Response Bias in International Marketing Research

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Preface

At last the mighty task is done. After the spring of inspiration, the summer of work and the autumn of completion, I can now take a hibernal rest and survey what has been achieved. In fact, this thesis is the fruit of the work of many, because you always need friends and helpers to accomplish your aims. They have led me into the best possible position. The professional course of a Ph.D. is not an easy one, but with the help of many, my path has been relatively smooth. For that I am most grateful, as I realize that this is the exception rather than the rule.

Before mentioning all those who have helped me, I have to thank Eric Bradlow from the USA to sit on the dissertation committee. It is a great honor that such an outstanding scholar in the field of marketing was willing to read and evaluate my thesis. I am also grateful to the other members of the committee: Jan-Benedict Steenkamp, Theo Verhallen, Hans Baumgartner, Philip Hans Franses, and Rik Pieters.

Looking back upon my formative years at the universities of Rotterdam and Tilburg, I want to thank a number of people. As a student at Erasmus University it was Harry Commandeur and Philip Hans Franses who were the first to see academic potential in me. They aroused my interest in academia. So it is not really a coincidence that I returned to my alma mater when I was asked for the position of assistant professor at the Rotterdam School of Management. As for my time in Tilburg, I would first and foremost like to express my deepest gratitude to my scientific mentor Jan-Benedict Steenkamp. When I came to Tilburg four years ago I immediately felt inspired and motivated to work under his guidance. He supplied me with a most valuable dataset to work with. Moreover, he has been a veritable mentor under whose guidance I have learnt the tricks of the scientific trade. He helped me with revisions and strengthened my awareness of the political process in a high-context environment such as academia. I will never forget the Attic salt with which he seasoned his lectures, his indefatigable energy, his encyclopaedic knowledge of the literature, and the speed with which he always read my work. He also made me look into the mirror, pointed out my weaknesses and strengths, and gave me advice on how to improve myself. I feel blessed to have been his Ph.D. student. I sincerely hope that we will continue our collaboration in the future because I am convinced I can still learn a lot from him.

Then I want to mention my co-authors, Hans Baumgartner, Jean-Paul Fox and Bernard Veldkamp. Hans is a warm-hearted person whose company I have enjoyed. His input has improved the two papers he co-authored tremendously. I also thank him for his hospitality during my visit to Penn State last June. I am greatly indebted to Jean-Paul Fox, the co-author on my first two projects. It goes without saying that his great psychometric and statistical expertise, combined with the help related to software issues was indispensable. I very much look forward to working with him in the future. Finally I would like to mention Bernard Veldkamp, the co-author on my last project. I appreciate his contribution and I hope and expect that our collaboration may lead to interesting results.

I am grateful to the people at Europanel, for their massive data collection effort. They laid the foundation for this doctoral thesis. The English biologist Thomas Huxley phrased it quite well: "what you get out depends on what you put in; and as the grandest mill in the world will not extract wheat-flower from peascods, so pages of formulae will not get a definite result out of loose data". My sincere thanks to Jane Outten from Europanel, the people at MetrixLab & GFK, and especially Alfred Dijs. Without their contribution this thesis would not have been possible.

I should not forget to pay tribute to the marketing department in Tilburg. It has really been a seat of learning, an inspiring place to work. I am grateful to all the members of the department, but I would like to mention a few staff members in particular. I thank Inge Geyskens, who always listened to me when I was in doubt and gave me sound advice; Els Gijsbrechts, for teaching the Marketing Research course with me; Vincent Wiegerinck, for the nice discussions on international marketing topics; Rik Pieters, for participating in the project on taboo consumer marketing.

Then, of course, there are the Ph.D. students: Ralf van der Lans, Man-Wai Chow, Maciej Szymanowski, and my buddies Berk Ataman, Rita Coelho do Vale and Robert Rooderkerk. It was great to work together, to feel the mutual support, to fight the challenges to come up higher.

Social life often suffers during a Ph.D., but fortunately this well-known phenomenon did not apply to me. I would like to thank all my friends, the people from Peerke Donders, the Roman

Catholic Student Fraternity, the Navigators Student Fraternities, and all the the other people whom I have not mentioned for playing an important role in my social life these last four years.

Also, I want to express my deepest gratitude to my parents, Annemiek and Martin, and my identical twin brother, Bas. Their love, continual support and advice have kept me on the right track.

Finally I want to give thanks to my Creator. He has given me the talents I have been trying to exploit. Now I can say with all my heart: thank God, the work is done!

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Chapter 1

I.1 Introduction

The saturation of domestic markets in the industrialized parts of the world, combined with increased competition in home markets from foreign competitors forces many companies to look for opportunities beyond their national boundaries (Kotabe and Helsen 2004). This trend urges the need for development of marketing and consumer behavior theories that incorporate institutional, socio-economic and cultural variables. All too often, it is assumed that models developed in the U.S. generalize to other parts of the world. The large cultural, economic and demographic differences between industrialized Western countries and emerging markets make it less than obvious that established theories are applicable to these markets. Steenkamp (2005) argues that many theories (and even the most established ones) lack cross-national generalizability because key country characteristics moderate the structural relationships between the constructs in marketing theories.

Apart from investigating cultural and socio-economic contingencies, there are many inherently international issues that need to be studied in much greater detail. For instance, the desirability of pursuing standardization of the marketing mix and other competitive strategy variables versus adaptation to individual national markets has been discussed frequently, even though empirical evidence on the pros and cons remains scarce (Szymanski, Bharadwaj and Varadarajan 1993). Most large multinational companies such as Mars, Pepsi-Cola, L'Oreal recognize the diversity in world markets and rely on local consumer knowledge and marketing practices (Usunier and Lee 2005). Yet, many uncertainties remain with respect to the desired degree of standardization of the strategic resource mix (pattern of resource allocation among advertising, promotion, personal selling, and other mix variables), and desired degree of standardization of the strategy content (decisions on product positioning, brand name, appropriate media, content of advertisements, etc.).

Given these shortcomings in the literature, it is important to expand the intellectual boundaries. Editors of the top journals in the field concur. Monroe (1993) urges consumer behavior researchers "to move beyond the relative security of our own backyards and investigate issues relative to consumption on an international basis." Winer (1998) submits that more international marketing studies are needed in the top journals, and Steenkamp (2005) urges researchers to move out of the 'U.S. silo'. Due to the ubiquitous Internet and its related

developing technologies, the trend towards more global studies should intensify in the years to come. However, before valid inferences can be drawn from any international research project, there are several important measurement issues that need to be addressed. In this dissertation, I focus on measurement issues when data is collected via surveys.

I.2 International survey-based marketing research

Surveys are a crucial source of data in marketing for theory building and answering managerial questions. According to Rindfleisch et al. (2006), of the 520 empirical articles published in the *Journal of Marketing* (*JM*) and *Journal of Marketing Research* (*JMR*) from 1995 to 2005, over 40% (225) employed survey methods. In international settings, surveys are even more important, as secondary data is seldom satisfactory. Especially in emerging consumer markets, secondary information often simply does not exist or if it is available it may be hard to track down.

Scientific marketing research based on surveys can be conceptualized as a process consisting of four stages (Burgess and Steenkamp 2006). The first stage is theory development, where one defines the constructs and carefully specifies hypotheses. The second stage is concerned with the acquisition of data, while in the third stage the data are analyzed. Finally, in the fourth stage, findings are evaluated and key learnings extracted. My dissertation is mainly concerned with stages two and three, that is, acquisition and analysis of international survey data.

When acquiring and analyzing international survey data, there are four issues that require attention: a) choice of countries (based on convenience or based on sound theorizing), b) unit of observation (individual consumer / manager vs. larger decision units), c) measurement instruments, and d) proper analysis of the data. For an overview of issues a) and b), I refer the interested reader to Burgess and Steenkamp (2006). Below, I discuss issues c) and d) and the shortcomings in the literature.

Measurement instruments

Ever since Ray's call for a measurement tradition in marketing (Ray 1979), scholars have devoted considerable attention to developing valid measurement instruments (Bearden and Netemeyer 1999). Yet, many measurement instruments developed in the U.S. require a high degree of respondent sophistication and assume that respondents are familiar with Likert rating

scales. The established scales are frequently too long and difficult for easy administration in other countries (Steenkamp 2005). Moreover, the scales may contain items that are inappropriate in other countries. Finally, the direction of the item (positively worded vs. negatively worded) can be an issue (Wong, Rindfleisch, and Burroughs 2003). Hence, much work is needed to construct short and simple scales, scales that possibly use different wording and response formats, tailored to the local environment.

Data analysis

In international data analysis, a key concept is cross-national measurement invariance. Loosely speaking, measurement invariance indicates whether items relate to the underlying constructs in the same way across countries. If psychometric properties of a measurement scale vary widely across countries, cross-national comparisons based on the scale may be hampered due to unreliability and lack of validity. Lack of invariance can be due to differences in responses to individual items, as well to complete sets of measures (Baumgartner and Steenkamp 2006). At the level of individual items, tests to detect differential item functioning based on the multigroup confirmatory factor analysis model are well-known in marketing (Steenkamp and Baumgartner 1998). Nonetheless, there are a number of important limitations. First, despite the fact that researchers use the Likert format for their items, they do not take the ordinal nature of the data into account in their model. Second, the models cannot make substantive comparisons when there are no invariant items. When studying many different countries, lack of invariance is the norm, rather than the exception (Baumgartner 2004). The field needs methods that allow substantive comparisons between countries despite lack of invariance.

Lack of invariance in the complete set of measures can occur due to cross-national differences in response styles. A response style is a tendency to utilize the rating scale in a particular way, relatively independently of specific item content (e.g., Baumgartner and Steenkamp 2001; Fisher 1993; Greenleaf 1992a, 1992b; Johnson 2003; Mick 1996; Rossi et al. 2001). If styles have a similar impact on all items, tests for differential item functioning are not appropriate: a difference would be reflected either in the mean or variance of the latent construct.

Cross-national variation in scale usage indicates that the relationship between respondents' true opinion and the observed score is different across nations. There are different kinds of response styles in surveys, such as yeah-saying (uncritical agreement with statements), extreme

responding (using the ends or midpoint of rating scales often, relatively independently of specific content), and socially desirable responding (people's tendency to give answers that make them look good). Response styles introduce extraneous variation in scale scores, which compromises validity. Unfortunately, the score-invalidating and relationship obscuring effects of response styles have been largely ignored in the international (and domestic) marketing literature (see Baumgartner and Steenkamp 2001). Response style models that have been used to date are relatively naïve, and much remains unknown about accurate measurement of stylistic responding, about proper ways to control for response styles, and what factors drive stylistic responding across individuals and nations.

I.3 Measurement tradition in marketing

This section is a primer on measurement models. IRT models, which are useful to address the shortcomings of the literature concerning the construction of measurement instruments and data analysis, are introduced as an improvement over classical test theory (CTT). In general, marketing and consumer researchers' concern with the validity and reliability of construct measurement has greatly increased since the publication of Jacoby's (1978) review of the early marketing literature. CTT has become the dominant measurement paradigm in marketing. The roots of CTT go back to early work by Spearman (1904). The central feature of CTT is the notion of errors in measurement. Measurement theory is needed because marketing phenomena are often not directly measurable but must be studied through the measurement of other observable phenomena. Any measurement theory supposes that the score of a respondent on some measurement instrument can be predicted by defining respondent characteristics, referred to as unobservable latent traits.

In the marketing literature, articles by Churchill (1979) on measure development and Peter (1979, 1981) on reliability and construct validity introduced important CTT concepts as multi-item measurement, item-total correlations, coefficient alpha, convergent and discriminant validity, and did much to inspire consumer researchers to pay greater attention to the quality of construct measurement. The advent and application of structural equation models further contributed to advanced CTT investigations of construct validity (Bagozzi 1980; Baumgartner and Homburg 1996; Bagozzi and Yi 1991; Gerbing and Anderson 1988; and Steenkamp and van Trijp 1991).

Nonetheless, CTT has several problems. First, typical CTT statistics such as item-total correlations or coefficient alpha estimates depend on the particular sample of respondents in which they are obtained. The average trait levels and the range of the trait scores in a sample influence the values of such statistics.

Second, comparisons of respondents on some trait measured by a set of items comprising a measure are limited to situations in which respondents are administered the same items. Especially in international marketing this is a problem, as similar items in different countries might be differentially useful for validly measuring latent traits. What is needed is a method that can calibrate respondents on the same latent scale, despite the fact that they have answered different items.

Third, CTT presumes that the variance of errors in measurement is the same for all respondents. It is not uncommon to observe that the consistency in responses varies with the trait level. For example, the scores of respondents high on satisfaction might be expected to be more consistent on several parallel forms of a test than the scores of respondents who have average satisfaction levels. Test models should thus be able to provide information about the measurement precision at various trait levels.

Because of the limitations of CTT, psychometricians have started to develop item response theory (IRT) models. The mathematical basis of IRT is a function that relates the probability of a person responding to an item in a specific manner to the standing of that person on the trait that the item is measuring. The basis of IRT as an item-based test theory is often attributed to Lawley (1943), Lord (1952, 1980), Rasch (1960, 1966, 1977), and Birnbaum (1968). Even though IRT models have been most popular for dichotomous items, there are also models for polytomous items (e.g. Samejima 1969; Van der Linden and Hambleton 1997). In marketing, these ordinal data models are especially interesting (MacKenzie 2003), because 5-point and 7-point (Likert) scales are the most commonly used response format (Bearden and Netemeyer 1999). The most important features of IRT models are:

1) Given the existence of a set of items all measuring the same trait, the estimate of a respondent's latent score is independent of the particular sample of items administered to the respondent.

2) Given the existence of a large population of examinees, the descriptors of an item are independent of the particular random sample of respondents drawn for the purpose of calibrating the item.

3) A statistic indicating the precision with which each respondent's latent trait is estimated, is provided.

The key differences between IRT and CTT models are outlined in table 1. Here, X_{ik} denotes the ordered categorical response of individual $i \in \{1,...,I\}$ to item $k \in \{1,...,K\}$. $\Pr(X_{ik}=c|\xi_i, a_k, \gamma_k)$ is the cth category response function for item k, $c \in \{1,...,C\}$. The parameter a_k is called the discrimination parameter (low values of a indicate that an item does not measure a latent construct well, i.e., the item does not discriminate persons high and low on ξ), while the parameter $\gamma_{k,c}$ is called the threshold parameter for category c.

In both measurement worlds, the latent variable is assumed to be intervally scaled. On the other hand, the observed variables can be assumed to be ordinal for IRT, but continuous for CTT. CTT assumes that the observed data can take all values, including values between e.g. 1 and 2, 2 and 3, 3 and 4, and 4 and 5 on a 5-point scale. The mathematical form of the relationship between latent and observed variables reflects this property. In reality, the data can only take values 1, 2, 3, 4 and 5, which is appropriately modelled by the nonlinear IRT model.

There are many different IRT models, depending on the assumptions of the response process. For dichotomous data, the Rasch model, the two and three-parameter logistic model and the two and three-parameter normal ogive model are well-known. For Likert-type response scales, the graded response model and the partial credit model are often used. For the purpose of this dissertation, I focus on the graded response model (Samejima 1969), for which the mathematical shape of the normal ogive version is given in Table 1.

In contrast to CTT, IRT models can accommodate different measurement precision for respondents high and low on the trait, the item parameters do not depend on the particular sample of respondents used for calibration purposes, and different items can be administered to respondents.

It is peculiar to see that the progress and development of IRT methods in psychometrics in the last decade has hardly diffused into the field of marketing. One can only speculate about the reasons for the conspicuous absence of articles in the top journals of our field. Some reasons

might be that IRT models are nonlinear in nature and generally more complicated than the CTT methods. Software is also more readily available for CTT methods.

Table 1
CHARACTERISTICS OF MEASUREMENT MODELS FOR RATING SCALES

	CTT	IRT
Characteristics of observed variables		
Scale property	Interval	Ordinal
Characteristics of latent variables		
Scale property	Interval	Interval
Mathematical model for relationships		
Form	Linear	Non-linear
Item Parameters	λ_k	a_k, γ_k
Equation	$X_{ik}=\lambda_k\xi_i + \varepsilon_i$	$\Pr(X_{ik}=c\|\xi_i, a_k, \gamma_k) = \Phi(a_k\xi_i - \gamma_{k,c-1}) - \Phi(a_k\xi_i - \gamma_{k,c})$, $\gamma_{k,0}=-\infty$, $\gamma_{k,C}=+\infty$
Model Properties		
Items	Need to be similar	Can be different
Variance of measurement	Similar for all respondents	Respondent specific
Item parameters	Sample dependent	Sample independent

I.4 Cross-national measurement models

As I will argue below and demonstrate in the various essays, the field of international marketing can benefit tremendously from applying so called "hierarchical IRT" models (see for overviews e.g. Johnson, Sinharay, and Bradlow 2005). Examples of hierarchical IRT models in the psychometric literature include the hierarchical rater model (Patz et al. 2002), the testlet model (Bradlow et al. 1999), the related siblings model (Janssen et al. 2000; Sinharay et al. 2003), and the multilevel IRT model (Fox and Glas 2001; 2003). Especially the work by Fox and associates is ideally suited to address validity challenges I discussed in section I.2, since the multilevel IRT model was developed to measure latent constructs when respondents are nested within larger clusters (e.g. schools or countries). Structural modelling of such hierarchical data is a relatively recent area of methodological research. Apart from a few IRT-based studies, there are several SEM-based articles (Ansari et al. 2001; Bauer 2003; Bentler and Liang 2003; Curran 2003; du Toit and du Toit 2003; Kaplan and Elliot 1997; Lubke and Muthén 2004; Mehta and Neale 2005; Muthén 1991; 1994; 1997; Rovine and Molenaar 2000). These models often ignore the ordinal nature of the data (which is problematic in multi-group research; see Lubke and Muthén 2004). Moreover, it would be useful to have random-effects structures for item parameters. Especially with more countries / groups, lack of invariance of item parameters is the norm and in such cases

the hierarchical SEM models with invariant measurement models cannot be used to draw conclusions from the data. In this dissertation, a model is presented which recognizes the ordinal nature of Likert data, and has random-effects structures both for the latent variable, as well as for all item parameters in the measurement model. To the best of my knowledge, such models do not exist in the psychometric literature.

Central cross-national measurement model

Let ξ_{ij} denote a latent trait of respondent *i* in country *j*, and let Y_{ijk}, k=1,....,K denote the observed scores on the K items measuring this latent trait. Assume that there are K polytomous items with C response categories for each item (e.g., for a 5-point Likert scale, the C=5 categories are "Strongly disagree", "Disagree", "Neutral", "Agree", and "Strongly agree"). Then the basic model which will be used throughout the dissertation is given by:

$$\Pr(Y_{ijk} = c \mid \xi_{ij}, a_{kj}, \gamma_{kj}) = \Phi(a_{kj}\xi_{ij} - \gamma_{kj,c-1}) - \Phi(a_{kj}\xi_{ij} - \gamma_{kj,c}) \quad (1)$$

$$\xi_{ij} = \beta_{0j} + \varepsilon_{ij},\ \varepsilon_{ij} \sim N(0,\sigma^2) \quad (2)$$

$$\beta_{0j} = \gamma_{00} + u_{0j},\ u_{0j} \sim N(0,\tau^2) \quad (3)$$

$$a_{kj} = \tilde{a}_k + \eta_{kj},\ \eta_{kj} \sim N(0,\sigma_a^2),\ a_{kj} \in A,\ \tilde{a}_k \in A \quad (4)$$

$$\gamma_{kj,c} = \tilde{\gamma}_{k,c} + \upsilon_{kj,c},\ \upsilon_{kj,c} \sim N(0,\sigma_{\gamma_k}^2),\ \gamma_{kj,1} \le \gamma_{kj,2} \le \ldots \le \gamma_{kj,C} \quad (5)$$

where A is a bounded interval in $\Re^+$. The structural part (2)-(3) consists of a random-effects structure for the latent variable ξ_{ij}, while the measurement part (1)-(4)-(5) is a graded response IRT model (Samejima 1969), with random-effects structures for item parameters $\boldsymbol{a}$ and $\boldsymbol{\gamma}$. A more elaborate exposition of the meaning of these item parameters, and the way the model functions can be found in chapter 2. The structural part (2)-(3) does not include covariates at either the individual or national-cultural level. When covariates are included, the model becomes more elaborate with additional equations:

$$\xi_{ij} = \beta_{0j} + \beta_{1j}X_{1j} + \ldots + \beta_{Kj}X_{Kj} + \varepsilon_{ij},\ \varepsilon_{ij} \sim N(0,\sigma^2) \quad (6)$$

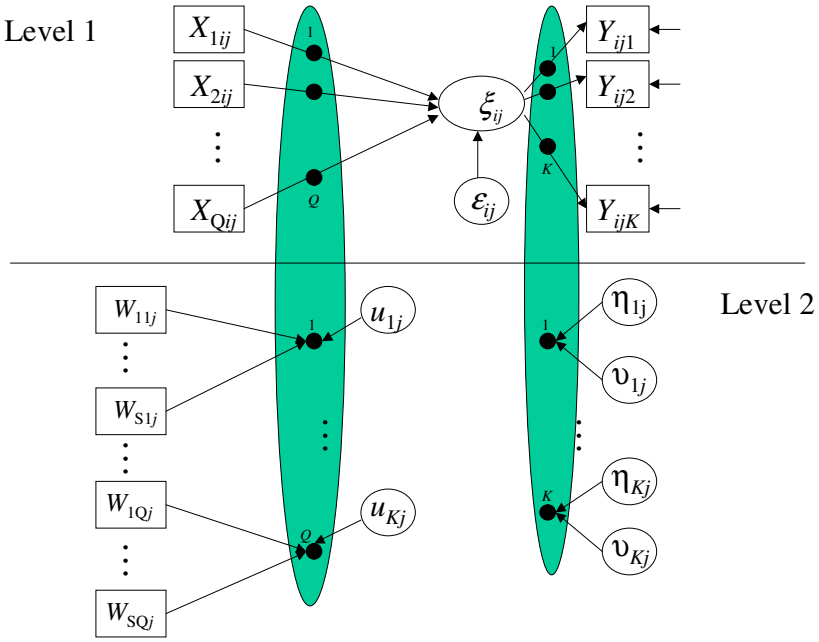
$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_{10j} + \ldots + \gamma_{0S}W_{S0j} + u_{0j} \quad (7)$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11}W_{11j} + \ldots + \gamma_{1S}W_{S1j} + u_{1j} \quad (8)$$

$$\beta_{Kj} = \gamma_{K0} + \gamma_{K1}W_{1Kj} + \ldots + \gamma_{KS}W_{SKj} + u_{Kj} \quad (9)$$

$$[u_{0j}, u_{1j}, \ldots, u_{Kj}]^T \sim N_{K+1}(0,T) \quad (10)$$

In a figure, the hierarchical latent variable model (1)-(10) looks as follows:



In this figure, there are two levels of analysis: the individual level and the country level. At the individual level, the latent dependent variable ξ_{ij} is influenced by multiple observed variables X_{1ij} to X_{Qij} (the upper left part of the figure). Note that the level-1 predictors can also be latent (see Fox and Glas 2003) although this is not pursued here. The latent dependent variable is measured by K polytomous items (upper right part of the panel). The strength of the relationship between the latent dependent variable and the observed explanatory variables varies across nations (see the lower left part of the figure). The black dots indicate that the structural relationships are influenced by country-level variables, contained in the variables $\boldsymbol{W}$. The measurement part of the model is displayed in the upper right part of the model. It should be recognized that the IRT model is nonlinear in nature, so the arrows emanating from ξ_{ij} do not indicate linearity. The relationship between the latent dependent variable and each observed indicator is governed by the discrimination and threshold parameters. Finally, the lower right part of the figure captures the fact that the discrimination and threshold parameters of the measurement model also vary across nations through random-effects structures.

In the next section, I describe how each essay contributes to the literature, and how our hierarchical IRT is applied.

I.5 Objectives of the various chapters

In this section, I shortly discuss the four essays (Chapters 2 to 5) included in the dissertation. Table 1 provides an overview of the various chapters. Both the statistical model, the substantive topic, and the type of data are displayed in the table. Double multilevel IRT indicates multilevel structures for both item parameters as well as the latent variable. Chapter 6 concludes the dissertation with a summary and suggestions for further research.

Objective first essay

In the first essay, I focus on measurement invariance for specific items. As mentioned, measurement invariance implies that the instruments in different countries function similarly and produce comparable estimates of latent constructs. We focus on the current 'golden standard' model for testing measurement invariance (the CFA model) and identify two key limitations. The first limitation is related to the fact that the ordinal nature of the data is ignored, while the second limitation is that invariance is *necessary* for substantive comparisons. The polytomous hierarchical item response theory measurement model (1)-(5) is then introduced, which solves both these problems. With the new ordinal model, countries can be substantively compared, even in case of absence of cross-national measurement invariance. An empirical application is provided for the consumer susceptibility to normative influence scale, using a sample of 5,484 respondents from 11 countries on four continents.

The next two essays study in depth two of the most ubiquitous response styles that have been identified in the literature.

Objective second essay

In the second essay, I consider Extreme Response Style (ERS). ERS is the tendency of respondents to favor or avoid using the endpoints of a rating scale, relatively independently of specific item content. Based on a heterogeneous set of items (i.e., the items are from many different content domains), we propose a new IRT-based method to measure ERS and study

antecedents of ERS at the individual and national-cultural level. Mathematically, we use a hierarchical item response theory measurement model (1)-(5) for *binary* data (C=2), and *simultaneously* integrate the measurement model with a structural part, as in (6)-(10). In addition, we build testlet structures into the IRT models (e.g., Bradlow et al. 1999). The testlet structures are necessary, because although the set of items used to measure ERS is diffuse in terms of content, there might be excess dependencies among substantively correlated items. The model is applied to a large data set involving 12,500 consumers from 26 countries on 4 continents.

Objective third essay

The third essay discusses another response style: socially desirable responding (SDR). SDR is people's tendency to give answers that make them look good (Paulhus 1991). A cogent conceptual model is developed, linking personality and culture to differences in SDR. Both the main effects of personality and national culture on SDR are considered, as well as the moderating role of the cultural context in which the respondent lives on the effects of the various personality factors. The hypotheses are tested using a large data set, involving a random sample of 12,020 respondents in 25 countries in 4 continents. The model (1)-(5) is used to measure the latent variables cross-nationally. The latent scores are subsequently used in a multilevel model for SDR. Both the dependent variable and the personality predictors in the multilevel model are latent.

Objective fourth essay

In the final essay, I consider the design of cross-national measurement instruments. The fourth essay contributes to the marketing literature by developing a procedure that yields *fully country-specific, yet cross-nationally comparable short form marketing scales*. The procedure is based on a combination of a two powerful psychometric tools: the hierarchical item response theory model (1)-(5) and optimal test design methods (Van der Linden 2005). In the empirical part, our procedure is applied to the impression management (IM) scale (Paulhus 1984), yielding country-specific yet cross-nationally comparable short-form scales in 28 countries of the world.

Table 2
Chapter overview

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Model	Double multilevel IRT	Double multilevel IRT, including testlet structures	Double multilevel IRT	Double multilevel IRT combined with test assembly methods
Data format	Polytomous	Dichotomous	Polytomous	Polytomous
Covariates	No	Yes, simultaneously modelled with measurement model	Yes, but not simultaneously modelled with measurement model	No
International topic	Relaxing measurement invariance: applied to SNI scale	Response bias: measuring ERS, and investigating drivers of ERS	Response bias: SDR and drivers of SDR	International scale construction: short-form IM scales
Data	11 countries, 8 items of the Susceptibility to Normative Influence scale	26 countries, 100 items based on many different Consumer Behavior scales	28 countries, 20 items of the Balanced Inventory of Desirable Responding (BIDR)	28 countries, 10 items of the IM inventory

Chapter 2

Relaxing Measurement Invariance In Cross-National Consumer Research Using a Hierarchical IRT Model

Abstract:

With the growing interest of consumer researchers to test measures and theories in an international context, the cross-national invariance of instruments designed to measure consumer behavior constructs has become an important issue. Consumer researchers now routinely test for measurement invariance using multigroup confirmatory factor analytic (CFA) techniques before testing their substantive hypotheses in a cross-national context. Yet at least two issues still need to be addressed. First, in these analyses the ordinal nature of the rating scale is ignored, which has recently been shown to have deleterious effects on the validity of cross-national comparisons. Second, when few, if any, items in CFA exhibit metric and scalar invariance across all countries (i.e., when even partial invariance is not supported), comparison of results across countries is difficult, if not impossible. We propose to solve these problems using a hierarchical item response theory measurement model. The model takes differential item functioning, including scale usage differences into account. Countries can be substantively compared, even in case of absence of cross-national measurement invariance. An empirical application is provided for the consumer susceptibility to normative influence scale, using a sample of 5,484 respondents from 11 countries on four continents.

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II.1 Introduction

Consumer researchers are becoming increasingly interested to test their measures and theories in an international context (Bagozzi 1994; Durvasula et al. 1993; Wong, Rindfleisch, and Burroughs 2003). It is in this vein that Monroe (1993) urges consumer behavior researchers "to move beyond the relative security of our own backyards and investigate issues relative to consumption on an international basis." Consider the following substantive questions that consumer researchers may want to address:

- A consumer researcher is interested in testing whether materialism is largely an ("emic") U.S. construct, or an ("etic") pan-cultural construct. To address this question, s/he wants to test the nomological relations between this construct and antecedents, consequences, and concurrent constructs as identified in U.S. research (Richins 1994; Richins and Dawson 1992) in other cultures.
- Cultural theory (Schwartz 2006) predicts that in countries high on embeddedness, the subjective norm is more important than a person's own attitude in shaping consumer behavior while the converse is expected to be true in countries high on autonomy. Is this truly the case? Or are personal opinions the key driver of behavior, across cultures? What are the implications for decision theory and purchase models?
- Ever since Mick's (1996) seminal article, consumer researchers are well aware of the biasing effects of socially desirable responding in survey research. But is this really a problem around the world? In which countries is this bias strongest, and in which countries can it be ignored?
- There is growing interest in issues related to consumer well-being, as well as a growing realization that transformative consumer research can make a difference around the world (Mick 2005). What are the key drivers of consumer well-being, is their effect moderated by people's cultural and socioeconomic context, and are there systematic and predictable differences in consumer well-being across countries?
- Novak, Hoffman, and Yung (2000, p. 39) have urged consumer researchers to evaluate "Web sites in terms of the extent to which they deliver these two types [i.e., utilitarian and an emotional] of experience." Given the global reach of the Internet, and its great influence on consumer behavior, we need to understand these consumption experiences better. Are there universals here? Or is the importance consumers attach to experiential consumption a "luxury" of industrialized countries?
- Brands are important conduits through which cultural meanings are transferred to individuals (McCracken 1986). Three important brand-related meanings are quality, social responsibility, and prestige (Batra et al. 2000; Roth 1995). Does their importance vary across cultures? Cultural theory would alternatively suggest that prestige connotations be more important in countries high on power distance, social image meanings be more important in "feminine" countries, and quality associations be more important in individualistic countries.
- Researchers have noted the construct of guanxi plays an important role in social relations in China (Steenkamp 2005). Is this construct unique to China, or does it play a similar role in other collectivistic countries, and perhaps even individualistic countries? How can we integrate such constructs in our theories of consumer behavior?

All these issues have in common that they involve data collection in multiple countries, which requires that the measurement instruments are cross-nationally invariant (Durvasula et al. 1993; Netemeyer, Durvasula, and Lichtenstein 1991; Steenkamp and Baumgartner 1998). Measurement invariance refers to "whether or not, under different conditions of observing and studying phenomena, measurement operations yield measures of the same attribute" (Horn and McArdle 1992, 117). The generally accepted view is that if evidence supporting a measure's invariance is lacking, conclusions based on a research instrument are at best ambiguous and at worst erroneous (Horn 1991). The multigroup confirmatory factor analysis model (CFA) is the dominant approach to investigate cross-national measurement invariance, both in consumer research (Steenkamp and Baumgartner 1998) and other social sciences (Byrne, Shavelson, and Muthén 1989; Vandenberg and Lance 2000).

Despite the advances in cross-national invariance testing using multigroup CFA, two key issues remain unresolved. First, consumer researchers often use five and seven point ordinal Likert items to measure latent constructs and the number of scale points may affect reliability and validity (Weathers, Sharma, and Niedrich 2005). However, the multigroup CFA model completely ignores the ordinal nature of the Likert rating scales, which may lead to invalid conclusions regarding measurement invariance (Lubke and Muthén 2004). Measurement invariance may be either over- or understated, thus threatening the validity of cross-national comparisons in consumer research. These results provide further evidence that ordinal data modeling should receive more attention in consumer research (MacKenzie 2003).

Second, the multigroup CFA model requires at least partial invariance, in that at least two items exhibit invariance across all countries to make valid cross-country comparisons (Steenkamp and Baumgartner 1998). It is not at all guaranteed that at least two items are invariant, and this constraint becomes ever more problematic to fulfill the larger the number of countries in one's study (Baumgartner 2004).

The purpose of the present paper is to introduce a new cross-national measurement model that addresses both limitations of multiple-group CFA. The model is based on item response theory (IRT; Lord and Novick 1968; Samejima 1969). Our model recognizes the ordinal nature of the rating scale, incorporates scale usage, and allows for fully non-invariant item parameters across countries. Although our model allows assessment of measurement invariance for diagnostic purposes, measurement invariance is *not* needed to make meaningful cross-national comparisons.

The remainder of the chapter is as follows. First, we review the cross-national measurement invariance literature based on CFA. Next, we introduce our IRT model. Subsequently, we conduct a simulation study to assess the ability of the model to recover its parameter estimates as well country means and variances. Then, we provide an empirical application of our model, involving an important consumer behavior construct, viz., consumer susceptibility to normative influence (SNI) (Bearden, Netemeyer, and Teel 1989), using samples from 11 countries on four continents. We compare the results with the results obtained with multigroup CFA and show that the latter leads to erroneous substantive conclusions. Finally, we present conclusions, limitations, and issues for future research.

II.2 MULTIGROUP CFA MODEL

In the CFA model, the relationship between an observed variable and a latent construct is modeled as (Steenkamp and Baumgartner 1998):[1]

$$x_{ik}^g = \tau_k^g + \lambda_k^g \xi_i^g + \delta_{ik}^g \quad (1)$$

where x_{ik}^g is the observed response to item k (k=1,…,K) for respondent i in country g (with i=1,…,N_g and g=1,…,G) , λ_k^g is the slope (or "factor loading") of the regression of x_{ik}^g on the value of latent construct for respondent i in country g, ξ_i^g , and τ_k^g indicates the expected value of x_{ik}^g when ξ_i^g =0. The model can also be written as $x_i^g = \tau^g + \Lambda^g \xi_i^g + \delta_i^g$, where x_i^g is a K×1 vector of observed variables in country g, δ_i^g is a K×1 vector of errors of measurement, τ^g is a K×1 vector of item intercepts, and Λ^g is a K×1 vector of factor loadings. Assuming that the measurement errors have zero means, the expectation of x_i^g can be written as $E(x_i^g) = \tau^g + \Lambda^g \kappa^g$, where κ^g is the latent mean of the construct. The variance-covariance matrix among the observed variables x_i^g can be expressed as $V(x_i^g) = \Sigma^g = \Lambda^g \Phi^g \Lambda^{g\prime} + \Theta^g$. In this formula, Φ^g is the variance of the latent construct and Θ^g is the (usually diagonal) matrix of measurement error variances.

To identify the multiple-group CFA model, two constraints are necessary (Steenkamp and Baumgartner 1998). First, it is necessary to assign a unit of measurement to the latent construct.

[1] For comparability with the IRT specification, we assume a single construct. Consistent with usual applications of the multigroup CFA model, and without loss of generality, we assume that the number of items is equal across countries. See Baumgartner and Steenkamp (1998) for an extension of the multigroup CFA model that accommodates varying numbers of items across countries.

Although there are various ways to do this, the most common approach is to constrain the factor loading of one item (referred to as the marker item) to unity in all countries. Only items that have the same factor loading across countries (i.e., are metrically invariant) may be selected as marker item. Second, the origin of the scale needs to be identified. Usually, researchers fix the intercept of a latent variable's marker item to zero in each country, so that the mean of the latent variable is equated to the mean of its marker variable. Alternatively, researchers can fix the latent mean at zero in one country and constrain one intercept per factor to be invariant across countries. This item should have invariant factor loadings across countries, which can be checked using empirical criteria such as modification indices and expected parameter changes.

Levels of Invariance

Several tests of cross-national measurement invariance are performed as a prerequisite to conducting comparisons across countries. These tests are *necessary* in CFA because valid cross-country comparisons require that the scale of the latent variable be the same across countries. Steenkamp and Baumgartner (1998) recommend the use of hierarchical nested models in which the fit statistics of an unconstrained invariance model are examined and compared with the fit statistics of a constrained invariance model by means of a chi-square difference test, which is a likelihood ratio test. Apart from standard chi-square difference tests, the use of fit indexes such as CFI, TLI, and RMSEA is recommended. The type of invariance in CFA-based models that is required generally depends on the goals of the study (Steenkamp and Baumgartner 1998). Configural invariance is necessary when the goal is to explore the basic structure of the construct across cultures. Configural invariance is supported if the specified model fits the data well, and all factor loadings are significantly and substantially different from zero.

Metric invariance provides a stronger test of invariance by introducing the concept of equal metrics or scale intervals across countries. Since the factor loadings carry the information about how changes in latent scores relate to changes in observed scores, metric invariance can be tested by constraining the loadings to be the same across countries. Metric invariance (equality of factor loadings) of at least two items is required to compare structural relationships between constructs (Byrne et al. 1989; Steenkamp and Baumgartner 1998). Although one formally only needs one invariant item, an additional invariant item is necessary because of exact identification in case of a single invariant item (any change of metric in the factor loading can be compensated for by

change in the metric of the latent construct). To test the item's invariance, an overidentified model is necessary with another invariant item.

Consumer researchers are often interested in comparing the means on the construct across countries. In order for such comparisons to be meaningful, scalar invariance (equality of intercepts) of the items is required (Meredith 1993). Scalar invariance addresses the question whether there is consistency between cross-national differences in latent means and cross-national differences in observed means. Even if an item measures the latent variable with equivalent metrics in different countries (metric invariance), scores on that item can still be systematically upward or downward biased. Meredith (1995) refers to this as additive bias. Comparisons of country means based on such additively biased items is meaningless unless this bias is removed from the data (Meredith 1993). Scalar invariance of at least two items that also exhibit metric invariance is necessary to conduct valid cross-national comparisons in construct means (Steenkamp and Baumgartner 1998), for the same reason as for metric invariance.

Limitations of CFA

The multigroup CFA framework has several important limitations. First, testing for partial invariance is generally an exploratory post-hoc method, subject to capitalization on chance. MacCallum, Roznowski, and Necowitz (1992) recommend that the number of model modifications should be kept low and only those respecifications that correct for relatively severe problems of model fit should be introduced. In addition, if there are few invariant items, the usual tests for differential item functioning may identify an invariant item as being noninvariant due to the fact that the model also tries to fit the other noninvariant items (Holland and Wainer 1993).

Second, to make substantive comparisons, at least two items should exhibit invariance across countries. This requirement is independent of scale length. But when the measurement instrument consists of only few items, or when the number of countries increases, this requirement is likely to be problematic (Baumgartner 2004). When measurement invariance is not satisfied, subgroups of countries have to be found that are measurement invariant (Welkenhuysen-Gijbels, Billiet, and Cambré 2003). However, researchers usually want to compare all countries.

Third, multigroup CFA does not recognize the ordinal nature of the rating scale. Recent simulation studies have shown that ignoring the ordinal nature of the data is problematic in multi-group research (Lubke and Muthén 2004). The CFA methodology assumes that the observed data is multivariate normally distributed, and therefore, tests of measurement invariance focus on the

regression intercepts τ_k^g, and factor loadings λ_k^g. However, the set of parameters required to achieve measurement invariance across countries is different for ordinal data. Although there are multiple ways to conceptualize ordinal data, a common data generating mechanism starts with an unobserved continuous outcome, and states that a response category is chosen above a lower category if the continuous latent variable exceeds a certain threshold. These thresholds are not modeled in CFA. As a result, measurement invariance tests based on the CFA methodology can indicate that measurement invariance is satisfied, when it is not, and vice versa, complicating cross-national comparisons of the latent construct (Lubke and Muthén 2004). However, these thresholds can be modeled by IRT models for polytomous (ordinal) data.

II.3 IRT MODEL

Below, we describe the IRT approach. We start with an overview of the general aspects of IRT for polytomous data. Although IRT models have been popular for dichotomous items, Samejima (1969, 1972) extended IRT models to polytomous items with multiple ordered response categories. Next, we discuss the traditional multigroup IRT model and how the different countries can be linked together so that the latent variable is measured on the same scale across countries. Like CFA, previous multigroup IRT models require certain levels of invariance to allow for valid country comparisons (May 2005; Meade and Lautenschlager 2004).

Subsequently, our new IRT model is introduced. Our model takes not only mean differences into account (like Holland and Wainer 1993) but also scale-usage differences. Moreover, our model does not require cross-national measurement invariance for valid country comparisons. Nevertheless, invariance tests may be useful for *diagnostic* purposes, e.g., to better understand response behavior in different countries (cf. Wong et al. 2003). Hence, we conclude this section with a discussion on invariance tests in the context of our IRT model.

IRT for ordinal response data

IRT models posit a reflective (cf. Jarvis, MacKenzie, and Podsakoff 2003), nonlinear relationship between an underlying latent construct and the observed score at the item level. Despite many advantages over the classical test theory paradigm, IRT models have been conspicuously absent from the marketing literature (see Balasubramanian and Kamakura 1989, Singh, Howell, and Rhoads 1990, Bechtel 1985 for exceptions).

IRT has mainly been used in marketing for adaptive surveys, i.e., surveys in which questions are adapted based on an individual's previous responses (see Balasubramanian and Kamakura

1989 for an example of the tailored interview process). IRT models for ordinal data are conceptually somewhat similar to ordinal/limited dependent data models in the econometrics literature (Franses and Paap 2001; Greene 2003; Maddala 1983). However, in IRT models, there are *multiple* ordinal items that reflect a latent construct, while for the ordinal data models in econometrics, there is usually a single ordinal variable.

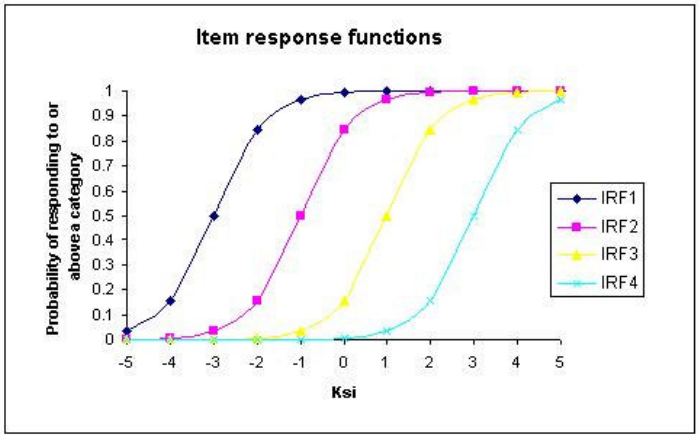
The item response function (IRF) is the nonlinear monotonic function that accounts for the relationship between a respondent's value for latent variable ξ_i^g and the probability of a particular response on an item. Local independence is assumed, i.e., there is no relationship between the respondent's item responses given ξ_i^g. Polytomous IRT models deal with responses to items measured on *C* ordered response categories. For example, the 5-point Likert item commonly used in marketing research has *C*=5 ordered response options, such as "Strongly disagree", "Disagree", "Neither agree nor disagree", "Agree", "Strongly Agree". In a cross-national setting with *G* countries, the graded response model (GRM) for country *g* is given by:

$$\begin{aligned} P(x_{ik}^g = c \mid \xi_i^g, a_k^g, \gamma_{k,c}^g, \gamma_{k,c-1}^g) &= \Phi(a_k^g \xi_i^g - \gamma_{k,c-1}^g) - \Phi(a_k^g \xi_i^g - \gamma_{k,c}^g) \\ &= IRF_{k,c-1}^g - IRF_{k,c}^g \end{aligned} \tag{2}$$

where Φ(.) is the standard normal cumulative distribution function. This model specifies the conditional probability of a person *i* in country *g*, responding in a category *c* (*c*=1,…,*C*) for item *k*, as the probability of responding above *c*-1, minus the probability of responding above *c*. The parameter a_k^g is called the *discrimination* parameter for item *k* in country *g*, and is conceptually similar to the factor loading λ_k^g in the CFA setting, in that it represents the strength of the relationship between the latent variable and item responses (Reise, Widaman, and Pugh 1993). Useful items have a large discrimination parameter.

The thresholds $\gamma_{k,c}^g$ are measured on the same scale as ξ_i^g and determine the *difficulty* of responding above a certain response category *c*. The threshold $\gamma_{k,c}^g$ is defined as the value on the ξ_i^g scale so that the probability of responding above a value *c* is 0.5, for *c*=1,…,*C*-1. In (2), one can put $\gamma_{k,0}^g = -\infty, \gamma_{k,C}^g = \infty$, so that only the thresholds for the categories 1 through *C*-1 need to be considered. For illustration, we draw the IRFs for an item *k* on a 5-point Likert scale in country *g* with $a_k^g = 1, \gamma_{k1}^g = -3, \gamma_{k2}^g = -1, \gamma_{k3}^g = 1, \gamma_{k4}^g = 3$ in figure 1.

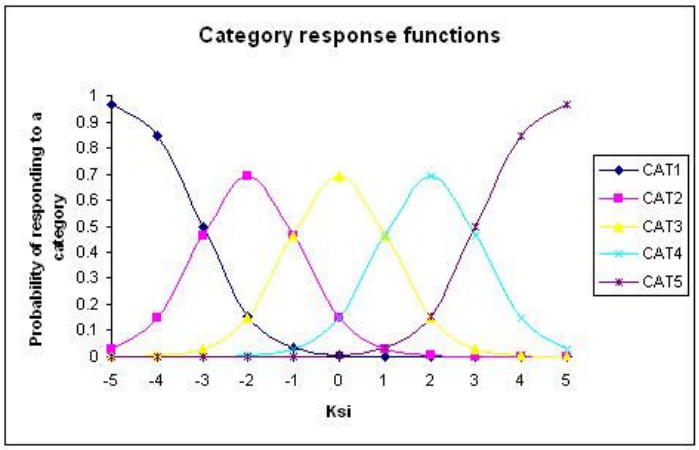
FIGURE 1
ILLUSTRATIVE ITEM RESPONSE FUNCTIONS



The IRF curves display the probability of responding above a certain rating scale point as a function of a person's position on the underlying latent construct. Only four curves are shown, as by definition, the probability of responding above c=5 is 0. For instance, IRF_2 graphs the probability of responding above c=2 for varying levels of ξ_i^g. Suppose a respondent has $\xi_i^g = -2$, then s/he has a probability of 0.85 of responding above c=1, a probability of 0.15 of scoring above c=2, and a probability of almost 0 to respond above c=3,4,5. Thus, c=2 is the most likely outcome.

The IRFs, displayed in figure 1, can be used to compute the probability of a category response by equation (2). The category response functions (CRF) for the item with the item parameters given above are displayed in figure 2. Note that the values for γcorrespond to the intersection of two successive CRFs. For instance, for $\xi_i^g = \gamma_{k1}^g = -3$, the CRFs for categories 1 and 2 intersect. Further, it can be seen that a respondent with $\xi_i^g = -2$ has a probability of 0.15 to respond c=1, a probability of 0.69 to respond c=2, a probability of 0.15 to answer c=3, a probability of 0.01 to respond c=4, and a probability of 0 to respond c=5. Across all categories, the response probabilities within respondents sum to 1.

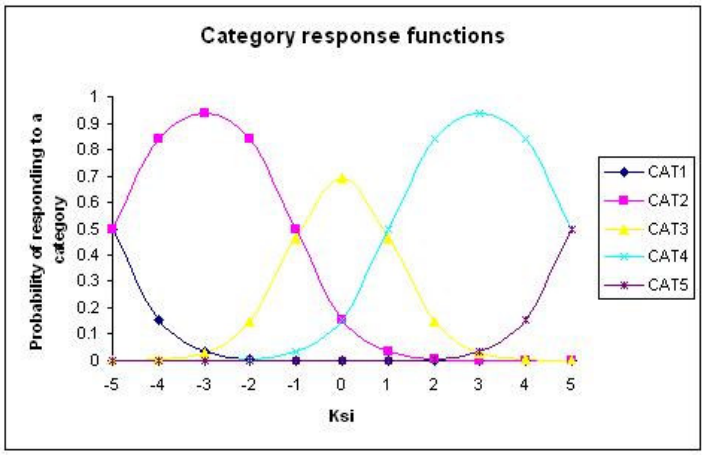
FIGURE 2
ILLUSTRATIVE CATEGORY REPONSE FUNCTIONS



Cross-national differences in scale usage

An important advantage of using IRT is that the ordinal nature of the rating scale, and thus rating scale usage (Rossi, Gilula, and Allenby 2001), is taken into account. Indeed, it has been shown that countries differ in rating scale usage such as extreme responding and yea-saying, and that this may seriously bias one's substantive findings (Baumgartner and Steenkamp 2001). To illustrate how IRT accounts for scale usage, consider a country where respondents are reluctant to use the ends of the rating scale for a particular item *k*. In this case, the outer category thresholds would be larger in absolute sense, increasing the probability of middle responses, while simultaneously reducing the odds of an extreme response. This process is illustrated in figure 3, where we set $a_k^g = 1, \gamma_{k1}^g = -5, \gamma_{k2}^g = -1, \gamma_{k3}^g = 1, \ \gamma_{k4}^g = 5$.

FIGURE 3
CRFs FOR COUNTRY WITH LOW TENDENCY TO EXHIBIT EXTREME RESPONDING



Comparing figures 2 and 3, it can be seen that, for the same values of ξ_i^g, the probability of responding in categories 2 or 4 becomes larger, while the odds of responding in categories 1 and 5 are very small. So, although the latent score is the same, scale usage in a country on item *k* determines the response on the rating scale. Analogously, if a country is high on yea-saying on a particular item, the thresholds for categories 4 and 5 become smaller.[2]

Identification and linking groups

As in the CFA models, two issues need to be addressed. First, the IRT model needs identification restrictions, since the latent variable has no definite origin. Second, we specified a separate IRT model for each country *g*, without linking the *G* models. To make meaningful substantive comparisons across countries, the IRT models should be linked to ensure that the numerical values for the latent variable across countries are on the same measurement scale. If the scores on the latent variables are not on the same scale, differences between countries in mean levels or in structural relations of the construct with other constructs might be spurious.

To scale the latent variable, single-group IRT models usually specify a distribution for the latent variable with mean zero and variance one. It is also possible to use item parameter restrictions to fix the scale of the latent variable. In cross-national settings, mere standardization in each country without linking the countries renders item parameters incomparable across groups. An approach that has been commonly used in previous research is fixing the mean to zero and variance to one in the reference group, freely estimating the mean in the other groups, while fixing the variance in the other groups to some value determined by a trial and error analysis (Reise et al. 1993). Thus, the variance of the latent variable is not estimated freely across groups.

If no further restrictions are employed, and all items are estimated freely across countries, the model is identified, but the metric for ξ is not common across countries. Therefore, additional restrictions are necessary to link the groups. Multigroup IRT models to date impose invariance restrictions on the item parameters (May 2005; Meade and Lautenschlager 2004; Reise et al. 1993), to make the scale common across countries. A minimum identifying constraint is that for at least one anchor item, the item parameters are invariant across countries. In that case, calibrating the rest of the items together with the anchor item results in a common scale for ξ

[2] We note that the bias should not be completely uniform across items (cf. Thissen, Steinberg, and Gerrard 1986). Recent evidence indeed shows that the bias is different for different items (De Jong et al. 2007).

across countries. Note that this still requires an item that is *known* (or *assumed*) to be fully invariant across countries.

Hierarchical IRT

We propose a new approach to identify and link groups. We first model differential item functioning, including scale usage differences across countries using a random-effects ANOVA formulation.[3] We model random item parameter variation as:

$$\gamma_{k,c}^{g} = \gamma_{k,c} + e_{k,c}^{g},\ e_{k,c}^{g} \sim N\left(0, \sigma_{\gamma_k}^2\right) \text{ for } c = 1,\ldots,C-1,\ \gamma_{k,1}^{g} \le \ldots \le \gamma_{k,C-1}^{g} \quad (3)$$

$$a_k^g = a_k + r_k^g,\ r_k^g \sim N(0, \sigma_{a_k}^2),\ a_k^g \in (0, A] \quad (4)$$

Equation (3) implies that each scale threshold $\gamma_{k,c}^{g}$ for a particular item *k* in country *g* is modeled as an overall mean threshold $\gamma_{k,c}$, plus a country-specific deviation $e_{k,c}^{g}$. Analogously, equation (4) posits that the discrimination parameter a_k^g is the sum of an overall mean discrimination parameter and country-specific deviation (and the discrimination parameter should be positive, and in a bounded interval; *A* is a positive number). The variances of the threshold and discrimination parameters are allowed to vary across items. In our model, there is no longer a need to classify items as being invariant or non-invariant.

When calibrating the item parameters, it is important to model the heterogeneity in the latent variable. Thus, a hierarchical structure is imposed on ξ_i^g by letting:

$$\xi_i^g = \xi^g + \upsilon_i^g,\ \upsilon_i^g \sim N(0, \sigma_g^2) \quad (5)$$

$$\xi^g \sim N(\xi, \tau^2) \quad (6)$$

In other words, the position on the latent scale for respondent *i* in country *g* is sampled from the country average ξ^g with variance σ_g^2. The country average is drawn from a distribution with average ξ and variance τ^2. This random-effects approach for the latent variable is consistent with recent work on multilevel latent variable modeling in psychometrics (Fox and Glas 2001; 2003).

When the random-effects structure for item parameters is combined with the random-effects structure for the latent variable, there is an identification problem. Each country mean can be shifted by changing the country mean, ξ^g, as well as by uniformly shifting the country-specific

[3] Random-effects IRT specifications for binary response data that allow for random item variation were proposed by Janssen et al. (2000). However, in their article, the grouping was based on items, rather than on countries. In addition, the data in our setting is polytomous.

threshold values, $\gamma_{k,c}^{g}\ \forall k$. We fix the mean of country *g*, by restricting the country-specific threshold parameters in such a way that a common shift of these threshold values is not possible. This can be done by setting $\sum_{k}\gamma_{k,3}^{g}=0$. Since this restriction is applied in each country, the mean of the metric of the latent variable is identified via restrictions on the country-specific threshold parameters.

Analogously, the country variances can be shifted both by σ_{g}^{2}, as well as by uniform changes in the discrimination parameters (that is, setting $a_{k,new}^{g}=a_{k}^{g}\times d\ \forall k$). To fix the country-specific variances, we need to impose a restriction that a common shift of country-specific discrimination parameters is not possible, which can be done by imposing that across items, the product of the discrimination parameters equals one in each country *g* ($\prod_{k}a_{k}^{g}=1\ \forall g$). Hence, both the mean and variance of the latent variable in each country is fixed, and the scale remains common due to the simultaneous calibration of the multilevel structures for item parameters and latent variable.

The hierarchical Bayesian framework allows for borrowing of strength across countries. Previous multigroup CFA research models country means/variances, factor loadings, and item intercepts as separate parameters, without borrowing strength across countries. The same holds for previous multigroup IRT research (i.e., discrimination, threshold, country mean and variance are modeled as separate parameters). By borrowing strength, we can place less restrictive assumptions on measurement invariance, while retaining the possibility to let the various parameters fluctuate across countries. In table 1, we present an overview table to contrast our specification with previous multigroup IRT and CFA models.

Table 1
OVERVIEW OF MULTIGROUP LATENT VARIABLE MODELS

	Latent variable heterogeneity (separate country means and variances)	**Random effects structure for item parameters**	**Invariance requirements on items**
Previous multigroup IRT approaches	Yes (separate means and variances)	No	Yes
Multigroup CFA approach	Yes (separate means and variances)	No	Yes
This chapter	Yes (random-effects structure)	Yes	No

IRT estimation

Both marginal maximum likelihood techniques and Bayesian techniques have been used in previous multigroup IRT research (e.g. Bolt et al. 2004; May 2005; Meade and Lautenschlager 2004; Reise et al. 1993; Thissen, Steinberg, and Wainer 1988; 1993). We use Bayesian techniques to estimate the model parameters. The Bayesian approach requires the specification of a full probability model. To obtain draws from the posterior distribution, we use a data-augmented Gibbs sampler (Tanner and Wong 1987) with a Metropolis-Hastings step for the threshold parameters. Estimation details, including the priors are described in Appendix A.

IRT-based invariance testing

Although our hierarchical IRT model does not require invariance across countries to make substantive comparisons, we describe the various levels of invariance that can be imposed on the IRT model below. These tests of invariance would mainly serve as a diagnostic tool, e.g., to see whether or not items are culturally biased, or to investigate other aspects of either the measurement or the structural model (e.g., Raju, Byrne, and Laffitte 2002; Reise et al. 1993; Wong et al. 2003). Previous research has only considered invariance of the discrimination parameters (7) and the threshold parameters (8), and not the invariance of the latent variable variance because it could not be freely estimated (see Bolt et al. 2004; Meade and Lautenschlager 2004; Reise et al. 1993). Our model also allows tests of factor variance invariance, i.e., invariance of the latent variable variance across countries. Full item parameter invariance is satisfied if for all items k:

$$a_k^1 = a_k^2 = \ldots = a_k^G \tag{7}$$

$$\begin{aligned} &\gamma_{k1}^1 = \gamma_{k1}^2 = \ldots = \gamma_{k1}^G \\ &\vdots \\ &\gamma_{kC-1}^1 = \gamma_{kC-1}^2 = \ldots = \gamma_{kC-1}^G \end{aligned} \tag{8}$$

We assess item parameter invariance via Bayes factors (Kass and Raftery 1995; Newton and Raftery 1994). The proposed model, M_1, with varying item parameters is compared to a model, M_2, with fixed item parameters across countries. The Bayes factor is the ratio of the two marginal likelihoods, the marginal likelihood of the data under model M_1 and M_2. Large values of the Bayes factor BF_{12} indicate a preference for model M_1. The Bayes factors are computed via importance sampling (Newton and Raftery 1994). Bayesian inferences regarding the variances of the item parameters are based on their marginal posterior distributions. Factor variance invariance

is tested, using a Bayesian parallel to Bartlett's test of equal variances, while means can be compared using a Bayesian ANOVA. We refer to appendix B for more details.

II.4 SIMULATION STUDY

The purpose of the simulation study was to examine: 1) whether the country-specific discrimination and threshold parameters can be recovered, and 2) whether the country-specific latent means and variances can be recovered, under 3) the condition that no measurement invariance constraints are imposed on the model. For this purpose, we generate a dataset with *no* cross-nationally invariant items. That is, there is variation in the values of the item parameters for each item across countries. The multigroup CFA approach would not be feasible in this case, because metric invariance is not satisfied for any item. In addition, mean comparisons would not be possible due to differences in scale usage for all items. However, as shown below, the IRT model does allow researchers to conduct substantive cross-national comparisons, even though measurement invariance is not fulfilled, because all respondents in all countries are calibrated on the same latent scale.

Data was generated according to the random effects specifications in (3) to (6) with 10 countries, 1,000 respondents per country. There are 10 items, and each item is measured on a 4-point Likert scale. In the simulation design, both the discrimination parameters and the threshold parameters are generated so that they vary randomly across nations. For the threshold parameters, the standard deviations range from 0.45 to 0.65 across items k, while for the discrimination parameters, standard deviations range from 0.15 to 0.40 across items k.

For the item parameters, we present scatter plots of estimated vs. true parameters in figure 3. The true values are accurately recovered by the model. This applies to both the discrimination parameters, and the threshold parameters. Regressing the estimated discrimination parameters on the true discrimination parameters results in a regression slope of 0.97, where the 95% confidence interval includes 1, and an R^2 of 0.91. Similarly, a regression of estimated threshold parameters on true threshold parameters yields a regression slope of 0.99, with a 95% confidence interval that includes 1, and an R^2 of 0.99.

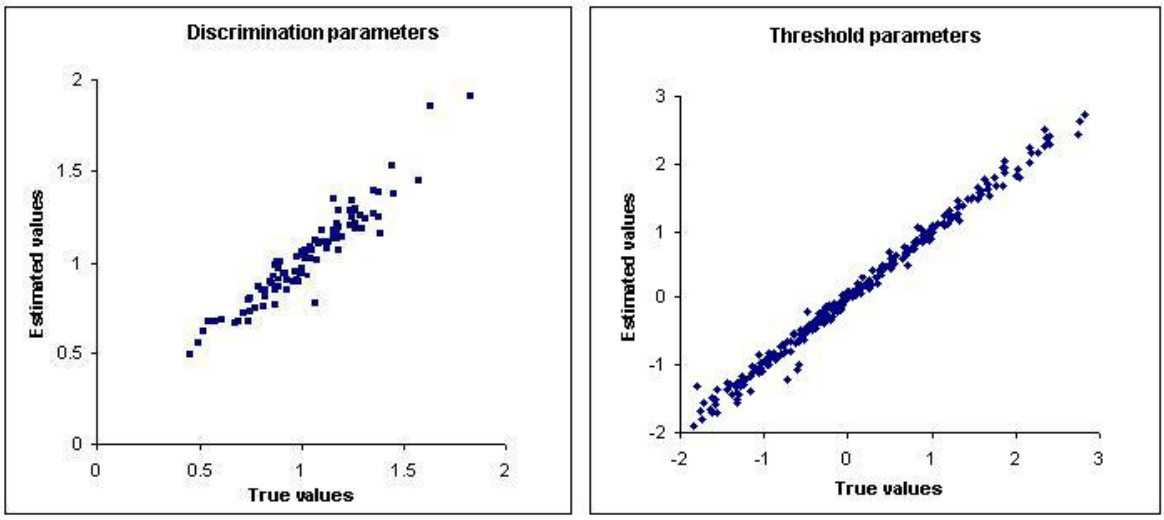
In table 2, we present the true versus the estimated country means and variances. As can be seen, parameter recovery is accurate. On average, estimated country means differ only 1.33% from the true country means, while the difference in the country latent score variances is 5.68% due to sampling error. Thus, the simulation study revealed that our model was able to accurately

recover country-specific means, variances, discrimination, and threshold parameters, although there was not a single invariant item.

Table 2
TRUE AND ESTIMATED COUNTRY MEANS AND VARIANCES

	Country mean		**Country variance**	
	True value	Estimated value	True value	Estimated value
Country 1	-0.299	-0.323	0.332	0.314
Country 2	2.399	2.274	0.645	0.510
Country 3	0.154	0.161	1.212	1.230
Country 4	-0.823	-0.800	0.889	0.870
Country 5	-0.273	-0.241	0.461	0.484
Country 6	-0.121	-0.131	0.593	0.598
Country 7	0.271	0.276	0.466	0.461
Country 8	-0.862	-0.812	1.467	1.234
Country 9	0.321	0.303	1.381	1.329
Country 10	1.688	1.607	1.910	1.626

FIGURE 4
ESTIMATED VS. TRUE ITEM PARAMETERS



II.5 APPLICATION TO CONSUMER SUSCEPTIBILITY TO NORMATIVE INFLUENCE

Consumer Susceptibility to Normative Influence

We apply our model to real cross-national data on consumers' susceptibility to normative influence. Consumers differ in the degree to which they are influenced in their attitudes and behavior by the norms of the social system, i.e., in their susceptibility to normative influence (SNI). The consumer behavior literature recognizes that individuals' behavior cannot be fully

understood unless consideration is given to the effect of a person's SNI on development of attitudes, aspirations, and behavior (Bearden et al. 1989). SNI has been linked to various aspects of consumer behavior such as attitudes toward brands (Batra et al. 2000), advertising (Mangleburg and Bristol 1998), and consumption alternatives resulting from globalization (Alden, Steenkamp, and Batra 2006), consumer confidence (Bearden, Netemeyer, and Teel 1990), protective self-presentation efforts (Wooten and Reed 2004), purchase of new products (Steenkamp and Gielens 2003), and consumer boycotts (Sen, Gürhan-Canli, and Morwitz 2001), among others. Consumers high on SNI tend to be lower on self-esteem, and higher on motivation to comply with the expectations of others, interpersonal orientation, and attention to social comparison information (Bearden et al. 1989, 1990). Most SNI research has been carried out in the U.S., despite the obvious importance of normative influences in other, e.g., collectivistic cultures (Kagitcibasi 1997).

Consumers in some countries may be on average higher on SNI than consumers in other countries, due to systematic differences in the national cultural environment. Culture is a powerful force shaping people's perceptions, dispositions, and behaviors (Triandis 1989) and is reflected in "persistent preferences for specific social processes over others" (Tse et al. 1988, p. 82). We expect that *national-cultural individualism* is especially important for understanding cross-national differences in SNI. National-cultural individualism pertains to the degree to which people in a country prefer to act as individuals rather than as members of a group. Collectivistic cultures are conformity oriented, and show a higher degree of group behavior and concern to promote their continued existence.

The conformity pressure and the close-knit social structure will also result in less divergence in attitudes compared to individualistic countries because divergence in attitudes is less valued in collectivistic cultures (Kagitcibasi 1997). In individualistic societies, the social fabric and group norms are much looser. People tend not to follow social norms but rather make decisions and initiate behaviors independently of others (Roth 1995). A child already learns very early to think of itself as "I" instead of as part of "we" while the converse holds for collectivistic societies (Hofstede 2001).

Thus, consumer cultural theory suggests that consumers living in individualistic countries 1) are on average lower on SNI and 2) exhibit more divergence in their SNI attitudes compared to consumers living in collectivistic countries.

Method

The data collection was part of a large global study on consumer attitudes. Data collection was carried out by two global marketing research agencies, GfK and Taylor Nelson Sofres. The total sample for the present application comprises 5,484 respondents in 11 countries, from four continents, viz., Brazil, China, France, Japan, the Netherlands, Poland, Russia, Spain, Taiwan, Thailand, and the U.S. The number of respondents per country varies between 396 (Taiwan, Russia) and 546 (Spain). Given the importance of the U.S., the marketing research agencies decided to put an additional effort in sampling respondents from the U.S. Therefore, the number of respondents for the U.S. is 1,181. The samples in each country were drawn so as to be broadly representative of the total population in terms of region, age, education and gender.

For the U.S., France, Spain, Japan, and the Netherlands, a web survey was used in which respondents in script panels of GfK and Taylor Nelson Sofres were invited to participate in the project by an e-mail in the local language. The e-mail contained a short description, a hyperlink to go to the survey, and an estimate of the time needed to complete the survey. At the end of the fieldwork period, respondents were paid by the local subsidiary of the global marketing research agencies.

For China and Russia, Internet surveys were administered using mall intercepts. For the mall intercepts, the first step was to select multiple regions/locations for the fieldwork. Next, a space was rented which had an Internet connection for 2-5 PCs or laptops (e.g., Internet cafes, subsidiaries of offices, test halls for product tests) and offered the possibility to 'intercept' appropriate shoppers/respondents walking in the street using street recruiters.

Finally, in Brazil, Taiwan, and Thailand, a hard-copy survey instrument was used, which was also administered in mall intercepts. The hard-copy tool was designed so that the layout was exactly the same as in the Internet survey. The staff for the hard-copy mall intercepts generally consisted of a field supervisor, responsible for answering respondents' questions and monitoring the whole fieldwork, a logical controller, responsible for logical control and sampling quotas, and 3-4 street recruiters.

SNI was measured using the 8-item scale developed by Bearden et al. (1989). This unidimensional scale has been extensively validated, and is the most frequently used instrument to measure SNI. The items are listed in table 3. The SNI items were translated into all local languages by professional agencies. Next, the translated items were backtranslated into English,

using native speakers from the local countries. In each survey, modifications were made based on discussions between the backtranslators, one of the authors, and the headquarters of the marketing research agencies to maintain consistency in changes across all countries. All items were measured on a 5-point Likert scale.

We randomly dispersed the items throughout the questionnaire. There is a debate in the literature whether items pertaining to the same construct should be randomized in the questionnaire or grouped together (Bradlow and Fitzsimons 2001). The idea behind randomization is to hide the purpose of the instrument from the respondent, thus reducing response biases such as a desire to look good to others (e.g., evaluation apprehension) and to oneself (cognitive consistency and ego defense mechanisms). But randomization may also reduce reliability (Bradlow and Fitzsimons 2001). However, low reliability was not an issue in our study as in all countries, the reliability of SNI exceeded the .70 cutoff.

We used Bayesian routines programmed in Fortran for the IRT model. The Bayesian routines are linked to S-Plus®.[4]

Table 3
SNI ITEMS

Item	Description
Item 1	If I want to be like someone, I often try to buy the same brands that they buy.
Item 2	It is important that others like the products and brands I buy.
Item 3	I rarely purchase the latest fashion styles until I am sure my friends approve of them.
Item 4	I often identify with other people by purchasing the same products and brands they purchase.
Item 5	When buying products, I generally purchase those brands that I think others will approve of.
Item 6	I like to know what brands and products make good impressions on others.
Item 7	If other people can see me using a product, I often purchase the brand they expect me to buy.
Item 8	I achieve a sense of belonging by purchasing the same products and brands that others purchase.

IRT results

We estimate our hierarchical IRT model using MCMC techniques. Convergence of the chains is checked using the CODA software (Best, Cowles, and Vines 1995), which contains multiple standard convergence diagnostics. Multiple chains for different starting values were run, and

[4] The software to estimate this model can be obtained from the authors. Other researchers can easily estimate their own models by adapting the number of items and countries. The number of countries groups matters for the choice of a fixed vs. random effects approach.

convergence occurred quickly for most parameters. We ran multiple chains for different starting values. The first 10,000 iterations are discarded, and 30,000 posterior draws are subsequently used to estimate the model parameters. We present the results of the model, and in the next section we consider a number of invariance tests for diagnostic purposes.

Table 4 presents the estimation results for the discrimination parameters. The items generally discriminate well for each country, given the posterior distribution of the latent variable. Table 4 further shows that there are substantial cross-national differences in the discimination power of any specific item.

On average, item 3 has a lower discrimination parameter than the other items, indicating that this item measures the SNI construct somewhat less well than the other items. Interestingly, it is the only item that refers to a specific consumption domain (fashion styles). From a scale reliability point of view (although not necessarily from a content/predictive validity standpoint), items 5, 7 and 8 are on average the best items. These results are quite consistent across countries. Thus, if a researcher wants to use a maximally reliable short-form of SNI because 8 items is too much (cf. Burisch 1984), items 5, 7, and 8 would be prime candidates.[5]

Next, we turn to the threshold parameters. Since the items are measured on a 5-point scale, there are 4 thresholds per item. Thus, each country has 4×8 = 32 threshold parameters, so in total, there are 352 threshold parameters. As was the case for the discrimination parameters, there is substantial cross-national variation. For illustrative purposes, we plot the posterior means of the threshold parameters for item 6 in figure 5.

To illustrate the effect of the threshold parameters on the probability of responding to a certain Likert response category, we plot the CRFs for item 8 for Thailand and Russia in figure 6. Comparing Thailand and Russia, we see that for equal true scores, the probability of responding in categories 1 and 5 (i.e., "Strongly disagree" and "Strongly agree") is much smaller in Thailand than in Russia. Consider for instance a respondent with a moderately low latent SNI score of ξ=-1. In Thailand, this respondent has a probability of 0.24 to choose the response category 1, while in Russia, this probability is 0.66. Thus, for this item, there is a difference of 0.42 in the probability between Russian and Thai respondents in checking response category 1 on the 5-point scale, even though they hold the same underlying true opinion! On the other hand, Thai

[5] For the IRT model, it doesn't matter whether items 5, 7, and 8 are invariant. For CFA, we would need two items in the short scale to be invariant.

respondents with a latent SNI score of ξ=-1 have a vastly greater probability of checking response category 2 than Russian respondents with the same underlying score (0.69 versus 0.28, a difference of 0.41). A respondent with ξ=2 only has probability 0.31 to choose the response "Strongly agree" in Thailand, while this probability is 0.71 in Russia.

Summarizing, there is substantial evidence of differential item functioning across countries. The hierarchical IRT model accommodates these differences, and puts the estimates of the latent variable in different groups on the same scale. Furthermore, we can test whether countries differ significantly in their mean SNI score. We do this by computing a Bayesian ANOVA, based on an $F(10,5473)$-statistic (see appendix B). Indeed, countries differ in their mean score on SNI ($p<0.001$). The Bayesian Bartlett test for factor variance invariance shows that there are also cross-national differences in within-country heterogeneity on SNI ($p<0.001$). The heterogeneity in SNI scores is properly modeled by taking the hierarchical structure for the latent variable into account and by allowing for different within-country variances.

Table 4
DISCRIMINATION PARAMETERS FOR SNI SCALE

	Item 1	Item 2	Item 3	Item 4	Item 5	Item 6	Item 7	Item 8
France	0.862	0.654	0.582	1.260	1.272	1.171	1.526	1.089
Netherlands	0.794	0.826	0.585	1.231	1.328	1.087	1.150	1.292
Spain	0.883	0.710	0.894	0.946	1.312	0.895	1.265	1.287
China	1.028	1.036	0.644	1.299	1.078	0.703	1.320	1.152
Poland	0.931	0.881	0.276	1.246	1.420	1.101	1.581	1.512
Brazil	0.880	0.734	0.843	0.768	1.478	1.174	1.337	1.063
Thailand	0.845	0.814	0.524	1.309	1.244	1.033	1.232	1.381
Russia	0.879	1.227	0.403	1.106	1.413	1.265	0.855	1.418
USA	0.767	0.822	0.610	1.137	1.319	1.045	1.281	1.306
Taiwan	0.897	0.914	0.581	1.307	1.308	0.592	1.563	1.378
Japan	1.040	0.781	0.724	1.305	1.251	0.682	1.258	1.248

FIGURE 5
CROSS-NATIONAL VARIATION OF POSTERIOR MEAN THRESHOLD PARAMETERS FOR SNI ITEM 6

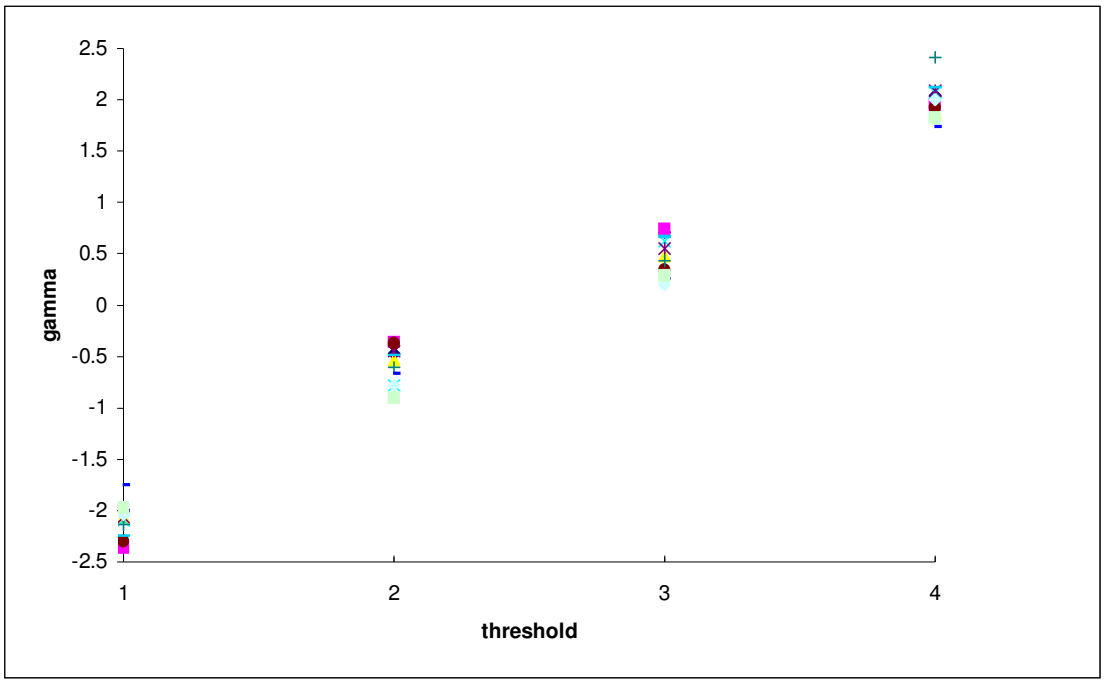
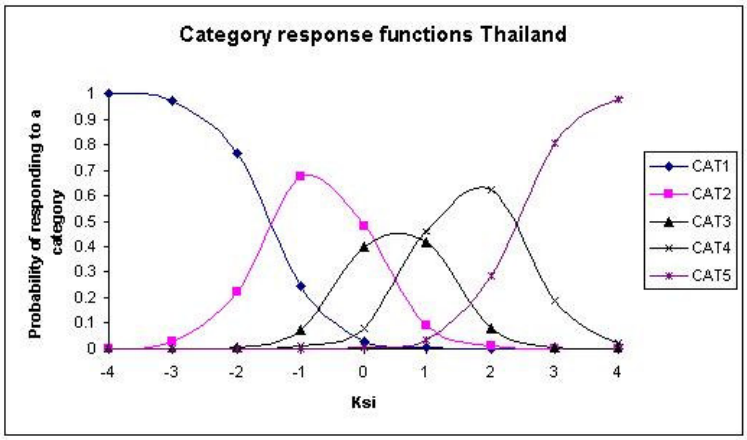
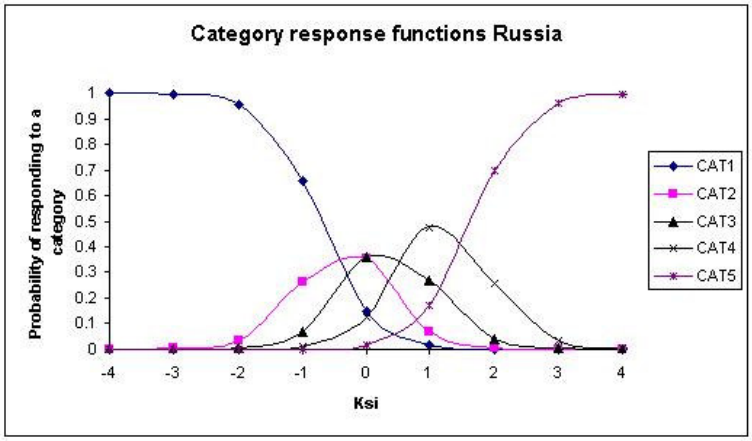
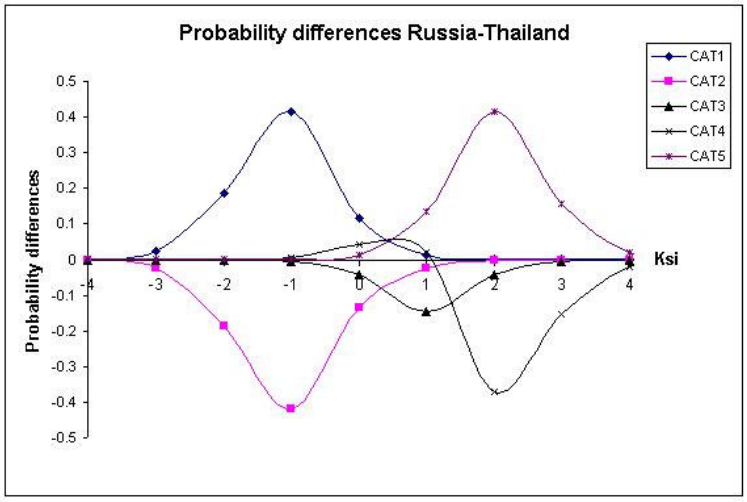


FIGURE 6
CRFS FOR ITEM 8







IRT-based invariance tests

Although our model does not require invariance of parameters across countries for valid cross-national comparisons, invariance tests are of interest for diagnostic purposes, i.e., to better understand response behavior for specific items and countries (e.g., Raju et al. 2002; Reise et al. 1993; Wong et al. 2003). We test the plausibility of several competing models using marginal log-likelihoods and Bayes factors (Kass and Raftery 1995). Three models are considered. The first model (M_1) has invariant discrimination and threshold parameters, i.e. $a_k^g = a_k \ \forall g$, and $\gamma_{kc}^g = \gamma_{kc}$, c=1,…,C-1 $\forall g$. The second model (M_2) relaxes all invariance constraints on the threshold parameters $\boldsymbol{\gamma}$(thus, only the discrimination parameters $\boldsymbol{a}$ are kept invariant across countries), and the third model (M_3), which is the most flexible one and for which the results are reported above, relaxes all invariance constraints (both on $\boldsymbol{a}$ and $\boldsymbol{\gamma}$). The marginal log-likelihoods and Bayes factors (assuming $P(M_1)=P(M_2)=P(M_3)$) of the different models vs. model M_3 all

indicate that the posterior probability of M_3 given the data (Berger and Delampady 1987) is much higher than the probability of models M_1 and M_2. Relaxing the invariance constraints on the discrimination parameters and on the threshold parameters yield a large improvement in fit.

The model comparison results are consistent with the earlier observation that there is substantial variation in the discrimination and threshold parameters. This indicates that a particular item does not perform equally well in different countries (i.e., does not discriminate equally well between respondents in different countries), and that there are substantial cross-national differences in response behavior on the 5-point rating scale.

CFA results

We estimated a one-factor model for the 11 countries, using LISREL. The configural invariance model specifies the same pattern of factor loadings across countries, and serves as a baseline model. We choose item 2 as the marker item (based on modification indices, this choice seemed best).[6] The fit of the configural invariance model is good (see table 5). Although the χ^2 was significant –which is not unexpected given the large sample size - other indicators exceeded conventional cutoff levels (Byrne, 1998): $\chi^2(220)=914.4$ ($p<0.001$), RMSEA=0.0791, CFI = 0.973, TLI=0.962. The within-country completely standardized loadings are relatively high. Of the 11x8=88 factor loadings, 38 standardized loadings exceed 0.6, and 49 loadings exceed 0.5. Based on these results, we conclude that the SNI scale exhibits configural invariance.

In the next step, we test for full metric invariance by constraining all factor loadings to be equal across countries. The fit of this model deteriorates substantially ($\Delta\chi^2(70)=343.4$, $p<0.001$). RMSEA and TLI, which both take fit and model parsimony into account deteriorate. In a recent extensive simulation study, Cheung and Rensvold (2002) found that ΔCFI is a particularly robust statistic for testing multigroup invariance constraints and reported that "a value of ΔCFI smaller than or equal to -.01 indicates that the null hypothesis of invariance should not be rejected" (Cheung and Rensvold 2002, p. 251). Since in our application, ΔCFI decreased by 0.019, we conclude that full metric invariance is not supported.

Examination of the modification indices (MIs) revealed that the deterioration in fit was largely due to a lack of invariance of four factor loadings, viz., the loadings of items 3 and 8 in Spain (MI=20.8, MI=31.2), and factor loadings for item 6 in Taiwan and China (MI=57.7,

MI=29.9). Item 2 displayed small (and non-significant) modification indices, so our choice of this marker item is justified. Freeing the loadings with high modification indices in those countries resulted in acceptable model fit. Although the change in chi-square is still significant ($\Delta\chi^2(66)=186.4$, $p<0.001$) RMSEA, and TLI improve compared to the configural invariance model, while the deterioration of CFA is below the 0.01 threshold. Thus, partial metric invariance is satisfied.

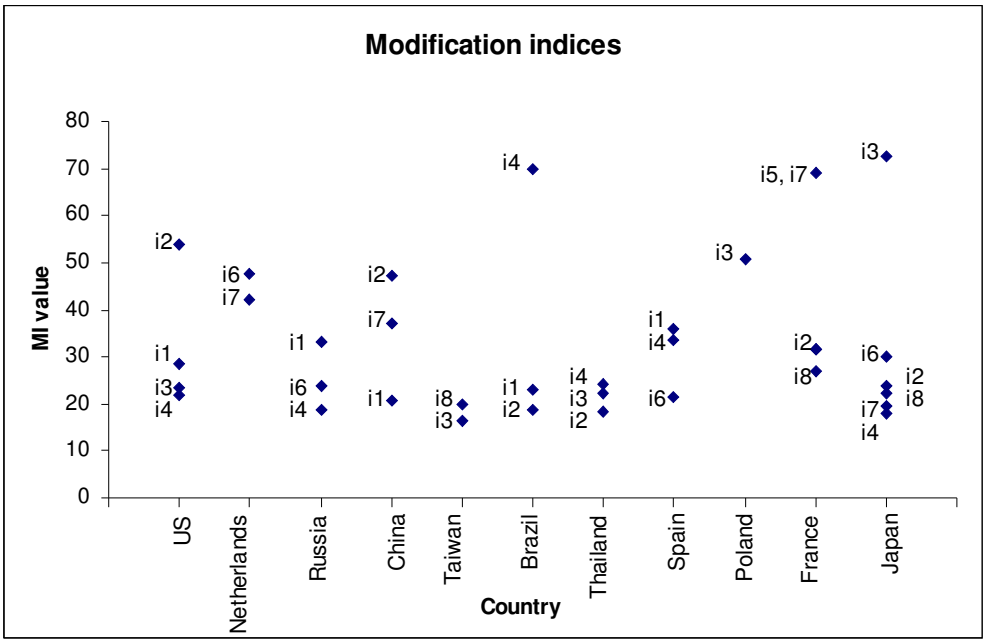
Next we tested scalar invariance for those factor loadings that are metrically invariant for the country in question (Steenkamp and Baumgartner 1998). Model fit deteriorated dramatically compared to the partial metric invariance model ($\Delta\chi^2(66) =1052.9$, $p<0.001$; ΔRMSEA = 0.0262; ΔCFI=-0.068; ΔTLI=-0.048). There are numerous large MIs for the item intercepts. We plot the largest MIs in figure 7.

Table 5
MULTI-COUNTRY CFA MODEL COMPARISONS FOR SNI SCALE

	χ^2	Df	RMSEA	CFI	TLI
Configural invariance	914.4	220	0.0791	0.952	0.933
Metric invariance	1257.8	290	0.0820	0.933	0.929
Final partial metric invariance	1100.8	286	0.0748	0.943	0.939
Scalar invariance	2153.7	352	0.101	0.875	0.891
Final partial scalar invariance	1279.8	322	0.0767	0.934	0.936
Factor variance invariance	1369.1	332	0.0784	0.928	0.933
Partial factor variance invariance	1289.5	327	0.0762	0.933	0.937

[6] In multigroup CFA, one does not know a priori which item can be used as marker item. The usual procedure is to select one item, impose full metric invariance and examine the modification indices. If another item has smaller modification indices, the model is re-estimated using this item as marker item (Steenkamp and Baumgartner 1998).

Figure 7
LACK OF SCALAR INVARIANCE OF THE SNI SCALE: MODIFICATION INDICES PER COUNTRY



Relaxing these invariance constraints on the item intercepts improves model fit substantially compared to the full scalar invariance model ($\Delta\chi^2(30)=873.9$, $p<0.001$). However, the increase compared to the partial metric invariance model remains significant ($\Delta\chi^2(36)=179.0$, $p<0.001$), and more importantly, ΔCFI exceeds the –0.01 threshold. Thus, even partial scalar invariance is not supported. In any case, no items remain that are scalar invariant across all countries. Therefore, within the CFA framework, no means analysis can be undertaken for all countries in the study.

Finally, we tested factor variance invariance (which requires (partial) metric invariance but not scalar invariance; Steenkamp and Baumgartner 1998). Full factor variance invariance is not satisfied ($\Delta\chi^2(10)=89.3$, $p<0.001$). When we release the constraints on France, Spain, China, Russia, and Japan, we obtain a satisfactory model ($\Delta\chi^2(5)=9.7$, $p>0.05$). Table 6 presents the factor variances.

Table 6
COUNTRY MEANS AND VARIANCES FOR SNI SCALE

Country	Latent mean IRT	Within-country variance on SNI: IRT model	Within-country variance on SNI: CFA model
France	-1.023	1.106	0.458
Netherlands	-1.560	1.408	0.325
Spain	-0.986	1.462	0.463
China	0.930	0.523	0.221
Poland	-0.198	0.832	0.325
Brazil	-0.402	0.769	0.325
Thailand	0.136	0.730	0.325
Russia	0.040	0.758	0.497
U.S.	-1.200	1.388	0.325
Taiwan	0.510	0.527	0.325
Japan	-0.216	0.809	0.415

Comparison of IRT and CFA results

In this subsection, we compare the substantive insights obtained by our IRT model and the CFA model. Several interesting differences can be observed. In the IRT analysis, it was found that there was substantial variation in the discrimination parameters. However, these results are not mirrored in the CFA factor loadings. Since the discrimination parameters are conceptually similar to factor loadings, the CFA model underestimates the degree of cross-national fluctuation in scale metrics.[7] This finding is consistent with Lubke and Muthén (2004), who find that ignoring the ordinal structure of the data has deleterious effects on tests of measurement invariance.

The estimated country means and variances of SNI based on the IRT analysis are shown in table 6. We also include the SNI variances based on CFA. Note that the latent means cannot be obtained in CFA because scalar invariance was not supported for any item. Even if scalar invariance would be supported, the general differences in scale usage across countries (see figures 5 and 6 and table 4) would still make the latent scores problematic to compare.

Consistent with our expectations, the correlation between the IRT-based country mean and a country's score on individualism/collectivism (Hofstede 2001) is significant and negative: r=-0.734 (p<0.01). In addition, there are systematic differences in within-country heterogeneity concerning SNI. Using the IRT results, respondents in relatively individualistic countries such as

[7] We conducted a simulation study to further investigate this issue. Detailed results of this study can be obtained from the authors.

the U.S. exhibit a higher divergence in their susceptibility to normative influence than respondents in relatively collectivistic countries such as China and Taiwan. As predicted, the correlation between the IRT-based country variance in SNI and national-cultural individualism/collectivism is significant and positive: r=0.740 (p<0.01). On the other hand, the correlation between national-cultural individualism/collectivism and the CFA-based latent variable variances is insignificant (r=0.02, p>0.5), a result that lacks face validity in the light of theory.

II.6 IMPLICATIONS FOR CROSS-NATIONAL CONSUMER RESEARCH

We showed that CFA may produce misleading results, that the IRT model appropriately models the ordinal nature of the data, and that measurement invariance restrictions are no longer necessary with the IRT specification. So what are the implications for consumer researchers? First, we advise researchers to be prudent in relying on multigroup CFA:

i) It may produce invalid results due to the ordinal nature of the data;

ii) It runs into problems when the number of groups is large, or more generally, when there are no measurement invariant items;

iii) It can only compare subgroups of countries when invariance is not satisfied, while the IRT model allows a comparison of *all* countries.

Each of these issues associated with multigroup CFA hinders consumer researchers in deriving substantively meaningful conclusions from cross-national consumer behavior studies.

Many consumer researchers are interested in conducting cross-national mean comparisons and/or comparing structural relationships across countries. How should consumer researchers integrate our approach with their substantive interests? If the goal is to conduct mean comparisons, the IRT model can be used straightaway, since the model provides latent factor scores that are all on the same scale across countries. As we discussed, a Bayesian ANOVA test can be performed to test for mean differences.

If the goal is to compare structural relationships, the optimal way is to model all structural relationships and the IRT measurement part simultaneously. However, such models do not yet exist in either marketing and/or psychometrics because of data limitations and high complexity. As a "second best" option, researchers might use a two-step approach, similar in spirit to Anderson and Gerbing (1988). Such an analysis would require that in a first step, the latent construct scores are estimated. In the second step, these latent scores are used in

regression/ANOVA type of techniques to estimate the consumer researcher's substantive hypotheses. Even though simultaneous modeling of measurement and structural model is preferable, the two-step procedure is consistent with the widespread practice in both cross-sectional and experimental research in the social sciences to examine first measurement quality of constructs, and thereafter use construct scores (factor scores or summated scores) in regression/ANOVA models (see also Jöreskog 2000, who advocates a similar procedure to deal with interactions and non-linear effects in LISREL models).

II.7 GENERAL DISCUSSION

The dominant logic in consumer behavior research has been that constructs should display certain levels of measurement invariance in order to make valid substantive cross-national comparisons. Indeed, it has been argued that if measurement invariance across countries is lacking, conclusions based on that scale are at best ambiguous and at worst erroneous (Horn 1991). Heeding these recommendations, numerous articles have tested for measurement invariance of constructs, using the multigroup CFA model (e.g., Durvasula et al. 1993; Netemeyer et al. 1991; Steenkamp and Baumgartner 1998; Wong et al. 2003; see Vandenberg and Lance 2000 for an overview of other social sciences). If invariance constraints are not (partially) fulfilled, cross-national comparisons cannot be made. For example, in our application, latent means could not be compared as even partial scalar invariance was not achieved. However, claims of the necessity of certain levels of measurement invariance for particular research objectives are mainly the result of the particular methodology (multigroup CFA) that is used.

In this chapter we present a model that addresses these problems. Our hierarchical IRT model allows consumer researchers to compare countries substantively despite lack of invariance for any of the items. Moreover, because the ordinal nature of the data is recognized, cross-national differences in scale usage are also accommodated. We found strong noninvariance of scale metrics and of scale usage across countries for SNI. Current CFA-based methodologies are not well suited to account for differences in scale usage because they ignore the ordinal nature of the data (Lubke and Muthén 2004).

Our approach is not limited to studies with many countries. A fixed-effects specification rather than a random-effects specification can be used in studies involving few countries. The estimation procedure would change: the fixed-effects model can be estimated by using

noninformative reference priors for the discrimination and threshold parameters in the MCMC procedure. Also, the hierarchical structure for the latent variable can be relaxed in such cases.

There are many issues for further research. Understanding the sources of cross-national differences in discrimination and scale use, as revealed in the discrimination and threshold parameters, is an important topic in its own right. Which cultural processes give rise to cross-national differences in these parameters? The CFA study by Wong et al. (2003) provides an interesting example how studying cross-national differences in response behavior increases our understanding of other cultures. Statistically, covariates that explain variation in item parameters across countries can be incorporated in the IRT measurement model, but more theory and larger datasets are necessary to study relationships between culture and response behavior.

Future work can also focus on extending the current modeling framework in other ways. In consumer research, there is a growing interest in formative measurement models (Jarvis, MacKenzie, and Podsakoff 2003). Future research might extend IRT models – which specify a reflective relation between indicator and construct – to the formative context. In addition, it would be desirable to integrate the IRT measurement model with a hierarchical structural latent variable model that also contains latent predictors. Some recent work has started to address this issue (see Fox and Glas 2003; Fox 2005a), but these models cannot yet accommodate varying item parameters across countries in the measurement models.

Although using the same response format for any specific item across countries is common practice in cross-national consumer research, perhaps it is preferable to use different response formats for any specific item across countries. Like other IRT models (and CFA models), our model allows the scale format to be different for different items, but does *not* allow a different format across countries for the same item. Future research might extend our model to accommodate such differences in response format across countries for similar items, while still arriving at latent scores that are comparable across countries.

Although many important issues remain for future research, to the best of our knowledge, this is the first piece of research in the social sciences that relaxes all invariance requirements across groups, while retaining the possibility to make substantive comparisons. We hope that our research contributes to stimulating consumer behavior researchers to pay more attention to cross-national measurement issues, and thus further advances the rigor of cross-national consumer research.

II.8 APPENDIX A: MCMC ALGORITHM

We use Bayesian inference for the IRT model, in which we specify the posterior distribution of all model parameters. For our hierarchical IRT model, the full posterior is given by:

$$f(\boldsymbol{\xi},\boldsymbol{\gamma},\boldsymbol{a},\{\sigma_\gamma^2\},\{\sigma_a^2\},\{\sigma_g^2\},\tau^2 \mid x) \propto$$

$$\prod_g \left[\prod_i \left[\prod_k \left[f(x_{ik}^g \mid \xi_i^g, \boldsymbol{\gamma}_k^g, a_k^g) \right] f(\xi_i^g \mid \xi^g, \sigma_g^2) \right] f(\xi^g \mid \tau^2) \right] \times$$

$$\prod_g \left[\prod_k \left[f(\boldsymbol{\gamma}_k^g \mid \boldsymbol{\gamma}_k, \sigma_{\gamma_k}^2) \right] f(a_k^g \mid a_k, \sigma_{a_k}^2) \right] \times$$

$$\prod_g \left[f(\sigma_g^2) \right] \prod_k \left[f(\sigma_{\gamma_k}^2) f(\sigma_{a_k}^2) f(\boldsymbol{\gamma}_k) f(a_k) \right] f(\tau^2)$$

We use data augmentation (Tanner and Wong 1987) to facilitate estimation. A Metropolis-Hastings step is used to sample the threshold parameters, for which the full conditional distribution is complex. The Gibbs sampler consists of the following steps:

1) Sample from $\left[Z_{ik}^g \mid X_{ik}^g, \xi_i^g, a_k^g, \boldsymbol{\gamma}_k^g \right]$, for k=1,…,K, i=1,…, N_g, and g=1,…, G.

Given the variables $X_{ik}^g, \xi_i^g, a_k^g,$ and $\boldsymbol{\gamma}_k^g$ the variables Z_{ik}^g are independent and normally distributed: $Z_{ik}^g \mid X_{ik}^g, \xi_i^g, a_k^g, \boldsymbol{\gamma}_k^g \sim N\left(a_k^g \xi_i^g, 1\right) I\left(\gamma_{k,c-1}^g < Z_{ik}^g < \gamma_{k,c}^g\right)$ if $X_{ik}^g = c$.

2) Sample from $\left[\xi_i^g \mid Z_{ik}^g, a_k^g, \xi^g, \sigma_g^2 \right]$, for i=1,…, N_g, and g=1,…, G.

The full conditional distribution is a product of two normal distributions, and from standard properties it follows that:

$$\xi_i^g \mid \boldsymbol{Z}_i^g, \boldsymbol{a}^g, \xi^g, \sigma_g^2 \sim N\left(\frac{\sum_{k=1}^K a_k^g Z_{ik}^g + \xi^g / \sigma_g^2}{\sum_{k=1}^K (a_k^g)^2 + \sigma_g^{-2}}, \frac{1}{\sigma_g^{-2} + \sum_{k=1}^K (a_k^g)^2} \right).$$

3) Sample from $\left[a_k^g \mid \boldsymbol{\xi}^g, \boldsymbol{Z}_k^g, a_k, \sigma_{a_k}^2 \right]$, g=1,…,G, k=1,…,K.

The prior is $a_k^g \sim N\left(a_k, \sigma_{a_k}^2\right)$. Therefore, the full posterior is normal, with

$$a_k^g \mid \boldsymbol{\xi}^g, \boldsymbol{Z}_k^g, a_k, \sigma_{a_k}^2 \sim N\left(\frac{\sum_{i=1}^{N_g} \xi_i^g Z_{ik}^g + a_k / \sigma_{a_k}^2}{\sum_{i=1}^{N_g} \left(\xi_i^g\right)^2 + \sigma_{a_k}^{-2}}, \frac{1}{\sum_{i=1}^{N_g} \left(\xi_i^g\right)^2 + \sigma_{a_k}^{-2}} \right) I(a_k^g > 0).$$

For identification, it is imposed that $\prod_{k=1}^K a_k^g = 1$

4) Sample from $\left[\boldsymbol{\gamma}_k^g \mid \boldsymbol{\gamma}_k, \sigma_{\kappa_k}^2, a_k^g, Z_{ik}^g, X_{ik}^g \right]$, g=1,…,G, k=1,…,K, and c=1,…,C-1.

The full conditional posterior of the threshold parameters is proportional to:

$$\prod_{i|g} P(\gamma_{k,x_{ik}^g}^g > Z_{ik}^g > \gamma_{k,x_{ik}^g-1}^g \mid \xi_i^g, a_k^g, \boldsymbol{\gamma}_k^g) f(\boldsymbol{\gamma}_k^g \mid \boldsymbol{\gamma}_k, \sigma_{\gamma_k}^2)$$

A Metropolis-Hastings algorithm is used to simulate a realization from this posterior distribution. In the *m*-th iteration of the MCMC chain we draw a candidate $\gamma_k^{g,*}$ from (Fox 2005a):

$\gamma_{k,c}^{g,*} \sim N\left(\gamma_{k,c}^{g,m-1}, \sigma_{MH}^2\right) I\left(\gamma_{k,c-1}^{g,*} < \gamma_{k,c}^{g,*} < \gamma_{k,c+1}^{g,m-1}\right)$ for c=1,…,C-1,

where σ_{MH}^2 is a tuning parameter to adjust the accept/reject rate of the algorithm. The Metropolis-Hastings acceptance probability is then given by:

$$\min\left[\prod_{i|g}\frac{\Pr(X_{ik}^g = x_{ik}^g \mid \xi_i^g, a_k^g, \boldsymbol{\gamma}_k^{g,*})}{\Pr(X_{ik}^g = x_{ik}^g \mid \xi_i^g, a_k^g, \boldsymbol{\gamma}_k^{g,m-1})}\frac{f(\boldsymbol{\gamma}_k^{g,*} \mid \boldsymbol{\gamma}_k, \sigma_{\gamma_k}^2)}{f(\boldsymbol{\gamma}_k^{g,m-1} \mid \boldsymbol{\gamma}_k, \sigma_{\gamma_k}^2)}\frac{f(\boldsymbol{\gamma}_k^{g,m-1} \mid \boldsymbol{\gamma}_k^{g,*}, \sigma_{MH}^2)}{f(\boldsymbol{\gamma}_k^{g,*} \mid \boldsymbol{\gamma}_k^{g,m-1}, \sigma_{MH}^2)}, 1\right]$$

The first two parts of this expression represent the contribution from the likelihood, the second part comes from the proposal distributions. For identification, we set $\sum_{k=1}^{K}\gamma_{k3}^g = 0$.

5) Sample from $\left[a_k \mid a_k^g, \sigma_{a_k}^2\right]$, and $\left[\boldsymbol{\gamma}_k \mid \boldsymbol{\gamma}_k^g, \sigma_{\gamma_k}^2\right]$, for k=1,…,K.

The full conditionals are normal:

$$\boldsymbol{\gamma}_k \mid \boldsymbol{\gamma}_k^g, \sigma_{\gamma_k}^2 \sim N\left(\frac{1}{G}\sum_{g=1}^{G}\boldsymbol{\gamma}_k^g, \frac{\sigma_{\gamma_k}^2}{G}\right),$$

$$a_k \mid a_k^g, \sigma_a^2 \sim N\left(\frac{1}{G}\sum_{g=1}^{G}a_k^g, \frac{\sigma_a^2}{G}\right) I(a_k > 0).$$

6) Sample from $\left[\sigma_{a_k}^2 \mid a_k^g, a_k\right]$, $\left[\sigma_{\gamma_k}^2 \mid \boldsymbol{\gamma}_k^g, \boldsymbol{\gamma}_k\right]$ for k=1,…,K, and $\left[\sigma_g^2 \mid \xi_i^g, \xi^g\right]$, $\left[\tau^2 \mid \xi^g\right]$.

For each variance parameter an inverse gamma prior is specified with parameters g_1 and g_2. As a result, each full conditional has an inverse gamma distribution with shape parameter $G/2+g_1$, $(C\text{-}1)G/2+g_1$ for each of the K items, $N_g/2+g_1$, and $G/2+g_1$, respectively, and scale parameter

$$g_2+\sum_{g=1}^{G}\left(a_k^g-a_k\right)^2/2,\ g_2+\sum_{c=1}^{C-1}\sum_{g=1}^{G}\left(\gamma_{kc}^g-\gamma_{kc}\right)^2/2,\ g_2+\sum_{i=1}^{N_g}\left(\xi_i^g-\xi^g\right)^2/2,\ g_2+\sum_{g=1}^{G}\left(\xi^g\right)^2/2$$

respectively. Noninformative proper priors were specified with $g_1 = g_2 = 1$.

7) Sample from $\left[\xi^g \mid \sigma_g^2, \tau^2\right]$ for $g = 1,\ldots,G$. The prior is $\xi^g \sim N(\xi, \tau^2)$, so that

$$\xi^g \mid \xi, \tau^2, \sigma_g^2 \sim N\left(\frac{\sum_{i|g}\xi_i^g/\sigma_g^2 + \xi/\tau^2}{N_g/\sigma_g^2+\tau^{-2}}, \frac{1}{N_g/\sigma_g^2+\tau^{-2}}\right).$$

8) Sample from $\left[\xi \mid \xi^g, \tau^2\right]$. With a noninformative prior, we have

$$\xi \mid \xi^g, \tau^2 \sim N\left(G^{-1}\textstyle\sum_g \xi^g, G^{-1}\tau^2\right).$$

II.9 APPENDIX B: BAYESIAN TESTS

In order to test factor variance invariance, consider *G*-1 linearly independent contrasts $\Delta_g = \log \sigma_g^2 - \log \sigma_G^2$. Then, the hypothesis $\boldsymbol{\Delta}_0 = \mathbf{0}$ corresponds with equal factor variances across groups. The density function $p(\boldsymbol{\Delta}|\mathbf{x})$ is a monotonic decreasing function of a function Q_0 which is asymptotically distributed as χ^2_{G-1}, as $N_g \to \infty$ (see Box and Tiao 1973). Hence, for large samples, the vector $\boldsymbol{\Delta}_0 = \mathbf{0}$ is included in the highest posterior density (HPD) region of $1-\alpha$ if and only if:

$$\lim_{N_g \to \infty} P\left[p(\boldsymbol{\Delta}|\mathbf{x}) > p(\boldsymbol{\Delta}_0|\mathbf{x})|\mathbf{x} \right] = P\left(\chi^2_{G-1} < \frac{Q_0}{1+A} \right) < 1\text{-}\alpha$$

where:

$$Q_0 = -\sum_{g=1}^{G} N_g \left(\log s_g^2 - \log \overline{s}^2 \right)$$

$$A = \frac{1}{3(G-1)} \left(\sum_{g=1}^{G} N_g^{-1} - N^{-1} \right)$$

and s_g^2 and $\overline{s}^2$ are the mean sum of squares in group g and the overall mean sum of squares, respectively. N_g is the sample size in country g, and $N = \Sigma N_g$. The MCMC algorithm can be used to compute the right-hand side of Equation (10) (see Fox 2005b). It follows that the hypothesis of equal variances across countries is rejected when

$$P\left(\chi^2_{G-1} < \frac{Q_0}{1+A} \right) > 1-\alpha.$$

For latent means, we can consider G-1 linear contrasts $\Delta_g = \xi^g - \xi^G$. Then, it holds that $p(\boldsymbol{\Delta}|\mathbf{x})$ is a monotonic decreasing function of a function Q_0 which is asymptotically distributed as $F_{(G\text{-}1,\ N\text{-}G)}$ as $N_g \to \infty$. For large samples, the vector $\boldsymbol{\Delta}_0 = \mathbf{0}$ is included in the highest posterior density (HPD) region of $1-\alpha$ if and only if:

$$\lim_{N_g \to \infty} P\left[p(\boldsymbol{\Delta}|\mathbf{x}) > p(\boldsymbol{\Delta}_0|\mathbf{x})|\mathbf{x} \right] = P\left(F_{(G-1,N-G)} < \frac{\sum_g N_g (\xi^g - \overline{\xi})^2}{(G-1)s^2} \right) < 1\text{-}\alpha$$

where $\overline{\xi} = \frac{1}{N} \sum_g N_g \xi^g$. Again the hypothesis of equal means across countries is rejected when

$$P\left(F_{(G-1,N-G)} < \frac{\sum_g N_g (\xi^g - \overline{\xi})^2}{(G-1)s^2} \right) > 1-\alpha.$$

Chapter 3

Using Item Response Theory to Measure Extreme Response Style in Marketing Research: A Global Investigation

Abstract:

Extreme Response Style (ERS) is an important threat to the validity of survey-based marketing research. In this chapter, we present a new, IRT-based model for measuring ERS. This model contributes to the ERS literature in three ways. First, our method improves upon existing procedures by allowing different items to be differentially useful for measuring ERS and by accommodating the possibility that an item's usefulness may differ across groups (e.g., countries). Second, our method relaxes the requirement that the items in an ERS measure be uncorrelated. This allows marketing researchers to construct an ERS measure based on substantively correlated items and eliminates the need for a dedicated ERS scale. Third, our model integrates an advanced IRT measurement model with a structural hierarchical model for studying antecedents of ERS. We simultaneously estimate a person's ERS score and individual- and group-level (country) drivers of ERS, thus providing insights into the determinants of this important response style across people and countries. Through simulations we show that the new method improves upon traditional procedures. We further apply our model to a large data set involving 12,500 consumers from 26 countries on 4 continents. The findings show that our model extensions are necessary to adequately model the data. Finally, we report substantive results about the effects of socio-demographic and national-cultural variables on ERS.

This chapter is based upon Martijn G. de Jong, Jan-Benedict E.M. Steenkamp, Jean-Paul Fox and Hans Baumgartner (2007), "Using Item Response Theory to Measure Extreme Response Style in Marketing Research: A Global Investigation," *Journal of Marketing Research*, forthcoming. We thank AiMark for the providing the data, the three editors, and anonymous reviewers for valuable comments.

III.1 INTRODUCTION

Valid measurement is a cornerstone of marketing as a science. Although the measurement of marketing constructs has greatly improved in recent years, systematic error is often neglected. However, it is well-known that responses to questionnaires are often influenced by content-irrelevant factors called response styles (Baumgartner and Steenkamp 2001). A response style can be defined as a tendency to respond systematically to questionnaire items on some basis other than what the items were specifically designed to measure (Paulhus 1991).

In this chapter, we focus on Extreme Response Style (ERS), one of the most pervasive and frequently studied response styles in the social sciences (see, e.g., Baumgartner and Steenkamp 2001; Greenleaf 1992b; Johnson 2003; Paulhus 1991). ERS is the tendency of respondents to favor or avoid using the endpoints of a rating scale, relatively independently of specific item content. Although the literature on ERS is extensive, the phenomenon has received relatively little attention in marketing journals (see Greenleaf (1992a) and Baumgartner and Steenkamp (2001) for two exceptions). This is surprising since ERS has biasing effects on both the mean level of responses and the correlation between marketing constructs (Baumgartner and Steenkamp 2001; Greenleaf 1992a; Rossi, Gilula, and Allenby 2001). Furthermore, in cross-national marketing research, country-specific variations in ERS may easily be misinterpreted as substantive differences in the marketing constructs examined, which could have adverse effects on the decisions made by international marketers (Kumar 2000). Thus, ERS is an important threat to the validity of both domestic and cross-national survey-based marketing research.

The present research contributes to the ERS literature in three ways. First, we propose a new, item response theory (IRT)-based method for measuring ERS. This method improves upon existing procedures (Greenleaf 1992b; Baumgartner and Steenkamp 2001) by allowing different items to be differentially useful for measuring ERS and by accommodating the possibility that an item's usefulness may differ across groups (e.g., countries).

Second, our method relaxes the requirement that the items in an ERS measure should be (marginally) uncorrelated (Greenleaf 1992b). This allows marketing researchers to construct an ERS measure based on substantively correlated items and eliminates the need for a dedicated ERS scale. Through simulations we show that the new method improves upon traditional procedures, and a detailed analysis of a large-scale data set indicates that the modifications are necessary to adequately model the data.

Third, our model integrates the advanced IRT measurement model with a structural hierarchical model for studying the antecedents of ERS. We simultaneously estimate a person's ERS score and individual- and group-level (country) drivers of ERS, thus providing insights into the determinants of this important response style across people and countries. Specifically, we study both socio-demographic and national-cultural determinants of ERS using a dataset involving 12,500 consumers from 26 countries in 4 continents.

III.2 MEASURING ERS

The observed score on any marketing scale X can be partitioned into three components:

$$X_i = T_i + S_i + E_i \quad (1)$$

where T_i is the latent true score of respondent i, S_i is systematic error, and E_i is random error. One of the most important causes of systematic error is ERS (Greenleaf 1992b). In order to purge ERS from construct measurements, marketing researchers have proposed partialing systematic influences due to ERS from scale scores, using a three-step procedure: (1) construct an estimate of a person's ERS score based on a set of items; (2) regress observed scores for other scales on ERS; and (3) use the purified scale scores in further analyses (Baumgartner and Steenkamp 2001; Podsakoff et al. 2003).

An estimate of a person's latent ERS score is typically constructed by summing the number of extreme responses that a respondent endorses across a set of items (Steenkamp and Baumgartner 2001). For example, with a 5-point Likert scale an ERS measure corresponds to the number of questionnaire statements with which a respondent 'strongly agrees' or 'strongly disagrees' (Greenleaf 1992b). We can display this as:

$$\hat{ERS}_i = \sum_{k=1}^{K} I_{\{Q_{ik}=1 \vee Q_{ik}=5\}} = \sum_{k=1}^{K} EXTR_{ik} \quad (2)$$

where $EXTR_{ik} = I_{\{Q_{ik}=1 \vee Q_{ik}=5\}}$ is an indicator variable that takes on the value 1 when an extreme response option is used by respondent i on the Likert scale for question k (Q_{ik}) and 0 otherwise, $\hat{ERS}_i$ represents an estimate of the person's latent ERS score, and K equals the number of items.

Equation (2) specifies that at the *observed* level of individual items, ERS is measured on a dichotomous scale. We will retain this basic operationalization of ERS measurement in our proposed IRT-based model because of the following reasons. First, this specification is commonly used in the marketing literature and in other social sciences (Bachman and O'Malley 1984; Baumgartner and Steenkamp 2001; Chen et al. 1995; Greenleaf 1992b; Grim and Church

1999; Hui and Triandis 1989; Johnson et al. 2005; Marín et al. 1992). Second, it is an obvious and intuitive operationalization of extreme responding for the 5- or 7-point scales most commonly used in marketing survey research (cf. Bearden and Netemeyer 1999). In fact, scaling experts sometimes operationally define ERS in this way. For example, Paulhus (1991, p. 49) says that ERS is the "tendency to use the extreme choices on a rating scale (e.g., 1s and 7s on a seven-point scale)." Third, the dichotomization minimizes confounding ERS with acquiescence responding (ARS). ARS is often operationalized as follows:

$$\hat{ARS}_i = \sum_{k=1}^{K} (2 \times I_{\{Q_{ik}=5\}} + I_{\{Q_{ik}=4\}}) \quad (3)$$

As disacquiescence is much less common than acquiescence (Baumgartner and Steenkamp 2001), this implies that an absolute deviation measure of ERS (e.g., by coding a response of 2 or 4 on a 5-point scale as 1, and a response of 1 or 5 as 2) will overlap substantially with ARS. This will be much less the case for a dichotomous ERS measure. In fact, this is a major reason why researchers have used the dichotomous measure.

Limitations of traditional approaches to ERS measurement[8]

Two approaches for measuring ERS can be distinguished, based on which items are included in equation (2): (1) the use of dedicated ERS instruments, and (2) the use of ad hoc measures of ERS based on items intended to assess substantive constructs.

Dedicated ERS instruments. Survey researchers sometimes use a separate set of items that were specifically designed to measure ERS. Although seemingly attractive at first sight, this approach has some significant disadvantages. First, few dedicated ERS scales exist (Greenleaf 1992b is a notable exception). Second, adding non-substantive items to a survey is costly, both in terms of money and respondent fatigue. It is often difficult to get marketers to pay for additional survey items that will be used solely for estimating stylistic responding. Using items that are already included in the survey can lower the cost and time involved. Third, if the ERS properties of dedicated ERS scale items vary across subgroups (which will probably be the norm), it may be futile for researchers to try to assemble a set of items that will work equally well across cultural and linguistic subgroups. This issue is particularly problematic in international marketing research. Fourth, using proven items from existing substantive scales is advantageous in cross-

[8] We thank an anonymous reviewer for suggesting a number of arguments in this section.

linguistic research because these are exactly the kinds of items that have been thoroughly tested in many languages, using procedures such as back-translation.

Ad hoc ERS items based on substantive scales. For all these reasons, it is common to use items that were originally designed to measure substantive constructs as indicators of ERS (e.g., Baumgartner and Steenkamp 2001; Greenleaf 1992a; Van Herk, Poortinga, and Verhallen 2004). If such ad hoc ERS scales are used to partial stylistic variance from substantive scales, it is critical that there is *no item overlap between the ERS measure and the substantive scales that are to be purged of systematic error variance* (Baumgartner and Steenkamp 2001).

However, even if item overlap is avoided, the traditional method still has serious limitations. First, as noted by Greenleaf (1992b), items in an ERS measure should have low average inter-item correlations for substantive reasons (in order to avoid confounding of style and content). However, when ad hoc measures of ERS are constructed based on substantive scales, items from the same scale will be correlated and in fact *should* be correlated (Bearden and Netemeyer 1999). The traditional ERS formula (2) ignores this dependence structure.

Second, ERS is best understood as an interaction of personal dispositions and item characteristics (Podsakoff et al. 2003). Respondents differ in their tendency to go to the extremes of the rating scale, and items elicit ERS to differing degrees. Equation (2) does not allow for this, as it does not separate item and person effects and assigns equal weights to all items.

Third, the usefulness of an item for measuring ERS may vary across countries/linguistic subgroups. Cross-national differences in the ERS properties of items may arise because of differences in item semantics and cultural meaning (Podsakoff et al. 2003). Proportions of extreme responses are likely to differ across nations/subgroups, and ERS measures based on different items would be incomparable across countries.

Finally, when survey researchers want to examine individual and national drivers of ERS, it is important to integrate the measurement model for ERS with a structural hierarchical latent variable model and estimate all parameters simultaneously, in order to avoid bias in parameter estimates (Ansari, Jedidi, and Jagpal 2000; Fox and Glas 2001).[9]

What is needed is a model that adjusts for differences in item characteristics across items and subgroups, accounts for substantive correlations among items from the same scale, and allows the

[9] Note that these last three limitations also hold for the dedicated ERS measure.

researcher to simultaneously study the antecedents of ERS. Such a model is proposed in the next section.

III.3 MEASURING ERS USING IRT

The basic IRT model

To address the limitations of the existing operationalization of ERS, we propose to use a binary item response theory (IRT) measurement model (Lord and Novick 1968). Binary IRT models are a powerful approach for relating multiple dichotomous observed variables to an underlying continuous latent trait (Lord and Novick 1968; Hambleton and Swaminathan 1985). We assume that a continuous, stable latent ERS trait underlies a person's observed extreme response pattern (Baumgartner and Steenkamp 2001; Greenleaf 1992b), that is, the dichotomous pattern of zeros and ones contained in $\boldsymbol{EXTR}_i=(EXTR_{i1},\ldots, EXTR_{iK})'$. We follow previous research in assuming that the observed indicators of ERS are measured on a dichotomous scale because the reasons supporting this practice in the context of the traditional ERS measurement apply equally well to the IRT model.[10] However, we adopt a radically different approach for modeling the relationship between the latent ERS construct and its observed indicators.

IRT models have a cross-classified character with separate item and person characteristics. This makes IRT very suited to separating the influence of items (how easily does item *k* elicit ERS) and persons (what is the latent ERS score of person *i*) with respect to an observed extreme response $EXTR_{ik}$. Note that, except for Greenleaf (1992b), researchers have typically assumed that each item is equally useful for measuring ERS. However, it is likely that items differ in their tendency to elicit extreme responses (Bradlow and Zaslavsky 1999; Podsakoff et al. 2003).

One of the most frequently used IRT models is the two-parameter normal ogive model (Lord and Novick 1968). For this model, the probability of an extreme response for respondent *i* on Likert item *k* (i.e., 'strongly disagree' or 'strongly agree' so that $EXTR_{ik}=1$) is driven by the respondent's latent ERS value, random error, and item characteristics (such as specific item content and semantics). Mathematically, the two-parameter normal ogive is formulated as:

$$\mathrm{P}(EXTR_{ik}=1 \mid ERS_i, a_k, b_k) = \Phi(a_k(ERS_i - b_k)) \qquad (4)$$

[10] Although for ordinal data, a graded response IRT model (Samejima 1969) is a higher information method of measuring item characteristics, a graded IRT model is not suited to measure ERS. This is because the latent trait in the graded IRT model would capture a general method factor (cf. Podsakoff et al. 2003), rather than ERS. The threshold parameters in a graded IRT model would not reflect item's *ERS properties*.

where a_k is the discrimination parameter for item k, b_k is the "difficulty" or threshold parameter for item k, and $\Phi(.)$ is the standard normal cumulative distribution function. The function $\Phi(a_k(ERS_i - b_k))$ is known as the item characteristic curve (ICC).

The *difficulty parameter* b_k, which is measured on the same scale as ERS_i, indicates how likely it is that an item k will elicit an extreme response. Items with a very negative b_k parameter elicit an extreme response very easily, while items with a very positive b_k parameter do not readily evoke an extreme response. Technically, b_k is defined such that a respondent i with $ERS_i = b_k$ has a probability 0.5 of making an extreme response on item k.

The *discrimination parameter* a_k determines whether an item discriminates well between people high and low on ERS. It is conceptually similar to a factor loading in confirmatory factor analysis, as it represents the relationship between the latent ERS score and observed item responses. Items with an a_k value close to zero are not useful for measuring *ERS*. Note that a_k assesses an item's effectiveness as an indicator of ERS, not its substantive validity. For a high value of a_k, an extreme response provides strong evidence that the ERS_i value is above b_k.

New IRT model for measuring ERS

The standard IRT model in equation (4) addresses one of the limitations of the traditional measure of ERS by clearly separating item (a_k, b_k) and person (ERS_i) effects and allowing items to be differentially useful for measuring ERS (i.e., some items discriminate better between people relatively low and high on ERS, and discrimination depends on the item's difficulty). However, the model does not address the remaining three limitations of the traditional ERS measure. We therefore extend the standard IRT model and include three novel features in our approach. First, we adapt testlet IRT models, which were originally developed by Bradlow and colleagues (e.g., Bradlow, Wainer, and Wang 1999) for a different purpose, to accommodate substantive correlations among blocks of items that measure the same underlying substantive construct.

Second, we allow for non-invariant ERS properties across groups of respondents such as different countries, by using a varying item parameter model (i.e., item parameter values for *each* item are allowed to differ across countries). This provides a unique contribution to multigroup IRT research. To date, all cross-group IRT models have required measurement-invariant *anchor* items to make the scale of the latent variable common across groups (e.g., Holland and Wainer 1993; May 2005; Reise et al. 1993). In other words, the item parameters need to be the same in all countries for these anchor items in order to identify the model. Apart from the difficulties of

testing for invariance, there may not be invariant items when many groups are considered. In such cases, existing multigroup IRT models cannot be applied. In our model, there is no longer a need to classify items as invariant or noninvariant.

Finally, we integrate the advanced IRT measurement model with a structural multilevel model, which allows us to study the antecedents of ERS. Previously, researchers have only considered structural multilevel models in connection with the basic IRT model assuming invariant item parameters across groups (Fox and Glas 2001). We extend the basic measurement model using testlets and varying item parameters, and subsequently integrate this model with a structural multilevel model for ERS.

Testlet structures

Conditional independence is an important assumption in IRT models. It means that for a given respondent, there is no relationship between the respondent's extreme responses to any pair of Likert items given the latent ERS score. When the ERS measure contains blocks of items that are correlated for substantive reasons (because they measure the same substantive construct), the estimates of the latent ERS score and item parameters will be biased due to the dependence structure between items from the same multi-item scale.

We draw on the educational measurement literature and extend the basic IRT model by incorporating "testlet" effects (Bradlow, Wainer, and Wang 1999). In a series of papers, Bradlow and his colleagues have shown the biasing effects of testlet structures on IRT person and item parameters (Bradlow, Wainer, and Wang 1999; Wang, Bradlow, and Wainer 2002; Wainer, Bradlow, and Du 2000). In the present context, each testlet is a multi-item scale, and there are as many testlets as there are multi-item scales. The common content among the items in the multi-item scale is due to the fact that the items measure the same latent marketing construct. Mathematically, the normal ogive model (4) is adapted as follows:

$$\mathrm{P}(EXTR_{ik} = 1 \mid ERS_i, \psi_{i,r_k}, a_k, b_k) = \Phi(a_k(ERS_i - \psi_{i,r_k} - b_k)) \qquad (5)$$

where r_k indicates the testlet of item k. We assume that there are R testlets in total so that $r_k \in \{1, 2, \ldots, r, \ldots, R\}$, and that testlet r contains N_r items. In equation (5), ψ_{i,r_k} is a person-specific testlet effect, which is independent of ERS_i and the item parameters. It is formulated as a deviation from a person's average ERS value. The parameter ψ_{i,r_k} allows respondents to have a higher ($\psi_{i,r_k} < 0$) or lower ($\psi_{i,r_k} > 0$) probability of giving an extreme response to item k due to the particular

testlet r_k (i.e., depending on which substantive construct the item measures). Following Wang, Bradlow, and Wainer (2002), we assume the prior specification $\psi_{i,r_k} \sim N(0,\sigma^2_{\psi_{r_k}})$. That is, we allow for testlet-specific variance parameters.

Cross-nationally varying item parameters

Measuring ERS in different countries (or different linguistic subgroups) poses additional difficulties, as the item parameters are likely to be non-invariant across countries. The model needs to be able to adjust item characteristics for *each* item across countries. To accommodate this, we extend recent psychometric models and propose a random-effects ANOVA structure for the item parameters. Indexing country by *j*, *j*=1,…,*J*, we use an independent prior specification for a_{kj} and b_{kj}, that is, $a_{kj} \sim N(\tilde{a}_k,\sigma^2_a)$, $b_{kj} \sim N(\tilde{b}_k,\sigma^2_b)$, and a multivariate prior for $\tilde{a}_k$ and $\tilde{b}_k$:

$$\tilde{\xi}_k = \begin{bmatrix}\tilde{a}_k \\ \tilde{b}_k\end{bmatrix} \sim N\left(\begin{bmatrix}\mu_{\tilde{a}} \\ \mu_{\tilde{b}}\end{bmatrix},\begin{bmatrix}\sigma^2_{\tilde{a}} & \sigma_{\tilde{a}\tilde{b}} \\ \sigma_{\tilde{a}\tilde{b}} & \sigma^2_{\tilde{b}}\end{bmatrix}\right) = N(\mu_{\tilde{\xi}},\Sigma)I(\tilde{a}_k \in A) \quad (6)$$

with *A* being a bounded interval in $\Re^+$, *I*(.) an indicator function, $\log(\mu_{\tilde{a}}) = 0$, $\mu_{\tilde{b}} = 0$, $\Sigma \sim Inv-W(n_0,S)$, n_0=2, and *S*=diag(100,100). In other words, the discrimination and difficulty parameters in a particular country *j* are draws from independent normal distributions with means of $\tilde{a}_k$, and $\tilde{b}_k$, and the discrimination parameter should be positive. At level 2, we allow these parameters to be correlated with covariance $\sigma_{\tilde{a}\tilde{b}}$. The prior for the variance-covariance matrix is assumed to be a noninformative Inverse-Wishart distribution. Random-effects specifications for item parameters were previously considered by Janssen et al. (2000), although in their article the grouping was based on items, rather than on countries as in our setting. Also, independent rather than multivariate priors were used. We combine the random-effects specifications for item parameters with a random-effects structure for ERS (cf. Fox and Glas 2001).

Summarizing, the IRT measurement model for ERS is given by:

$$P(EXTR_{ijk} = 1 \mid ERS_{ij},\psi_{ij,r_k},a_{kj},b_{kj}) = \Phi(a_{kj}(ERS_{ij} - \psi_{ij,r_k} - b_{kj})) \quad (7)$$

$$a_{kj} \sim N(\tilde{a}_k,\sigma^2_a) \quad (8)$$

$$b_{kj} \sim N(\tilde{b}_k,\sigma^2_b) \quad (9)$$

$$[\tilde{a}_k,\tilde{b}_k]^T = \tilde{\xi}_k \sim N(\mu_{\tilde{\xi}},\Sigma)I(\tilde{a}_k \in A) \quad (10)$$

$$\psi_{ij,r_k} \sim N(0,\sigma^2_{\psi_{r_k}}) \quad (11)$$

$$ERS_{ij} \sim N(\beta_{0j},\sigma^2) \quad (12)$$

$$\beta_{0j} \sim N(\gamma_{00}, T) \quad (13)$$

where ERS_{ij} denotes the latent ERS score for respondent i in country j (i =1,…, n_j, j=1,…, J).

The random-effects specifications for ERS and the item parameters yield an identification problem. Restrictions are necessary that fix the mean and variance of the ERS scale in each country. Each latent ERS country mean can be shifted by changing β_{0j}, as well as by uniformly shifting the country-specific difficulty values b_{kj}. To solve this problem, the latent ERS mean of country j is fixed by restricting the country-specific difficulty parameters in such a way that a common shift of country-specific difficulty values is not possible. This can be done by setting $\sum_k b_{kj} = 0 \ \forall j$ (Albert 1992). Since this restriction is applied in each country, the mean of the metric of the latent variable is identified via restrictions on the country-specific difficulty parameters. Analogously, the country variances can be shifted by uniform changes in the discrimination parameters. To fix the country variances, we need to impose a restriction such that a common shift of the country-specific discrimination parameters is not possible, which can be done by specifying that, across items, the product of the discrimination parameters equals one in each country j ($\prod_k a_{kj} = 1 \ \forall j$; see Albert 1992). [11] Hence, the mean and variance of the latent ERS variable in each country is fixed, and the scale remains common due to the simultaneous calibration of the multilevel structures for item parameters and the latent variable. The model allows respondents to be calibrated on the same latent ERS scale even when all items display differential item functioning across groups.

The hierarchical Bayesian framework allows for borrowing of strength across countries. Previous multigroup IRT research models country means and variances, as well as item parameters, as separate parameters, without borrowing strength across countries. By borrowing strength, we can place less restrictive assumptions on measurement invariance, while retaining the possibility to let the various parameters fluctuate across countries.

Structural multilevel latent variable model

Apart from considering the ERS value as a bias estimate, survey researchers are also interested in understanding what drives the variation in ERS across individuals and nations (e.g., Baumgartner and Steenkamp 2001; Greenleaf 1992a, 1992b; Rossi, Gilula and Allenby 2001). To

[11] The estimated a parameters have a product of one because they affect the probability of extreme responding in a multiplicative way, while the estimated b parameters sum to zero because their effect is additive (see equation (4)).

examine individual and national drivers of ERS, the multilevel model of ERS with testlets can be further extended. We specify:

$$ERS_{ij} = \beta_{0j} + \beta_{1j} X_{1ij} + \ldots + \beta_{Qj} X_{Qij} + \eta_{ij} \quad (14)$$

$$\beta_{qj} = \gamma_{q0} + \gamma_{q1} W_{1qj} + \ldots + \gamma_{qS} W_{Sqj} + u_{qj} \quad (15)$$

where X_{1ij} to X_{Qij} are individual-level covariates, W_{1qj} to W_{Sqj} are country-level variables, and η_{ij} and u_j are level 1 and level 2 error terms, respectively, with $\eta_{ij} \sim N(0, \sigma^2)$ and $\boldsymbol{u_j}=(u_{0j}, \ldots, u_{Qj})' \sim N_{Q+1}(0, \boldsymbol{T})$. Note that the ERS_{ij} term is unobserved and estimated by the IRT model.

Estimation

Equations (7) to (11), (14), and (15) combined yield a complex multilevel IRT structure. MCMC methods are used to simultaneously estimate all parameters, avoiding the evaluation of high-dimensional integrals. The MCMC algorithm uses data augmentation in order to draw samples from the conditional distributions of the parameters (Tanner and Wong 1987). The full conditionals of all parameters can be specified in closed form, and a Gibbs sampler is used to estimate the parameters. Each iteration of the Gibbs sampler consists of sequentially sampling from the full conditional distributions associated with the unknown parameters. See the appendix for more details.

III.4 SIMULATION STUDY

Purpose

In the simulation study, we compare the performance of our proposed IRT model to the traditional ERS operationalization. We evaluate the traditional model given by equation (2) and our IRT model with regard to their ability to recover true latent ERS values, when there are (a) substantively correlated blocks of items and (b) within- and across-country differential item functioning (DIF). In addition, we investigate whether the item parameters of the IRT model can be recovered accurately and whether our IRT model is prone to indicate spurious differences between items and countries when none is present.

Design

It is assumed that there are 20 countries, with 300 respondents per country. Fifty items are used to construct the ERS measure, based on five 10-item "substantive" scales. Thus, there are five testlets. We consider three different testlet specifications and two specifications about differential item functioning (DIF) for a total of 6 different conditions.

Respondent-specific testlet parameters were chosen so as to reflect either no, moderately strong, or relatively strong dependencies between the items within a testlet (i.e., $\psi_{ij,r} = 0; \psi_{ij,r} \sim N(0, 0.25); \psi_{ij,r} \sim N(0, 0.5)$ – in combination with $ERS_{ij} \sim N(0,1)$).

For the item parameters, we consider two specifications. As a baseline model, we assume no DIF, that is, identical item parameters across items and countries ($a_{kj}=1$, $b_{kj}=0$ $\forall k, j$). This specification is useful for investigating whether the IRT model might spuriously indicate variation in item parameters across countries when there is actually no variation. The alternative model allows for DIF, that is, different item parameters within and across countries: $a_{kj} \sim N(\tilde{a}_k, 0.2^2), b_{kj} \sim N(\tilde{b}_k, 0.3^2)$, $\tilde{a}_k \sim N(1, 0.1^2)$, $\tilde{b}_k \sim N(0.5, 0.1^2)$. These values reflect realistic heterogeneity in item functioning as will be shown in our illustration using real data.

Observed, binary extreme response patterns ***EXTR*** are generated from our parameter specifications. We use a root mean squared error (RMSE) loss function as our measure of accuracy, in which the deviation between the true and estimated latent ERS score is squared and summed across individuals. To compare the IRT model and the traditional ERS operationalization, we scale the observed sum score variable so that it has the same mean and variance as the estimated ERS scores from the IRT model.[12] As a result, we can compare the parameter estimates of the IRT model and the model based on (2).

Results

For estimation of the parameters of interest, 30,000 iterations from the Gibbs sampler were used, after discarding the first 10,000 iterations. The RMSE values for the traditional operationalization of ERS and for the IRT model are shown in Table 1.

[12] According to Lord (1980), the IRT latent score and the true score are "the same thing expressed on different scales of measurement" (p. 46).

Table 1
RECOVERY OF TRUE ERS VALUES

	No testlet dependence	Moderately strong testlet dependence	Stronger testlet dependence
No DIF	Traditional method: RMSE=29.0	Traditional method: RMSE=34.9	Traditional method: RMSE=38.5
	IRT method: RMSE=21.1	IRT method: RMSE=22.8	IRT method: RMSE=24.3
DIF	Traditional method: RMSE=35.0	Traditional method: RMSE=37.7	Traditional method: RMSE=40.5
	IRT method: RMSE=25.1	IRT method: RMSE=26.0	IRT method: RMSE=26.6

The message from Table 1 is clear: As the dependencies among the items from the same scale get stronger and DIF increases, the performance of the traditional model deteriorates significantly. In contrast, the latent ERS scores can be recovered much more accurately under the IRT model. As may be expected, RMSE increases somewhat when model complexity increases (i.e., when testlets and DIF are present), but the IRT model generally performs well and outperforms the traditional model in each condition.

Furthermore, the simulation shows that the item parameters of the IRT model are estimated accurately in every condition (they are not shown because there are no equivalent parameters for the traditional ERS measure). The correlation between the estimated and true IRT discrimination parameters is 0.97 (p<0.01), and the corresponding correlation for the difficulty parameter is 0.99 (p<0.01). Finally, there is not much variation in the item parameter estimates across countries when there is no true variation across countries (i.e., a_{kj}=1 and b_{kj}=0 $\forall kj$). Within and across-country averages for the discrimination parameters vary between 0.97 and 1.04, while for the difficulty parameters, the averages vary between –0.04 and 0.05. Thus, the complex IRT model is not prone to indicate spurious differences between items and countries.

III.5 EMPIRICAL APPLICATION

In this section we present an empirical application to illustrate the IRT model. We estimate the model in a cross-national setting, assess the necessity of allowing for differential item functioning and testlet effects, conduct item parameter validation tests, and investigate individual and cultural drivers of ERS.

The data collection was part of a large multi-national study. Two global marketing research agencies, GfK and Taylor Nelson Sofres, collected the data in 26 countries on four continents (see Table 4 for the countries). The sample in each country was drawn so as to be broadly representative of the total population in terms of region, age, education, and gender. For countries with high Internet penetration, a Web survey was used. In countries with low Internet penetration, data were collected by mall intercepts in multiple regions/locations. The number of respondents per country varies between 355 (U.K.) and 640 (Germany). Given the importance of the U.S., the marketing research agencies wanted to have a larger sample for that country (1,181 respondents). The total number of respondents is 12,506.

The questionnaire was developed in English and then translated into all local languages by professional agencies, using back-translation. To assess ERS, we used a heterogeneous set of 19 multi-item scales as well as 2 single items. The total number of items was 100. For all constructs, 5-point Likert items were used, and the items for each construct were randomly dispersed throughout the questionnaire.[13] Information was collected on age (measured in years), gender (1 for women, 0 for men), and education. In the analyses, a within-country median split for education was used.

III.6 RESULTS

Model selection

Based on equations (7) to (13), which summarize the full testlet multilevel IRT specification with cross-nationally varying item parameters, we calibrate four nested IRT models.[14] The first model (M_1) has cross-nationally invariant item parameters and no testlet structure (i.e., $a_{kj}=a_k$ and $b_{kj}=b_k$, $\forall j$, and $\psi_{ij,r}=0$, $\forall ij$, r). The second model (M_2) has item parameters that vary across countries and no testlet structure. In other words, equations (8)-(10) are specified for the item parameters, but $\psi_{ij,r}=0$, $\forall ij$, r. The third model (M_3) has cross-nationally invariant item parameters and a testlet structure (i.e., $a_{kj}=a_k$ and $b_{kj}=b_k$, $\forall j$, and equation (11) for the testlets).

[13] There is a debate in the literature on whether items pertaining to the same construct should be randomized in the questionnaire or grouped together (Bradlow and Fitzsimons 2001). The idea behind randomization is to hide the purpose of the instrument from the respondent, thus reducing response biases such as the desire to look good to others (e.g., evaluation apprehension) or to oneself (e.g., cognitive consistency and ego defense mechanisms). However, randomization may also reduce reliability (Bradlow and Fitzsimons 2001).

[14] Prior to conducting these analyses, we estimated a model with a dummy variable V_j in equation (13), i.e. $\beta_{0j} \sim N(\gamma_{00}+\gamma_{01}V_j, T)$, where V_j indicates whether the survey in a given country was a hard-copy (V_j=1) or internet version (V_j=0). The parameter γ_{01} was not significantly related to ERS in any hierarchical model.

Finally, the fourth model (M_4) has both cross-nationally varying item parameters (i.e., equations (8)-(10) for the item parameters and equation (11) for the testlet structure).

To assess which model provides the best fit, we compute the marginal log-likelihood value via importance sampling (Newton and Raftery 1994), log $p(\boldsymbol{EXTR})$, for each ERS measurement model, where ***EXTR*** contains the binary coded extreme responses for all items and all respondents. Based on the marginal log-likelihood value, the Bayes factor BF_{21} for different models M_2 and M_1 can be computed as exp[log $p(\boldsymbol{EXTR} \mid M_2)$ - log $p(\boldsymbol{EXTR} \mid M_1)$]. Large values for BF_{21} provide evidence in favor of model M_2. We present the marginal log-likelihoods and the Bayes factors of the model with testlets and varying item parameters versus the other models in Table 2. It is apparent that incorporating the testlet structure and allowing the IRT item parameters to vary across countries both lead to a substantial improvement in model fit.

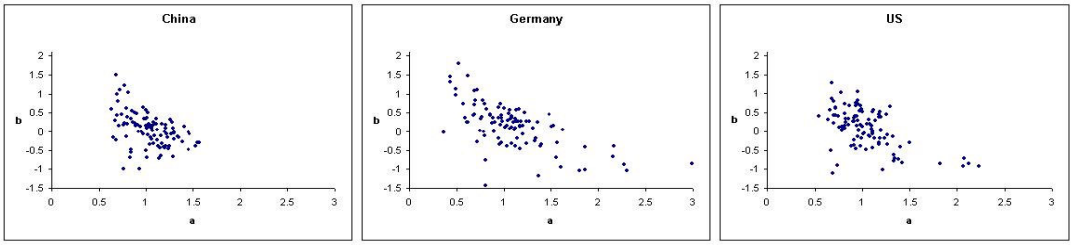
Table 2
MARGINAL LOG-LIKELIHOOD VALUES AND BAYES FACTORS
FOR DIFFERENT IRT MODELS

Model	Marginal LL	Bayes Factor
M_1: Invariant item parameters and no testlets	-461,384	BF_{41}=Exp(40,859)
M_2: Varying item parameters and no testlets	-449,088	BF_{42}=Exp(28,563)
M_3: Invariant item parameters and testlets	-432,861	BF_{43}=Exp(12,336)
M_4: Varying item parameters and testlets	-420,525	-

Item parameter variation

The standard ERS measure assumes that each item contributes equally to the overall ERS score, that is, that each item provides an equally good "test" for the ERS value. Both within and across countries, items should function the same. However, this assumption is seriously violated. For illustrative purposes, we plot the average posterior estimated values of the discrimination and difficulty parameters (i.e., a_{kj} and b_{kj}) for all items in China, Germany, and the U.S. in Figure 1. There is considerable variation in both discrimination and difficulty across items, and these results are also obtained for other countries. The notion that items differ in their sensitivity to ERS is a general phenomenon, not restricted to specific cultures only.

Figure 1
ITEM PARAMETERS FOR CHINA, GERMANY, AND U.S.



In addition to variation *within* countries, there is also considerable variation in the item parameters a_{kj} and b_{kj} *across* countries. For most items, the standard deviation in parameter estimates across countries is about 0.4-0.5. Moreover, the cross-national variation in a_{kj} and b_{kj} is not homogeneous across items. To substantiate this, we computed the correlation between the a_{kj} or b_{kj} parameters across countries for each pair of items. Low correlations indicate that a country's standing on a_{kj} or b_{kj} is not consistent across items. The average of the 4,950 distinct pairwise correlations for a is -0.007 (p>0.1), while for b the average is 0.011 (p>0.1).

Item parameter stability

We assessed item parameter stability by splitting the within-country samples into equal halves and then estimated the IRT model on both halves. In each split half, the model with testlets and varying item parameters (model M_4) is preferred. The correlation between the two split halves is 0.78 (p<0.001) for the discrimination parameters and 0.87 (p<0.001) for the difficulty parameters. Thus, both model selection and item parameters estimates are stable across samples, indicating that the differences in difficulty and discrimination across items and countries are replicable and do not simply capture random noise.

Item interpretation

In the IRT model, the discrimination parameter a_k and the difficulty parameter b_k have a clear interpretation. The former determines whether an item discriminates well between people relatively high or low on ERS, while the latter refers to the probability that an item elicits an extreme response. But are there characteristics of items that are systematically related to a_k and b_k? To examine this, we correlated a_k and b_k within countries with several item characteristics. Given the relative absence of theory to guide us, we approach this issue in an exploratory fashion. Using the strength of the dataset, we then performed a meta-analysis on the correlations across our sample nations using the method of adding Z's (Rosenthal 1991). We consider the number of

words in an item (Wang, Bradlow, and Wainer 2004), the number of characters in the item (we excluded the Asian languages because sentence structures are different), the way the item is worded, either positively or negatively (Wong, Rindfleisch, and Burroughs 2003), and an item's deviation from the midpoint of the scale (Baumgartner and Steenkamp 2001).

We find that the *difficulty* parameter is negatively correlated with the item's absolute deviation from the midpoint (r = -0.730, p<0.001). This result has face validity because when the absolute deviation from the scale midpoint is large, the item has elicited many extreme responses so that the difficulty parameter should be negative. More words (r = -0.276, p<0.001) and more characters (r = -0.295, p<0.001) are also negatively associated with the difficulty parameter.

We further find that items that *discriminate* better between people who are relatively high or low on ERS deviate more strongly from the midpoint of the scale (r = 0.180, p<0.001), are longer (r = 0.436, p<0.001), contain more characters (r = 0.441, p<0.001) and are worded positively (r = -0.117, p<0.001).

III.7 DRIVERS OF ERS

Socio-demographic variables

Previous research has investigated whether extreme responding is related to characteristics of individuals. The socio-demographic variables age, gender, and education have attracted the most attention (Greenleaf 1992a; 1992b; Marín, Gamba and Marín 1992). We also include these three socio-demographics in our model. The results of prior research have not been very consistent and we use the improved measurement of ERS and the large multi-national data set to investigate whether the socio-demographic variables studied are reliably related to ERS.

Cultural drivers of ERS

ERS may not only differ systematically between individuals, but also between countries (Baumgartner and Steenkamp 2001; Chen, Lee and Stevenson 1995; Grimm and Church 1999; Johnson et al. 2005). There is clear evidence of variation in ERS scores across countries in our study as shown in Table 3, which reports the average ERS value in each country as a deviation from the grand ERS mean. What gives rise to these cross-national differences? We propose that a country's culture is a major driver of country differences in ERS.

Table 3
MEAN ERS SCORE FOR SAMPLE COUNTRIES

Thailand	-0.759	Slovakia	-0.113	Germany	0.148
Taiwan	-0.656	Poland	-0.105	Italy	0.172
China	-0.393	US	-0.061	Austria	0.183
Czech Republic	-0.214	Denmark	0.064	Belgium	0.192
Brazil	-0.178	Hungary	0.075	France	0.217
UK	-0.147	Norway	0.076	Romania	0.315
Japan	-0.125	Portugal	0.121	Argentina	0.343
Ireland	-0.123	Switzerland	0.141	Russia	0.758
Netherlands	-0.117	Spain	0.146		

To investigate the effect of culture on ERS, we employ Hofstede's (2001) framework of cultural dimensions. Desire for uniqueness and independence are core elements of cultural individualism (Oyserman, Coon, and Kemmelmeier 2002). In individualistic societies, a person's attitudes are regulated largely by individual preferences, and the expression of unique opinions is valued (Chen et al. 1995). An individual's identity is clearly distinct from that of other people (Hofstede 2001). In contrast, in collectivistic societies attitudes are relatively more heavily influenced by society's preferences. These cultures are characterized by an interdependent self-concept and encourage modesty and harmony (Triandis 1989). We therefore expect a positive relationship between a country's degree of individualism and ERS.

At the individual level, studies in psychology have repeatedly shown that extreme responding is positively related to intolerance of ambiguity, rigidity and need for certainty (see Baumgartner and Steenkamp 2001 for a review). Hofstede (2001) argues that differences in intolerance of ambiguity are also a cultural characteristic (termed uncertainty avoidance). Uncertainty avoidance measures the degree to which societies are made nervous and feel threatened by uncertain, risky, ambiguous, or undefined situations. To avoid such situations, they tend to adopt rigid attitudes and rules. Thus, we expect a positive relationship between uncertainty avoidance and ERS.

Cultural masculinity/femininity is defined as the degree to which a society is characterized by assertiveness versus nurturance (Hofstede 2001). Masculine societies place great emphasis on achievement and ambition, and encourage assertiveness and decisive/daring behavior, which should lead to a tendency to select the strongest available choices on Likert rating scales. Feminine societies value social harmony, gentleness, and modesty, which implies that ERS should be less common.

For completeness, we also include power distance in the model, although we do not have strong a priori expectations concerning its effect on ERS. Johnson et al. (2005) theorized that it is positively related to ERS, as high power distance societies demand decisiveness and definiteness in communications by superiors, while subordinates should respond modestly, if not deferentially. But this implies that the effect depends on a person's position in the social hierarchy, and hence, in general a null effect seems more likely.

In sum, we hypothesize that ERS will be higher in countries whose culture is characterized by higher levels of individualism, uncertainty avoidance, and masculinity. No relationship is predicted for power distance.

Results

In the simultaneous estimation of the measurement (equations 7 to 11) and structural model (equations 14 and 15), we first considered the necessity of including random coefficients for the level-1 predictors. Raudenbush and Bryk (2002) recommend constraining slope coefficients that do not display random variation across countries to be fixed for increased parameter stability and efficiency. We found significant variation across countries for gender and education, but not for age. Hence, we constrained the coefficients for age to be fixed while the slopes for the other two variables were specified as random. The results for this model are given in Table 4.

The socio-demographic variables explain about 2 percent of the level-1 variance. Women tend to score higher on ERS than men (γ_{03}=0.0324), and both younger and older individuals are more prone to respond extremely (γ_{01}= -0.1463, γ_{02}=0.1278). For education, no cross-nationally generalizable effect was found, although there was significant random variation across countries.

Culture plays an important role in explaining cross-national differences in ERS. The four culture dimensions explained 59 percent of the between-country variance in ERS. As hypothesized, ERS is positively related to national-cultural individualism (γ_{05}= 0.0037), uncertainty avoidance (γ_{06}=0.0051), and masculinity (γ_{07}=0.0029). As expected, ERS is not related to power distance. Recently, Johnson et al. (2005) also investigated the relationship between Hofstede's dimensions and extreme responding across 19 nations. They found no statistically significant effects in their initial analysis using the original Hofstede scores. This suggests that the proposed methodology can help reveal drivers of ERS that cannot be observed with other ERS measures.

Table 4
MULTILEVEL STRUCTURAL IRT MODEL WITH COVARIATES

	Coefficient	Standard Deviation
γ_{00} (Constant)	-1.2411[a]	0.0554
Socio-demographic variables		
γ_{01}(Age)	-0.1463[a]	0.0469
γ_{02} (Age*Age)	0.1278[a]	0.0411
γ_{03} (Gender (1=female; 0=male)	0.0324[a]	0.0093
γ_{04} (Education)	0.0010	0.0103
National-Cultural variables		
γ_{05} (Individualism)	0.0037[a]	0.0021
γ_{06} (Uncertainty avoidance)	0.0052[a]	0.0020
γ_{07} (Maculinity)	0.0030[a]	0.0017
γ_{08} (Power distance)	-0.0024	0.0558
Variance parameter		
σ^2 (level 1 variance)	0.5661[a]	0.0084

[a] Indicates that the 95% posterior probability interval excludes zero.

III.8 CONCLUSIONS

In the introduction, we identified several contributions this research makes to the study of ERS. We structure our conclusions around these contributions. First, our new, IRT-based method improves upon the traditional ERS method by allowing different items to be differentially useful for measuring ERS and by accommodating the possibility that an item's usefulness may differ across groups (e.g., countries). Our simulations show that ignoring differential item functioning within and across countries leads to seriously biased results, while our large-scale empirical study provides strong evidence that survey items do not provide equally useful information about ERS, either within or across countries. People differ in their tendency to use the extremes of the rating scale, and items also differ in the extent to which they elicit extreme responses, both nationally and cross-nationally. The cross-classified character of IRT, that is, disjunct item and person parameters, is well suited to capture this interactive phenomenon, whereas the use of simple sum scores (Equation (2)) is rendered problematic by our findings. The results provide support for the notion that stylistic responding is best understood as an interaction of personal dispositions and item characteristics (Podsakoff et al. 2003). A unique feature of our model is that *each* item is allowed to function differently across countries. Thus, measurement invariance for item parameters is relaxed.

Second, unlike the traditional model, our model allows researchers to purge item scores of ERS even when they only have correlated items measuring substantive constructs. In a simulation study, we showed that ignoring the correlation between items biases the traditional ERS estimate, whereas the inclusion of testlets effectively controls for this problem.

Third, our model integrates the advanced IRT measurement model with a structural hierarchical model for studying the antecedents of ERS. Applying this integrated IRT-hierarchical model to a large data set involving 12,500 consumers from 26 countries, we find that the socio-demographic variables studied have a minor influence on ERS, but that culture exerts a strong and predictable effect on ERS. Implications for international marketing are evident, because ERS differences might bias comparisons between countries.

There are several promising avenues for future research. First, most research on individual-level drivers of ERS has examined socio-demographics. Results are often inconsistent and effect sizes small. Future research could examine more fundamental characteristics of individuals such as personality factors or value priorities. In addition, our model assumes that the items in each survey are the same. However, it often happens that there are both common and country-specific items (e.g., May 2005). Our model could be extended to accommodate such situations. Another interesting option is to include 'No Answer' options in the survey. It may sometimes be more valid to allow NA answers, rather than forcing respondents to provide an answer on the rating scale. Future research may integrate our ERS model with response models that have been developed for such situations (cf. Bradlow and Zaslavsky 1999). Finally, the highest-information measurement method for ordinal data is the graded-response (ordinal) IRT model. However, for such a model to accurately identify ERS and ERS properties of items it should include all relevant response styles. Future research could work on the specification and interpretation of such generalized response models. Although many issues remain for further research, we hope this research stimulates marketing researchers to pay more careful attention to the issue of ERS in both domestic and international survey research.

III.9 APPENDIX

This section presents the full MCMC algorithm for the multilevel testlet IRT model with varying item parameters. The model without covariates is a special case of the model that is developed here. Let the observed data be (***EXTR***, ***X***, ***W***) measuring the item responses ***EXTR*** for the latent trait *ERS*, ***X*** the individual-level explanatory variables, and ***W*** the country-level variables. The Gibbs sampler draws stepwise from the full conditional distributions. The first step is to augment the observed data with latent data ***Z***. By defining a continuous latent variable ***Z*** that underlies the dichotomous responses contained in ***EXTR,*** it is easier to sample from the conditional distributions of the parameters of interest. Data augmentation has been widely applied. To identify the model, we use the restriction $\prod_k a_{kj} = 1,$ and $\sum_k b_{kj} = 0,$ in each country *j*.

1) Sample from $[Z_{ijk} \mid EXTR_{ijk}, ERS_{ij}, a_{kj}, b_{kj}, \psi_{ij,r_k}]$, for $k = 1,\ldots,K,\ i = 1,\ldots,n_j,$ and $j = 1,\ldots,J.$ Given the parameters $ERS_{ij}, a_{kj}, b_{kj}, \psi_{ij,r_k}$ the variables Z_{ijk} are independent and normally distributed, that is,

$$Z_{ijk} \mid EXTR_{ijk}, ERS_{ij}, a_{kj}, b_{kj}, \psi_{ij,r_k} \sim \begin{cases} N(a_{kj}(ERS_{ij} - \psi_{ij,r_k} - b_{kj}, 1) \text{ truncated right by 0 if } EXTR_{ijk} = 0 \\ N(a_{kj}(ERS_{ij} - \psi_{ij,r_k} - b_{kj}, 1) \text{ truncated left by 0 if } EXTR_{ijk} = 1 \end{cases}$$

2) Sample from $\left[ERS_{ij} \mid \boldsymbol{Z}_{ij}, \boldsymbol{a}, \boldsymbol{b}, \boldsymbol{EXTR}, \boldsymbol{\psi}, \boldsymbol{\beta}_j, \sigma^2 \right]$ for $i = 1,\ldots,n_j,\ j = 1,\ldots,J.$ This full conditional distribution is a product of two normal distributions and from standard properties of normal distributions it follows that

$$ERS_{ij} \mid \boldsymbol{Z}_{ij}, \boldsymbol{a}, \boldsymbol{b}, \boldsymbol{\psi}, \boldsymbol{\beta}_j, \sigma^2 \sim N\left(\frac{\sum_{k=1}^{K} a_{kj}(Z_{ijk} + b_{kj} + a_{kj}\psi_{ij,r_k}) + \boldsymbol{X}_{ij}\boldsymbol{\beta}_j / \sigma^2}{1/\sigma^2 + \sum_{k=1}^{K} a_{kj}^2}, \frac{1}{1/\sigma^2 + \sum_{k=1}^{K} a_{kj}^2} \right)$$

3) Sample from $\left[\psi_{ij,r} \mid \boldsymbol{Z}_{ij}, \boldsymbol{a}, \boldsymbol{b}, \sigma^2_{\psi_r} \right]$, for $i = 1,\ldots,n_j,\ j = 1,\ldots,J$ and $r = 1,\ldots,R$ where *R* is the total number of testlets. Consider testlet *r* of size N_r, and let r_k denote the testlet of item *k*. If N_r=1 then $\psi_{ij,r} = 0$ for all *i* and *j*. The full conditional distribution for $\psi_{ij,r}$ is normal with parameters

$$E\left(\psi_{ij,r} \mid \boldsymbol{Z}_{ij}, \boldsymbol{a}, \boldsymbol{b}, \sigma^2_{\psi_r}\right) = \frac{\sum_{\{k:r_k = r\}} a_{kj}\left(a_{kj} ERS_{ij} - b_{kj} - Z_{ijk}\right)}{\sum_{\{k:r_k = r\}} a_{kj}^2 + 1/\sigma^2_{\psi_r}}$$

$$Var\left(\psi_{ij,r} \mid \boldsymbol{Z}_{ij}, \boldsymbol{a}, \boldsymbol{b}, \sigma^2_{\psi_r}\right) = \frac{1}{\sum_{\{k:r_k = r\}} a_{kj}^2 + 1/\sigma^2_{\psi_r}},$$

4) Sampling $[\boldsymbol{\xi}_{kj} \mid \tilde{\boldsymbol{\xi}}_k, \boldsymbol{ERS}, \boldsymbol{\psi}, \boldsymbol{\Sigma}]$
Consider the augmented likelihood. Then,

$$\boldsymbol{Z}_{kj} = \boldsymbol{H}_j \boldsymbol{\xi}_{kj} + \boldsymbol{\varepsilon}_{kj},\ \boldsymbol{H}_j = [\boldsymbol{ERS}_j^*, -\mathbf{1}]$$

$$\boldsymbol{\xi}_{kj} \sim N\left(\tilde{\boldsymbol{\xi}}_k, \boldsymbol{\Psi}\right) = N\left(\begin{bmatrix} \tilde{a}_k \\ \tilde{b}_k \end{bmatrix}, \begin{bmatrix} \sigma_a^2 & 0 \\ 0 & \sigma_b^2 \end{bmatrix}\right)$$

$$\boldsymbol{\xi}_{kj} \mid \tilde{\boldsymbol{\xi}}_k, \boldsymbol{Z}_{kj}, \boldsymbol{ERS}_j^*, \boldsymbol{\Psi} \sim N\left(\boldsymbol{\Omega}\boldsymbol{\mu}_{kj}, \boldsymbol{\Omega}\right) I(a_{kj} \in A)$$

$$\boldsymbol{\mu}_{kj} = \boldsymbol{H}_j^t \boldsymbol{Z}_{kj} + \boldsymbol{\Psi}^{-1} \tilde{\boldsymbol{\xi}}_k$$

$$\boldsymbol{\Omega}^{-1} = \left(\boldsymbol{H}_j^t \boldsymbol{H}_j\right)^{-1} + \boldsymbol{\Psi}^{-1}.$$

5) Sample from $[\tilde{\boldsymbol{\xi}}_k \mid \boldsymbol{\xi}_k, \boldsymbol{\Sigma}, \boldsymbol{a}, \boldsymbol{b}]$.

Given the prior $\begin{bmatrix} \tilde{a}_k \\ \tilde{b}_k \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_{\tilde{a}} \\ \mu_{\tilde{b}} \end{bmatrix}, \begin{bmatrix} \sigma_{\tilde{a}}^2 & \sigma_{\tilde{a}\tilde{b}}^2 \\ \sigma_{\tilde{a}\tilde{b}}^2 & \sigma_{\tilde{b}}^2 \end{bmatrix}\right) = N\left(\boldsymbol{\mu}_{\tilde{\xi}}, \boldsymbol{\Sigma}\right) I\left(\tilde{a}_k \in \mathrm{A}\right)$,

we have that

$$\tilde{\boldsymbol{\xi}}_k \left| \boldsymbol{\xi}_k, \boldsymbol{\Sigma} \right. \sim N\left(\boldsymbol{\Xi}_k \boldsymbol{\zeta}_k, \boldsymbol{\Xi}_k\right) I\left(\tilde{a}_k \in \mathrm{A}\right)$$

$$\boldsymbol{\zeta}_k = \boldsymbol{\Lambda}^{-1} \bar{\boldsymbol{\xi}}_k + \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_{\tilde{\xi}}$$

$$\boldsymbol{\Xi}_k^{-1} = \boldsymbol{\Lambda}^{-1} + \boldsymbol{\Sigma}^{-1}$$

where $\bar{\boldsymbol{\xi}}_k = \begin{bmatrix} \sum_j^J a_{kj} / J \\ \sum_j^J b_{kj} / J \end{bmatrix}$

6) Sample from $[\sigma_a^2 \mid a, \tilde{a}], [\sigma_b^2 \mid b, \tilde{b}], [\sigma_{\psi_r}^2]$. For each variance parameter an inverse gamma prior is specified with parameters g_1 and g_2. As a result, the full conditionals are inverse gamma distributions with shape parameters $KJ/2 + g_1$, $KJ/2 + g_1$, and $N/2 + g_1$, respectively, and scale parameters $g_2 + \sum_{j=1}^{J}\sum_{k=1}^{K}\left(a_{kj} - \tilde{a}_k\right)^2/2$, $g_2 + \sum_{j=1}^{J}\sum_{k=1}^{K}\left(b_{kj} - \tilde{b}_k\right)^2/2$, $g_2 + \frac{1}{2}\sum_{j=1}^{J}\sum_{i=1}^{n_j}\psi_{ij,r_k}^2$ respectively.

In this paper, a noninformative proper prior was specified with $g_1 = g_2 = 1$.

7) The conditional distribution of the covariance matrix $\boldsymbol{\Sigma}$ has an inverse-Wishart distribution, $\boldsymbol{\Sigma} \mid \tilde{\boldsymbol{\xi}} \sim Inv - W\left(K + n_0, \left(\sum_{k=1}^{K}(\tilde{\boldsymbol{\xi}}_k - \mu_{\tilde{\xi}})(\tilde{\boldsymbol{\xi}}_k - \mu_{\tilde{\xi}})^t + \mathbf{S}\right)^{-1}\right)$. We used $\boldsymbol{S}$=diag(100,100), n_0=2.

8) Sample from $\left[\boldsymbol{\beta}_j \mid \boldsymbol{ERS}_j, \sigma^2, \boldsymbol{\gamma}, \boldsymbol{T}\right]$, for $j = 1, \ldots, J$. Define $\boldsymbol{X}_j = \left(\boldsymbol{X}_{1j}, \ldots, \boldsymbol{X}_{ij}, \ldots, \boldsymbol{X}_{n_j j}\right)$, with $\boldsymbol{X}_{ij} = \left(X_{0ij}, \ldots, X_{Qij}\right)'$. So, $\boldsymbol{X}_j$ is of dimension $n_j \times (Q+1)$. The Level 2 explanatory variables for goup j are stored in $\boldsymbol{W}_j$. This matrix is the direct product of $\left(W_{0qj}, \ldots, W_{Sqj}\right)$ and a $Q+1$ identity matrix. The prior of the random regression coefficients at Level 1 is $\boldsymbol{\beta}_j \sim N\left(\boldsymbol{W}_j \boldsymbol{\gamma}, \boldsymbol{T}\right)$. Then, the full conditional posterior of $\boldsymbol{\beta}_j$ is given by,

$$\boldsymbol{\beta}_j \mid \boldsymbol{ERS}_j, \sigma^2, \boldsymbol{\gamma}, \boldsymbol{T} \sim N\left(\left(\boldsymbol{\Upsilon}_j^{-1} + \boldsymbol{T}^{-1}\right)^{-1}\left(\boldsymbol{\Upsilon}_j^{-1}\hat{\boldsymbol{\beta}}_j + \boldsymbol{T}^{-1}\boldsymbol{W}_j\boldsymbol{\gamma}\right), \left(\boldsymbol{\Upsilon}_j^{-1} + \boldsymbol{T}^{-1}\right)^{-1}\right)$$

where $\hat{\boldsymbol{\beta}}_j = \left(\boldsymbol{X}_j{}'\boldsymbol{X}_j\right)^{-1}\boldsymbol{X}_j{}'\boldsymbol{ERS}_j$ and $\boldsymbol{\Upsilon}_j = \sigma^2\left(\boldsymbol{X}_j{}'\boldsymbol{X}_j\right)^{-1}$. In case of fixed Level 1 regression coefficients, a noninformative prior is used and the resulting conditional distribution is also normal with mean $\hat{\beta}_F = \left(\boldsymbol{X}_F{}'\boldsymbol{X}_F\right)^{-1}\boldsymbol{X}_F{}'\left(\boldsymbol{ERS} - \boldsymbol{X}_R\boldsymbol{\beta}_R\right)$ and variance $\sigma^2\left(\boldsymbol{X}_F{}'\boldsymbol{X}_F\right)^{-1}$, where $\boldsymbol{X}_F$ and $\boldsymbol{X}_R$ are the explanatory variables related to the fixed and random regression coefficents, respectively.

9) Sample from $[\boldsymbol{\gamma} \mid \boldsymbol{\beta}, \mathbf{T}]$. The full conditional for the Level 2 regression coefficients $\boldsymbol{\gamma}$ with a noninformative prior equals

$$\boldsymbol{\gamma} \mid \boldsymbol{\beta}, \mathbf{T} \sim N\left(\left(\sum_{j=1}^{J}\boldsymbol{W}_j{}'\boldsymbol{T}^{-1}\boldsymbol{W}_j\right)^{-1}\sum_{j=1}^{J}\boldsymbol{W}_j{}'\boldsymbol{T}^{-1}\boldsymbol{\beta}_j, \left(\sum_{j=1}^{J}\boldsymbol{W}_j{}'\mathbf{T}^{-1}\boldsymbol{W}_j\right)^{-1}\right)$$

10) Sample from $\left[\sigma^2 \mid \boldsymbol{ERS}, \boldsymbol{\beta}\right]$. A prior for the variance is specified in the form of an inverse gamma distribution with shape and scale parameters g_1 and g_2, respectively. It follows that

$$\sigma^2 \mid \boldsymbol{ERS}, \boldsymbol{\beta} \sim IG\left(N/2 + g_1, \frac{N}{2}\sum_j\left(\boldsymbol{ERS}_j - \boldsymbol{X}_j\boldsymbol{\beta}_j\right)^2 + g_2\right).$$

A noninformative but proper prior is specified with $g_1 = g_2 = 1$.

11) Sample from $[\boldsymbol{T} \mid \boldsymbol{\beta}, \boldsymbol{\gamma}]$. An inverse Wishart distribution with small degrees of freedom, but greater than the dimension of $\boldsymbol{\beta}_j$, n_0 and unity matrix S_0 can be used to specify a diffuse proper prior for **T**. It follows that

$$\mathbf{T} \mid \boldsymbol{\beta}, \boldsymbol{\gamma} \sim Inv\text{-}W\left(J + n_0, \left(\sum_j\left(\boldsymbol{\beta}_j - \boldsymbol{W}_j\boldsymbol{\gamma}\right)\left(\boldsymbol{\beta}_j - \boldsymbol{W}_j\boldsymbol{\gamma}\right)' + S_0\right)^{-1}\right).$$

Chapter 4

The Interplay of Personality and Culture in Shaping Socially Desirable Responding

Abstract:

This paper investigates the role of personality and culture in influencing socially desirable responding (i.e., the tendency of respondents to give answers that make them look good), which is an important threat to the validity of survey-based research. We develop a conceptual framework that considers the effects of personality (the Big Five dimensions of personality), culture (Hofstede's dimensions of cultural variation), and certain interactions on respondents' disposition to engage in socially desirable responding. The hypotheses are tested using a large data set involving a random sample of over 12,000 respondents in 25 countries on 4 continents, and the analysis is based on a recently developed multilevel item response theory-based scaling technique that estimates latent scores for all constructs on a cross-nationally common scale. The findings support most of the proposed hypotheses and provide evidence for the cross-national generalizability of the personality and national-cultural drivers of socially desirable responding.

This chapter is based upon a paper with the same title authored by Jan-Benedict E.M. Steenkamp, Martijn G. de Jong and Hans Baumgartner, and is presently under review. We thank AiMark for providing the data. Order of authorship is arbitrary, all authors contributed equally.

IV.1 INTRODUCTION

Surveys play a crucial role in marketing research. For example, of the 520 empirical articles that appeared in the Journal of Marketing and Journal of Marketing Research in the last decade (1995-2005), 43 percent employed surveys (Rindfleisch et al. 2006). Unfortunately, survey data are often contaminated by socially desirable responding (SDR), that is, people's tendency to give answers that make them look good (Paulhus 1991). This introduces extraneous variation in scale scores, which compromises the validity of the marketing survey data. The role of SDR in biasing scores on substantive scales and in attenuating, inflating, or moderating relations between substantive constructs is well established in marketing and other social sciences (Ballard, Crino, and Rubenfeld 1988; Fisher 1993; Ganster, Hennessey, and Luthans 1983; Jo, Nelson, and Kiecker 1997; Mick 1996; Podsakoff et al. 2003; Zerbe and Paulhus 1987).

In marketing, SDR has sometimes been associated with "dark side" topics such as materialism (Mick 1996), compulsive buying (Mick 1996), and consumption of taboo products (McGraw and Tetlock 2005). However, it is generally acknowledged that SDR is also operant in "mainstream" areas important to marketers (Netemeyer, Bearden, and Sharma 2003), such as brand familiarity and brand liking (Rindfleisch and Inman 1998), consumption motivations (Fisher 1993), consumer innovativeness (Goldsmith 1987), satisfaction (Sabourin et al. 1989), and value priorities (Fisher and Katz 2000). SDR has also been found to bias managerial decision making (Chung and Monroe 2003) and performance evaluations (Bearden, Manning, and Tian 2004). Thus, it is not surprising that SDR has been identified as "one of the most pervasive response biases" in survey data (Mick 1996, p. 106).

SDR research has primarily addressed two issues. A first stream of research has focused on reducing the biasing influence of SDR, either prior to or during data collection and/or in data analysis (Fisher 1993; Fox 2005c; Nederhof 1985; Jo 2000; Podsakoff et al. 2003). A second stream of research has investigated SDR as an important construct in its own right. For example, researchers have tried to answer such questions as what intra- and interpersonal goals are served by engaging in SDR, what types of respondents are most prone to distort their responses in surveys, and what situational influences give rise to overly positive self-descriptions (Lalwani et al. 2006; Bearden, Manning, and Tan 2004). Our study belongs to this second stream of research.

Although past research has established systematic relationships between certain personality and socio-demographic characteristics of respondents and SDR (Mick 1996; Ones, Viswesvaran,

and Reiss 1996; Ones and Viswesvaran 1998; Paulhus 2002), important issues remain to be addressed in order to more fully explore the antecedents of SDR and to better understand the implications of SDR for the validity of marketing research efforts involving survey data, especially in international settings. The following areas are of particular interest.

First, we have only limited knowledge of the links between cultural orientation and SDR. The only dimensions of cultural variation for which data are available are individualism/collectivism and power distance (Heine and Lehman 1995; Lalwani et al. 2006; Triandis et al. 2001; Van Hemert et al. 2002), and generally the findings have not been very consistent across studies. Furthermore, previous research has examined personality and culture in isolation, even though theorists have acknowledged that personality and culture *interact* in shaping people's responses to the environment (McCrae 2000). More generally, it has been repeatedly observed that a fuller understanding of individual dispositions such as SDR requires the investigation of both *micro-individual* and *macro-cultural* antecedents (Erbring and Young 1979), and the simultaneous investigation of individual-level variables and culture seems necessary to identify whether the individual-level effects of personality on SDR are systematically and predictably moderated by the cultural context in which respondents live.

Second, most of the research that has sought to investigate the personality and socio-demographic correlates of SDR has been conducted with samples of respondents from the U.S. Furthermore, in studies in which the relationship between SDR and different cultural orientations is investigated, it is not uncommon for researchers to recruit participants (usually students) from different cultural groups that reside in the U.S. (e.g., Lalwani et al. 2006). It would be preferable if the cultural determinants of SDR were studied in a truly international context.

Third, cross-national research introduces a host of measurement challenges (Van de Vijver and Leung 1997). Unfortunately, in cross-cultural SDR research, scale usage differences by respondents from different countries and other possible sources of lack of measurement invariance are usually not accounted for, which renders conclusions from such research problematic (Steenkamp and Baumgartner 1998).

The present chapter sets out to address these limitations. More specifically, our contribution is threefold. First, we develop a conceptual model that specifies the main effects of personality and national culture on SDR and, most importantly, considers the moderating role of the cultural context in which a respondent lives on the effects of the various personality factors. Second, the

hypotheses are tested using a large data set involving a random sample of over 12,000 respondents in 25 countries on 4 continents. This dataset provides a unique basis for deriving empirical generalizations concerning the main and interaction effects of personality and culture on SDR. Third, we use a recently developed scaling technique that is well-suited to analyzing data from a large number of countries (DeJong, Steenkamp, and Fox 2007). The traditional multi-group confirmatory factor analysis methodology is ill-equipped to satisfy minimum invariance constraints in such research settings (Baumgartner 2004). The new item response theory-based technique estimates latent scores for all constructs on a cross-nationally common scale, and hence holds great promise for conducting marketing research in many different nations or subcultures/subgroups within one country.

In the following sections, we first introduce our conceptual framework and develop our research hypotheses. Next, we discuss the data set, the measures, and the mathematical model. Finally, we present the results and end with a discussion and some future research suggestions.

IV.2 CONCEPTUAL FRAMEWORK

Socially desirable responding

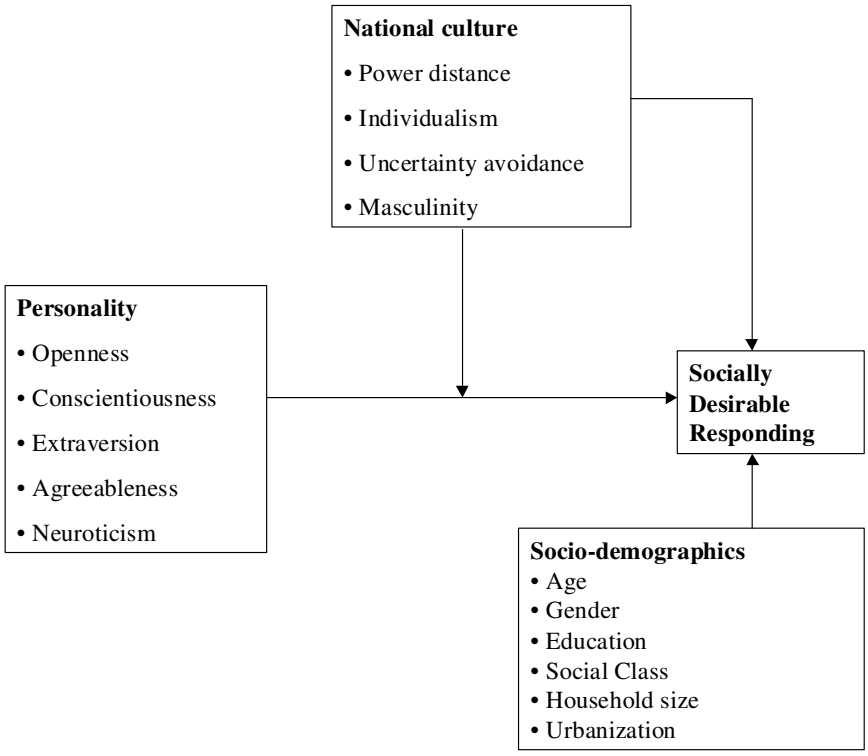
Socially desirable responding (SDR) can be defined as "the tendency for people to present themselves favorably according to current cultural norms when answering survey questions" (Mick 1996, p. 106). SDR may be either a response set or a response style (Mick 1996). In the former sense, it refers to a transitory reaction to a situational contingency such as time pressure or expected public disclosure of answers. One frequently used method to prevent SDR as a response set has been to assure respondents of their anonymity. Here we focus on SDR as a response style. Mick (1996) argues that SDR as a response style exists when individuals consistently engage in SDR across time, situations, and measurement instruments. It is a stable individual characteristic and making assurances of anonymity helps little if at all (Mick 1996).

Some researchers have treated SDR as a unidimensional construct (e.g., Crowne and Marlowe 1960; see Paulhus 1991 for a comprehensive overview). Others, notably Paulhus (1984; 1991), have argued that SDR consists of two (positively correlated) factors, namely, impression management (respondents' conscious tendency to present themselves in the most positive manner) and self-deceptive enhancement (people's unconscious tendency to provide inflated self-reports). Although several studies have shown differential relationships between the two components of SDR and a variety of other constructs and behaviors (e.g., Bearden, Manning, and

Tian 2004; Furnham, Petrides, and Spencer-Bowdage 2002; Lalwani et al. 2006; Mick 1996; see also Paulhus 2002), impression management and self-deceptive enhancement are sometimes fairly highly correlated (e.g., between .40 and .70; see Ones et al. 1996), and the pattern of correlations with other constructs has often been similar across the two SDR dimensions, especially with regard to their relationship with the Big Five dimensions of personality (Barrick and Mount 1996; Ones et al. 1996). For this reason, we will primarily focus on the antecedents of SDR as a whole, although we will briefly consider the separate effects on impression management and self-deceptive enhancement in the results section.

In developing our hypotheses, we follow Koestler's (1967, p. 56) dictum that "No man is an island – he is ... a Janus-faced entity who, looking inward sees himself as a self-contained unique whole, looking outward as a dependent part." A person's dispositions and behaviors are affected by his or her own makeup as well as by the norms and beliefs of the cultural environment (Triandis 1989). We propose and test a framework (see Figure 1) in which respondents' tendencies to provide socially desirable responses are hypothesized to be affected by their personality (as well as socio-demographics), the culture in which they live, and the interplay between personality and culture.

Figure 1
Conceptual Framework



The Role of Personality

Personality traits are "relatively enduring styles of thinking, feeling, and acting" (McCrae and Costa 1997, p. 509), representing basic human ways of experiencing and reacting to the world. The most influential conceptualization of personality is the Big Five factor model, which distinguishes between five fundamental personality traits, namely, extraversion, neuroticism (or its opposite, emotional stability), agreeableness, conscientiousness, and openness to experience (Digman 1990; John 1990). The Big Five structure has been replicated in a wide variety of populations (e.g., men and women, older and younger adults, different ethnic groups), in scores of countries on five continents, and in a host of language families (ranging from various branches of the Indo-European family to Hamito-Semitic, Malayo-Polynesian, Uralic, Bantu, and Sino-Tibetan varieties) that together include the native tongues of most of the world's population (McCrae, Terracciano, et al. 2005). The Big Five personality factors have also begun to attract attention in marketing, especially in the context of services (Brown et al. 2002; Mowen and Spears 1999).

Ones, Viswesvaran, and Reiss (1996) conducted a comprehensive meta-analysis of the relationship between social desirability and the Big Five dimensions of personality, in which they cumulated between 126 (for openness to experience) and 467 (for neuroticism) separate correlations involving between 39,314 and 143,794 respondents. They found estimated population correlations (corrected for unreliability in both measures) of -.37, .20, .14, .06, and .00 with neuroticism, conscientiousness, agreeableness, extraversion, and openness to experience (except for the last, all were significant).[15]

Although these findings provide strong empirical evidence concerning the effect of personality on SDR, Ones et al. did not discuss the theoretical rationale underlying these effects because their focus was on the criterion-related validity of personality measures for predicting job performance.

[15] Significant correlations between the Big Five personality factors and SDR may be interpreted as evidence that either personality factors affects SDR or that the measurement of personality factors is contaminated by SDR (suggesting reverse causality). If the latter interpretation is correct, correlations between SDR and the Big Five dimensions *as rated by others* and SDR should be negligible. Importantly, Ones, Viswesvaran, and Reiss (1996) found that this is not the case. They reported that the correlations between the SDR score provided by the focal person and others' ratings of the Big Five factors of personality of the focal person are similar in magnitude to the correlations between SDR scores and own ratings on the Big Five factors. Further, Ellingson, Smith, and Sackett (2001) found that social desirability does not alter the Big Five factor structure, which also argues against reverse causality.

Thus, one goal of the present research is to explicate the conceptual reasons for expecting certain relationships between the Big Five dimensions and SDR. In addition, most of the prior evidence concerning the link between personality and SDR comes from studies conducted with U.S. respondents. Even from an empirical perspective, there is thus some need to investigate the generalizability of previous findings in a global context. Finally, in contrast to previous research, we estimate the effect of each personality factor while controlling for the effect of the other personality factors (as well as for consumer demographics). It is well-known that bivariate correlational tests can lead to erroneous conclusions.

Individuals high on *neuroticism* tend to be anxious, fearful, self-pitying, insecure and low in self-esteem. Those low on this trait (i.e., emotionally stable people) are calm, relaxed, even-tempered, and unflappable. Neurotic individuals have been found to have a higher level of disclosure, even when it is inappropriate, due to maladaptive behavior patterns (Nelson-Jones and Coxhead 1980). This suggests that neurotics will be less concerned with upholding their public image by means of active response distortion. Furthermore, the lower self-esteem characteristic of neurotics implies that they are less likely to engage in self-deceptive enhancement. The findings of Mick (1996) in the context of research on materialism are consistent with the predicted negative correlation between neuroticism and SDR.

People high on *conscientiousness* tend to be cautious and high on social conformity and socially prescribed impulse control (Hogan and Ones 1997). According to socio-analytic theory (Hogan 1983), conscientious individuals are consciously or unconsciously motivated by social acceptance. They are skilled in social performance and attentive to processes that will support getting ahead and being socially accepted. Hogan and Ones (1997, pp. 865-866) theorized that a conscientious person "thinks about the question, considers the impression he or she would make with a particular response, and endorses the item to convey the desired image." Therefore, conscientiousness is expected to be positively associated with SDR.

Individuals who score high on *agreeableness* tend to be compliant and cooperative, and have a strong desire for harmonious interpersonal relationships. They are characterized by a motivational system that fosters a craving for intimacy, union, and solidarity with the groups to which they belong. Because agreeable people are especially motivated to maintain positive relations with other people, they are likely to make themselves look good in the eyes of others. Hence, we expect a positive relation between agreeableness and SDR.

Extraverts tend to be dominant and sociable, and they enjoy being with other people. Various personality theorists have argued that, in order to present themselves favorably, extraverts tend to conform to social standards, while introverts are nonconformists (Watson and Clark 1997). Extraverts achieve adaptation to the environment through social interaction and interpersonal relationships (Watson and Clark 1997), which suggests a positive relationship between extraversion and SDR. The empirical evidence for this hypothesis is somewhat equivocal, although overall Ones et al. (1996) report a small but reliable positive correlation between extraversion and SDR.

Finally, *openness to experience* is associated with tolerance of ambiguity, risk taking, autonomy of thought and action, receptivity to new ideas and novel situations, and a preference for complexity. All this implies a negative relation with SDR. However, the empirical evidence does not support this expectation. The estimated correlation in the meta-analysis of Ones et al. (1996) was .00, with a 90 percent confidence interval ranging from -.02 to .02. One possible explanation might be that openness to experience is the only Big Five factor that is related to cognitive ability and intellect (McCrae and Costa 1997). If, as argued by Stricker (1969), the ability to accurately assess the desirability of items and to respond in accordance with prescribed roles is one of the key abilities of test-wise individuals, and test-wiseness is positively correlated with SDR, then this would lead to a countervailing positive influence of openness to experience on SDR, resulting in an overall null effect of this personality dimension. We refrain from making a prediction and will investigate the relationship between openness to experience and SDR empirically.

In sum, we hypothesize:

H1: SDR is negatively associated with (a) neuroticism, but positively related to (b) conscientiousness, (c) agreeableness, and possibly (d) extraversion.

The Role of National Culture

As noted by Mick (1996), cultural norms are important determinants of SDR. Culture influences SDR in two ways. First, culture has direct effects on SDR (Triandis and Suh 2002; Van Hemert et al. 2002). Respondents in some countries may on average be higher in SDR than respondents in other countries, due to systematic differences in the cultural environment. Second, culture moderates the relation between personality and SDR. In this paper, the moderating role of culture is most

relevant, but we first develop the direct effects of culture to set the stage for our moderating hypotheses.

A country's culture is reflected in "general tendencies of persistent preference for particular states of affairs over others, persistent preferences for specific social processes over others, and general rules for selective attention, interpretation of environmental cues, and responses" (Tse et al. 1988, p. 82). Theorists such as Hofstede (2001) and Triandis (Triandis and Suh 2002) emphasize that culture is shared between members of a society. We will use Hofstede's (2001) well-known dimensions of national culture – individualism/collectivism, uncertainty avoidance, power distance, and masculinity/femininity – to examine the role of culture in encouraging people to provide socially desirable responses.

Individualism/collectivism pertains to the degree to which people in a country prefer to act as individuals rather than as members of a group. People in individualistic societies are emotionally detached from in-groups (other than their immediate family) and place their personal goals, motivations, and desires ahead of those of the in-group (Kagitcibasi 1997). Individualists tend to make decisions and initiate behaviors relatively independently of others and have a greater ability to withstand social pressure (Markus and Kitayama 1991). In contrast, collectivistic cultures are conformity oriented, and show a higher degree of group behavior and concern for promoting the group's continued existence. This suggests that in collectivistic societies, there will be a greater tendency for people to present themselves in a favorable light in order to meet interpersonal goals (Triandis 1995; Triandis and Suh 2002; Van Hemert et al. 2002). Thus, we expect that SDR will be higher in countries whose national culture is characterized by lower levels of individualism (or, conversely, higher levels of collectivism).

Uncertainty avoidance measures the degree to which societies tend to feel threatened by uncertain, risky, ambiguous or undefined situations, and the extent to which they try to avoid such situations by adopting strict codes of behavior. Individuals in high uncertainty-avoidance cultures will be more focused on risk avoidance and reduction, including social risk. Providing answers that are socially desirable is one way of reducing social risk. Therefore, uncertainty avoidance should be positively associated with socially desirable responding.

In high *power distance* cultures, the unequal distribution of power, roles, and resources is seen as legitimate. Institutions are likely to have a centralized structure, emphasize the chain of authority, assign well-defined roles in a hierarchical structure, and demand compliance in the

service of goals set at the top. The hierarchical relations are characterized by a strong degree of dependence and a desire for conformity. People are less inclined to show their true feelings, and it is important to make a good impression (Hofstede 2001). Hence, we expect that SDR will be higher in high power distance cultures.

In *masculine* cultures, the dominant values are ego enhancement, achievement and success, while the dominant values in *feminine* cultures are quality of life, equality, and caring for the weak (Hofstede 2001). At first sight, it might appear that SDR will be higher in feminine cultures because of their 'softer' orientation toward people. However, this ignores the fact that socially desirable responding serves an important ego-enhancing purpose in groups and societies (Paulhus 1984; Furnham, Petrides, and Spencer-Bowdage 2002). By providing "overly positive self-descriptions" (Paulhus 2002, p. 50), a person can enhance his or her stature in society. Moreover, cultural masculinity is related to Inglehart and Baker's (2000) survival values (Hofstede 2001, p. 266). Survival values express an orientation toward low tolerance of deviating opinions and low appreciation of imaginative, out-of-the-box thinking (Inglehart and Baker 2000), both of which are negatively associated with SDR. Thus, we expect SDR to be more pronounced in masculine cultures.

In summary, we hypothesize the following relationships between Hofstede's dimensions of cultural variation and SDR:

H2: SDR will be higher in countries whose national culture is characterized by (a) lower levels of individualism but higher levels of (b) uncertainty avoidance, (c) power distance, and (d) masculinity.

Although a few studies have examined the effect of culture on SDR, past research provides equivocal evidence concerning H_2. Individualism has attracted the most attention, which is not surprising given its pivotal role in cultural studies (Oyserman, Coon, and Kemmelmeier 2002). Van Hemert et al. (2002) found a significant negative bivariate correlation between a country's national-cultural individualism and its score on the Lie scale of the Eysenck Personality Inventory (a surrogate for SDR). Also, a significant positive bivariate correlation was found with power distance, although the authors did not offer a theoretical rationale for these effects. Lalwani, Shavitt, and Johnson (2006) measured cultural orientation at the individual level and found that individualism was positively related to the self-deceptive enhancement component of

SDR and collectivism was positively related to impression management (especially the horizontal forms of individualism and collectivism). However, Heine and Lehman (1995) found no differences between (collectivistic) Japanese exchange students and (individualistic) European-Canadians on either self-deceptive enhancement or impression management, while Triandis et al. (2001) found evidence of greater tendencies toward deception among collectivistic samples in business negotiation scenarios. Finally, Church (2000) reviewed several studies suggesting that collectivistic societies are higher on SDR. One possible explanation for these inconsistencies is that SDR may be a joint function of personality and culture so that both have to be considered in interaction. The theoretical evidence in favor of this possibility is considered next.

Interactions between Personality and Culture

The shared cultural priorities in society help to shape the social and economic reward contingencies to which people must adapt in the institutions in which they spend most of their time (families, schools, businesses, etc.) in order to function smoothly and effectively (Smith and Schwartz 1997). Triandis and Suh (2002) theorize that behavior is a function of not only culture and personality but also their interaction. McCrae (2000) similarly argues that "personality and culture are relatively independent forces that *interact* to shape people's lives" (p. 14, emphasis added), and notes that "culture affects ... the expression of personality" (p. 21; see also Church 2000, p. 663).

Individuals may thus experience compatibilities and conflicts between their own personality makeup and national-cultural priorities. These positive or negative social reinforcement mechanisms – which operate between the two types of constructs – give rise to interactions between individual-level and national-cultural variables. More specifically, personality traits that are *congruent* with national-cultural priorities will be encouraged, while the expression of personality traits that are *incongruent* with national priorities are discouraged (Triandis 1989). We posit five interactions involving the moderating influence of culture on the relationship between personality and SDR, based on the relative congruence or incongruence between a specific personality factor and a particular national-cultural dimension.

Neuroticism. People high on neuroticism are anxious, nervous, and tense. Hofstede (2001) characterizes countries high on uncertainty avoidance as anxious cultures and describes their

citizens as "fidgety." Prior research clearly shows that country-level neuroticism scores correlate substantially with various measures of anxiety and Hofstede's uncertainty avoidance index (see Lynn and Martin, 1995, and the research reviewed in Hofstede, 2001, Chapter 4). Due to the mechanism of characteristic adaptation (McCrae 2000), we can expect that high national-cultural uncertainty avoidance reinforces the effect of high individual-level neuroticism on SDR.

H3: The negative effect of neuroticism on SDR will be stronger when national-cultural uncertainty avoidance is higher.

Conscientiousness. There is also a basic congruence between conscientiousness and uncertainty avoidance. The conventional, thorough, organized, and cautious thinking that characterizes individuals high on conscientiousness (Hogan and Ones 1997) is more valued in high uncertainty avoidance cultures, which shun unpredictable and ambiguous situations while valuing clarity and structure (Hofstede 2001). Further, conscientiousness reflects tendencies toward rule compliance and obedience (Noller, Law, and Comrey 1987), and rule orientation is a key aspect of the operational definition of uncertainty avoidance (Hofstede 2001). Since uncertainty avoidance is thus conducive to the expression of conscientiousness, we predict that it will strengthen the effect of conscientiousness on SDR.

H4: The positive effect of conscientiousness on SDR will be stronger when national-cultural uncertainty avoidance is higher.

Agreeableness. People high on agreeableness tend to be modest and cooperative. They are more concerned about the welfare of others, are more strongly motivated to maintain positive relations with others, and have a strong desire for harmonious interpersonal relationships (Graziano and Tobin 2002). This personality factor is therefore highly compatible with the focus of national-cultural collectivism on interdependence, relationships, harmony, humility, moderation, and conformity (Triandis 1989; Markus and Kitayama 1991). The converse is true for societies high on individualism, which emphasize independence, ability to withstand social pressure, and uniqueness. Furthermore, in individualist cultures, confrontations are much more accepted (Kagitcibasi 1997). Thus, it is reasonable to expect that individualism/collectivism will moderate the effect of agreeableness on SDR.

H5: The positive effect of agreeableness on SDR will be stronger when national-cultural individualism is lower or collectivism is higher.

Extraversion. Peabody (1999) argues that the Big Five factor of extraversion is closely related to an assertive-unassertive dimension, which he links to masculinity-femininity. Hofstede (2001) has referred to the masculinity-femininity dimension as a contrast between assertiveness and modesty, and some of the traits often associated with extraversion (e.g., dominance, competitiveness, a desire to boost one's ego; see De Raad 2000) are clearly congruent with values associated with national-cultural masculinity (Hofstede 2001). This suggests that the positive effect of extraversion on SDR will be strengthened by a masculine cultural environment.

In addition, extraverts like to be the center of attention in social situations, are forceful, enjoy controlling and/or influencing others, and are willing to work hard to pursue their life goals (Watson and Clark 1997). Since in high power distance cultures, people are highly motivated by social status and prestige (Roth 1995), this cultural orientation is thus congruent with extraversion. We therefore predict that the effect of extraversion will be reinforced by the cultural dimension of power distance. Combining both hypotheses, we specify the following:

H6: The positive effect of extraversion on SDR will be stronger when (a) national-cultural masculinity and (b) national-cultural power distance are higher.

Sociodemographics

Although they are not of primary theoretical interest in this research, several important sociodemographics are included in our model for control purposes. Some researchers (e.g., Fisher 1993; King and Bruner 2000) have hypothesized that SDR might systematically vary across sociodemographic groups in society, but few, if any, generalizable results have emerged. This may be partly due to the fact that most research has used fairly homogeneous populations (university students). Ones and Viswesvaran (1998) conducted a meta-analysis of the effects of gender and age on social desirability (based on 66 and 19 studies, respectively) and found that men and older people scored higher on social desirability scales, although the effects sizes were small. Paulhus (1991) reported that men rated higher on self-deceptive enhancement, but women had higher scores on impression management. There is also some evidence that respondents from lower social classes are higher in social desirability (Ross and Mirowsy 1984). In addition, SDR

has been hypothesized to be positively associated with education (which should increase "test smartness"), although Ones, Viswesvaran, and Reiss (1996) actually found the opposite.

Given the dearth of theory to guide us, we refrain from developing formal hypotheses. Instead, we will use the richness of our data set to examine the effect of several sociodemographics in an exploratory fashion. This serves two purposes. First, it allows us to assess whether any cross-nationally generalizable effects can be found. These findings are of practical relevance as sociodemographics are readily available in marketing research. Second, controlling for these variables removes extraneous variance from the data and hence provides for a more precise test of our hypotheses.

IV.3 METHOD

Data collection

Two global marketing research agencies, GfK and Taylor Nelson Sofres, collected the data in 25 countries around the world: Argentina, Austria, Belgium, Brazil, China, Czech Republic, Denmark, France, Germany, Hungary, Ireland, Italy, the Netherlands, Norway, Poland, Portugal, Romania, Russia, Spain, Switzerland, Taiwan, Thailand, Ukraine, UK, and the U.S. The sample in each country was drawn so as to be broadly representative of the total population in terms of region, age, education, and gender.

For countries with a high penetration of the Internet, a web survey was used. In some countries with a lower Internet penetration, we used mall intercepts. For the mall intercepts, the first step was to select multiple regions/locations for the fieldwork. Next, a space was rented which had an Internet connection for 2-5 PCs or laptops (e.g., Internet cafes, subsidiaries of offices, test halls for product tests) and which offered the possibility to 'intercept' appropriate shoppers/respondents walking in the street using street recruiters. Finally, in some countries a hard-copy survey instrument was used, which was also administered through mall intercepts. The hard-copy tool was designed so that the layout was exactly the same as in the Internet survey.

The number of respondents per country varied between 355 (U.K.) and 640 (Germany), but in the U.S. the sample was considerably larger (1,181). Given the importance of the U.S., the marketing research agencies wanted to have a larger sample for that country. The total number of respondents is 12,022.

Measures

The questionnaire was developed in English and then translated into all local languages by professional agencies. Next, the translated surveys were backtranslated into English, using native speakers from the local countries. In each survey, modifications were made based on discussions between the backtranslators, one of the authors, and the headquarters of the marketing research agencies to maintain consistency across all countries.

SDR was measured using a subset of 20 items (10 impression management items and 10 self-deceptive enhancement items) of the 40-item Balanced Inventory of Desirable Responding (Paulhus 1991). Item selection was based on the magnitude of factor loadings, but potentially offensive and/or in appropriate items were omitted (e.g., "I never read sexy books or magazines" or "I am not a safe driver when I exceed the speed limit") and an effort was made to retain the balanced structure of the scale. Thus, we selected five positively and five negatively worded items per SDR dimension. The market research agencies considered the full 40-item scale too long and too costly to administer. Moreover, shorter scales decrease response fatigue, reduce boredom, and increase cooperation (Burisch 1984). The average reliability across countries was 0.72, with a standard deviation of 0.05.

The Big Five factors were measured with 6 items each, based on Benet-Martínez and John (1998). For each factor, we selected three highly loading positively and negatively worded items. The average reliability was 0.66. Both the SDR and Big Five items were measured on five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Following Stöber, Dette, and Musch (2002), continuous scoring was used for the SDR scale.

We also collected data on gender (coded 1 for women and 0 for men), age (in years), education (no formal education, education up to age 12, 14, 16, 18, higher education, university), social class (lower class, working class, lower-middle class, middle class, upper-middle class, upper class), and household size. Ratings of each country on the four dimensions of national culture were taken from Hofstede (2001).

Analytical Procedure

Received wisdom holds that before mean differences across countries and relations between constructs can be examined in cross-national research, one must first establish that the measurement instruments are cross-nationally comparable (Steenkamp and Baumgartner 1998). The multi-group confirmatory factor analytic procedure is the standard method for assessing the cross-national

invariance of measurement instruments. Unfortunately, when the number of countries is large, even partial measurement invariance is unlikely to be fulfilled, which renders the multi-group CFA procedure problematic (Baumgartner 2004; Lubke and Muthén 2004). We use a new procedure based on item response theory, which relaxes the condition of measurement invariance and accommodates scale usage differences across countries (see De Jong, Steenkamp, and Fox 2007). This procedure calibrates all latent scores for the constructs of interest on the same scale. Thus, the scores are cross-nationally comparable even when there are differences in scale usage and measurement invariance does not hold. See the Appendix for details on this measurement procedure.

We use the latent scores in a multilevel model for SDR. Our conceptual framework of the drivers of SDR involves variables at two levels of aggregation: the individual and the country level. The levels are hierarchical in that respondents are nested within countries. Multilevel modeling (Hox 2002; Raudenbush and Bryk 2002) has been specifically developed to deal with nested data. It enables the simultaneous estimation of relationships of constructs at two (or more) levels. It borrows strength from all the data in each of the countries, and makes it possible to estimate cross-level effects, thus enabling us to test hypotheses about the moderating effect of culture on the relationship between personality and SDR. More specifically, the level-1 (individual-level) and level-2 (country-level) models for testing the hypotheses are formulated as follows:

Level-1:

$$(1) \quad SDR_{ij} = \beta_{0j} + \beta_{1j}N_{ij} + \beta_{2j}C_{ij} + \beta_{3j}A_{ij} + \beta_{4j}E_{ij} + \beta_{5j}O_{ij} + \beta_{6j}GENDER_{ij} + \beta_{7j}AGE_{ij} + \beta_{8j}EDUC_{ij} + \beta_{9j}SocClass_{ij} + \beta_{10j}HHSize_{ij} + r_{ij}$$

Level-2:

$$(2) \quad \beta_{0j} = \gamma_{00} + \gamma_{01}IND_j + \gamma_{02}UA_j + \gamma_{03}PD_j + \gamma_{04}MAS_j + u_{0j}$$

$$(3) \quad \beta_{1j} = \gamma_{10} + \gamma_{11}UA_j + u_{1j}$$

$$(4) \quad \beta_{2j} = \gamma_{20} + \gamma_{21}UA_j + u_{2j}$$

$$(5) \quad \beta_{3j} = \gamma_{30} + \gamma_{31}IND_j + u_{3j}$$

$$(6) \quad \beta_{4j} = \gamma_{40} + \gamma_{41}MAS_j + \gamma_{42}PD_j + u_{4j}$$

$$(7) \quad \beta_{qj} = \gamma_{q0} + u_{qj} \quad \text{for } q = 5, \ldots, 10$$

where i denotes individuals (i = 1,…, 12,022) and j countries (j = 1,..., 25); SDR refers to a person's latent score on socially desirable responding; *N*, *C*, *A*, *E*, and *O* indicate a person's latent score on neuroticism, conscientiousness, agreeableness, extraversion, and openness to experience, respectively; GENDER, AGE, EDUC, SocClass, and HHSize represent the sociodemographics gender, age, level of education, social class, and household size, respectively; and IND, UA, PD, and MAS are national-cultural individualism, uncertainty avoidance, power distance, and masculinity, respectively.

The individual-level error term r_{ij} is assumed to be normally distributed with zero mean and variance σ^2. The random effects u_{qj} (q = 0, .., 10) are multivariate normally distributed over countries, each with an expected value of zero, var(u_{qj}) = τ_{qq}, and cov(u_{qj}, $u_{q'j}$) = $\tau_{qq'}$ (q, q' = 0, .., 10). All level-1 coefficients are specified as random coefficients; that is, their effect is allowed to vary across countries. The multilevel model was estimated using HLM 5 (Raudenbush, Bryk, and Congdon 2000), using the latent scores for SDR and the five personality factors obtained from the hierarchical IRT measurement model.

IV.4 RESULTS

Two sets of results will be presented in this section. First, we will report the tests of the proposed hypotheses and the estimated effects of the demographics on SDR. Second, we will briefly describe the findings when the two dimensions of SDR (impression management and self-deceptive enhancement) are analyzed separately.

The effects of personality and culture on SDR

Before going into the specific hypothesized effects we estimate an unconditional random intercept model, that is, a model with a random intercept and without individual-level or country-level covariates. The intraclass correlation is 15.1%, indicating that a reasonably high portion of variation in SDR is associated with differences between countries. When we add the Big-5 personality variables with random-effects specifications for the slope coefficients, 22.8% of the variation in SDR at level-1 is explained. Next, the socio-demographic variables are introduced in the model. These variables explain an additional 2.4% of the variance.

Finally, we include the cultural variables in the equations for the intercept and slope coefficients, and specify fixed effects for slope coefficients that do not display significant variation across countries (Raudenbush and Bryk 2002). Our cultural variables explain 26.1% of the variation at level 2. The estimates of the individual-level effects, the national cultural effects, and

the cross-level interactions are reported in Table 1. Note that we report unstandardized coefficients. In multilevel analyses, standardized coefficients are not used as the variance is partitioned across different levels.

Table 1
ESTIMATION RESULTS

Independent variables	*Hypothe-sized effect*	*Unstand. coefficient*	*t-value*	*P*
Intercept (γ_{00})		0.5873	28.00	<.01
Main effects of Personality				
Neuroticism (γ_{10})	-	-0.0745	-14.87	<.01
Conscientiousness (γ_{20})	+	0.1326	22.60	<.01
Agreeableness (γ_{30})	+	0.1125	12.91	<.01
Extraversion (γ_{40})	+	0.0003	0.06	n.s.
Openness (γ_{50})		0.0138	2.39	<.05
Main effects of National-cultural Dimensions				
Individualism (γ_{01})	-	-0.0037	-3.56	<.01
Uncertainty avoidance (γ_{02})	+	0.0013	1.62	<.10
Power distance (γ_{03})	+	0.0020	2.09	<.05
Masculinity (γ_{04})	+	0.0020	3.32	<.01
Cross-level interactions				
Neuroticism × Uncertainty Avoidance (γ_{11})	-	-0.0001	-0.20	n.s.
Conscientiousness × Uncertainty Avoidance (γ_{21})	+	0.0006	2.91	<.01
Agreeableness × Individualism (γ_{31})	-	-0.0010	-2.61	<.01
Extraversion × Masculinity (γ_{41})	+	0.0004	3.05	<.01
Extraversion × Power Distance (γ_{42})	+	0.0007	3.62	<.01
Sociodemographics				
Age (γ_{60})		0.0031	11.11	<.01
Gender (γ_{70}) (1=women; 0=men)		0.0049	0.97	n.s.
Education (γ_{80})		0.0043	1.58	n.s.
Social Class (γ_{90})		-0.0046	-2.51	<.01
Household Size ($\gamma_{10,0}$)		0.0019	1.28	n.s.
Explained variance				
Individual-level		25.2%		
Country-level		26.1%		

[a] *p*-values are for one-sided tests when a hypothesis was stated.
[b] n.s. = not significant ($p > .10$)

The role of personality. As hypothesized in H1a, H1b and H1c, neuroticism had a highly significant negative effect (γ_{10} = -.0745, $p < .01$), and conscientiousness and agreeableness had highly significant positive effects (γ_{20} = .1326, $p < .01$, and γ_{30} = .1125, $p < .01$, respectively), on SDR. SDR was also positively affected by openness to experience (γ_{50} = .0138, $p < .05$), although the magnitude of this effects was much smaller than that for the other significant personality variables. Contrary to prediction, but not completely unexpectedly (see H1d), extraversion was not significantly related to SDR (γ_{40} = .0003, n.s.). Overall, we find strong support for the cross-national generalizability of relationships between personality and SDR for three of the five Big-Five dimensions (conscientiousness, agreeableness, and neuroticism, in decreasing order of magnitude).

The role of national culture. Consistent with H2a, we found that the degree of individualism of a nation-culture had a negative effect on the extent of socially desirable responding (γ_{01} = -.0037, $p < .01$). H2b proposed that national-cultural uncertainty avoidance would have a positive effect on SDR. Support was found for this hypothesis, although the effect was a bit weaker than for the other dimensions (γ_{02} = .0013, $p<0.10$). The main effect of national-cultural power distance was positive and significant (γ_{03} = .0020, $p < .05$), which supports H2c. Finally, as expected (H2d), SDR was higher in countries characterized by higher national-cultural masculinity (γ_{04} = .0020, $p < .01$).

Interactions between personality and culture. Our framework also posits an important role of national culture in moderating the effect of personality on SDR. H3 proposed that uncertainty avoidance would strengthen the negative effect of neuroticism on SDR. However, no support was found for this hypothesis (γ_{11} = -.0001, n.s.). As hypothesized in H4, the effect of conscientiousness was stronger in cultures high on uncertainty avoidance (γ_{21} = .0006, $p < .01$). Also as expected (H5), the positive effect of agreeableness on SDR was weaker when national-cultural individualism was higher (γ_{11} = -.0010, $p < .01$). Finally, in support of H6a and H6b, the effect of extraversion on SDR was stronger when national-cultural masculinity and national-cultural power distance were higher (γ_{41} = .0004, $p < .01$, and γ_{42} = .0007, $p < .01$, respectively). In summary, four of five hypotheses about the interactive effects of personality and culture were supported.

Sociodemographics. Two main effects of the sociodemographics were strongly supported. Specifically, older respondents were found to be much more likely to engage in socially desirable responding than younger respondents (γ_{70} = .0031, p < .01). In addition, there was evidence that individuals from lower social strata of society have a greater tendency to distort their answers in a socially desirable direction (γ_{90} = -.0046, p < .01).

IM and SDE as separate dimensions of SDR

As mentioned earlier, Paulhus (1984; 1991) distinguished between two components of SDR, namely, impression management and self-deceptive enhancement. Our hypotheses were developed for the overarching SDR construct rather than for the specific dimensions. Combining impression management and self-deceptive enhancement also leads to more reliable SDR scores, which capture the entire domain rather than only one component. This procedure is also consistent with other work that focuses on SDR per se, which often uses the major alternative to the Paulhus scale, the Marlowe-Crowne scale. The latter scale loads on both the impression management and self-deception factors (Paulhus 1984).

However, as a robustness check, and to examine whether major new insights emerge when the two components of SDR are considered separately, we estimated equations (1) – (7) using respondents' scores on impression management (IM) and self-deceptive enhancement (SDE) as criterion variables. The results were highly stable across the two dimensions of SDR, although the p-values were sometimes lower. This is not unexpected, given the lower reliabilities for the two subscales. The correlation between the (unstandardized) path coefficients for SDR (combined scale) and IM was .992, while the correlation between the coefficients for SDR and SDE was .978. The correlation between the coefficients for IM and SDE was .953. Finally, the correlation between the latent IM and SDE scores was 0.316.

However, there were two notable exceptions to the general stability of the results across the two SDR operationalizations. First, extraversion had a significantly *positive* effect on SDE ($\gamma_{E,SDE}$ = .0225, p < .01), while the effect on IM was significantly *negative* ($\gamma_{E,IM}$ = -.0252, p < .01). This finding is partly consistent with prior research showing that extraversion is primarily related to SDE (e.g., Barrick and Mount 1996; Pauls and Stemmler 2003).

Second, while the effect of gender on overall SDR was not significant, we did find significant but opposing effects for the two SDR components. A cross-nationally generalizable finding is that, on average, men are higher than women on self-deceptive enhancement ($\gamma_{Gend,SDE}$= -.0133, p

< .01), while women are higher on impression management ($\gamma_{Gend,IM}$ = .0385, p < .01). These results are consistent with earlier work reporting significant gender differences in the tendency to exhibit IM and SDE response styles (Paulhus 1991).

IV.5 DISCUSSION

In this paper, we examined the antecedents of SDR, one of the most important response biases in marketing surveys, in a truly global setting. We proposed and tested a framework (see Figure 1) in which respondents' tendency to provide socially desirable responses was hypothesized to be affected by their personality and sociodemographics, the culture in which they live, as well as the interplay between personality and culture. Drawing on insights from personality research and culture theory, specific hypotheses were developed to operationalize this framework. The hypotheses were tested across 25 countries, using large representative samples of consumers, thus allowing for a strong test of the empirical generalizability of our findings in an international context. In general, our findings supported the proposed hypotheses.

People's tendency to provide socially desirable answers was systematically affected by their personal makeup. SDR increased with conscientiousness and agreeableness, and decreased with neuroticism. Openness to experience also had a small positive effect on SDR, but the effect of extraversion was nonsignificant. In addition, national-cultural dimensions played a prominent role. Respondents in individualistic countries were less likely to engage in socially desirable responding, while respondents in high power distance, uncertainty avoiding, and masculine countries tended to exhibit a greater degree of socially desirable responding.

Most importantly, a nation's culture systematically moderated the effects of the personality dimensions on SDR. The positive effect of conscientiousness on SDR was stronger in countries high on uncertainty avoidance, whereas an individualistic cultural environment reduced the positive effect of agreeableness on SDR (or conversely, collectivism strengthened the effect of agreeableness on SDR). Although the main effect of extraversion on SDR was nonsignificant, this personality factor was involved in two significant interactions with national-cultural power distance and masculinity. Both dimensions of cultural variation enhanced the effect of extraversion on SDR. Overall, the moderating role of culture is clearly illustrated by our finding that the effect on SDR of three of the five personality factors depended on the national-cultural context in which a person lives.

We also found several interesting effects for the sociodemographics. SDR was lower among younger people and among persons from higher social classes. Furthermore, although SDR did not differ by gender, men were higher on self-deceptive enhancement, while women were higher on impression management. The other sociodemographics did not exert a cross-culturally generalizable effect on SDR in our study.

Two hypotheses were not supported. First, the effect of extraversion was completely moderated by the country context, in the sense that the predicted main effect of extraversion was not significant, even though the interactions of extraversion with masculinity and power distance were (i.e., extraversion had a more positive effect on SDR in masculine and high power distance cultures, as predicted). Our follow-up analyses showed that extraversion had a significant positive effect on self-deceptive enhancement and a significant negative effect on impression management. This result is partially consistent with recent theorizing by Paulhus (2002) and empirical evidence by Pauls and Stemmler (2003) that SDE is indicative of (unconscious) egoistic bias, which is related to extraversion.

Second, no support was found for the interaction between neuroticism and uncertainty avoidance. Although neuroticism had a strong negative influence on SDR, this effect was not moderated by a culture's degree of uncertainty avoidance, even though neuroticism at the individual level and uncertainty avoidance at the cultural level are strongly linked. Uncertainty avoidance basically reflects anxiety about unstructured situations and a preference for rules and structures that ensure that such situations do not arise. It is possible that uncertainty avoidant cultures do not reinforce neurotic tendencies of lack of concern for one's public image and lower self-esteem in general but instead encourage caution and compliance with rules, as expressed in H4 and confirmed by the significant interaction of conscientiousness and uncertainty avoidance.

In sum, the results provide broad support for our conceptualization and the relevance of the different types of variables included in the proposed framework for understanding the construct of SDR. Multiple personality dimensions as well as sociodemographics exerted significant effects on SDR. The findings of the present study also underline the important role of national-cultural variables in explaining systematic differences in SDR between countries. In particular, our results suggest that it is important to consider the joint effect of personality and culture on SDR since culture moderated the effects of personality on SDR. This shows that combining variables from the macro-level of national cultures and the micro-level of individuals' personality in an

integrated framework enhances our understanding of the drivers of an important bias in marketing surveys. These findings are also important from an applied perspective, as more and more firms are dependent on their international activities for survival and growth (Kotabe and Helsen 2004). Survey data are a key instrument in formulating effective marketing strategies in an international context, and firms need to better understand the role of the environment in undermining the validity and cross-national comparability of marketing survey data (Craig and Douglas 2000).

Although the results in Table 1 provide evidence about the dimensions of cultural variation that encourage socially desirable responding, researchers may be interested in the SDR scores of the countries included in our research. Table 2 provides these data, corrected for cross-national scale usage differences (as described in the Appendix). For ease of interpretation, we have set the mean score of the U.S. to zero. It is apparent that the U.S. tends to rate on the lower side of the SDR continuum. On average, SDR is least prevalent in the U.K. and Ireland. In contrast, SDR seems relatively common in some of the Eastern European and South American countries, Taiwan, and especially China.

Table 2
Country Scores on SDR

Country	SDR
UK	-.188
Ireland	-.181
Germany	-.111
Switzerland	-.107
Thailand	-.099
Denmark	-.058
Austria	-.049
Norway	-.035
Belgium	-.022
France	-.010
USA	.000
Netherlands	.001
Czech Rep.	.022
Russia	.022
Spain	.079
Portugal	.080
Italy	.090
Ukraine	.117
Brazil	.132
Argentina	.179
Romania	.184
Hungary	.188
Taiwan	.198
Poland	.226
China	.295

Future research

Future research could go in several directions. Our framework should be tested in other countries as well. Most notably, African countries were missing in our study. Our conceptual model may be extended by introducing subculture dimensions. A subculture preserves the important patterns of the national culture, but also develops its own unique patterns of dispositions and behavior through a specific set of shared norms and beliefs.

Our work shows that SDR is a stable characteristic of people, related to basic personality traits as well as age and one's social standing in society, and the culture in which one lives. As such, it cannot be expected that socially desirable responding can be completely eliminated from marketing surveys (Mick 1996). However, marketing researchers can do at least two things to

reduce its biasing influence. First, any stable characteristic of people may be more or less activated in specific situations. How can we minimize the expression of SDR in marketing surveys? In the literature, researchers have suggested methods such as indirect questioning (Fisher 1993), the randomized response technique (Fox 2005c), and assuring respondents anonymity (Mick 1996). More research is needed to assess the effectiveness of these recommendations in the U.S. and elsewhere (e.g., is assurance of anonymity equally effective in individualistic and collectivistic cultures?). New methodological developments in the randomized response technique proposed in the educational area look especially interesting for marketing research. For example, Fox (2005c) has developed a randomized response model that guarantees anonymity at the item-level through randomization, but by using multiple intercorrelated items one can make individual-level inferences at the construct level. Future research could also examine other ways to reduce the expression of SDR in marketing surveys. For example, does the extent of socially desirable responding differ between telephone, mail, Internet, and face-to-face surveys?

A second way in which marketing researchers can reduce the biasing influence of socially desirable responding is to control for this bias after the data have been collected. This requires two things, both of which offer avenues for future research. First, an SDR measurement instrument could be included in the survey. All too often, this is not done, even in academic research. For example, only 12 percent of the scales included in the seminal *Handbook of Marketing Scales* (Bearden and Netemeyer 1999) report evidence on social desirability. It is safe to assume that this percentage will be even lower in applied marketing research. A review of two decades of published marketing research reveals that SDR has been consistently neglected in scale construction, evaluation, and implementation (King and Bruner 2000). We believe a major reason is that SDR scales are too long. Consider Paulhus' (1991) Balanced Inventory of Desriable Responding, arguably the standard for measuring SDR. Even our subset of 20 items is too long for most marketing research applications. Adding non-substantive items to a survey is costly, both in terms of money and respondent fatigue. It is often difficult to get marketers to pay for so many additional survey items which will be used "solely" for estimating socially desirable response tendencies. Research is therefore needed to develop and rigorously validate short forms of the Paulhus scale. Recent work by Bearden, Manning, and Tian (2004), who developed a 9-

item short-form for measuring SDR in business contexts, is an important step in the right direction.

If an SDR scale is included in the survey, the next issue is how to control for SDR in one's analyses. A common way to do this is to correlate the substantive constructs with SDR, and the researcher hopes that the resulting correlations will be small (King and Bruner 2000). However, this procedure may seriously underestimate the biasing influence of SDR since it fails to distinguish between SDR bias at the measurement level from SDR bias at the construct level, and it ignores measurement error in SDR and the substantive constructs involved (Podsakoff et al. 2003). Future research should simultaneously estimate the structural relations among the substantive constructs and the measurement model, where each item is modeled as a function of a substantive construct and SDR. Resultant construct scores and relations among substantive constructs are corrected for the biasing influence of SDR. In sum, although important issues remain for future research, we hope that researchers will take our lead and make SDR the substantive focus of some of their substantive and methodological work.

IV.6 APPENDIX

A suitable IRT model for ordinal 5-point Likert data of the kind used in our survey is the graded response model (Samejima 1969). If we index countries by j, j=1,…,J , and denote by x_{ijk}^{l} the observed response on item k of construct l for respondent i in country j, a hierarchical IRT measurement model can be formulated as:

$$P(x_{ijk}^{l} = c \mid \xi_{ij}^{l}, a_{kj}^{l}, \gamma_{kj,c}^{l}, \gamma_{kj,c-1}^{l}) = \Phi(a_{kj}^{l}\xi_{ij}^{l} - \gamma_{kj,c-1}^{l}) - \Phi(a_{kj}^{l}\xi_{ij}^{l} - \gamma_{kj,c}^{l}) \quad \text{(A1)}$$

$$\gamma_{kj,c}^{l} = \gamma_{k,c}^{l} + e_{kj,c}^{l},\ e_{kj,c}^{l} \sim N(0, \sigma_{\gamma_k}^{2(l)}) \text{ for } c = 1,\ldots,C,\ \gamma_{kj,1}^{l} \le \ldots \le \gamma_{kj,C-1}^{l} \quad \text{(A2)}$$

$$a_{kj}^{l} = a_{k}^{l} + r_{kj}^{l},\ r_{kj}^{l} \sim N(0, \sigma_{a_k}^{2(l)}) \quad \text{(A3)}$$

$$\xi_{ij}^{l} = \xi_{j}^{l} + \upsilon_{ij}^{l},\ \upsilon_{ij}^{l} \sim N(0, \sigma_{j}^{2(l)}) \quad \text{(A4)}$$

$$\xi_{j}^{l} \sim N(\xi^{l}, \tau^{2(l)}) \quad \text{(A5)}$$

where $\Phi(.)$ is the standard normal cumulative distribution function. Equation (1) specifies the conditional probability of a person i in country j, responding in a category c (c=1,…,C) on item k of construct l, as the probability of responding above c-1, minus the probability of responding above c. The parameter a_{kj}^{l} is called the *discrimination* parameter for item k of construct l in country j, and is conceptually similar to a factor loading in CFA settings. The scale thresholds $\gamma_{kj,c}^{l}$ are measured on the same scale as ξ_{ij}^{l} and determine the *difficulty* of responding above a certain response category c. The threshold $\gamma_{kj,c}^{l}$ is defined as the value on the ξ_{ij}^{l} scale so that the probability of responding above a value c is .5, for c=1,…,C-1. In (A2), one can put $\gamma_{kj,0}^{l} = -\infty$, $\gamma_{kj,C}^{l} = \infty$, so that only the thresholds for the categories 1 through C-1 need to be considered.

Equation (A2) indicates that each scale threshold $\gamma_{kj,c}^{l}$ for a particular item k in country j is modeled as an overall mean threshold $\gamma_{k,c}^{l}$, plus a country-specific deviation $e_{kj,c}^{l}$. Thus, scale usage differences across countries are accommodated. Analogously, equation (A3) posits that the discrimination parameter a_{kj}^{l} is the sum of an overall mean discrimination parameter and country-specific deviation.

Equations (A4) and (A5) model the country heterogeneity of the latent variable with random-effects structures. In other words, the position on the latent scale for respondent i in country j on construct l is sampled from the country average ξ_{j}^{l} with variance $\sigma_{j}^{2(l)}$. The country average is drawn from a distribution with average ξ^{l} and variance $\tau^{2(l)}$.

Estimation of the hierarchical IRT model is demanding because of the large number of parameters and model complexity. Using data augmentation, an 8-step Gibbs sampler with a Metropolis-Hastings step for the order-constrained thresholds can be constructed, with item parameter restrictions in each country to identify the model. We refer to De Jong, Steenkamp, and Fox (2007) for further details.

Chapter 5

Construction of Country-Specific, Yet Internationally Comparable Short Form Marketing Scales

Abstract:

The increasing trend toward the globalization of business implies that the world is rapidly becoming an interdependent marketing system, providing a compelling reason for developing global theories and for studying associated methodological challenges. Cross-national research presents researchers with a host of methodological challenges that hamper validity. An issue that has received only limited attention to date has to do with designing cross-national measurement instruments. We develop a procedure that yields fully country-specific, yet cross-nationally comparable short form marketing scales. The procedure is based on a combination of a two powerful psychometric tools: a hierarchical item response theory model and optimal test design methods. In the empirical part, our procedure is applied to the impression management (IM) scale, yielding country-specific yet cross-nationally comparable short-form scales in 28 countries of the world.

This chapter is based upon a paper with the same title authored by Martijn G. de Jong, Jan-Benedict E.M. Steenkamp and Bernard Veldkamp. We thank AiMark for providing the data.

V.1 INTRODUCTION

It has been recognized that consumer behavior and marketing theories are frequently dependent on socioeconomic, institutional and cultural contexts (Maheswaran and Shavitt 2000). The increasing trend toward the globalization of business implies that the world is rapidly becoming an interdependent marketing system, providing a compelling reason for developing global theories and for studying associated methodological challenges (Winer 1998). Indeed, various researchers have called for "exploration of cross-cultural dynamics" (Bagozzi 1994), or have pressed for a need to "move out of the U.S. silo and conduct more research on an international basis" (Steenkamp 2005).

Many current theoretical frameworks remain to be validated across cultures. One important force that stymies the comparison of findings across countries is methodological in nature. Cross-national research presents researchers with a host of methodological challenges that hamper validity, such as response styles, measurement invariance, and wording issues (Baumgartner and Steenkamp 2001; De Jong, Steenkamp, and Fox 2007; Durvasula et al. 1993; Van de Vijver and Leung 1997; Wong et al. 2003). An additional research challenge that has received only limited attention to date has to do with designing cross-national measurement instruments (Steenkamp 2005).

Many of the popular marketing and consumer behavior scales included in the *Handbook of Marketing Scales* (Bearden and Netemeyer 1999) consist of too many items for effective administration, especially in non-student settings and in applied marketing research (cf. Richins 2004). Several authors have also noted that many established measurement instruments are simply too long to be useful in international marketing research (Steenkamp 2005, Tellis, Yin and Bell 2005).

Apart from scale length, it is not known whether the psychometric properties of the items remain invariant across nations. It might well be that items suited to measure a construct in a particular country such as the U.S. are not suited in other countries with different cultural norms. Culture is an important force affecting behaviors, perceptions and cognitions (Markus and Kitayama 1991), and measurement properties of items may be influenced by cultural factors.

Ideally, researchers would use country-specific short forms, consisting of good items *in each country*. That is, items would be different across countries, whilst retaining the important feature of cross-national comparability. Unfortunately, methodological limitations have prevented the

realization of this ideal state of affairs. The current chapter contributes to the marketing literature by developing a procedure that yields *fully country-specific, yet cross-nationally comparable short form marketing scales*. The procedure is based on a combination of two powerful psychometric tools: hierarchical item response theory (HIRT; De Jong, Steenkamp and Fox 2007) and optimal test design methods (OTD; Van der Linden 2005). HIRT models have only been recently introduced in marketing, while OTD methods have not been used in marketing. The unique merger of these tools lies at the heart of our proposed methodology.

The set-up of this chapter is as follows. First, we briefly discuss key differences between item response theory and classical test design. Next, short-form scale construction is discussed using OTD and it is shown how this can be applied in international contexts. In the empirical part, our procedure is applied to the impression management (IM) scale (Paulhus 1984), yielding country-specific yet cross-nationally comparable short-form scales in 28 countries of the world.

V.2 SCALE CONSTRUCTION IN INTERNATIONAL MARKETING RESEARCH

Emic versus etic

Two measurement schools can be distinguished in international marketing research, viz., the 'emic' school and the 'etic' school (Craig and Douglas 2001, Kumar 2000). Emic researchers reject the notion of cross-national measurement. They argue that marketing phenomena are specific to each culture. They favor within-culture approaches, i.e., separately studying phenomena in each culture. For measure construction, this implies that one develops a unique scale in each country, at the expense of cross-national comparability. The emic researcher cannot compare respondents in different countries because the scales are completely country-specific. As there are 200 countries in the world, and even more cultures, this means that scale development effort is humongous and since results are country-specific and not comparable across countries, empirical generalizations are problematic, if not impossible. This poses a serious challenge to marketing as academic discipline. Apart from using the scientific method, marketing's claim to be a science is grounded in its ability to develop empirical generalizations (Hanssens, Parsons, and Schultz 2001). Indeed, "empirical generalizations are the building blocks of science" (Bass and Wind 1995, p. G1).

Etic researchers usually assume universal applicability of constructs and their measurement instruments. Theoretical constructs are universal, and cross-nationally validated with the same

measurement instrument across countries. In the etic philosophy, cross-national comparisons are entirely justified and can form the basis for empirical generalizations. Hence, it is not surprising that the etic perspective is the dominant paradigm in international marketing research. However, etic studies lead to invalid conclusions if, in fact, items suited to measure a latent construct in one country, may not necessarily be useful in other countries. It could very well be that idiosyncracies of a culture dictate that the same construct be measured with different items, which is in line with the emic school of thought.

Researchers have acknowledged the problems with so-called 'imposed etic' scales. Baumgartner and Steenkamp (1998) propose the use of imaginary indicators and constructs to accommodate both group-specific and common items in a multi-group confirmatory factor analysis framework. Comparisons between countries are based on the common items. The approach proposed by May (2005) uses item response theory, and allows researchers to collect different items in different countries, as long as there are also common items.

Both the Baumgartner and Steenkamp (1998) and the May (2005) approach to overcome the imposed etic problem suffer from several limitations. First, in both approaches measurement invariance *must* be imposed for the common items. In settings with many countries, as well as in settings invariance is unlikely to be satisfied for *any* item (Baumgartner 2004). Moreover, measurement invariance is also unlikely to be fulfilled for short scales as there are simply fewer items that might be invariant, while shorter scales are actually preferred in international marketing research (Tellis, Yin, and Bell 2005).

Second, when working with a short-form scale, neither approach allows the researcher to select an optimal set of items for each country. To date, international marketing researchers typically construct a short-form scale on an ad-hoc basis, by selecting items that exhibited high factor loadings in previous research, conducted in other countries (typically limited to the U.S.). (e.g., Batra et al. 2000, Ter Hofstede, Steenkamp, and Wedel 1999, Ter Hofstede, Wedel, and Steenkamp 2002).

We propose a pseudo emic method to international marketing research to address the limitations of existing approaches to scale construction for international marketing research. We start from a set of items where at least a set of items overlaps across countries, calibrate a hierarchical item response theory model, and select 'optimal' items in each country, according to criteria that can be set by the researcher. None of the items need to be invariant across countries.

Moreover, no cross-nationally common set of (core) items is required and the country-specific scales can be of different length. However, we can still make cross-national comparisons. The method is 'pseudo emic': it approximates the emic 'ideal' in that sets of items can be completely different across countries, but does require that we start from a larger pool of common items. This pool of items may either be developed based on qualitative research, preferably conducted in multiple countries, and/or may be based on existing marketing scales (Bearden and Netemeyer 1999).

Item response theory versus classical test theory for scale construction

As mentioned, our model is based on item response theory (IRT; Lord and Novick 1968). Although less well known in marketing than Classical Test Theory (CTT; Churchill 1979; Nunnally 1978), in psychometrics IRT has largely replaced CTT as the dominant measurement paradigm. This is due to several important advantages of IRT vis-à-vis CTT. First, CTT uses inter-item and item-total correlations to assess measurement error. Reliability is assessed using Cronbach's alpha, which is a single number that assesses the average measurement precision for all respondents and scale items. Thus, the measurement error is assumed to be constant over all attitude levels. In IRT, measurement error is allowed to vary across levels of the underlying construct.

Second, Cronbach's alpha is a joint property of all items in the scale and the particular individuals sampled. In cross-sectional data, individual items cannot be generally indexed by a reliability measure. When items are added to or dropped from a scale in CTT, the usefulness of each item to the quality of the scale will change. In IRT, items contribute independently to measurement precision. When measurement precision is not sufficiently accurate at certain levels of the construct, items can be added that increase the precision at those levels. A key advantage of this additive property is that the effect of an item, and its impact on the scale is easily determined.

Third, estimates of Cronbach's alpha are likely to vary across samples since alpha is a function of observed variance, which in turn is a function of sample homogeneity (Duhachek, Coughlan, and Iacobucci 2005). In IRT, the measurement precision of items is theoretically invariant from sample to sample, because the precision implied by items depends solely on sample invariant item parameters.

Finally, to allow comparisons among respondents, the CTT approach dictates that *all respondents* answer *all items*. IRT has item-free calibration which implies that respondents who have answered different questions can still be compared, provided that the items have all been calibrated onto a common scale and are stored in an *item bank* that contains the item parameters describing the items. The unique item-free calibration feature of IRT will be of paramount importance for constructing country-specific scales, whilst retaining comparability.

V.3 A MODEL FOR THE CONSTRUCTION OF SHORT-FORM MARKETING SCALES

In this section, we first discuss the 'backbone' of our model, viz., Samejima's graded response IRT model. Next, we elaborate on item information functions, which can be derived from the Samejima model and which form the basis of construction of a short-form versions of scale, using optimal test design techniques. The model development in this section is for one country only, and is useful for 'domestic' researchers interested in developing short-forms of marketing scales, e.g., for use in general populations, where respondent participation and costs of data collection are relevant considerations. Subsequently, in the next section, we extend this model to the international context, allowing for the construction of derived emic scales that can be used in cross-national research, yet yielding scores that can be compared across countries.

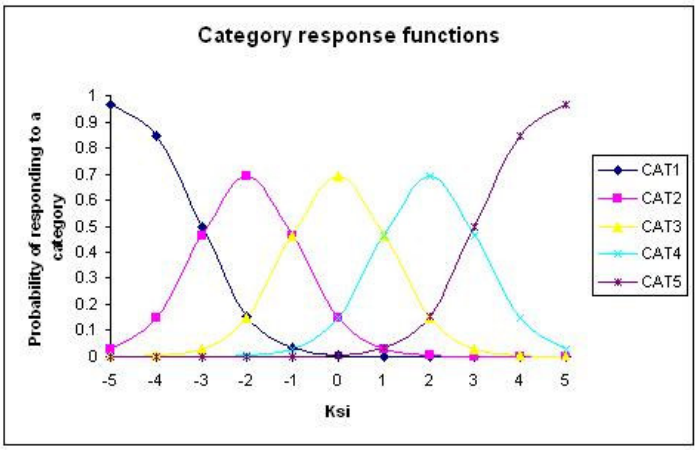
Samejima's graded response IRT model

Our point of departure is a set of items, rated on Likert items, arguably the standard scale format for marketing scales (Bearden and Netemeyer 1999). The most suitable IRT model for such data is Samejima's graded response model (Samejima 1969). The graded response model is an ordinal data model that models the probability that respondent *i* answers category *c* on item *k*, as a function of an item-specific discrimination parameter a_k, thresholds γ_k, and a latent trait ξ_i. Mathematically:

$$P(x_{ik} = c \mid \xi_i, a_k, \gamma_{k,c}, \gamma_{k,c-1}) = \Phi(a_k\xi_i - \gamma_{k,c-1}) - \Phi(a_k\xi_i - \gamma_{k,c}) \qquad (1)$$

A graph is shown in Figure 1 to illustrate how the model works for a hypothetical 5-point scale with a_k=1, γ_{k1}=-3, γ_{k2}= -1, γ_{k3}=1, γ_{k4}=3 (note that γ_{k0}=-∞ and γ_{k5}=∞).

Figure 1
Category response functions



As can be seen, the probability of category one (five) goes down (up) as the latent trait increases, while the probabilities for the other categories follow a bell shape, with a maximum probability between two threshold values. The thresholds are measured on the same scale as the latent trait ξ and determine the intersection points of the category response functions. The discrimination parameter a_k determines the steepness of the curves, that is, the sensitivity to variation around inflection point (determined by the threshold parameter) of item response curves. Items with a very low discrimination parameter have category response curves that are almost horizontal rather than bell-shaped, indicating that the item cannot discriminate among respondents high and low on the latent trait.

The key advantage of IRT is item-free calibration. Respondents who answer different items can still be compared and are on the same latent scale when in a previous run, items have been calibrated jointly. This is in sharp contrast with CTT where the scores of individuals are only comparable if the same set of items has been answered.

Item information functions

Measurement accuracy in IRT is based on the notion of information. The information function $I(\xi)$ is the inverse of the asymptotic variance of a maximum likelihood estimator $\hat{\xi}$, and defined as $I(\xi)=-E[\partial^2/\partial\xi^2 \ln L(\boldsymbol{x}|\xi)]$. Now, the category information function $I_{kc}(\xi)$ is defined as (Samejima 1969):

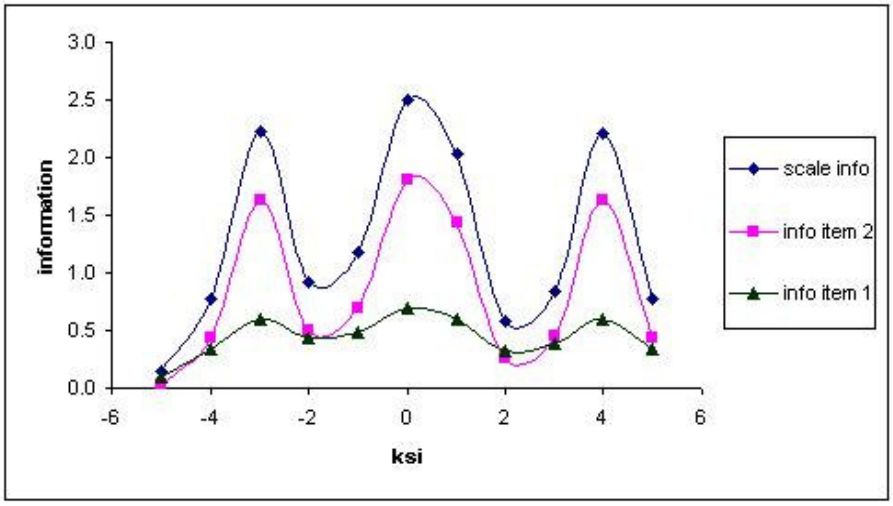
$$I_{kc}(\xi_i) = \frac{[\partial P(x_{ik} = c \mid \xi_i, a_k, \gamma_{k,c}, \gamma_{k,c-1})/\partial\xi_i]^2}{P(x_{ik} = c \mid \xi_i, a_k, \gamma_{k,c}, \gamma_{k,c-1})^2} - \frac{\partial^2 P(x_{ik} = c \mid \xi_i, a_k, \gamma_{k,c}, \gamma_{k,c-1})/\partial\xi_i^2}{P(x_{ik} = c \mid \xi_i, a_k, \gamma_{k,c}, \gamma_{k,c-1})} \qquad (2)$$

These functions can be merged to yield the item information function $I_k(\xi)$:

$$I_k(\xi_i) = \sum_{c=1}^{C} I_{kc}(\xi_i) P(x_{ik} = c \mid \xi_i, a_k, \gamma_{k,c}, \gamma_{k,c-1}) = \sum_{c=1}^{C} \frac{[\partial P(x_{ik} = c \mid \xi_i, a_k, \gamma_{k,c}, \gamma_{k,c-1}) / \partial \xi_i]^2}{P(x_{ik} = c \mid \xi_i, a_k, \gamma_{k,c}, \gamma_{k,c-1})} \quad (3)$$

The Scale Information Function (SIF) is simply the sum of the item information functions $I_k(\xi)$. It is a nonlinear function of the latent variable. As an example, we plot a SIF in Figure 2 for a hypothetical 2-item scale, where the item parameter specifications are a_1=0.9, γ_{11}=-3, γ_{12}= -0.2, γ_{13}=0.7, γ_{14}=4 and a_2=1.5, γ_{21}=-3, γ_{22}= -0.2, γ_{23}=0.7, γ_{24}=4. In practice, the threshold parameters will also vary from item to item, and the configurations merely serve as an illustration. Also displayed are the item information functions (IIF), denoted that jointly determine the SIF.

Figure 2
INFORMATION FUNCTIONS



The SIF has various interesting features. First, note that the contribution of each item to the SIF is additive. In Figure 2, the plot for the total scale information is obtained by simply summing the two item information functions. The general level of information for the total scale will be higher than for individual items. When measurement precision is not accurate enough at certain levels of the latent variable, items can be added with threshold values that equal those levels. This way, the SIF is increased at those levels. Naturally, the amount of information, and thus the precision, increases as the number of items to measure ξ increases. A key advantage of the additive property is that the effect of an item, and its impact on the scale is easily determined.

Second, note that measurement precision of the scale varies along the trait range. In Figure 2, the scale provides most accurate measurement around trait values that are equal to the thresholds.

However, when a respondent is located at the extremes of the ξ distribution, measurement precision is much less. In IRT, measurement precision is defined locally, that is, measurement precision is not the same for each level of the latent variable.

Third, it can be seen that the amount of information for a particular item is symmetric around the maxima attained at the threshold parameters. Items are most informative when the threshold parameters match a respondent's ξ value. In addition, the maximum value is approximately proportional to the square of the item discrimination parameter. The larger the value of a_k, the greater the information.

Scale construction using optimal test design

The standard (CTT) way to construct short forms is to select items with the highest factor loadings (Bollen and Lennox 1991). This way, the loss in internal consistency reliability is minimized, even though the *bandwidth* of the construct might be compromised. That is, it could be that only accurate measurement is provided for certain attitude levels, with low precision at other levels. IRT is much more advanced in this respect, as both *bandwidth* and *fidelity* (measurement accuracy) can be monitored (Singh 2004). If bandwidth should be maintained, items should be selected that provide accurate measurement at different grid-points along the latent scale. On the other hand, when the goal is to maximize precision for particular levels of the construct, items that are informative at that level should be chosen. In other words, an optimal short form can be constructed depending on the wishes of the researcher. This is a key advantage of IRT.

There are many substantive situations in which researchers might be interested to vary measurement precision across the range of the underlying construct. To illustrate, consider the construct customer satisfaction. Satisfaction has been linked to key outcome variables like loyalty and profitability, but the effect is not linear over the range of the construct (Gupta and Zeithaml 2006). Whether the customer is dissatisfied or extremely dissatisfied is managerially not really relevant. On the other hand, whether a customer is very satisfied or extremely satisfied can have a large effect on e.g., loyalty. Hence, it is much more important to measure the latent construct of satisfaction very precisely at high levels of satisfaction than at low levels of satisfaction.

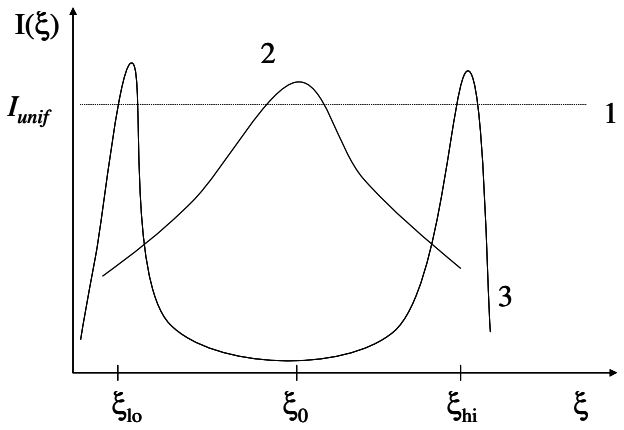
The process of selecting items subject to various constraints with some target information function for the measure in mind can be formalized to yield a combinatorial optimization

problem. In the psychometric literature, test construction using optimization is known as optimal test design (OTD).

Optimal Test Design

The first step is to specify a target information function (TIF) for the scale. For instance, if the goal would be to have uniformly good measurement with information level I_{unif} along the trait range, then a possible target could be curve 1 in Figure 3.

Figure 3
TARGET INFORMATION FUNCTIONS



If the goal would be only to have accurate measurement for most respondents, assuming a bell-shaped normal distribution for ξ with mean ξ_0, a target could be curve 2. Finally, target 3 would be suited to have high measurement precision at low (ξ_{lo}) and high values (ξ_{hi}) of the latent variable. Note that the specification of different shapes of the TIF allows much more flexibility than in CTT where only Cronbach's alpha is usually considered. Using IRT, measurement precision can be specified in a variety of ways, depending on what the researcher wants to measure.

Next, a distinction is made between two types of test specifications (Van der Linden 1998):

1) **Constraints**. Constraints require a scale attribute or a function of item attributes to meet an upper and/or lower limit. They can be formulated as mathematical inequalities.
2) **Objectives.** Objectives require a scale attribute or function of item attributes to take a minimum or maximum value. They can be formulated as mathematical functions to be optimized.

Naturally, the constraints should leave a nonempty set of feasible solutions. A target for a TIF is a function $\tau(\xi)$ that provides the goal values for L grid points ξ_l along the ξ scale. Since the TIFs that we consider are smooth functions, it holds that if we require a TIF to meet a smooth target $\tau(\xi)$ at one point on the latent scale, neighborhoods approximate the target as well. Specifying only a small number of grid points therefore suffices in normal applications. Now, to assemble the scale, with an information function that meets a target, we have a multiobjective assembly problem. In particular, since we want to minimize differences between the TIF and its target at the L grid points, there are L objectives. Multiobjective problems for these types of models can be solved in various ways, such as by weighting objectives, by goal programming, maximin approaches, or sequential optimization (Van der Linden 2005).

Absolute vs. relative targets

There is an important distinction between absolute and relative targets. Targets are *absolute* if a fixed number of information units is required at the grid points ξ_l. To specify a useful absolute target, the researcher must be familiar with the latent scale and with the unit of information it implies because strange optimization solutions might otherwise be found. Alternatively, *relative* targets can be used, where the shape of the target is most important, not the height. A relative target is a set of number $R_l>0$ that represent the required amount of information at ξ_l, relative to the other points in the set $l=1,...,L$. If a test must have three times as much information at ξ_l as at ξ_{l+1}, the numbers R_l and R_{l+1} will have to satisfy $R_l / R_{l+1}=3$. The advantage here is that one need not be familiar with the exact unit of the information measure. Ultimately, the choice between absolute or relative targets depends on the goals of the study.

For absolute targets, a minimax approach can be used (Van der Linden 2005), where the optimization is:

minimize y

subject to

$$\begin{aligned}
&\sum_{k=1}^{K} I_k(\xi_l) ITEM_k \le \tau_l + y \quad \forall l, \\
&\sum_{k=1}^{K} I_k(\xi_l) ITEM_k \ge \tau_l \quad \forall l, \\
&y \ge 0. \\
&ITEM_k \in \{0,1\},\ k=1,\ldots,K
\end{aligned} \tag{4}$$

$ITEM_k$ is an indicator (1: item k included in the scale, 0: item not included in the scale). In this formulation, the TIF is larger than the target values while y is defined as the upperbound to all positive deviations from these values. Alternatively, if negative deviations from the target are also deemed undesirable, the second constraint can be replaced by $\sum I_k(\xi_l)ITEM_k \geq \tau_l - y \ \forall l$. Note that many additional constraints can be added to the set of constraints. For instance, if we would require that only items can be selected with maximally 6 words, then we could add the constraint: $ITEM_k W_k \leq 6$, where W_k denotes the number of words for item k.

For relative targets, the formulation changes. The height of the target is maximized at each grid point, and at the same time, the relative shapes of the TIF must be maintained, leading to an additional set of constraints. Because there is no fixed unit, R_l can be set equal to 1, while adjusting the other values accordingly. If R_1=1, we should then have L-1 constraints that require the TIF at ξ_l to be R_l times as large as at ξ_1, resulting in the constraints $\sum I_k(\xi_l)ITEM_k = R_l \sum I_k(\xi_1)ITEM_k$ for l>1. This leaves only 1 objective, so that the total optimization problem is

$$
\begin{aligned}
&\textit{maximize} \ \sum I_k(\xi_1)ITEM_k \\
&\text{subject to} \\
&\sum I_k(\xi_l)ITEM_k = R_l \sum I_k(\xi_1)ITEM_k \ \ \forall l \geq 2 \qquad (5) \\
&ITEM_k \in \{0,1\},\ k=1,\ldots,K
\end{aligned}
$$

Unfortunately, the equality constraints in the first set of constraints may easily yield infeasible solutions. It is therefore better to use a maximin formulation:

$$
\begin{aligned}
&\textit{maximize} \ y \\
&\text{subject to} \\
&\sum_{k=1}^{K} I_k(\xi_l)x_k \geq R_l y \quad \forall l, \qquad (6) \\
&y \geq 0. \\
&ITEM_k \in \{0,1\},\ k=1,\ldots,K
\end{aligned}
$$

Here, a new variable *y* has been substituted for the common factor $\sum I_k(\xi_1)ITEM_k$. This variable represents an explicit common lower bound to the relative information $R_l^{-1}\sum I_k(\xi_1)ITEM_k$ at the points ξ_l.

V.4 EXTENSION OF THE MODEL TO ALLOW FOR DEVELOPMENT OF DERIVED EMIC SCALES IN INTERNATIONAL MARKETING RESEARCH

Hierarchical IRT model

Samejima's GRM can be extended to multi-country settings by imposing a hierarchical structure on item parameters, and the latent variable. We model random item parameter variation as (De Jong, Steenkamp, and Fox 2007):

$$\gamma_{k,c}^g = \gamma_{k,c} + e_{k,c}^g,\ e_{k,c}^g \sim N\left(0,\sigma_{\gamma_k}^2\right) \text{ for } c = 1,\ldots,C-1,\ \gamma_{k,1}^g \le \ldots \le \gamma_{k,C-1}^g \quad (7)$$

$$a_k^g = a_k + r_k^g,\ r_k^g \sim N(0,\sigma_{a_k}^2),\ a_k^g \in A, \quad (8)$$

where *A* is a bounded interval in $\Re^+$. Equation (7) implies that each scale threshold $\gamma_{k,c}^g$ for a particular item *k* in country *g* is modeled as an overall mean threshold $\gamma_{k,c}$, plus a country-specific deviation $e_{k,c}^g$. Analogously, equation (8) posits that the discrimination parameter a_k^g is the sum of an overall mean discrimination parameter and country-specific deviation. Moreover, the discrimination parameter should be positive. The variances of the threshold and discrimination parameters are allowed to vary across items.

The heterogeneity in the latent variable is modeled by hierarchical structure for ξ_i^g by letting:

$$\xi_i^g = \xi^g + \upsilon_i^g,\ \upsilon_i^g \sim N(0,\sigma_g^2) \quad (9)$$

$$\xi^g \sim N(\xi,\tau^2) \quad (10)$$

In other words, the position on the latent scale for respondent *i* in country *g* is sampled from the country average ξ^g with variance σ_g^2. The country average is drawn from a distribution with average ξ and variance τ^2.

For identification purposes, we impose that across items, the product of the discrimination parameters equals one in each country *g* ($\prod_k a_k^g = 1\ \forall g$). Also, for one scale threshold parameter,

the thresholds should sum to zero across items in each country g (say $\sum_k \gamma_{k,3}^g = 0 \ \forall g$, if the third threshold is chosen).

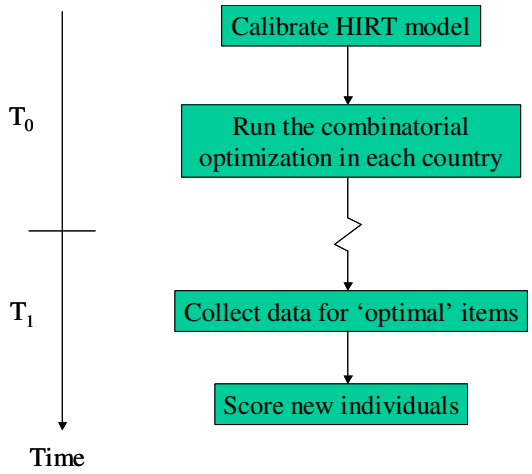
Several important features of this model should be mentioned. First, all respondents can be calibrated on the same latent scale, even though *all* items may display lack of invariance. De Jong, Steenkamp, and Fox (2007) have shown that the requirement of measurement invariance can be relaxed, so that measurement-invariant anchor items are not necessary.

Second, once the IRT model has been fitted and the item parameters are known, items can be stored in an *item bank*. The item bank contains items and their associated calibrated item parameters. Subsequently items can be selected in the constrained combinatorial optimization routine to optimize some objective, subject to various constraints, such as scale length, minimum levels of measurement precision, maximum number of words in an item, etcetera.

Cross-national short forms

The item-free calibration property of IRT models ensures that respondents can answer different items and still be compared, as long as the items have been calibrated on the same latent scale. Thus, after the model has been calibrated, and new data is collected for the items that have been calibrated, respondents who would answer different items can be compared. In the cross-national setting, the same principle applies. Running the hierarchical IRT model yields item parameters that can be stored in an item bank. Next, the "optimal" items in each country can be selected, and when new data is then collected for these "optimal" items, we still retain comparability across countries, even though the scale length and items in the scale per country may be different. The four steps are graphically illustrated in Figure 4.

Figure 4
Flowchart country-specific scale construction



The procedure starts at T_0 by estimating the HIRT model. Next, the optimization routine is run in each country and the optimal items are selected. Now, the optimal items, and their item parameters are known, and if at a later point in time (T_1) new data is collected, researchers only have to collect data for these short forms based on "optimal items". Finally item parameters can be fixed at their known values and new individuals can be scored.

The choice between absolute vs. relative targets depends on the aims of the researcher. For instance, if equal measurement precision is required in every country, an absolute target can be used that specifies some absolute precision that must be reached for each and every country. Naturally, this choice might imply that we get long scales in particular countries and short scales in others. On the other hand, if the scale length is fixed to a maximum length, and only the shape of the TIF is important, relative targets could be used. In the empirical section we compare both procedures.

V.5 EMPIRICAL APPLICATION

Socially desirable responding

We apply our proposed procedure to the measurement of impression management (IM). IM is an important component of socially desirable responding (SDR). In marketing, SDR has sometimes been associated with "dark side" topics, such as materialism (Mick 1996), compulsive buying (Mick 1996), and consumption of taboo products (McGraw and Tetlock 2005). However, it is generally acknowledged that SDR is also operant in "mainstream" areas important to marketers (Netemeyer, Bearden, and Sharma 2003), such as brand familiarity and brand liking

(Rindfleisch and Inman 1998), consumption motivations (Fisher 1993), consumer innovativeness (Goldsmith 1987) and satisfaction (Sabourin et al. 1989), and value priorities (Fisher and Katz 2000). SDR has also been found to bias managerial decision making (Chung and Monroe 2003) and performance evaluations (Bearden, Manning, and Tian 2004). Thus, it is not surprising that SDR has been identified as "one of the most pervasive response biases" in survey data (Mick 1996, p. 106).

Measures

The standard scale for measuring SDR is Paulhus' (1991) 40-item Balanced Inventory of Desirable Responding. According to Paulhus (1991), SDR consists of two (positively correlated) factors, namely, IM (respondents' conscious tendency to present themselves in the most positive manner) and self-deceptive enhancement (SDE; people's unconscious tendency to provide inflated self-reports). The 40-item scale consists of 20 items that tap SDE, and 20 items measuring IM. In our empirical illustration, we focus on IM, measured using a subset of 10 items of the Paulhus scale. The items are reported in Table 1.

Table 1
IM scale

	Impression management
i1	I sometimes tell lies if I have to.
i2	I never cover up my mistakes.
i3	I always obey laws, even if I am unlikely to get caught.
i4	I have said something bad about a friend behind his or her back.
i5	When I hear people talking privately, I avoid listening.
i6	I have received too much change from a salesperson without telling him or her.
i7	When I was young I sometimes stole things.
i8	I have done things that I don't tell other people about.
i9	I never take things that don't belong to me.
i10	I don't gossip about other people's business.

Item selection was based on the magnitude of factor loadings reported in previous U.S. studies, subject to two constraints. Consistent with the philosophy of the full Paulhus scale, the balanced structure of the scale was retained by selecting an equal number of positively and negatively worded items. Moreover, the market research agencies that collected the data for us insisted that potentially offensive items (e.g., "I never read sexy books or magazines") were omitted. It would have been ideal to administer all 20 items, but the market research agencies considered the full 20-item scale too long and too costly to administer.

A review of two decades of published marketing research reveals that SDR has been consistently neglected in scale construction, evaluation, and implementation (King and Bruner 2000). A major reason is that the Paulhus scale is too long. Adding non-substantive items to a survey is costly, both in terms of money and respondent fatigue. It is often difficult to get marketers to pay for additional survey items that will be used "merely" for estimating socially desirable response tendencies. There is an urgent need for a short form for especially the impression management dimension of the Paulhus scale, since this dimension is often used to see whether SDR biases construct scores (Mick 1996).

Data collection

Two global marketing research agencies collected data on 20 SDR items for 28 countries around the world: Argentina, Austria, Belgium, Brazil, China (mainland), Czech Republic, Denmark, France, Germany, Hungary, Ireland, Italy, Japan, the Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovakia, Spain, Switzerland, Taiwan, Thailand, United Kingdom and the United States. The samples in each country were drawn so as to be broadly representative of the total population in terms of region, age, education and gender. Some countries used a web-survey, others a mall intercept, and other hard-copy surveys.

The number of respondents per country varies between a minimum of 355 (UK) and a maximum of 1181 (U.S.). The percentage of males and females is balanced, so that distributions close to 50% of both sexes are obtained. Education and age sampling quotas are also respected, so that the respondents matched population statistics.

The questionnaire was developed in English and then translated into all local languages by professional agencies. Next, the translated surveys were backtranslated into English, using native speakers from the local countries. In each survey, modifications were made based on discussions between the backtranslators and the headquarters of the marketing research agencies to maintain consistency in changes across all countries. The SDR items were measured on five-point Likert scales (1 = strongly disagree, 5 = strongly agree).

V. 6 RESULTS

We follow the flowchart in Figure 4 and start by estimating the HIRT model for IM (step 1). In Table 2 the posterior means of the discrimination parameters are presented.

Table 2
Discrimination parameters IM scale

	I1	i2	i3	i4	i5	i6	i7	i8	i9	i10
U.K.	1.204	0.775	1.148	0.912	0.740	1.038	1.356	0.756	1.302	1.065
Germany	1.255	0.562	1.021	1.223	0.798	1.223	1.182	1.067	0.896	1.090
Ireland	1.182	0.741	0.974	1.208	1.026	1.152	1.100	0.653	1.100	1.084
France	0.825	0.861	0.966	1.186	1.114	0.905	1.116	0.813	1.193	1.195
Austria	1.203	0.661	0.999	0.983	0.681	1.338	1.342	1.042	1.045	1.022
Netherlands	1.437	0.767	0.686	1.126	0.779	0.952	1.292	1.166	1.075	1.023
Belgium	1.115	0.590	0.847	1.002	0.910	1.047	1.334	0.946	1.292	1.209
Italy	0.914	0.624	1.134	1.192	1.173	1.493	1.003	0.592	1.123	1.169
Norway	1.013	0.669	0.890	1.035	1.011	1.323	1.147	0.565	1.342	1.438
Slovakia	0.919	0.646	1.104	1.150	1.112	1.201	0.941	1.002	1.092	1.022
Poland	0.558	0.763	0.964	0.974	0.902	1.192	1.549	1.233	1.182	1.073
Sweden	1.355	0.775	0.971	1.041	0.875	1.159	1.083	0.703	1.071	1.204
Denmark	1.669	0.709	0.824	0.963	0.846	0.991	1.363	0.685	1.218	1.183
Hungary	1.366	0.419	0.930	1.872	1.281	0.894	1.525	0.975	1.112	1.126
Romania	0.679	0.643	1.368	1.314	0.700	1.638	1.216	0.858	1.005	1.108
United States	1.355	0.689	0.984	1.040	0.953	1.193	1.230	0.627	1.244	0.982
Argentina	0.892	0.645	1.011	1.237	1.140	1.201	1.408	0.734	0.966	1.062
Portugal	1.205	0.675	0.698	1.378	1.107	1.294	1.348	0.504	1.100	1.258
Switzerland	1.285	0.780	1.072	1.021	0.680	1.159	1.208	1.078	0.897	1.061
Czech. Rep.	0.920	0.643	0.915	1.169	0.965	1.257	1.312	0.821	1.167	1.089
Taiwan	0.649	0.721	0.756	1.166	0.910	1.424	1.496	0.936	1.234	1.154
Russia	0.288	0.730	1.148	1.561	1.119	1.709	1.529	0.652	1.296	1.197
Ukraine	0.458	0.665	1.004	1.586	1.289	1.798	1.479	0.836	0.904	0.858
Brazil	0.295	0.813	1.228	1.239	1.818	1.855	1.129	0.843	0.962	1.313
Thailand	0.891	0.704	0.930	0.974	1.227	1.131	1.342	0.690	1.114	1.291
China	0.370	0.915	1.275	1.175	1.092	1.359	1.355	0.869	1.153	1.046
Spain	1.225	0.718	0.980	0.916	0.881	1.321	1.303	0.914	1.065	0.892
Japan	0.800	0.924	1.037	1.187	0.811	1.241	1.329	1.117	0.832	0.930

There is substantial variation in the discrimination parameters across countries, and there are no invariant items. In other words, the traditional multi-group CFA model (Steenkamp and Baumgartner 1998) would not be able to fit this data, as invariant anchor items are required for identification. More importantly, the variation in discrimination parameters indicates that items measuring a construct well in one country are not always useful in other countries.[16] Consider the U.S. and China. The estimated discrimination parameter of item i1 from the IM scale ("I sometimes tell lies if I have to") has a posterior mean of $a_{US,1}$=1.355 in the U.S. and a posterior mean in China of $a_{CHI,1}$=0.370. In other words, the item seems suited to measure IM in the U.S.,

but the posterior mean in China is too low to make this a useful item. When we take the thresholds into account this is clearly visible in the item information functions. For the U.S., the posterior means of the thresholds are: $\gamma_{US,1}$=-1.641, $\gamma_{US,2}$= 0.127, $\gamma_{US,3}$=0.971, $\gamma_{US,4}$=2.175, while in China the posterior values are $\gamma_{CHI,1}$=-1.058, $\gamma_{CHI,2}$= 0.360, $\gamma_{CHI,3}$=1.359, $\gamma_{CHI,4}$=2.413. Together with the discrimination parameters this yields the posterior mean category response and information functions in the U.S. and China in Figures 5 and 6:

Figure 5
IIF FOR ITEM 1 OF IM SCALE

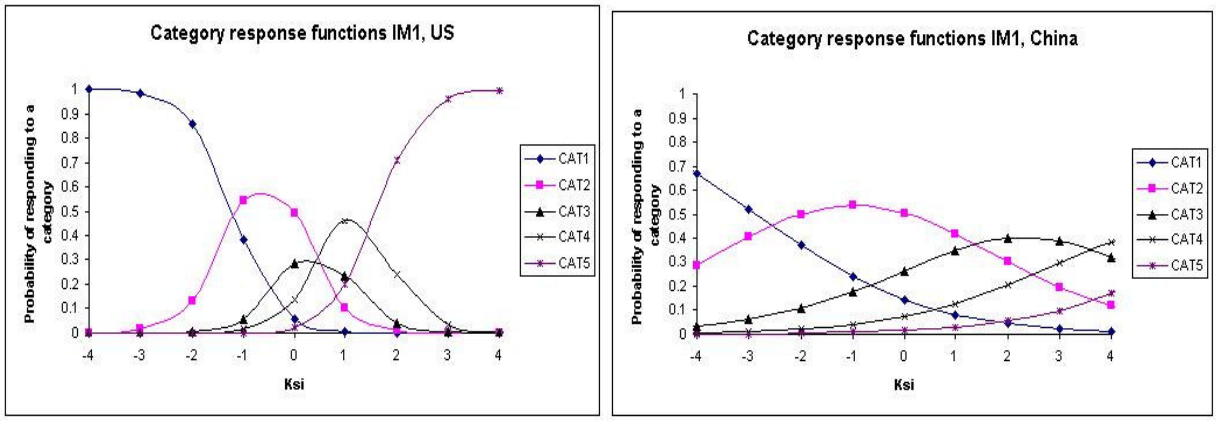
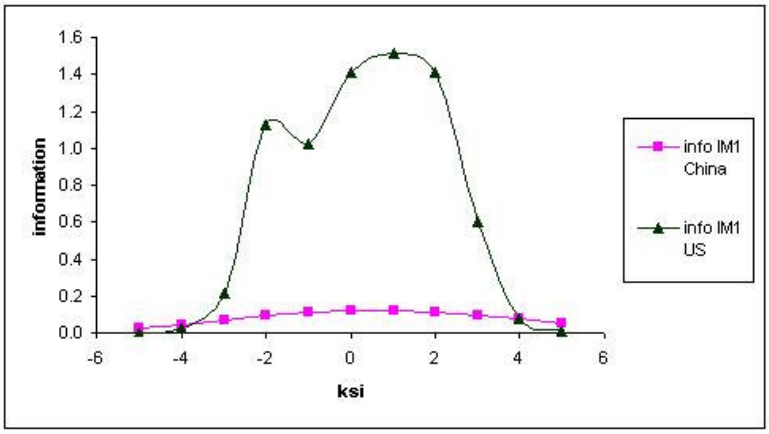


Figure 6
INFORMATION FUNCTIONS IM1



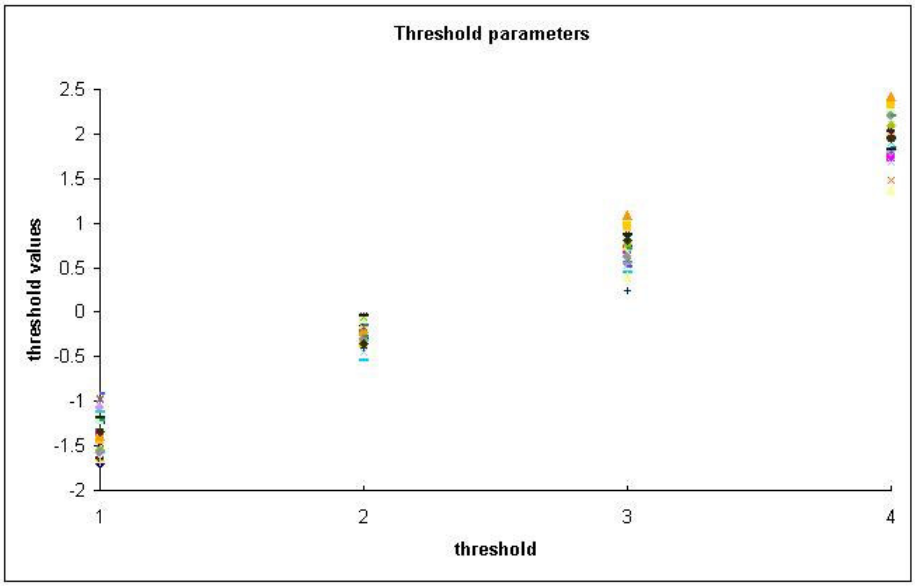
The posterior mean category response functions for China are much flatter than for the US due to the lower discrimination parameter (see Figure 5). Figure 6 shows that the information is much

[16] The threshold parameters are also important when considering the usefulness of items. An item with moderate discrimination parameter may sometimes be better than an item with high discrimination and threshold values that do not match the position of the scale where more accurate measurement is required (see Lord and Novick 1968).

higher in the U.S. than in China along the entire trait, and that the measurement precision varies along the ξ scale.

The 28x10x4=1120 threshold parameters cannot be meaningfully displayed for all other items and countries. The findings of varying thresholds are robust across items. For illustrative purposes consider item 10 ("I don't gossip about other people's business"). The threshold parameters for this item for 28 countries are shown in Figure 7. Concordant with the observation of fluctuation in discrimination parameters, there is substantial variation in threshold parameters as well.

Figure 7
THRESHOLD VALUES i20



Deriving short forms

Having calibrated the IRT model, the next step is to apply the optimization routine (step 2 in Figure 4). Various choices need to be made. First, we must specify whether absolute or relative targets are used, and second, the shape of the TIF. In the sequel we explore the resulting short scales under these 2x2=4 specifications.

Scenario 1: uniform TIF, absolute target

In this scenario, we place no restrictions on the number of items that is to be selected, but instead choose a level of information is in line with the variance of the latent scale and ensures a feasible optimization solution (in the sense that with a relatively small number of items, it is

possible to reach the target). The target information τ is set as τ=5 along the trait range, with three grid points, located at the mean, one standard deviation below the mean, and one standard deviation above the mean of the ξ-scale. Next, a 28-fold optimization program is formulated as:

$$
\begin{aligned}
&\textit{minimize } y \\
&\text{subject to} \\
&\sum_{k=1}^{K} I_{kj}(\xi_l) ITEM_{kj} \le \tau + y \quad \forall l, \\
&\sum_{k=1}^{K} I_{kj}(\xi_l) ITEM_{kj} \ge \tau \quad \forall l, \qquad (11) \\
&y \ge 0. \\
&ITEM_{kj} \in \{0,1\},\ k=1,\ldots,K,\ j=1,\ldots,28
\end{aligned}
$$

We present the selected items in Table 3. It can be seen that there is substantial variation in item selection across countries. Interestingly, there are no items that are selected in all countries, which indicates the importance of using items tailored to the local environment, and the lack of validity of the etic approach to scale construction. No scale construction method to date is able to calibrate items on the same latent scale if there is no overlap across countries, even though overlap is the exception rather than the rule when working with many countries.

Another interesting finding is that the *number* of items differs across countries. In other words, the measurement precision is reached more easily in some countries than in others. For example, to obtain the required measurement precision, six items are required in quite a few countries, while only four items are selected for the U.K. In most countries, five items are selected, indicating that the item parameters carry similar amounts of information in most countries. Even though results are quite variable, there are some consistencies as well, and culture does seem to have an impact on selection. As an example, consider item i2 ("I never cover up my mistakes"). In European countries, i2 is not often selected, but in collectivistic countries, such as Taiwan, China, Japan, Thailand it is selected. Apparently, covering up mistakes is something which is perceived differently in Europe than in Asian countries. Item i9 is chosen in almost any European country, but not in China, Thailand and Taiwan.

Finally, note that items are also selected with lower discrimination parameters. This is because the optimization program tries to reach the absolute value as accurately as possible.

Moreover, as indicated by Lord and Novick (1968), it is sometimes preferable to use items with somewhat lower discrimination parameters, because such items provide more information at points located farther from the threshold values.

Scenario 2: uniform TIF, relative target

For the relative target, the number of scale items will be identical across countries, while measurement accuracy will differ. We specified that the number of items should be smaller than five and maximize the information subject to that constraint. In other words, the optimization formulation is:

maximize y

subject to

$$\sum_{k=1}^{K} I_{kj}(\xi_l) ITEM_{kj} \geq y \quad \forall l,$$

$$\sum_{k=1}^{K} ITEM_{kj} \leq 5 \quad \forall j \qquad (12)$$

$$y \geq 0.$$

$ITEM_{kj} \in \{0,1\}$, $k=1,\ldots,K$, $j=1,\ldots,28$.

The resulting scales for IM are listed in Table 4. Several interesting findings emerge. It can be seen that the selected items frequently correspond to the items with the highest discrimination parameters in Table 2. In other words, the common practice of picking items with high discrimination parameters yields quite similar results. We do note that this requires the HIRT model, because items are not invariant across countries. An additional advantage of using an optimization program is that constraints on item length, content and wording can be easily specified.

Item i7 is selected in almost every country, which is consistent with the high discrimination parameter in most countries. Items i2, i5 and i8 are selected only occasionally. Item i1 is selected in a substantial number of European countries, but not in Asian countries.

Scenario 3: non-uniform TIF, absolute target

In this setting, we impose a positive linear trend for the target information. For τ_l we impose: $\tau_l=\zeta_0 + l\times\zeta_1$, and $\zeta_1>0$. Specifically, we chose $\zeta_0=4$ and $\zeta_1=1$, with $l=1,2,3$. Thus, measurement

precision is more accurate for individuals scoring higher on IM. Theoretically, one could argue that especially individuals who have tendency to edit their responses in socially approved directions create problems in surveys. Analogously, respondents who have low IM scores can be measured a less accurately, since they do not distort their true opinions. The optimization problem then is similar as in scenario 1 (with a different specification for τ_l). The selected items are displayed in the second panel of Table 3. If we compare the results to the specification with a uniform TIF, it can be seen that the selection of items is very different. Items 1, 2 and 3 are selected relatively often compared to scenario 1. In addition, the number of items is larger in many countries because a higher precision is required at the high-end of the latent scale.

Scenario 4: non-uniform TIF, relative target

In this scenario, we use a linear trend, which is absorbed now in the numbers R_l. R_l is set as 0.8, 1 and 1.2 for l=1,2,3. Table 4 lists the items. Under this specification, the IM item selection mirrors that in scenario 2, apart from a few exceptions. In Germany, the Netherlands, Slovkia, Switzerland, Denmark and Hungary different items are selected. In this case, all items are selected with the highest discrimination parameters.

Which of the four different scales should be chosen by researchers? We would advise to use an absolute target across countries. Using an absolute target ensures that reliable inferences can be made in every country in the sample and moreover that the precision does not vary across countries. Even though practitioners frequently want to use the same items across countries, our results show that some countries require more items in order to measure the latent construct with acceptable precision. Furthermore, we believe that the non-uniform TIF has benefits over the uniform TIF, which is more aligned with the CTT paradigm. The non-uniform TIF retains flexibility, and allows researchers to study in depth the consumer behavior of certain groups of respondents (say high or low on some trait).

Table 3
SELECTED ITEMS SCENARIO 1 & 3

	Scenario 1										*Scenario 3*									
	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10
U.K.	X					X	X		X		X	X	X	X		X				X
Germany				X			X	X	X	X	X	X	X		X			X		X
Ireland			X		X	X	X	X	X				X		X	X	X	X	X	X
France		X	X	X					X	X	X	X	X	X	X		X	X		
Austria			X	X		X		X	X		X	X	X	X				X	X	X
Netherlands				X		X	X		X	X	X	X			X	X		X		X
Belgium	X				X			X	X	X	X	X	X	X	X			X		X
Italy	X		X			X		X		X	X	X	X	X				X	X	X
Norway	X					X	X	X	X		X	X	X	X		X	X	X		
Slovakia	X	X	X		X			X	X		X	X	X	X			X	X		X
Poland	X	X		X		X		X	X		X	X		X		X		X	X	X
Sweden	X				X	X		X		X	X	X		X		X		X		X
Denmark				X	X	X		X	X	X		X	X		X				X	X
Hungary	X					X		X	X	X	X	X	X			X		X		X
Romania				X	X		X		X	X	X	X		X			X	X	X	X
U.S.	X				X		X	X	X		X	X	X	X	X					X
Argentina	X	X	X				X	X		X	X	X	X	X			X	X	X	
Portugal	X					X		X	X	X	X	X	X	X			X			
Switzerland						X	X	X	X	X	X	X	X	X	X	X				
Czech Rep.			X	X			X	X	X		X	X	X	X		X		X		X
Taiwan		X	X	X	X					X	X	X	X	X		X		X		X
Russia	X	X		X		X								X		X		X		X
Ukraine	X		X	X	X					X				X		X		X	X	
Brazil		X		X			X	X	X	X		X	X	X			X	X	X	X
Thailand	X	X	X	X		X	X				X	X	X	X	X	X		X	X	
China	X	X		X			X	X		X	X			X	X	X	X	X		
Spain	X			X	X		X		X			X	X	X		X		X	X	
Japan		X	X		X	X		X	X			X	X	X		X		X		X

Table 4
SELECTED ITEMS SCENARIO 2 & 4

	Scenario 2										*Scenario 4*									
	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10	i1	i2	i3	i4	i5	i6	i7	i8	i9	i10
U.K.	X		X				X		X	X	X		X				X		X	X
Germany	X		X	X		X	X				X			X		X	X			X
Ireland				X		X	X		X	X				X		X	X		X	X
France				X	X		X		X	X				X	X		X		X	X
Austria	X					X	X	X		X	X					X	X	X		X
Netherlands	X	X		X			X	X			X			X			X	X	X	
Belgium	X					X	X		X	X	X					X	X		X	X
Italy			X	X	X	X				X			X	X	X	X				X
Norway				X		X	X		X	X				X		X	X		X	X
Slovakia			X	X	X	X		X					X	X	X	X			X	
Poland						X	X	X	X	X						X	X	X	X	X
Sweden	X		X	X		X				X	X		X	X		X				X
Denmark	X	X	X				X		X		X	X	X				X		X	
Hungary	X		X	X	X		X				X			X	X		X			X
Romania			X	X		X	X			X			X	X		X	X			X
U.S.	X		X			X	X		X		X		X			X	X		X	
Argentina				X	X	X	X			X				X	X	X	X			X
Portugal	X			X		X	X			X	X			X		X	X			X
Switzerland	X		X			X	X	X			X		X			X	X			X
Czech Rep.				X		X	X		X	X				X		X	X		X	X
Taiwan				X		X	X		X	X				X		X	X		X	X
Russia				X		X	X		X	X				X		X	X		X	X
Ukraine			X	X	X	X	X						X	X	X	X	X			
Brazil				X	X	X	X			X				X	X	X	X			X
Thailand					X	X	X		X	X					X	X	X		X	X
China			X	X		X	X		X				X	X		X	X		X	
Spain	X		X			X	X		X		X		X			X	X		X	
Japan			X	X		X	X	X					X	X		X	X	X		

V.7 GENERAL DISCUSSION

International marketing has become an important domain in marketing science, and the imperative for cross-national research is all the more compelling given accelerating trends toward globalization (Winer 1998). Nonetheless, there are many methodological caveats that researchers need to take into account whenever an international study is undertaken (Van de Vijver and Leung 1997). In this chapter, we focused on cross-national measure construction. Even though valid measurement is a cornerstone of marketing as a science, there has been scant attention for developing scales in cross-national settings. Frequently, some ad-hoc procedure is followed, where items that perform well in the U.S. are also administered in other nations.

By combining hierarchical item response theory and optimal test design methods, we developed a procedure that yields country-specific scales, but at the same time maintains cross-national comparability. As such, we bridge the gap between emic and etic approaches to measuring latent phenomena. The procedure is flexible in the sense that the researcher can specify all kinds of constraints on item content, on scale length, and measurement precision (Van der Linden 2005). Researchers can either impose that the scale length various across countries, or impose a fixed precision across countries. Moreover, precision can vary for respondents high or low on the trait under investigation. This has several key advantages. For instance, interest often focuses on a specific group such as innovators, people high on satisfaction, impression managers, or individuals with a very favorable brand attitude. Especially for these individuals we need accurate measurement precision. In CTT, it is not possible to develop scales that have a precision which varies across respondents.

In the empirical section, we demonstrated the procedure on the impression management scale in a truly global setting. The dataset contained 28 countries across 4 continents. We developed cross-national scales for four different specifications:

i) Relative TIF & uniform precision;
ii) Relative TIF & non-uniform precision (i.e., better measurement for respondents scoring high on IM);
iii) Absolute TIF & uniform precision;
iv) Absolute TIF & non-uniform precision.

The results indicated that different items were selected in different countries, and that scale length indeed varied across nations when an absolute target was specified. In other words, an

item is differentially useful to measure latent constructs and some countries require more items than others to obtain a certain acceptable precision for the latent construct. Culture exerted an influence on item selection. There were differences depending on whether a uniform target information function, or an increasing information function was specified, giving better precision at higher levels of IM.

There are several issues for further research. First, we only provided an application for a single scale. Also, we had only 10 items. Ideally, we would have used all 20 items of the impression management component of the Paulhus scale. Using a full scale is in the spirit of derived emic, but this was not possible for practical reasons. However, the procedure that we built is general and should be applied to many other scales to build a stock of findings that could be incorporated into scaling handbooks. Item parameter values, as well as country-specific versions of a scale should be listed in books such as the *Handbook of Marketing Scales* (Bearden and Netemeyer 1999). Researchers would then be able to use a scale which has been emically tailored to the local environment. Currently, the *Handbook of Marketing Scales* lists items that have been largely developed in the U.S., but our empirical illustration showed that not all SDR items are equally useful across the world, and these types of results are very likely to generalize to other constructs. For instance, Wong et al. (2003) showed that the materialism scale had problems in Asia, and that it would probably be better if the scale and item format would be adapted. Another example would be the construct of values. The Schwartz Value Survey (SVS; Schwartz 1992) is a rigorous instrument to measure values. But Schwartz and colleagues found that respondents in emerging consumer markets had difficulty understanding and completing the SVS items (Schwartz, Lehmann and Roccas 1999).

Methodologically, one might include varying response formats for items across countries by changing the hierarchical structure in the IRT model. This would improve the general applicability of the procedure. In addition, fully country-specific items could be added to the set of common items (cf. May 2005). Even though many issues remain to be studied, we hope that this chapter contributes to better marketing measures in international marketing.

Chapter 6

VI.1 Conclusions

Globalization is an important factor in today's marketplace. Developments accelerating the trend toward global market convergence include rapidly falling national boundaries, regional unification, standardization of manufacturing techniques, global investment and production strategies, expansion of world travel, rapid increase in education and literacy levels, growing urbanization among developing countries, free flow of information, labor, money, and technology across borders, increased consumer sophistication and purchasing power, advances in telecommunication technologies, and the emergence of global media (Alden, Steenkamp, and Batra 1999; Hassan and Katsanis 1994; Mahajan and Muller 1994). Firms cannot ignore this trend toward globalization and academic research is needed that focuses on international marketing phenomena.

In this dissertation, I was concerned with measurement in international marketing surveys. Surveys are a crucial tool for obtaining managerial insights in international settings due to the scarcity of secondary data. Nonetheless, there is a host of factors in cross-cultural research that undermine the validity of survey data. I addressed several validity related issues. The four essays span three interrelated categories of research in international marketing research: 1) cross-national measurement invariance / differential item functioning, 2) response styles, and 3) international instrument development. The common measurement methodology throughout the chapters was the novel hierarchical IRT model with random-effects structures (both for item parameters and for the structural model). Below, I present the main conclusions of the various chapters, and end with future research suggestions.

Chapter 2: measurement invariance for specific items

I investigated the view that constructs should display certain levels of measurement invariance in order to make valid substantive cross-national (or more generally, cross-group) comparisons. Indeed, it has been argued that if measurement invariance across countries is lacking, it is not possible to draw conclusions based on the scale (Horn 1991). The multigroup CFA model has become the 'golden standard' to test for measurement invariance of instruments (e.g., Durvasula et al. 1993; Netemeyer et al. 1991; Steenkamp and Baumgartner 1998; Wong et al. 2003; see Vandenberg and Lance 2000 for an overview of other social sciences). The CFA model requires certain degrees of invariance depending on the goals of the study (Steenkamp and Baumgartner 1998). However, I have shown that claims of the

necessity of certain levels of measurement invariance for particular research objectives were mainly the result of the particular CFA methodology that has been used.

I introduced a new hierarchical IRT model that allows marketing researchers to compare countries substantively despite lack of invariance for any of the items. Moreover, because the ordinal nature of the data is recognized, cross-national differences in scale usage are also accommodated. In a simulation study I showed that measurement invariance can be relaxed, and I provided an empirical application for the consumer susceptibility to normative influence scale (SNI; Bearden, Netemeyer, and Teel 1989), using samples from 11 countries on four continents. SNI has been linked to various aspects of consumer behavior such as attitudes toward brands, advertising, and consumption alternatives resulting from globalization, consumer confidence, protective self-presentation efforts, purchase of new products, and consumer boycotts, among others.

I compared the estimation results based on IRT with the results obtained from a multigroup CFA analysis, and showed that the latter leads to erroneous substantive conclusions. Based on the IRT model, we found support for our hypothesis that consumers living in individualistic countries 1) are on average lower on SNI and 2) exhibit more divergence in their SNI attitudes compared to consumers living in collectivistic countries.

Chapter 3: Extreme Response Style

For ERS, the measurement model was based on a large heterogeneous set of items. Heterogeneity in content means that the entire set of items on which the response style measure is based does not refer to a substantively meaningful psychological construct and is psychologically diffuse. Operationally, heterogeneous items are selected by using items from a diverse set of scales that have little in common. Nonetheless, the set of items is allowed to contain multiple items from the same scale. I developed a new advanced hierarchical IRT measurement model, with testlet structures to deal with excess correlations among items due to shared substance, and examined the antecedents of this important response styles in a truly global setting. I found that people differ in their tendency to use the extremes of the rating scale, and items also differ in the extent to which they elicit extreme responses, both nationally and cross-nationally. I applied the model to a large data set involving 12,500 consumers from 26 countries, and found that socio-demographic variables had a minor influence on ERS, but that culture exerted a strong and predictable effect on ERS. Women tend to score somewhat higher on ERS than men, and both younger and older individuals are

more prone to respond extremely. ERS is also positively related to national-cultural individualism, uncertainty avoidance, and masculinity.

Chapter 4: Socially Desirable Responding

For SDR, I proposed and tested a framework in which people's tendency to provide socially desirable responses is hypothesized to be affected by their personality and socio-demographics, the culture in which they live, as well as the interplay between personality and culture. The analysis was based on the hierarchical item response theory-based scaling technique that estimates latent scores for all constructs on a cross-nationally common scale. People's tendency to provide socially desirable answers was systematically affected by their personal makeup. SDR increased with higher openness to experience, conscientiousness, and agreeableness, while neurotic people exhibited lower SDR. National-cultural dimensions also played a prominent role. Respondents in countries high on power distance, uncertainty avoidance, and masculinity tended to exhibit a greater degree of socially desirable responding. SDR was found to be lower in national cultures emphasizing individualism. Also, a nation's culture systematically moderated the effects of the personality dimensions on SDR. The positive effect of agreeableness on SDR will be stronger when national-cultural collectivism is higher (individualism is lower), while the effect on conscientiousness was stronger in countries high on uncertainty avoidance. The effect of extraversion was systematically moderated by national-cultural power distance masculinity, both of which increased the effect of extraversion. Finally, the effect of openness to experience on SDR was reduced in individualistic cultures.

Chapter 5: International scale construction

The last essay was concerned with international measure construction. Current cross-national measurement approaches most often use the same items in all countries, or at least require a common set of items (Baumgartner and Steenkamp 1998; May 2005). I developed a procedure that yields fully country-specific, yet cross-nationally comparable short form marketing scales. The procedure is based on the juxtaposition of the polytomous hierarchical IRT model and optimal test design methods. In the optimal test design step, a combinatorial optimization routine was used to ensure that the scale has a certain, *a priori* chosen measurement precision along the entire trait range. The precision can vary for different values of the latent variable. The scale construction methodology was applied to the Impression Management scale (Paulhus 1991), in 28 countries. For similar measurement precision in

every country, an absolute target was used that specified some absolute precision that had to be reached for each and every country. As was shown, this choice implies that longer scales are obtained in particular countries and shorter scales in others. On the other hand, I also considered a fixed scale length, which implies that measurement precision might vary across countries.

VI.2 Future research directions

There are many areas in which the present research might be extended. In each of the chapters, several areas for future research have already been discussed. Based on my own reading and knowledge of the literature, I see several broad areas for future research.

Model fit for hierarchical IRT

Assessing fit of item response models is not straightforward due to the large number of possible responses, which makes standard χ^2 tests of goodness of fit difficult to apply. Many different aspects of fit can moreover be assessed, such as unidimensionality, DIF, item fit, and person fit. For Bayesian IRT models, little attention has been given to assessing fit.

In the essays I discussed the use of Bayes factors to check the plausibility of various model specifications. A Bayes factor is the ratio of the marginal likelihood under one model to the marginal likelihood under a second model and it is therefore required that one specifies alternative models. However, there might be many sources of misfit, both in the measurement models and in the structural model and it is not feasible to estimate Bayes factors for every different possible violation. Initial fit analysis might therefore start with residual analysis. Bayesian residuals can be defined as (using the same notation as in chapter 1) $r_{ijk}^{(m)} = Y_{ijk} - E(Y_{ijk} \mid \xi_{ij}^{(m)}, a_{kj}^{(m)}, \gamma_{kj}^{(m)})$, where *m* denotes the *m*-th draw in the MCMC algorithm. These residuals have continuous-valued posterior distributions, and one can check whether they are normally distributed. A disadvantage is that the Bayesian residuals have different posterior variances, which makes the residuals difficult to compare. Alternatively, one can focus on the Bayesian latent residuals defined as $\varepsilon_{ijk}=Z_{ijk} - a_{kj}\,\xi_{ij}$, where Z is the latent variable. The latent residuals are easily obtained as a by-product from the MCMC-sampler and are identically distributed. Yet, even with residual-based tests, the presence of large residuals does not always lead to identification of the source of the misfit.

In IRT, researchers have proposed the use of Langrange Multiplier (LM) tests (Glas 1998; 1999). The null model is the IRT model, while the alternative model has certain model

violations, such as violation of the shape of the item characteristic curves, or violation of local independence. The LM tests can be computed using the parameter estimates under the null model. In the Bayesian framework, the LM-based approach can be generalized (Fox and Glas 2005) to yield Bayesian Modification Indices (BMI), even though these BMIs have not yet been developed for hierarchical IRT models. With Bayesian modification it is possible to test for various kinds of model violations. Further research in development of BMIs in complex hierarchical IRT models holds considerable promise for model checking purposes. Naturally, more detailed analyses using traditional approaches such as Bayes factors or posterior predictive checks are possible after identifying large BMIs. Posterior predictive checking has recently been advanced as a viable strategy for Bayesian IRT models (Sinharay 2005; Sinharay, Johnson and Stern 2006). In a posterior predictive check, a test statistic is defined and the values of the test statistic for observed and replicated data sets are compared. Sinharay and colleagues discuss a wide variety of test statistics for IRT models, but more work is needed to assess how well these statistics work in hierarchical models, and practical implications of misfit.

Measurement invariance area

In the first essay, I relaxed measurement invariance but considered only a single latent variable. Researchers are often interested in relating multiple latent variables each measured by their own scale, so there is a need to develop hierarchical multidimensional latent variable models with random-effects structures for both the structural part and the measurement part. Structural modeling of multilevel data is a relatively recent area of scientific research. To date, there have been some applications of multilevel latent variable models that incorporate multiple latent variables, although the ordinal nature of the rating scale is often ignored and in addition, the measurement models are invariant or at least partially invariant across groups / countries. In this dissertation, models are presented that do recognize the ordinal nature of the rating scale, and random-effects structures for item parameters are proposed so that the measurement properties of *all* items can fluctuate across countries. However, the structural models are restricted to univariate latent outcomes and manifest predictors. Models are necessary that can handle multiple latent dependent variables, and latent predictors.

Response styles

In chapters 3 and 4 I focused only on two response styles, ERS and SDR. There are also other response styles, such as acquiescence, and non-contingent responding (Baumgartner and

Steenkamp 2001) that influence the observed scores of items. Acquiescence refers to the tendency to agree with statements relatively independently of specific item content, while non-contingent responding refers to the tendency to respond to items carelessly or nonpurposefully. All response styles jointly influence observed scores, and hence, there is a need for models that integrate these various response styles into a single model. Baumgartner and Steenkamp (2001) present a regression-based approach to partial observed scale scores from all response styles, but this approach has limitations. More specifically, it is assumed that the styles have the same biasing influence on each item of a scale, the latent nature of the data is ignored, it is assumed that the styles have the same biasing effect for each individual, and it is not clear whether the various styles have a linear impact on the observed scores. Models that address all of these issues are necessary, even though the task seems daunting to come up with ordinal latent data models that incorporate all styles and simultaneously model substantive relationships between latent constructs.

Studies that investigate the validity of partialing SDR influences (especially impression management) from observed scores, as recommended by Paulhus (1991), have produced mixed effects at best. Many studies find no increase or even a decrease in validity when correcting for SDR (see e.g. Ellingson, Sackett and Hough 1999; Ellingson, Smith and Sackett 2001; Ones, Viswesvaran, Reis 1996; Piedmont et al. 2000; Smith and Ellingson 2002). The randomized response techniques seems much more promising (Fox 2005c) to elicit valid responses in cases where respondents are reluctant to display their true opinions, even though much research remains to be done for ordinal data. Once accurate ways to control for SDR have been found, this opens up interesting avenues for research in consumer behavior. For instance, research could address taboo consumer behavior, where respondents are often reluctant to disclose their true behaviors or opinions (De Jong, Fox, and Pieters 2006).

International scale construction

In the scale construction procedure we proposed in the fourth essay, we only considered a single scale (the impression management scale). However, the procedure that we built should be applied to many other scales to build a stock of findings that could be incorporated into scaling handbooks. Item parameter values, as well as country-specific versions of a scale could be listed in books such as the *Handbook of Marketing Scales* (Bearden and Netemeyer 1999). Researchers would then be able to use a scale which has been emically tailored to the local environment. Currently, the *Handbook of Marketing Scales* lists items that have been

developed in the U.S., but our analysis showed that not all SDR items are equally useful across the world, and these types of results are very likely to generalize to other constructs. For instance, Wong, Rindfleisch and Burroughs. (2003) showed that the materialism scale had problems in Asia, and that it would probably be better if the scale and item format would be adapted. Another example would be the construct of values. The Schwartz Value Survey (SVS; Schwartz 1992) is a rigorous instrument to measure values. But Schwartz and colleagues developed the Portraits Values Questionnaire because certain types of respondents in emerging consumer markets had difficulty understanding and completing the SVS. This was true especially among less educated and older respondents, and respondents living in rural areas (Schwartz, Lehmann and Roccas 1999).

Methodologically, one might include varying response formats for items across countries by changing the hierarchical structure in the IRT model. This would improve the general applicability of the methodology.

Although only some aspects of IRT models were discussed in this dissertation, I nonetheless hope that item response theory will get the place it deserves in the measurement toolbox of both domestic and international marketers. In addition, I hope this dissertation has increased the interest for international marketing, and advanced the rigor of cross-national research.

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Nederlandse Samenvatting

Globalisering is een belangrijke factor in hedendaagse afzetmarkten. Verzadigde thuismarkten en concurrentie van buitenlandse firma's die toetreden tot lokale markten zorgen ervoor dat vele bedrijven verder kijken dan de eigen landsgrenzen. Succesvolle internationale marketingstrategieën vereisen een gefundeerde analyse van consumentengedrag in de verschillende landen en van de toepasbaarheid van (Amerikaanse) marketingtheorieën. Grote culturele, institutionele en socio-economische verschillen dragen er toe bij dat bestaande theorieën niet zonder meer kunnen worden overgedragen naar alle markten.

Wegens beperkte beschikbaarheid van secundaire databronnen, is crossnationaal marketing- en consumentengedragonderzoek veelal gebaseerd op enquêtes die worden afgenomen in meerdere landen. Beantwoording van specifieke onderzoeksvragen geschiedt aan de hand van een stapsgewijs proces. In de eerste fase wordt een theoretisch kader ontwikkeld, waarin de relevante constructen en concepten worden gedefinieerd en relaties en hypothesen worden opgesteld. Vervolgens vindt dataverzameling plaats, waarna in de derde stap de data wordt geanalyseerd. Ten slotte kunnen conclusies worden geëxtraheerd uit de analyses.

In deze dissertatie staat vooral de verzameling en analyse van crossnationale enquêtedata centraal. Specifiek gaat het om het opstellen van geschikte, landspecifieke meetinstrumenten om latente marketingconcepten (bijvoorbeeld tevredenheid, loyaliteit, vertrouwen, innovativiteit, etc.) accuraat te kwantificeren. Een tweede doel is het bestuderen van de vergelijkbaarheid of meetinvariantie van data uit verschillende landen. Meetinvariantie impliceert dat geobserveerde antwoorden op items in een enquête in alle landen op dezelfde manier met t latente construct samenhangen en dat er dus betekenisvolle vergelijkingen gemaakt kunnen worden tussen landen.

Een gebrek aan meetinvariantie kan zich voordoen voor specifieke items, als ook uniform voor een complete set van items (een verschil in responsstijlen, waarbij de responsstijl specifieke items overstijgt). In dit proefschrift worden methoden ontwikkeld waarbij het mogelijk is om bij een gebrek aan meetinvariantie toch crossnationale vergelijkbaarheid te bewerkstelligen.

Meetinvariantie voor specifieke items (Hoofdstuk 2)

De dominante logica in de sociale en economische wetenschap is dat meetinstrumenten een zekere mate van invariantie moeten vertonen om landen op een valide manier te kunnen

vergelijken. Het multigroep confirmatief factor-analytisch model (CFA-model) is de 'gouden' standaard om te testen of een meetinstrument dat in meerdere landen is afgenomen invariant is. Om uitspraken te doen vereist het multigroep CFA-model een zekere mate van invariantie die afhankelijk is van het doel van de studie. In het algemeen moeten ten minste twee items invariant zijn voor crossnationale vergelijkbaarheid van de scores op de latente constructen.

In hoofdstuk 2 heb ik een hiërarchisch IRT-model geïntroduceerd dat marketingonderzoekers in staat stelt om vergelijkingen te maken tussen landen zonder dat enig item uit de enquête invariant hoeft te zijn. Hoewel het verband tussen items en het latente construct mag verschillen per land, geldt wel de eis dat er geen verschil in responsstijl is die exact hetzelfde is voor alle items. De ordinale aard van de data die via Likert-schaal zijn verkregen, wordt eveneens meegenomen in het model. In een simulatie toonden we aan dat de eis van meetinvariantie voor twee items kan worden losgelaten. Ik heb dit tevens geïllustreerd aan de hand van een empirische toepassing die betrekking had op een instrument dat de ontvankelijkheid van een consument voor normatieve invloed meet. Normatieve invloed is een belangrijk aspect binnen de marketing. Het is in verband gebracht met bijvoorbeeld attitudes ten aanzien van merken, receptiviteit voor advertenties, consumentenvertrouwen, aankoop van nieuwe producten etc.

In elf landen – verdeeld over vier continenten – hebben respondenten de vragen beantwoord die bij dit meetinstrument horen. Ik heb de resultaten van het multigroep CFA-model vergeleken met de resultaten op basis van het hiërarchisch IRT-model, en hieruit bleek dat het CFA-model onjuiste conclusies opleverde. Gebaseerd op het IRT-model vond ik dat, in overeenstemming met mijn hypothese, consumenten in individualistische landen lager scoren op ontvankelijkheid voor normatieve invloed dan consumenten in collectivistische landen. Bovendien bleek dat er meer divergentie in attitudes was in individualistische landen.

Extremen-responsstijl (Hoofdstuk 3)

In de dissertatie zijn twee responsstijlen in enquêtes besproken. Een eerste stijl is de zogenaamde 'extremen-responsstijl' (ERS), waarbij een respondent veel de uiterste opties van een Likert-schaal gebruikt (uiterste opties zouden kunnen zijn: 'helemaal niet mee eens, en 'helemaal mee eens'), relatief onafhankelijk van het onderwerp waarover hij/zij wordt ondervraagd.

Voor ERS heb ik een nieuw hiërarchisch IRT-model ontwikkeld om te kwantificeren in hoeverre mensen de uiterste opties van de antwoordschaal gebruiken. Dit model veronderstelt een set van items die heterogeen is, in de zin dat er tal van verschillende onderwerpen worden

aangekaart die niet veel met elkaar te maken hebben. Als respondenten op vele items die onderling erg verschillend zijn telkens een extreem antwoord geven, dan is het zeer waarschijnlijk dat iemand geneigd is de extremen op te zoeken. In het ontwikkelde meetmodel wordt het echter toegestaan dat de set van items ook uitspraken bevat die wel met elkaar samenhangen. Ook is onderzocht in hoeverre ERS varieert voor verschillende landen. De schattingsresultaten gaven aan dat consumenten inderdaad verschillen in ERS, maar ook dat niet ieder item even sterk wordt beïnvloed door ERS. Met andere woorden, in sommige gevallen kunnen substantieve overwegingen de overhand hebben, terwijl bij andere, meer ambigue stellingen de responsstijl kan domineren. Deze effecten zijn landspecifiek: in bepaalde landen gebruiken consumenten de uiteinden van een antwoordschaal significant minder dan in andere landen, en in hoeverre items worden beïnvloed door ERS hangt af van het specifieke land. Het model is toegepast op een grote dataset van 26 landen, met in totaal 12.500 respondenten. Individuele verschillen in ERS kunnen in beperkte mate worden verklaard uit sociodemografische kenmerken, en cultuur had een sterk en voorspelbaar effect op de geneigdheid tot ERS. Vrouwen scoren wat hoger op ERS dan mannen, en zowel jonge als oude consumenten zijn meer geneigd de extremen te gebruiken. Op cultuurniveau is ERS significant positief gerelateerd aan individualisme, vermijding van onzekerheid, en masculiniteit.

Sociaal wenselijk antwoordgedrag (Hoofdstuk 4)

Een tweede responsstijl die ik heb besproken is ‘sociaal wenselijk antwoordgedrag’ (SWA). In deze dissertatie is een conceptueel raamwerk ontwikkeld waarin de geneigdheid tot sociaal wenselijk antwoordgedrag wordt beïnvloed door persoonlijkheid, door sociodemografische factoren, door cultuur, en door de interactie van persoonlijkheid en cultuur. De analyse is gebaseerd op het hiërarchisch IRT-model dat de latente scores op elk van de persoonlijkheidsconstructen, en het SWA-construct op een gemeenschappelijke schaal schat. De tendens tot SWA is sterker als consumenten ouder zijn, tot lagere sociale klassen behoren, als ze open, gewetensvol/nauwgezet en vriendelijk zijn, en lager indien men neurotisch is. Respondenten in landen waar veel hiërarchie is, waar onzekerheid vermeden dient te worden, en waar veel masculiniteit is, waren eveneens meer geneigd tot SWA. In individualistische landen doet SWA zich minder voor. Verder waren er interacties tussen cultuur en persoonlijkheid. Het positieve effect van vriendelijkheid op SWA wordt versterkt in collectivistische landen, terwijl het positieve effect van een gewetensvolle/nauwgezette

houding op SDR sterker is in onzekerheidsmijdende landen. Het effect van extraversie op SDR werd significant versterkt in hiërarchische en in masculiene culturen.

Internationale schaalconstructie (Hoofdstuk 5)

In het laatste hoofdstuk stond de constructie van landspecifieke meetinstrumenten centraal. In de literatuur worden vaak exact dezelfde items in elk land gebruikt, en meetmodellen vereisen ten minste dat er een gezamenlijke set van items is om uitspraken te kunnen doen over een latent construct en om landen te vergelijken. In hoofdstuk 5 ontwikkel ik een procedure met als unieke eigenschap dat er volledig landspecifieke maar toch crossnationaal vergelijkbare korte meetinstrumenten uit voortvloeien. De procedure is gebaseerd op de juxtapositie van een ordinaal IRT-model en optimale testconstructie-technieken uit de psychometrie. In de optimale testconstructiestap wordt er een combinatorisch optimalisatieprobleem opgelost zodat het meetinstrument een zekere *a priori* gekozen meetprecisie oplevert die kan verschillen per respondent. De methodologie wordt geïllustreerd aan de hand van een schaal die de neiging tot impressie management meet. De schaal wordt zowel ingekort als landspecifiek gemaakt. Het is mogelijk om een vaste precisie op te leggen, waardoor de meetinstrumenten per land niet hetzelfde aantal items hoeven te bevatten, als ook om een vast aantal items op te leggen, waardoor de precisie kan verschillen per land. Dit levert verschillende schalen op.