explanatory variables at this level – are at least as stringent as requirements on the sample size in a single-level design with q explanatory variables. For a detailed discussion of the issue and the formulas to calculate the required sample sizes, please see Snijders and Bosker (1993, 1999, pp. 140-54), Hox (2002, pp. 173-96), and Maas and Hox (2005). On a practical note, Snijders and Bosker (1999, p. 154) define large sample size as "30 or higher" at either level, and this number is usually regarded as the "rule of thumb," although we see studies that employ smaller sample sizes at level-2.

Also, several simulation studies done on sample size and power issues using balanced versus unbalanced designs find no discernable differences (Cools *et al.*, 2009; Maas and Hox, 2005). This finding is especially important for international marketing researchers, who will probably not be able to get the same sample sizes across countries.

Grand-mean versus group-mean centering

Centering is simply linearly transforming independent variables by subtracting a meaningful constant. In grand-mean centering, this constant is the overall mean of the explanatory variable, whereas in group-mean centering, it is the mean within the group (level-2 unit). Grand-mean centering transforms the parameters in a way that makes it easier to interpret, but essentially keeps the same model. Group-mean centering, however, changes the meaning of the model in a complicated way and results in a completely different model, and thus should be used only if there are strong theoretical reasons to do so, such as growth curve modeling or investigating "frog-pond" effects (Luke, 2004). For a detailed discussion, please see Hox (2002, pp. 54-63) and Kreft *et al.* (1995).

Measurement invariance

Assessing cross-national invariance of measurement instruments is an important topic which has received substantial attention in the international marketing field (Steenkamp and Baumgartner, 1998). In our particular model illustration, this assessment could not be done because of the data limitations (i.e. measurement invariance tests for "differential item functioning," however, this concept is only identified when there are multiple items, not for single item measures). Ideally, a hierarchical Item Response Theory model should be used to assess measurement invariance for multiple-item measures before the actual analyses are conducted (instead of a CFA). Details of this method can be found at De Jong *et al.*'s (2007) excellent paper.

Summary and research implications

The interplay of variables that belong to different units of analysis usually presents the most interesting research questions for international marketing researchers. Examples include the interactions of: country economic development level and consumer behavior; country culture and firm behavior; headquarters market orientation, subsidiary country culture and employee behavior. Usually "context" interacts with the "actors" and analyzing this interaction properly helps us to fine-tune our theories. In order to contribute empirical generalizations in marketing, we need to take into account the nested data structures while conducting our analyses. If we neglect the dependence of data and treat those as unrelated, empirical conclusions from statistical analyses will not be reliable. If, on the other hand, we confine ourselves only to the study of relationships within a single level, the conceptual development of more comprehensive models will be restricted.

In this paper, we illustrate a contingency framework model, which includes a dichotomous dependent variable. By using data collected from more than 31,000 consumers across 31 countries, we demonstrate how to analyze, calculate, and interpret results in an HGLM model. We also include and cite a rich set of scholarly resources in multi-level modeling research for further information on specific modeling issues. Although it seems complicated at first, the basic idea of multi-level modeling is simple – we have different regression equations at each level of the data and we look at how variables at different levels influence the relationships occurring at other levels. We hope to have provided enough inspiration and encouragement, as well as a practical guideline, for international marketing researchers in their future research.

Notes

1. The list is retrieved from *JIBS*'s website on May 25, 2010 (www.palgrave-journals.com/jibs/most-cited.html).
2. The countries included in this research are: Argentina, Australia, Brazil, Canada, China, Czech Republic, Egypt, France, Germany, Hong Kong, Hungary, India, Indonesia, Italy, Japan, South Korea, Mexico, The Philippines, Poland, Russia, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Taiwan, Thailand, Turkey, UK, USA, and Venezuela. The research examined 36 global brands, which span six categories: automotive, technology, media services, consumer goods, personal care, and financial services.

3. GDP at PPP is the total value of all goods and services produced in the country, valued at market prices in the United States. According to the CIA*, "This is the measure most economists prefer when looking at per-capita welfare and when comparing living conditions or use of resources across countries" (www.cia.gov/cia/publications/factbook/docs/notesanddefs.html).
4. The World Bank's (2004) World Development Indicators were used. PPP Conversion Factor is "the number of units of a country's currency required to buy the same amount of goods and services in the domestic market as a US dollar would buy in the United States" Worldbank, "World Development Indicators," (www.wds.worldbank.org/external/default/WDSContentServer/IW3P/IB/2004/06/08/000160016_20040608153404/Rendered/PDF/289690PAPER0WDI02004.pdf).
5. Please note that, although step-by-step model building approach is common in practice, HLM is not suited for purely exploratory research. One needs to have certain hypotheses to test as a starting point; variance components can change drastically in every tested relationship which makes interpretation harder, especially in complex models.
6. The program provides two sets of estimates: one for unit-specific models, the other for population average models. This research tries to find an answer to a population-average question: the topic of interest is not country specific. Thus, population-average model estimates are appropriate. Population-average estimates have the additional benefit of being quite robust to erroneous assumptions about the distribution of random effects (Raudenbush and Bryk, 2002).

References

Anderson, E. and Gatignon, H. (1986), "Modes of foreign entry – a transaction cost analysis and propositions", *Journal of International Business Studies*, Vol. 17 No. 3, pp. 1-26.

Bijmolt, T.H.A., Paas, L.J. and Vermunt, J.K. (2004), "Country and consumer segmentation: multi-level latent class analysis of financial product ownership", *International Journal of Research in Marketing*, Vol. 21 No. 4, pp. 323-40.

Bryk, A.S. and Raudenbush, S.W. (1992), *Hierarchical Linear Models*, Sage Publications, Newbury Park, CA.

CIA (2004), *The World Factbook*, available at: www.cia.gov/cia/publications/factbook/

Cools, W., Van Den Noortgate, W. and Onghena, P. (2009), "Design efficiency for imbalanced multilevel data", *Behavior Research Methods*, Vol. 41 No. 1, pp. 192-203.

De Jong, M.G., Steenkamp, J.-B.E.M. and Fox, J.-P. (2007), "Relaxing measurement invariance in cross-national consumer research using a hierarchical IRT model", *Journal of Consumer Research*, Vol. 34 No. 2, pp. 260-78.

Dunning, J.H. (1988), "The eclectic paradigm of international production – a restatement and some possible extensions", *Journal of International Business Studies*, Vol. 19 No. 1, pp. 1-31.

Goldstein, H. (1991), "Nonlinear multilevel models, with an application to discrete response data", *Biometrika*, Vol. 78 No. 1, pp. 45-51.

Hofmann, D.A. (1997), "An overview of the logic and rationale of hierarchical linear models", *Journal of Management*, Vol. 23 No. 6, pp. 723-44.

Hofmann, D.A. and Gavin, M.B. (1998), "Centering decisions in hierarchical linear models: implications for research in organizations", *Journal of Management*, Vol. 24 No. 5, pp. 623-41.

Hofstede, G.H. (1983), "The cultural relativity of organizational practices and theories", *Journal of International Business Studies*, Vol. 14 No. 2, pp. 75-89.

Holt, D.B., Quelch, J.A. and Taylor, E.L. (2004a), "Managing the global brand: a typology of consumer perceptions", in Quelch, J. and Deshpande, R. (Eds), *The Global Market: Developing a Strategy to Manage across Borders*, The Jossey-Bass Business & Management Series, Jossey-Bass, San Francisco, CA, pp. 180-201.

Holt, D.B., Quelch, J.A. and Taylor, E.L. (2004b), "How global brands compete", *Harvard Business Review*, Vol. 82 No. 9, pp. 68-75.

Hox, J.J. (1995), *Applied Multilevel Analysis*, TT-Publikaties, Amsterdam.

Hox, J.J. (2002), *Multilevel Analysis: Techniques and Applications*, Lawrence Erlbaum Associates, Mahwah, NJ.

Interbrand/*BusinessWeek* (2009), "100 best global brands", *BusinessWeek*, No. 4148, p. 50.

JIBS (2010), "Most cited JIBS articles", available at: www.palgrave-journals.com/jibs/most-cited.html (accessed 25 May 2010).

Johanson, J. and Vahlne, J.-E. (1977), "The internationalization process of the firm – a model of knowledge development and increasing foreign market commitments", *Journal of International Business Studies*, Vol. 8 No. 1, pp. 23-32.

Klein, K.J., Dansereau, F. and Hall, R.J. (1994), "Levels issues in theory development, data collection, and analysis", *The Academy of Management Review*, Vol. 19 No. 2, pp. 195-229.

Kogut, B. and Singh, H. (1988), "The effect of national culture on the choice of entry mode", *Journal of International Business Studies*, Vol. 19 No. 3, pp. 411-32.

Kogut, B. and Zander, U. (1993), "Knowledge of the firm and the evolutionary theory of the multinational corporation", *Journal of International Business Studies*, Vol. 24 No. 4, pp. 625-45.

Kreft, I.G.G., de Leeuw, J. and Aaken, L.S. (1995), "The effect of different forms of centering in hierarchical linear models", *Multivariate Behavioral Research*, Vol. 30 No. 1, pp. 1-21.

Luke, D.A. (2004), *Multilevel Modeling*, Quantitative Applications in the Social Sciences Series, Sage Publications, Thousand Oaks, CA.

Maas, C.J.M. and Hox, J.J. (2005), "Sufficient sample sizes for multilevel modeling", *Methodology*, Vol. 1 No. 3, pp. 86-92.

Oviatt, B.M. and McDougall, P.P. (1994), "Toward a theory of international new ventures", *Journal of International Business Studies*, Vol. 25 No. 1, pp. 45-64.

Raudenbush, S.W. and Bryk, A.S. (2002), *Hierarchical Linear Models: Applications and Data Analysis Methods*, 2nd ed., Advanced Quantitative Techniques in The Social Sciences Series 1, Sage Publications, Thousand Oaks, CA.

Raudenbush, S.W., Bryk, A.S. and Congdon, R. (2000), *HLM6: Hierarchical Linear and Nonlinear Modeling*, 6.03 ed., Scientific Software International, Lincolnwood, IL.

Snijders, T.A.B. and Bosker, R.J. (1993), "Standard errors and sample sizes for two-level research", *Journal of Educational Statistics*, Vol. 18 No. 3, pp. 237-59.

Snijders, T.A.B. and Bosker, R.J. (1999), *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*, Sage Publications, London.

Song, M., Calantone, R.J. and Di Benedetto, C.A. (2002), "Competitive forces and strategic choice decisions: an experimental investigation in the United States and Japan", *Strategic Management Journal*, Vol. 23 No. 10, pp. 969-78.

Steenkamp, J.-B.E.M. and Baumgartner, H. (1998), "Assessing measurement invariance in cross national consumer research", *Journal of Consumer Research*, Vol. 25 No. 1, pp. 78-107.

Steenkamp, J.-B.E.M., Batra, R. and Alden, D.L. (2003), "How perceived brand globalness creates brand value", *Journal of International Business Studies*, Vol. 34 No. 1, pp. 53-65.

Subedi, B.R. (2005), *A Demonstration of the Three-level Hierarchical Generalized Linear Model Applied to Educational Research*, The Florida State University, Tallahassee, FL.

Wong, G.Y. and Mason, W.M. (1985), "The hierarchical logistic regression model for multilevel analysis", *Journal of the American Statistical Association*, Vol. 80 No. 391, pp. 513-24.

WorldBank (2004), "World development indicators", available at: http://devdata.worldbank.org/wdi2004

Zeithaml, V.A., Varadarajan, R.P. and Zeithaml, C.P. (1988), "The contingency approach: its foundations and relevance to theory building and research in marketing", *European Journal of Marketing*, Vol. 22 No. 7, pp. 37-64.

About the authors

Burcu Tasoluk received a BS degree in Economics from Middle East Technical University, Ankara, Turkey. After working as an Assistant Marketing Manager in the banking industry in Istanbul for three years, she received an MBA from the Vlerick Leuven Gent Management School, Belgium. She received a PhD in Marketing from Michigan State University, USA. She is currently working as an Assistant Professor of Marketing at Sabanci University, Istanbul, Turkey. Her research interests include brand management, global brand and new product management, headquarters-subsidiary relations in multi-national corporations, and international marketing. Burcu Tasoluk is the corresponding author and can be contacted at: tasolukb@sabanciuniv.edu

Cornelia Droge is Professor of Marketing at Michigan State University. Her research has been published extensively. Her research interests include organizational strategy and structure as related to marketing effectiveness; marketing and supply chain integration; and new product marketing.

Roger Calantone is the Eli Broad Chaired University Professor of Business Chair of Marketing Department at Eli Broad Graduate School of Business at Michigan State University. He is Co-director of the Institute for Entrepreneurship and has adjunct appointments in Economics and Information Systems. He has published numerous journal and proceedings articles and five books. His research is mostly in the areas of product design and development processes, innovation strategy, and decision support systems.