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RESEARCH ARTICLE

Xiaohui Yuan, Ziliang Deng, Ruer-Jer Bryan Jean, Daekwan Kim

Hierarchical Linear Modeling in International Marketing Research: A Review with an Application on Innovation and Export in China

Abstract While much of international marketing research involves two or more levels, limited work in the international marketing literature uses hierarchical linear modeling to examine different level effects. This study conducts a thorough literature review on hierarchical linear modeling (HLM) in 28 international marketing papers that employed HLM from 2005–2014 and evaluates the use of HLM in these papers on the objects, operating levels, and other issues. We call for more applications of HLM in international marketing research, particularly for research on emerging markets with significant sub-national and institutional variations. The paper provides an illustrative empirical study that employs HLM to test the moderating role of industry-level government subsidies in the relationship between firm innovation and exporter performance in China.

Keywords hierarchical linear modeling (HLM), multilevel modeling, international marketing, China, innovation; export; subsidy

1 Introduction

Scientifically rigorous methods have always been an important consideration in

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Xiaohui Yuan[a], Ziliang Deng[b] (✉)
School of Business, Renmin University of China, Beijing 100872, China
E-mail: [a]yuanxiaohui0111@ruc.edu.cn, [b]ziliang.deng@ruc.edu.cn

Ruey-Jer Bryan Jean
Department of International Business, National Chengchi University, Taipei 11605, Taiwan, China
E-mail: bryan@nccu.edu.tw

Daekwan Kim
College of Business, Florida State University, Tallahassee, FL 32306-1110, USA
E-mail: dkim@cob.fsu.edu

international marketing (IM) research. However, such rigor has been continuously challenged by the emergence of new data structures. Among them, multilevel data is particularly important. For example, as international marketing researchers have conducted studies on emerging economies, they have noticed that there have been many variances in sub-national factors, such as province-level institutional factors (Nguyen, Le, and Bryant, 2013) and the institutional environment surrounding top managers (Griffith, Yalcinkaya, and Rubera, 2014; Nam, Parboteeah, Cullen, and Johnson, 2014; Sahaym and Nam, 2013). To effectively deal with such within-group heterogeneity, researchers need to collect and scientifically analyze multilevel data with appropriate methods (Peterson, Arregle, and Martin, 2012).

Hierarchical linear modeling (HLM) is undoubtedly a capable candidate. HLM separates the variance within groups from variance between groups in the outcome variable, while the conventionally used ordinary least squares (OLS) regression only includes one single variance component. HLM performs separate regression analyses for each group, so that the within-group and between-group errors are separately estimated. These merits have attracted a rapidly emerging cohort of researchers conducting studies in international marketing using HLM. It is relatively difficult to apply HLM in international marketing research, due to the requirements for data structure and sample size in using HLM, as well as "the limited number of nations in the world, data quality and accessibility problems for many nations" (Peterson, Arregle, and Martin, 2012, p. 453). Despite these operational obstacles, it is imperative to import HLM into international marketing research to obtain more accurate coefficient estimates.

In this study, we briefly introduce HLM and its statistical advantages, and then systematically review the international marketing literature that has adopted HLM in the last ten years. This study is the first in the literature to review the applications of HLM specifically in international marketing research. We suggest that HLM is particularly suitable for the research in international marketing, since as many as five major levels of objects may be employed in the data collection and model design.

We then proceed with an empirical study that examines the relationship between innovation and the international performance of exporters in China and the moderating effect of government subsidies on institutional heterogeneity. As firm activity is embedded in and affected by the institutional environment, the data structure is embedded on two levels. By illustrating the strength of HLM in analyzing the nested data, this pedagogical example also highlights the negative moderating effect of government intervention and extends the literature on the innovation-export nexus from an institutional theory perspective.

2 A Review of HLM

2.1 Introduction to HLM

HLM deals with hierarchically nested data in which entities reside in nested arrangements. For example, individuals are nested in different work groups, which are nested in larger organizational units, such as strategic business units, which in turn are nested in bigger organizations. Furthermore, organizations are nested in a network of inter-organizational relationships such as strategic alliances, which in turn are nested in the economic environment (Hitt, Beamish, Jackson, and Mathieu, 2007). If research involves potential interaction between variables from two or more levels, one needs nested data.

In dealing with nested data, researchers tend to treat lower-level and higher-level effects separately. They either aggregate data from the lower level where it is collected to a higher level where their research is conducted, or disaggregate data in the reverse direction (Bamberger, 2008). Nonetheless, aggregation leads to overlooking individual-level information and reductionism, and commits an ecological fallacy—i.e., the "assumption that relationships between variables at the aggregate level imply the same relationships at the individual level" (Jargowsky, 2005, p. 715). Meanwhile, disaggregation commits an atomistic fallacy—i.e. it is statistically biased due to assigning high-level values to a lower level and treating those observations as independent (Kozlowski and Klein, 2000). A similar situation occurs in international marketing research, as many researchers focus on the firm-level effect, simply taking country or industrial environments as error variance. Alternatively, other researchers focus on the higher level effect (e.g., country-level or sub-national level) and aggregate firm-level effects to a higher level (Peterson, Arregle, and Martin, 2012).

HLM offers a scientific and effective approach to deal with hierarchically nested data and can overcome the weakness of the above two approaches by estimating lower and higher level residuals separately (Hofmann, 1997) so that the lower and higher level effects can both be fully accommodated. To do that, one needs to estimate at least two models. One model is for the relationship at a lower level, and the other model is for relationships across levels. Both models follow the form of general liner regression, so HLM is in nature a regression of regression:

Level 1: $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$. (1)

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}G_j + U_{0j}$. (2)

$\beta_{1j} = \gamma_{10} + \gamma_{11}G_j + U_{1j}$. (3)

In equation (1), Y_{ij} denotes the outcome measure for individual i in group j. The variable X_{ij} is the value of the predictor for individual i in group j. The variables β_{0j} and β_{1j} are intercepts and slope estimates separately for each group, and r_{ij} is the value of the residual. The difference of intercepts and slopes across each group is exhibited in equations (2) and (3). The intercept-as-outcome model—i.e., equation (2)—predicts that the average level of intercept at level-1 varies across groups and identifies how much the level-2 predictor may explain the differences. The slopes-as-outcome model—i.e., equation (3)—predicts that the relationship between the level-1 predictor and the dependent variable varies across groups and identifies how much the level-2 group predictor explains the differences. The variable G_j is a level-2 group predictor, γ_{00} and γ_{10} stand for the level-2 intercepts, γ_{01} and γ_{11} stand for the level-2 slopes, and U_{0j} and U_{1j} are level-2 residuals.

HLM may be applied in scenarios with more than two levels of nested research objects, such as individuals nested in specific organizational units and units nested in social-cultural contexts or institutional environments (Karam and Kwantes, 2011). In the simple HLM model shown above, for each level-1 observation there is only one level-2 group to be nested in. Yet in the cross-nested model, level-1 observations may be nested in more than one group. For instance, firms' activities are cross-nested in and affected by both industry and country context (Aulakh, Jiang, and Li, 2013). In that case, researchers usually run an HLM model for each of these dyadic nesting relationships, respectively. To handle the contexts when the units of observations form a hierarchy of variables of which some are not directly measurable, researchers employ multilevel structural equation modeling (SEM) to synthesize the strengths of SEM and HLM (Cheung and Au, 2005).

In the last twenty years HLM has been increasingly applied in organizational behavior (OB) research due to the greater availability of hierarchical nested data in that area (e.g., Liu and Fu, 2011, Yu, Fang, and Ling, 2009). In organizations, the interaction between the organizational environment (e.g., organizational diversity climate) and individual behavior (e.g. organizational citizen behavior, job involvement) is essential to explain and analyze an individual's performance. In the last decade, the use of HLM has started to spill over from OB to international business (IB) and, more specifically, international marketing research (e.g., Martin, Cullen, Johnson, and Parboteeah, 2007; Peterson, Arregle, and Martin, 2012).

2.2 Advantages of HLM

The parameter estimation of HLM is more statistically robust than that of OLS (Hofmann, Griffin, and Gavin, 2000). OLS regression assumes that its random errors are independent, normally distributed, and have constant variance. Raudenbush and Bryk (2002) criticize this assumption, as the random errors include group-level components in addition to individual-level components due to dependence among observations within the same cluster. The group-level errors vary across groups, so that the assumption of constant variance is violated. Simply applying OLS to multilevel data leads to the underestimation of standard errors and is subject to Type I errors so that the coefficients of independent variables seem to be significant, but actually are not. Compared with OLS regression, HLM is more statistically rigorous, mainly for the following three reasons: (1) *Separation of variance*. HLM explicitly separates the variance within groups from variance between groups in the outcome variable and also reports the magnitude and significance of these variance components, while OLS regression only includes one single variance component; (2) *Separation of regression*. HLM conducts separate regression analyses for each group respectively; thus the intercepts and slopes may vary across groups, which leads to more accurate estimations. However, in OLS regression only a single regression analysis is conducted; (3) *Separation of error estimation*. In HLM, the within-group and between-group errors are separately estimated, which cannot be done in OLS regression which only offers one error term (Hofmann et al., 2000).

3 HLM in International Marketing Research

3.1 Sample Literature Review

To systematically review the HLM applications in international marketing research in the past decade, we have scanned two types of journals. The first includes all potentially marketing-related journals among the leading business and management journals as listed in the "45 Journals Used in Financial Times Research Rank", namely, *Academy of Management Journal*, *Journal of Consumer Research*, *Journal of International Business Studies*, *Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science* and *Strategic Management Journal.* The other category includes journals specifically focusing on international marketing and related fields: *International Business Review*, *International Marketing Review*, *Journal of International Marketing*, *Journal of International Management*, *Journal of World Business*, and *Management International Review*.

We searched "hierarchical linear modeling," "multilevel," and related keywords within the above journals between January 2005 and December 2014 and identified 28 pieces of empirical research on international marketing using HLM. Except for five studies, all of these HLM studies were published within the past six years (2009–2014). It shows that the advantages of HLM are appreciated by the international marketing research community and that there has been a growing trend of applying this statistical approach in international marketing research (see Figure 1). Since the yearly average number of IM studies before 2005 is almost zero, we excluded those sporadic papers.

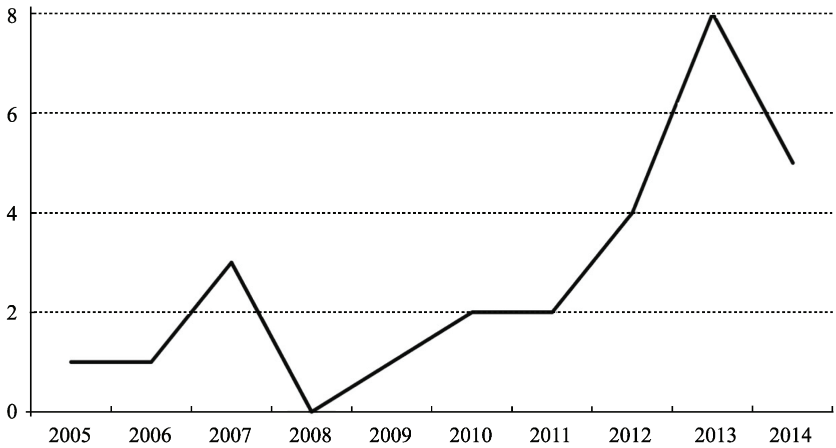

Figure 1 Numbers of IM Papers Using HLM (2005–2014)

3.2 Current Practices

Levels of research objects. HLM is particularly suitable for international marketing research, as a typical international marketing study usually involves at least two levels of the five-level object hierarchy—namely, nation, sub-nation, firm, sub-firm organization, and individual (see Figure 2).

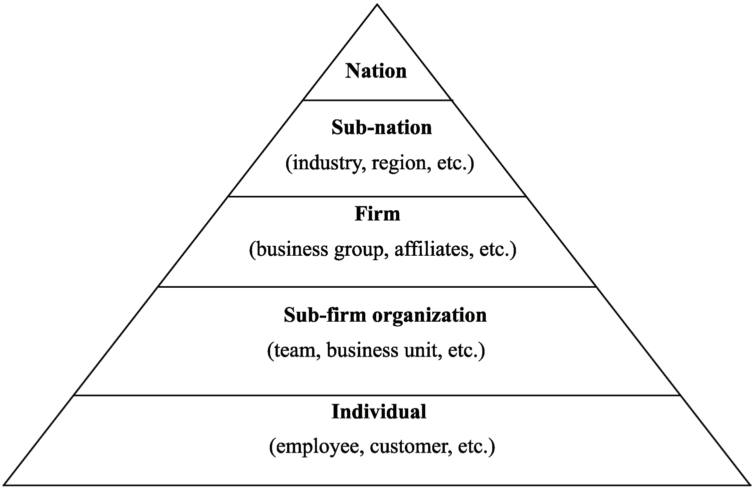

Figure 2 Five Levels of Nested Objects in International Marketing Research

Figure 3 shows the research questions and related conceptual or operational levels involved in the 28 HLM studies. We use nation and sub-nation to label the vertical axis. Although there are a few exceptions, these two dimensions are usually employed to construct the upper level variables. We use individual, sub-firm organization, and firm to mark the horizontal axis, as these dimensions are more often employed for constructing lower level variables. Thus, we divide the 28 studies into six domains. As individual customers have always been a centerpiece topic of international marketing research, eight of these 28 studies nest individual behavior in a cross-country setting.

Direction of cross-level effects. Research adopting the HLM approach mainly focuses on top-down cross-level models (Magnusson, Westjohn, and Boggs, 2009) that address the influence of macro-level environments (e.g. institution or culture) on micro-level objects (e.g. individuals or firms) (Kozlowski and Klein, 2000). Conceptually, there are potential impacts of lower-level constructs on

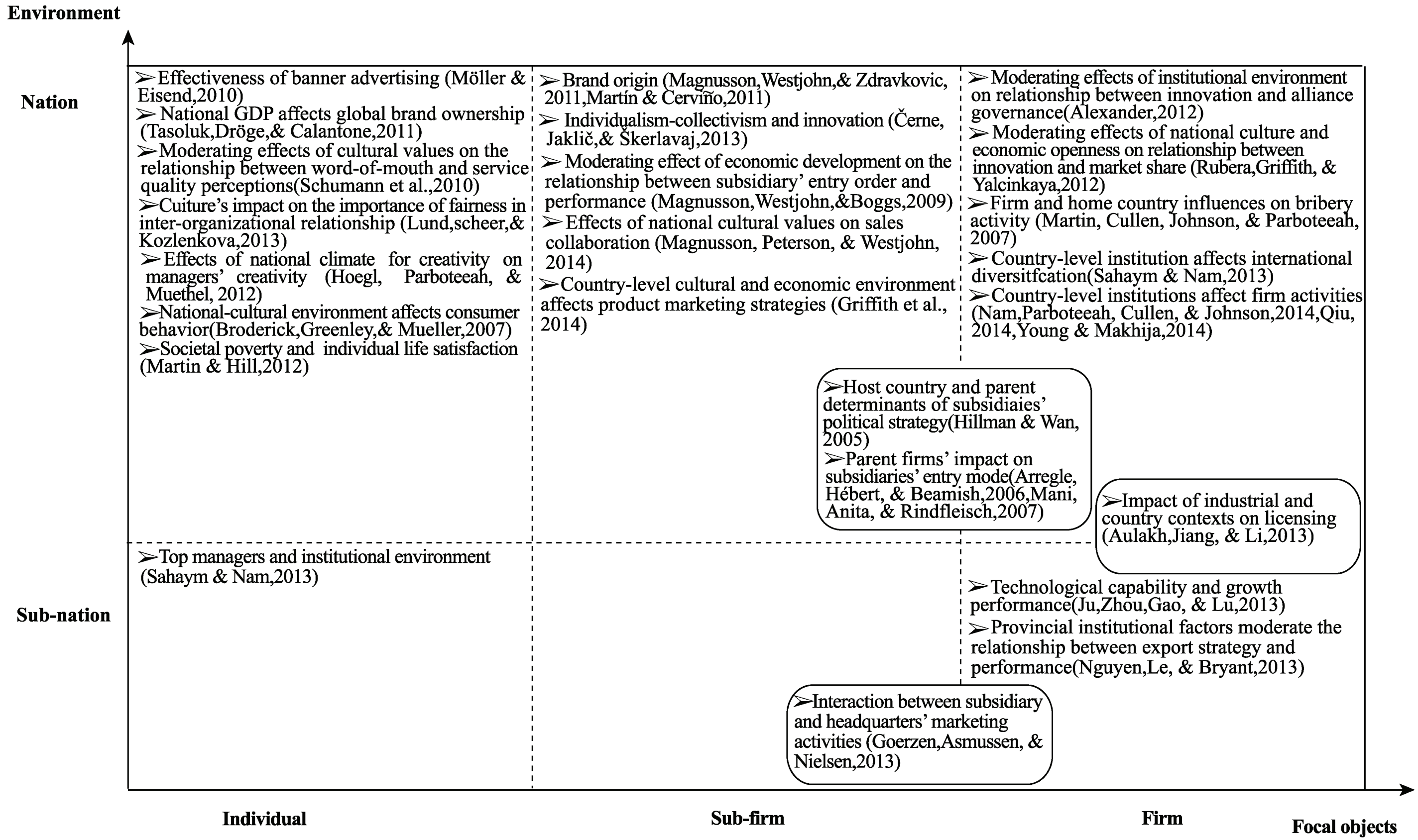

Figure 3 28 HLM Studies in International Marketing Research, 2005-2014

higher levels (e.g. the impacts of performance of new research and development (R&D) employees on team cohesion); however, bottom-up cross-level models are not found in the empirical literature as international marketing research usually concerns the micro-level behavior as the outcome. There are two types of primary application of top-down cross-level models. The first are direct effect models predicting the direct effect of higher-level constructs on lower-level objects. For example, masculinity affects sales collaboration (Magnusson, Peterson, and Westjohn, 2014). The other application is moderation models that predict the moderating effect of a higher-level construct on the relationship between two lower-level objects, and the higher-level entity is the context in which the two lower-level objects are embedded. As an example, consider the effect of national cultural values on the relationship between managerial incentive systems and sales collaboration (Magnusson, Peterson, and Westjohn, 2014). In collective and feminine societies, cooperation and collective goals are emphasized, which make the managerial motivation less effective than in individualistic and masculine societies.

Justification of HLM. The variance in variables measured at the lower level should be partially predicted by the higher level variables, and observations at the lower level should significantly differ across groups in which the lower level objects are embedded. Intra-class correlation (ICC) has been used to determine how much variance out of all the variance in the lower level observations can be explained by the higher level variables (Ozkaya, Dabas, Kolev, Hult, Dahlquist, and Manjeshwar, 2013):

$$\text{ICC} = \tau_{00}/(\tau_{00} + \sigma^2),$$

where σ^2 denotes variation among lower-level objects within higher-level objects and τ_{00} denotes variation across higher-level objects. Although there is no strict minimum level requirement in ICC, HLM methodologists have recommended minimum levels of ICC to test whether it is necessary to employ HLM. For example, Hox (2010) suggests 0.05, 0.10, and 0.15 as thresholds of small, medium, and large differences. Out of the 28 reviewed studies, ten studies report ICC as a justification for using HLM. One of the ten studies reports the variances explained by each level in a three-level model instead of reporting ICC directly (Mani, Anita, and Rindfleisch, 2007). ICC values range from 0.02 to 0.38 in these studies, except for a rather high value of 0.75 (Ju et al., 2013).

Sample size. HLM researchers suggest various minimum levels of sample size, as a small sample size will affect the validity of the HLM results. Kreft (1996) suggests a threshold of 30 for a minimum sample size for both lower and higher-level observations within each group. Somewhat differently, Snijders (2005) suggests that, compared with the higher-level sample size, the average lower level sample size needs a relative premium of about 3:2. Hox (2010) recommends that for a two-level model, testing a cross-level interaction needs at least a sample size of 50 at level-2 and 20 at level 1 within each group. For data with a very small number of level 2 groups, treating groups as control variables will be more appropriate than HLM (Meuleman and Billiet, 2009). We examine the sample size at each level in these 28 HLM studies and find that the higher-level sample size in some studies are not large enough, such as 4 at the country-level (Broderick, Greenley, and Mueller, 2007). In addition to industry-, province-, region- and subsidiary-level variables, there is a study using time as the level-1 object (Ju et al., 2013). It is tempting to scrutinize time-variant features in HLM when panel data become increasingly available in international marketing research. However, only when the time frame is sufficiently long can we appropriately employ time as a separate dimension.

Interaction between levels and centering. While a significant portion of these studies uses HLM to examine cross-level moderating effects, some studies use HLM simply to include higher-level or lower-level control variables to lend extra robustness to their analyses, such as including firm-level control variables to analyze the brand-level effect more precisely (Magnusson, Westjohn, and Zdravkovic, 2011). Many include lower-level control variables to examine relationships of higher-level variables more precisely (e.g. Hoegl, Parboteeah, and Muethel, 2012). Centering lower-level and higher-level variables before their interaction mitigates the potential multicollinearity problem (Kreft, 1996). By centering, a constant is subtracted from independent variables. The constant is the overall mean of the variable in *grand-mean* centering, whereas in *group-mean* centering it is the mean within groups in which the variable is nested. Grand-mean centering essentially retains the nature of the original data (Raudenbush and Bryk, 2002). However, when the number of observations in each group is large, group-centering the lower level variables may better alleviate the potential multicollinearity and make the estimated coefficients more robust. Twelve reviewed studies report centering choice. Eight of them choose group-mean centering for level-1 variables and grand-mean centering for level-2 variables, and four studies choose grand-mean centering for both level-1 and level-2 variables.

Other issues. (a) *Levels of models*. Most of these HLM applications choose two-level models rather than three-level ones. The overwhelming choice of two-level studies in international marketing research may probably be explained by the difficulty of data collection at many levels simultaneously. Moreover, high levels of hierarchical modeling renders it difficult to obtain stable statistical results and interpret them. (b) *Cross-nested HLM*. Among the two-level models, six of them use cross-nested HLM. For instance, firms' behaviors are nested in industries, and also in country-level contexts (Aulakh, Jiang, and Li, 2013). Industry-level and country-level contexts are independent of each other, and there is no nested relationship between those two levels. (c) *Primary versus secondary data*. Due to the limited availability of international secondary databases, nearly half of the 28 studies use secondary data and the others choose primary data as their data source. Ten studies use longitudinal or panel data rather than cross-sectional data. (d) *Software packages*. Some of these studies report the software packages they use, including HLM, Stata, SPSS, SAS, and Supermix. While HLM is the most widely used software package, the other software packages may provide reliable results as well.

In emerging economies there usually exists significant variations in sub-national institutions as institutions and organizations co-evolve at both the national and sub-national level (Meyer and Nguyen, 2005, Wright, Filatotchev, Hoskisson, and Peng, 2005). Most of the formal regulative institutions formulated by the central government will be implemented by industrial supervisory bodies or regional government agencies (Ramsey, 2014). This will lead to variations according to the fiscal conditions and enforcement power of these sub-national government agencies. When data on such institutional variables are collected at the regional or industrial level, they are rather different from the variables designed at the firm level, and exhibit some common firm-invariant features. Such features ought to be effectively controlled by the HLM approach. In that sense HLM offers an effective tool for analyzing the unique interactions between institutional factors and firm behavior in emerging markets.

4 An Illustrative Example

In order to illustrate how to properly employ HLM and report important results for HLM application, we chose a top-down cross-level model in which the relationship between innovation and export is the lower level baseline and government intervention acts as the higher level moderator. The example is a two-level model which is common and easy to illustrate.

4.1 Theoretical Background and Hypothesis

With the rapid development of economic globalization, the relationship between innovation and export has attracted more and more academic attention. Considerable empirical research about the effect of technology innovation on exports has generated mixed findings. Many studies have found that innovation activities have positive effects on export propensity and intensity (Caldera, 2010, Filatotchev, Liu, Buck, and Wright, 2009, Gourlay and Seaton, 2004). Exporters must possess competitive advantages such as premium technological knowledge to overcome the liability of foreignness in overseas markets (Zaheer, 1995). With innovative products, firms will be better able to satisfy the diversified demands of overseas buyers. Moreover innovation strategy can make exporters more productive (Cassiman and Golovko, 2011) and some research has found that there exists a reciprocal relationship between innovation and internationalization strategy (Golovko and Valentini, 2011).

However many empirical studies also argue that the relationship between R&D activities and export intensity is not significant (Willmore, 1992) or is even negative (Deng, Guo, Zhang, and Wang, 2014), due to various insurmountable challenges for innovation and intrinsic disadvantages of innovators. Depending on the stage in a product's life cycle, innovation type, timing of innovation and other firm-specific factors causing innovativeness liabilities, innovation does not have a positive effect on firm or product success (Argyres and Bigelow, 2007, Cefis and Marsili, 2006). Moreover exporters face international markets where buyers have a much wider range of preferences, and innovation activities in domestic laboratories cannot easily be well tailored for overseas clients (Zaheer, 1995). Third, profitability matters. For exporters with low profitability, the more innovation they invest in, the more likely they will be forced to exit the export market. Deng et al. (2014) identify the fact that more than half the exporters in China are conducting original equipment manufacturing in low-end value chains. Therefore their profit margin is too thin to afford export-oriented innovation. Fourth, export is the infancy stage of firm internationalization. Exporters are inclined to adopt "home replication" strategies at this stage and produce products highly similar to what they produce for home markets (Peng, 2006). Exporters in emerging economies such as China generally lack international experience, so it becomes even more challenging for them to implement substantial product innovation to better tailor their new products to overseas markets (Zhang, Liu, and Zheng, 2009). Such low suitability may bring fatal consequences in international markets. Finally for exporters in rapidly emerging economies such as China (Chen, Seong, and Woetzel, 2015), domestic demand may strongly support firms' local sales. Firms may find it more lucrative to focus their strategic innovation on domestic business rather than exports. Therefore:

Hypothesis 1: There is a negative relationship between R&D and the export performance of manufacturers in China.

We further postulate that the effect of firm-level innovation on exports in China is conditional on industry-level government subsidies. Government subsidies in China vary among different industries, depending on macroeconomic controls and the development of each industry. The subsidies Chinese firms have obtained since 2000 mainly include two types. Approximately 90 percent comes from the science and technology promotion funds and the other 10 percent from expenditures for loss-making state-owned enterprises (Girma, Gong, Görg, and Yu, 2009). Differentiated government subsidies may cause firms from the same industry to exhibit certain similarity and firms from different industries to act differently, necessitating the use of HLM.

Subsidy, as a form of direct government intervention in firm-level management, may enhance the resource slack of firms. As such slack come from institutional sources, it may aggravate the firms' dependence on the government and stimulate the firms to build stronger political ties (Sun, Mellahi, and Thun, 2010). In that sense subsidies may not necessarily strengthen the efficiency of firms (Görg, Henry, and Strobl, 2008). As exporting involves substantial sunk costs and entry barriers, less efficient firms will have a lower tendency to start exporting (Bernard and Bradford, 2004) and a weaker motivation to expand their export volume.

As the vast majority of subsidies aim to promote the innovative outcome of firms, such funds need to have a short-term immediate return. However the success and financial returns to the innovative inputs are much less guaranteed in the export market, considering the stage in product life cycle, innovation type, and timing of innovation (Argyres and Bigelow, 2007, Cefis and Marsili, 2006). Compared with innovation tailored for foreign markets, innovation efforts for domestic markets will have stronger support due to more convenient access to local market information, and thus are more likely to be embraced by home market buyers. Therefore to secure a more predictable innovation return, subsidized exporters may switch their more strategic innovation focus to the local rather than the export market.

Hypothesis 2: Government subsidies strengthen the negative relationship between innovation and export performance of manufacturers in China.

Our framework is shown in Figure 4.

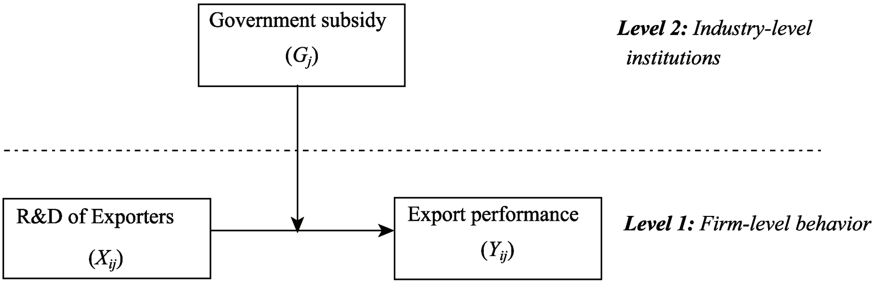

Figure 4 Theoretical Framework

4.2 Sample, Method and Results

We employ a firm-level panel dataset of Chinese manufacturing firms to test the research framework. The data are obtained from annual surveys of manufacturing firms, which were compiled by the National Bureau of Statistics of China during 2005 and 2006. This survey provides detailed firm-level financial and operational information for all non-state-owned enterprises with an annual turnover above RMB 5 million (equivalent to approximately USD 800,000 when the exchange rate is 6.25) and all state-owned enterprises in all 30 two-digit manufacturing industries throughout the 31 provinces of China. Accounting for about 90% of the total output in manufacturing industries, it is a comprehensive firm-level dataset which has been employed in various analyses in the literature (e.g. Deng et al., 2014; Deng, Hofman, and Newman, 2013). This study examines the impact of innovation on firm performance in export markets. We dropped firms without any exports during the sample period. We deleted some observations with inconsistent codes and removed firms for which missing values were observed. The cleaning process resulted in a final sample of 58,494 exporters within 30 industries. The sample size of the higher level is larger than the minimum threshold suggested by Kreft (1996), justifying the use of HLM.

Table 1 provides a summary of the main indicators of exporters in each of the

Table 1 A Summary of Main Indicators by Two-Digit Industry

Two-digit industries	No. of firms	Subsidy share (%)	Export intensity (%)	Share of innovators (%)
Food processing	2,487	0.172	51.068	7.499
Food	1,082	0.293	48.015	15.340
Beverage	405	0.230	36.589	17.383
Tobacco	28	0.334	11.693	62.857
Textile	6,483	0.119	63.563	6.874
Garments	5,496	0.083	81.455	3.910
Leather	2,906	0.073	81.683	5.411
Wood	1,079	0.205	67.618	5.861
Furniture	1,162	0.082	73.855	7.478
Papermaking	815	0.229	41.373	6.596
Printing	440	0.285	44.855	8.438
Culture & sport goods	1,833	0.086	81.597	7.716
Petroleum	107	0.630	20.365	20.741
Chemical materials	3,090	0.326	38.897	22.424
Pharmaceutical	850	0.257	35.672	46.190
Chemical fibers	187	0.178	33.510	16.456
Rubber	799	0.266	58.073	14.441
Plastic	2,793	0.127	63.686	7.412
Non-metal mineral products	2,970	0.310	46.848	13.833
Ferrous metals	525	0.275	30.618	17.594
Nonferrous metals	668	0.499	34.460	22.222
Metal products	3,313	0.131	66.030	8.276
General equipment	3,790	0.198	47.490	19.349
Special equipment	1,939	0.268	35.939	26.610
Transport equipment	2,063	0.247	44.901	26.427
Electric machinery	3,882	0.166	61.254	19.703
Electronic equipment	3,596	0.150	66.406	23.797
Instruments	1,149	0.225	63.919	25.103
Art work	2,544	0.140	82.787	6.460
Recycling	12	0.404	37.263	13.333
All	58,494	0.178	60.463	16.858

30 industries. It shows that the industries with the largest number of exporters are only at a low or medium level in terms of the share of innovators in exporters (e.g., garments, textiles and electric machinery). The industry-level subsidy share is calculated by the total subsidy received by firms divided by the total sales of all firms in each industry. This average subsidy level varies to a great extent across industries (see Table 1), implying that the Chinese government does adopt a differential subsidy policy for industries with different types of technology and strategic importance to the national economy. According to the justification for the use of HLM, the variance at the higher level needs to be large enough to justify the use of HLM. Table 1 provides primary support for our application of HLM. When applying HLM in our analysis, we will further break down the 30 two-digit industries listed in Table 1 into 510 sub-industries, and use the average subsidy share at the four-digit industry level. For example "furniture manufacturing (code 21)" may be further broken down into five four-digit sectors, namely "wood furniture manufacturing (2110)", "bamboo furniture manufacturing (2120)", "metal furniture manufacturing (2130)", "plastic furniture manufacturing (2140)" and "other furniture manufacturing (2190)". Scrutinizing the moderating effect of subsidies at such a disaggregated industry-level will help us develop a finer grouping of firms according to their upper level information.

We design the dependent and independent variables at two levels, as shown in equations (4) to (6).

Level 1: $Export_{ij} = \beta_{0j} + \beta_{1j}R\&D_{ij} + Control_{ij} + r_{ij}\,.$ (4)

Level 2: $\beta_{0j} = \gamma_{00} + \gamma_{01}Subsidy_j + U_{0j}\,.$ (5)

$\beta_{1j} = \gamma_{10} + \gamma_{11}Subsidy_j + U_{1j}\,.$ (6)

At the lower level (firm level), we employ *R&D* as the main independent variable which is calculated by the natural logarithm of (R&D expenditure + 0.001). We add 0.001 to avoid dropping mass firms without R&D, following a similar operationalization of export measure (Salomon and Jin, 2010). We employ two alternative dependent variables to measure *export*. One is export share in total sales and the other is logarithm of export value. *Control* collectively refers to a set of control variables. Among them *Financial leverage* is calculated by long-term loans divided by total assets. *Age* is the difference between the year of firm foundation and the current year. *Size* is the natural logarithm of total assets. *Value added share* is measured by the percentage of value added in output value. 30 province dummy variables are also included to control for regional disturbances. At the higher level (industry-level), we use the average percentage of subsidies in sales in each four-digit industry as the moderating variable. This variable reflects government intervention in firm production. All independent variables are lagged by one year to alleviate potential endogeneity problems, as enterprises involved in international business are more likely to carry out innovative activities by greater R&D input and faster updating of products (Baldwin and Gu, 2004, Salomon and Shaver, 2005). Because there are on average 115 firms in each of the 510 industries, we group-mean center R&D by industry before calculating the interaction term, so as to mitigate potential multicollinearity. The descriptive statistics of these variables are provided in Table 2.

Table 2 Descriptive Statistics and Correlation Coefficient Matrix

	Mean	S.D.	1	2	3	4	5	6	7
1. ln(*export*)	9.493	1.732	1.000						
2. *Export share*	0.597	0.386	0.484	1.000					
3. *R&D*	–5.066	4.595	0.137	–0.209	1.000				
4. *Subsidy share*	0.002	0.002	–0.095	–0.249	0.098	1.000			
5. *Financial leverage*	0.035	0.100	–0.015	–0.134	0.070	0.110	1.000		
6. *Age*	8.373	8.157	–0.001	–0.170	0.187	0.108	0.129	1.000	
7. *Size*	10.136	1.543	0.502	–0.247	0.398	0.135	0.150	0.253	1.000
8. *Value added share*	0.270	0.157	–0.081	–0.065	0.015	0.043	0.028	0.037	–0.016

We use command *mixed* in Stata 13.0 to perform HLM analysis. Table 3 reports the results obtained. In Model 1, the logarithm of export value is the sum of a fixed part—i.e., the grand mean γ_{00} and two random effects at the firm- and industry-level, respectively:

$$Export_{ij} = \gamma_{00} + U_{0j} + r_{ij}.$$

The empirical results suggest that there exists a variation among firms within industries ($\sigma^2 = 2.667$, $p < 0.001$) and across industries ($\tau_{00} = 0.581$, $p < 0.001$). Both variations significantly explain the different export values across firms. The value of ICC, or the proportion of the total variance that occurs across industries is ICC = $\tau_{00}/(\tau_{00} + \sigma^2)$ = 17.89%. This is much higher than the thumb rule threshold 10% (Ozkaya et al., 2013), and therefore justifies the use of HLM over

OLS. ICC value is important evidence to justify HLM application over OLS, indicating how variance between groups accounts for the total variance and whether it is large enough to be separately estimated.

Table 3 HLM Results

	Ln (export) as D.V.			Export share as D.V.		
	Model 1 Null model	Model 2 Firm level	Model 3 Interaction	Model 4 Null model	Model 5 Firm level	Model 6 Interaction
Fixed effects						
Intercept	9.262*** (0.035)	2.828*** (0.066)	2.864* (0.068)	0.457*** (0.009)	0.780*** (0.017)	0.797*** (0.017)
Financial leverage $_{t-1}$		−0.706*** (0.054)	−0.699*** (0.054)		−0.084*** (0.013)	−0.082*** (0.013)
Age $_{t-1}$		−0.018*** (0.001)	−0.018*** (0.001)		−0.002*** (0.000)	−0.002*** (0.000)
Size $_{t-1}$		0.641*** (0.004)	0.642*** (0.004)		−0.027*** (0.001)	−0.026*** (0.001)
Value added share $_{t-1}$		−0.458*** (0.035)	−0.447*** (0.035)		−0.085*** (0.009)	−0.083*** (0.009)
R&D $_{t-1}$		−0.009*** (0.001)	−0.005*** (0.003)		−0.007*** (0.000)	−0.006*** (0.001)
Industry subsidy $_{t-1}$			−43.864*** (6.596)			−6.872*** (1.722)
R&D $_{t-1}$ × *Industry subsidy* $_{t-1}$			−2.292*** (0.804)			−0.308* (0.177)
30 province dummy variables	Included	Included	Included	Included	Included	Included
Random effects						
Intercept τ_{00}	0.581*** (0.040)	0.321*** (0.025)	0.000*** (0.000)	0.043*** (0.003)	0.023*** (0.002)	0.000*** (0.000)
Industries τ_{11}			0.280*** (0.000)			0.022*** (0.000)
Residuals σ^2	2.667*** (0.010)	1.574*** (0.009)	1.560*** (0.009)	0.112*** (0.000)	0.097*** (0.001)	0.096*** (0.001)
Intra-class correlation (ICC)	17.89%	16.92%	15.24%	27.98%	19.09%	18.37%
Proportion of variance explained	--	41.69%	43.35%	--	22.85%	23.87%
Deviance (−2*log likelihood)	593,209	193,737	96,728	101,945	30,662	30,547
Deviance difference	--	399,472***	97,009***	--	71,283***	115***
Degree of freedom	3	8	10	3	8	10

In Model 2, we add into the model all control variables and the main regressor, R&D. The inclusion of firm-level variables explains 41.69% more in the firm's export variations (from (0.581 + 2.667) to (0.320 + 1.574)). The change of deviance is 399,472, which is significant with a change of degree of freedom 5. This shows that the inclusion of these variables significantly elevates the overall explanatory power of the model. The variance across industries is still significant, strongly calling for industry-level variables to enhance the explanatory power of the model.

The coefficient of R&D (–0.009) is significantly negative, suggesting that local R&D will negatively affect the importance of exports in total sales. This may be explained by booming domestic demand in China. As the income level of Chinese domestic consumers has been rapidly increasing, Chinese exporters are more likely to conduct R&D activities to enhance local sales rather than sales in overseas markets (Veldhoen, Mansson, McKern, Yip, and de Jonge, 2012). Indeed many major multinational enterprises such as GlaxoSmithKline have repositioned their China R&D centers from technology recipients into knowledge generation hubs for the Chinese market. The R&D center of General Electric in China has a clear strategic orientation "in China for China."

In Model 3, we further incorporate the industry subsidy and the interaction term between R&D and industry subsidy to test the moderating effect of competition (Deng, Jean, and Sinkovics, 2012). Industry-level subsidies will decrease the percentage of exports, suggesting that firms in well protected industries will more likely exploit the opportunities in local markets. The interaction term of innovation and subsidy has a negative coefficient in Model 3, indicating that when innovating exporters have financial support from the government, abundant organizational resources will reinforce the domestic market orientation of exporters. Models 4-6 use export share in sales as the dependent variables and obtain results similar to those in Models 1–3. This corroborates the negative moderating role of subsidies in the relationship between innovation and export.

To triangulate the robustness of the negative relationship between innovation and export and the negative moderating effect of industry-level subsidies, we have removed the sample of purely exporting firms and kept the sub-sample of firms whose *domestic* sales are greater than zero. We test the relationship between R&D and local sales and the moderating effects of industry-level subsidies as well. Consistent with the results in Table 3, we find a significantly positive relationship between R&D and local sales in all models. We also get positive moderating effects of industry-level subsidies in Model 6. The results are reported in Table 4.

Table 4 Robustness Tests, Domestic Sales as Dependent Variable

	ln (domestic sales) as D.V.			Share of domestic sales as D.V.		
	Model 1 Null model	Model 2 Firm level	Model 3 Interaction	Model 4 Null model	Model 5 Firm level	Model 6 Interaction
Fixed effects						
Intercept	9.907*** (0.049)	1.476*** (0.084)	1.463*** (0.085)	0.622*** (0.008)	0.411*** (0.017)	0.396*** (0.017)
Financial leverage $_{t-1}$		−0.263*** (0.073)	−0.266*** (0.073)		0.081*** (0.014)	0.080*** (0.014)
Age $_{t-1}$		−0.004*** (0.001)	−0.005*** (0.001)		0.002*** (0.000)	0.002*** (0.000)
Size $_{t-1}$		0.783*** (0.006)	0.782*** (0.006)		0.014*** (0.001)	0.014*** (0.001)
Value added share $_{t-1}$		0.323*** (0.049)	0.323*** (0.049)		0.114*** (0.010)	0.113*** (0.010)
R&D $_{t-1}$		0.028*** (0.002)	0.026*** (0.003)		0.005*** (0.000)	0.004*** (0.001)
Industry subsidy $_{t-1}$			8.557 (6.810)			6.455*** (1.505)
R&D $_{t-1}$ × *Industry subsidy* $_{t-1}$			0.623 (0.766)			0.270* (0.162)
30 province dummy variables	Included	Included	Included	Included	Included	Included
Random effects						
Intercept τ_{00}	1.137*** (0.077)	0.191*** (0.017)	0.000*** (0.000)	0.028*** (0.002)	0.013*** (0.001)	0.000*** (0.000)
Industry τ_{11}			0.188*** (0.016)			0.012*** (0.001)
Residuals σ^2	3.584*** (0.015)	2.093*** (0.015)	2.090*** (0.015)	0.095*** (0.000)	0.082*** (0.001)	0.082*** (0.001)
Intra-class correlation (ICC)	24.09%	8.37%	8.27%	22.83%	13.46%	12.71%
Proportion of variance explained	--	51.61%	51.73%	--	22.41%	23.34%
Deviance (−2*log likelihood)	466,370	139,889	139,880	55,975	14,254	14,198
Deviance difference	--	326,481***	9***	--	41,271***	56***
Degree of freedom	3	8	10	3	8	10

We suggest that reports of ICC value, data type (primary or secondary), and the sample size of each level are necessary because sample size (especially for the higher level) and variance at the higher level are important indices to justify the use of HLM over OLS. Moreover, centering and software choice should also be reported. To present the results of HLM instead of OLS, the theoretical model should be labeled by level and empirical tests should follow a step-by-step process from the null model to the full model where each step should be justified by the added explained variance.

5 Concluding Remarks

This study is the first in the literature reviewing the applications of HLM specifically in international marketing. Acknowledging the advantages of HLM in separating the variances at the upper and lower levels, the current research advocates that HLM be more widely employed in international marketing research whose context may span as many as five layers — namely, individuals, sub-firm business units, firms, sub-nation, and nations. For researchers interested in exploring the antecedents and consequences of international marketing related to emerging markets characterized by sub-national variations, HLM may offer a powerful tool to effectively tackle the statistical challenges arising from the mix of within-group and between-group variances. Based on a review of the HLM methodology and its application in extant international marketing research, we find that the international marketing research community has started to realize the advantages of HLM and has begun employing it for more statistically robust results.

The illustrative example discussed in the paper applies HLM to a scenario where Chinese government intervention in the form of production subsidies has a negative moderating effect on the relationship between exporters' innovation and export performance. In this example, we demonstrate stepwise how to analyze, calculate, and intercept results in an HLM model pedagogically. This example extends the literature on the relationship between innovation and exports from an institutional theory perspective. Since interaction between "context" and "actors" is prevalent in international marketing research, such as the aforesaid five layers in the object hierarchy, a nested data structure must be taken into consideration to alleviate dependence of data and constructs.

Based on our methodological review and empirical study, we propose several directions for the future employment of HLM in international marketing research. First, as international marketing covers a variety of levels, and in reality an HLM study may cover more than two levels, we suggest that future research explore better solutions for such issues apart from the widely adopted two-level HLM. Researchers may also try incorporating different level-two factors to enrich our understanding of the international marketing of firms (Magnusson, Westjohn, and Boggs, 2009). Second, the application of HLM in SEM by incorporating latent variables may be an intriguing direction of research to combine the strengths of these two models. Third, sub-national variations in terms of institutions in emerging economies, such as government support, financial underdevelopment, and protection of intellectual property rights, may affect the marketing behavior and performance of firms fundamentally (Deng et al., 2013), and therefore such features ought to be effectively controlled by the HLM approach. Finally, from an interdisciplinary perspective, as organizations are embedded in and affected by industrial or regional environments, application of HLM in international marketing research may construct lower level variables on organizational behavior, and therefore cross-fertilize international marketing research.

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