

Measuring Car Pride and its Implications for Car Ownership and Use across Individuals, Cities, and Countries

by

Joanna C. Moody

M.S. Transportation, Massachusetts Institute of Technology (2016)

B.S. Mathematics, Physics, and Japanese, Bates College (2014)

Submitted to the Department of Civil and Environmental Engineering
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Transportation

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2019

© 2019 Massachusetts Institute of Technology. All rights reserved.

Author
Department of Civil and Environmental Engineering
May 10, 2019

Certified by
Jinhua Zhao
Edward and Joyce Linde Associate Professor of City and Transportation Planning
Dissertation Supervisor

Accepted by
Heidi Nepf
Donald and Martha Harleman Professor of Civil & Environmental Engineering
Chair, Graduate Program Committee

Measuring Car Pride and its Implications for Car Ownership and Use across Individuals, Cities, and Countries

by

Joanna C. Moody

Submitted to the Department of Civil and Environmental Engineering
on May 10, 2019
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in Transportation

Abstract

As the world recognizes that its growing reliance on private, fossil fuel-based vehicles is unsustainable, understanding how to avoid growth in car ownership and how to shift current users towards more efficient, environmentally-friendly, safe, and inclusive alternatives is a critical vision for meeting sustainable (transportation) development goals. Policy makers looking to shift consumer behavior away from cars need a more rigorous understanding of how different attitudes play a role in influencing car ownership and use and how this might vary by people and place. In this dissertation we provide deep insight into one of the many symbolic and affective motives behind car consumption: “car pride” or the attribution of social status and personal image to owning and using a car.

Using data collected from individuals in two U.S. cities and in 51 countries around the world, we develop and demonstrate the reliability, validity, and invariance of polytomous (12, 7-point Likert-format statements) and dichotomous (9, dichotomous statements) survey measures for car pride using confirmatory factor analysis (CFA). With these measures, we explore variations in car pride across individuals, cities, and countries using Structural Equation Modeling (SEM). Across individuals, we find that those who are younger, male, and have higher incomes generally have higher car pride. Controlling for individual characteristics, we find that car pride is influenced by context. Between U.S. cities, we find that Houston has higher car pride than New York City. Across countries, we find that less developed countries exhibit higher car pride. We also disentangle the bidirectional causal relations between car pride and car consumption using instrumental variable (IV) techniques. We find that car pride strongly predicts car ownership, while no statistically significant relation exists in the opposite direction. Car pride additionally predicts car use, but only through its relation with car ownership (mediator). In the reverse direction, car use strongly reinforces car pride. While the directions of these relations appear almost universal across contexts, their strengths differ by country, emphasizing the importance of taking national context into account when measuring and interpreting symbolic motivations for car consumption.

This dissertation builds a systematic understanding of car pride and its relations with car consumption across individuals, cities, and countries. For researchers, it serves as an example of methodological good-practice for empirical studies of attitude-behavior relations in transportation. For policymakers, it builds awareness of how policies can target attitudinal, social, and cultural factors, such as car pride, that present additional obstacles to the adoption of more sustainable transportation alternatives at both the individual and national levels.

Dissertation Supervisor: Jinhua Zhao

Title: Edward H. Linde Associate Professor of City and Transportation Planning, MIT

Dissertation Committee Chair: Nigel Wilson

Title: Professor Emeritus of Civil & Environmental Engineering, MIT

Dissertation Committee Member: Christopher Knittel

Title: George P. Shultz Professor of Applied Economics, MIT Sloan School of Management

Dissertation Committee Member: Dario Hidalgo

Title: Executive Director of Fundación Despacio and former Director of Integrated Transport at the World Resources Institute Ross Center for Sustainable Cities

Acknowledgments

Thanks are due to so many people who have supported me and encouraged me throughout my time at MIT. First, I would like to acknowledge my incredible mentors. To the late Professor Joseph Sussman: thank you for recognizing and fostering my academic potential, for helping me build the confidence to pursue a Ph.D. and for instilling in me a lifelong appreciation for “systems-thinking.” I am truly fortunate to have been your student and will take your teaching with me wherever I go from here.

To my thesis supervisor, Professor Jinhua Zhao: thank you for your boundless energy and constant positivity even in the face of setbacks and for creating an environment that respects all ideas and encourages multidisciplinary, independent and collaborative thinking. I truly felt at home in your research group and could not have asked for a better place to grow as a scholar and as a person.

To the other members of my dissertation committee, Professor Emeritus Nigel Wilson, Professor Christopher Knittel, and Dr. Dario Hidalgo, thank you for bringing your unique perspectives to guide me through the final stages of the dissertation process. To Nigel, thank you for encouraging me to step back from the empirical results and articulate the choices behind each method and each variable as well as their consequences. To Chris, thank you for challenging my models and ensuring that each econometric method I applied was appropriate and properly specified. To Dario, thank you for bringing a practitioner’s perspective to all of our discussions and for encouraging me to connect my research to current issues of sustainable transportation policymaking around the world. Together, this committee has helped shape this dissertation to be a deep reflection of the research process, methodologically-rigorous, and (to the extent it can be) policy-relevant.

To Professor Andrew Ho of Harvard University: thank you for teaching me about the importance of measurement and for introducing me to the field of psychometrics. To Professor Dana McCoy of Harvard University: thank you for providing me with a solid foundation in applied latent variable analysis and structural equation modeling. Together, you have helped me bring new methodological rigor to analysis of attitude-behavior relations in transportation.

To all of my colleagues at MIT, from my early years in the Regional Transportation Planning and High Speed Rail (R/HSR) Research Group, through my final years in the JTL: Urban Mobility Lab: thank you for so many shared moments both academic and personal that challenged and broadened my thinking and made the experience of being a graduate student at MIT enjoyable.

To my partner, Nate: thank you for helping me find my work-life balance. Thank you for your understanding of the stresses of being a graduate student at MIT, for the many walks home hashing out ideas, for helping me understand probabilities, but most of all, for reminding me that we are so much more than our research. I am so fortunate to be able to share every day with someone so compassionate, intelligent, and fun-loving.

Thank you to all of my family, both immediate and extended, old and new. To my parents, Catherine Leslie and David Moody: thank you for fostering in me a lifelong love of learning and for providing me with the opportunities to succeed. I am so honored to be joining you as a Dr. (even if not the medical kind). To my sisters, Kate Moody and Emily Moody: thank you for always keeping life interesting, for forcing me out of my comfort zone, for keeping me humble, for teaching me when to be assertive and when to compromise, and for all of our shared meals, shared laughter, and shared values.

Last, but certainly not least, thank you to the MIT Energy Initiative Mobility of the Future study, the New England University Transportation Center, the Lee Schipper Memorial Scholarship and its partnership with the Volvo Research and Education Foundation (VREF) for financial and intellectual support of this research.

Contents

1	Introduction	19
1.1	Symbolic and Affective Motivations of Car Consumption: Theoretical Models	20
1.1.1	The Car as a Material Possession	21
1.1.2	Theories of Transportation Choice	22
1.2	Symbolic and Affective Motivations of Car Consumption: Empirical Evidence	25
1.2.1	Car Use	25
1.2.2	Car Ownership	26
1.3	Limitations of Existing Studies	27
1.4	Our Contributions	27
1.5	Dissertation Structure	28
2	Data Collection	31
2.1	U.S. Cities Survey	32
2.1.1	City Selection	32
2.1.2	Respondent Recruitment and Sample	34
2.1.3	Complementary Data	36
2.2	International Survey	36
2.2.1	Respondent Recruitment	37
2.2.2	Sample of Individuals	38
2.2.3	Sample of Countries	41
2.2.4	Complementary Data	42
2.3	Conclusions	45
3	Survey Measure Development	47
3.1	Confirmatory Factor Analysis (CFA)	47
3.1.1	Indices of Model Fit	49
3.1.2	Multilevel CFA	50
3.1.3	Primary Advantages and Uses of CFA	54
3.2	Psychometric Properties of a Measurement Scale	54
3.2.1	Reliability	55
3.2.2	Validity	58

3.2.3	Measurement Invariance	59
3.3	The Polytomous Car Pride Scale within U.S. Cities	61
3.3.1	Content Validity	61
3.3.2	Convergent Validity	62
3.3.3	Divergent Validity	65
3.3.4	Measurement Invariance	67
3.3.5	Reliability	72
3.3.6	Discussion	72
3.4	The Multilevel Dichotomous Car Pride Scale across Countries	72
3.4.1	Content Validity	73
3.4.2	Multilevel Construct Conceptualization	74
3.4.3	Measurement Invariance	75
3.4.4	Convergent Validity	78
3.4.5	Reliability	79
3.4.6	Discussion	80
3.5	Conclusions	81
3.5.1	Limitations and Future Work	81
3.5.2	Reflections	82
4	Implicit Measure Development	87
4.1	The Implicit Association Test	89
4.1.1	Psychometric Properties of the IAT	90
4.1.2	When Might the IAT Outperform Traditional Self-Report Measures	92
4.1.3	Addressing Practical Challenges with the IAT	93
4.1.4	Addressing Theoretical Critiques to the IAT	95
4.2	Previous Applications of the IAT in Transportation	96
4.3	The Car vs. Bus Social Status IAT	97
4.3.1	Experimental Design	97
4.3.2	Reliability	104
4.3.3	Validity	104
4.4	Conclusions	106
4.4.1	Limitations and Future Work	106
4.4.2	Reflections	107
5	Car Pride and its Bidirectional Relations with Car Ownership and Use Across Individuals in U.S. Cities	111
5.1	Bidirectionality of Attitude-Behavior Relations in Transportation	112
5.2	Structural Equation Modeling	113
5.2.1	SEM Process	113
5.2.2	Reciprocal Relations in SEM	116

5.3	Variations in Car Pride across Individuals and U.S. Cities	117
5.3.1	Mean Car Pride Scores across Cities	118
5.3.2	Regressions on Sociodemographic Variables	119
5.4	Car Pride of Car Owners and Car Users	121
5.4.1	Car-Owners vs. Non-Car-Owners	121
5.4.2	Drive Alone Commuters vs. Others	122
5.4.3	Discussion	123
5.5	Bidirectional Relations between Car Pride and Car Ownership	124
5.5.1	Analytic Plan	124
5.5.2	General Results	126
5.5.3	City-Specific Results	127
5.5.4	Discussion	128
5.6	Bidirectional Relations between Car Pride and Car Use	129
5.6.1	Analytic Plan	130
5.6.2	General Results	133
5.6.3	Addition of the Implicit Measure	135
5.6.4	Discussion	136
5.7	Conclusions	136
5.7.1	Contributions	137
5.7.2	Limitations and Future Work	138
6	Car Pride and its Associations with Car Ownership and Use Across Indi-	
	viduals and Countries	141
6.1	Multilevel Structural Equation Modeling	142
6.1.1	Variable Centering	143
6.1.2	Sample Size and Statistical Power	145
6.1.3	Bayesian Estimation	145
6.2	Individual Car Pride	148
6.2.1	Distributions by Country	149
6.2.2	Multilevel Regression of Individual Car Pride on Sociodemographics .	152
6.3	Association of Car Pride with Car Ownership	154
6.3.1	Car Pride of Car-Owners vs. Non-Car-Owners	154
6.3.2	Multilevel Structural Equation Model	155
6.3.3	Discussion	159
6.4	Association of Car Pride with Car Use	159
6.4.1	Car Pride of Car-Users vs. Non-Car-Users	160
6.4.2	Multilevel Structural Equation Model	161
6.4.3	Discussion	164
6.5	Country Car Pride	164
6.5.1	Visualizing Variation Across Countries	164

6.5.2	Correlations with National Indicators	166
6.5.3	Discussion	172
6.6	Conclusions	172
6.6.1	Contributions	173
6.6.2	Limitations and Future Work	174
7	Findings, Recommendations, and Implications	177
7.1	Main Findings	178
7.1.1	Measuring Car Pride	178
7.1.2	Variations in Car Pride	179
7.1.3	Car Pride and Car Consumption	180
7.2	Areas for Future Research	181
7.3	Recommendations for Transportation Research	183
7.4	Implications for Sustainable Transportation Policy	186
7.4.1	Policies Targeting Behavior	187
7.4.2	Policies Targeting Attitudes	187
7.4.3	Identifying the Right Audience	191
7.4.4	Transferring Policies	192
7.4.5	Packaging Policies	193
7.5	Conclusion	195
A	U.S. City Survey	197
B	International Survey	209
	Bibliography	217

List of Figures

1.1	Dimensions of car consumption and their related values	21
1.2	Diagram of the Theory of Planned Behavior	24
1.3	Diagram of the Theory of Interpersonal Behavior	25
2.1	Share of households by vehicle ownership in the U.S., NYC, and HOU	33
2.2	Share of commute to work trips by mode in the U.S., NYC, and HOU	34
3.1	Path diagram of a conceptual confirmatory factor analysis model - example of a single latent factor with 4 observed indicators	48
3.2	Path diagram of a conceptual multilevel CFA model - example of a single latent factor with 4 observed indicators	51
3.3	Path diagram for the 12-item polytomous car pride CFA	64
3.4	Path diagram for the 6-item general authentic pride CFA	66
3.5	Path diagram for the simultaneous estimation of the 12-item car pride and 6-item general authentic pride measures	67
3.6	Path diagram for the 9-item car pride MCFA modeled as a configural construct	76
3.7	Comparison of factor scores with mean scores for the polytomous car pride scale in the U.S.	84
3.8	Comparison of individual factor scores with simple sum and mean scores for the dichotomous car pride scale for our international sample	85
4.1	Example of an IAT experimental interface.	89
4.2	Images selected to represent cars and buses in the IAT	99
4.3	Representation of the experimental blocks of the car vs. bus social status IAT	102
5.1	Flowchart of the basic steps of structural equation modeling	114
5.2	Distributions of explicit and implicit measures of car pride across individuals in New York City ($n = 779$) and Houston ($n = 471$)	118

5.3	Distributions of explicit and implicit measures of car pride across individuals whose households do ($n = 1029$) and do not own cars ($n = 144$)	122
5.4	Distributions of explicit and implicit measures of car pride across individuals who do ($n = 859$) and do not ($n = 391$) drive alone as their primary commute mode	123
5.5	Path diagram for the structural equation model simultaneously estimating the bidirectional relationship between car pride and household car ownership . .	125
5.6	Path diagram for the alternative structural equation model simultaneously estimating the bidirectional relationship between car pride and car use, with household car ownership as a correlated predictor	131
5.7	Path diagram for the hypothesized structural equation model simultaneously estimating the bidirectional relationship between car pride and car use, mediated by household car ownership	132
6.1	Histogram and box plot distributions of individual car pride factor scores for the full international sample	149
6.2	Boxplot distributions of individual car pride factor scores for each of the 51 countries sampled	150
6.3	Histograms of individual car pride factor scores for select countries	151
6.4	Analytic path diagram for the MSEM predicting individual car pride with individual and household sociodemographics	152
6.5	Mean car pride scores for car-owners vs. non-car-owners by country	155
6.6	Analytic path diagram for the within-level of an MSEM predicting car ownership with car pride and sociodemographics	156
6.7	Random probit regression coefficient of car ownership (0/1) on individual car pride by country	158
6.8	Mean car pride scores for car-users vs. non-car-users by country	160
6.9	Analytic path diagram for the within-level of an MSEM predicting car use with sociodemographics and car pride (through car ownership)	161
6.10	Distribution of country car pride factor scores	165
6.11	World map of country car pride factor scores	166
6.12	Country car pride score vs. pump price for gas and diesel	167
6.13	Country car pride score vs. GDP per capita, GDP annual percent growth, and Gini index	168
6.14	Country car pride score vs. national personal car stock and sales	170
6.15	Country car pride score vs. road density, vehicle-km, and passenger-km . . .	171

7.1	Relations among car pride, car ownership, and car use	180
7.2	The role of branding sustainable alternatives and de-marketing the car among transportation policy interventions	186

List of Tables

1.1	Summary of empirical chapters	29
2.1	Comparison of sample representativeness against U.S. metropolitan area populations	35
2.2	Sample size and comparison of sample representativeness by gender and age against national populations, by country	38
2.3	Comparison of sample representativeness of household car ownership and urban populations, by country	40
2.4	Representativeness of sample national wealth, by type of country	42
2.5	List of national macroeconomic indicators collected and calculated, with years and number of sampled countries covered	43
2.6	List of national motorization indicators collected and calculated, with years and number of sampled countries covered	44
2.7	List of national vehicle use and road infrastructure indicators collected, with years and number of sampled countries covered	45
3.1	Results for the 20-item car pride CFA in in New York City and Houston	62
3.2	Results for the 12-item car pride CFA without correlated errors	63
3.3	Results for the 12-item car pride CFA with correlated errors	65
3.4	Results for the 6-item general pride CFA in New York City and Houston	66
3.5	Multigroup analysis of the invariance of the 12-item polytomous car pride scale between cities	68
3.6	Detection of partial or indicator-specific invariance between cities using a free baseline MLR-corrected scaled χ^2 difference test	69
3.7	Multigroup analysis of the invariance of the 12-item polytomous car pride scale between car-owners and non-car-owners	70
3.8	Detection of partial or indicator-specific invariance between car-owners and non-car-owners using a free baseline MLR-corrected scaled χ^2 difference test	70

3.9	Multigroup analysis of the invariance of the 12-item polytomous car pride scale between drive alone commuters and others	71
3.10	Detection of partial or indicator-specific invariance between drive alone commuters and others using a free baseline MLR-corrected scaled χ^2 difference test	71
3.11	Single-level reliability indices for the polytomous car pride scale for two U.S. cities	72
3.12	Content covered by the 9 items in the dichotomous car pride scale	73
3.13	Intraclass correlation coefficients (ICCs) for the 9 dichotomous car pride items	74
3.14	9-item dichotomous car pride scale: model fit indices for invariance testing .	77
3.15	WLSM-corrected scaled χ^2 difference tests against free baseline model for partial or indicator-specific invariance	78
3.16	Multilevel confirmatory factor analysis results for the 9-item car pride scale enforcing strong measurement invariance	78
3.17	Approximate level-specific reliability indices (and standard errors) for the 9-item dichotomous car pride scale for the international sample	80
4.1	Words selected to represent positive and negative social status in the IAT . .	100
4.2	Experimental process for the car vs. bus social status IAT	101
4.3	Estimated correlations among implicit and explicit car pride measures and car consumption	105
5.1	Regression of the polytomous survey measure of car pride on individual and household sociodemographics	120
5.2	Regression of the car vs. bus social status IAT DW-score on individual and household sociodemographics	121
5.3	Direct path parameter estimates for simultaneous estimation of the bidirectional relation between car pride and car ownership	127
5.4	Bidirectional relations between car pride and household car ownership by U.S. city subsample	128
5.5	Comparison of the overall fit of the hypothesized and alternative models . .	133
5.6	Estimated path parameters for the simultaneous estimation of the bidirectional relation between car pride and car use	134
5.7	Estimated path parameters for implicit association of social status with cars versus buses in the bidirectional car pride and car use SEM	136
6.1	Parameter estimates for MSEM predicting car pride factor scores with individual and household sociodemographics	153

6.2	Select parameter estimates for the fixed effect MSEM predicting car ownership	157
6.3	Select parameter estimates for the MSEM predicting car use	163
6.4	Correlation matrix of country car pride and national macroeconomic indicators	167
6.5	Correlation matrix of country car pride and national motorization indicators	169
6.6	Correlation matrix of country car pride and national indicators for road density, expenditure, and traffic	171

Chapter 1

Introduction

As the world recognizes that its growing reliance on private, fossil fuel-based vehicles is unsustainable, understanding how to avoid new car ownership growth and shift current users towards more efficient, environmentally-friendly, safe, and inclusive alternatives is a critical vision for meeting sustainable (transportation) development goals (IEA, 2012; Sum4All, 2017; UN General Assembly, 2015). Policy makers looking to shift consumer behavior away from cars need a more rigorous understanding of how different attitudes play a role in influencing car ownership and use and how this might vary by people and place.

For many years utility-based behavioral modeling has been the dominant framework for understanding individual’s transportation decision-making (Schwanen and Lucas, 2011). In such a framework, each individual makes travel decisions based on a rational process of maximization of utility considering the characteristics of the decision-maker, the situation (trip), and the available modes—primarily travel time (speed) and cost (Ben-Akiva and Lerman, 1985). Such an approach has been criticized for emphasizing the instrumental or functional aspects of travel decisions and ignoring the deep context of symbolic and affective relations between people, machines, and spaces of mobility (Schwanen and Lucas, 2011; Sheller, 2004; Urry, 2004).

Building on approaches in behavioral economics and social psychology, studies have begun to evidence the significance of symbolic and affective values (often collectively called “attitudes”) in relation to transportation choices. Choices regarding car consumption, in particular, can have strong symbolic and affective appeal because the car is commonly understood—and has been actively shaped by years of persistent marketing—to portray social status, confidence, power, and competence. These studies either adopt a qualitative approach through in-depth interviews or use latent variable approaches applied to survey data to quantify attitudes and incorporate them into existing utility-based modeling frameworks of travel behavior.

Collectively, these studies have shown that the symbolic and affective appeal of cars is related to their ownership and use; however, the literature still lacks specific definitions of

attitudinal variables, a clear understanding of the mechanism(s) by which attitudes and behavior interact, and an understanding of how attitudes and their relations to behaviors may vary across different populations. One of the challenges to answering these questions in the literature has been the lack of standardized measures for attitudinal variables that can be used to quantify and compare their relations to one another, model their directed relations with behavior, and compare across people and contexts.

In this dissertation we add to existing literature and inform sustainable transportation policy by providing deep insight into one of the many symbolic and affective motives behind car consumption: “car pride”—the attribution of social status and personal image to owning and using a car. By focusing on one key attitudinal factor, we can clearly define the attitude of interest, develop and evaluate potential measures across populations, and systematically model its relation with car consumption. In other words, by limiting the scope of our investigation we can drill down into the questions of causal mechanisms and cross-cultural comparison that must be answered to make actionable policy recommendations.

In this introduction, we provide a theoretical foundation for thinking about symbolic, affective, and instrumental motivations of car consumption as well as a review of existing empirical evidence of the associations between attitudes and car ownership and use. We present three general critiques to the existing literature and review how our dissertation helps to address these gaps. Finally, we provide a roadmap to the remaining chapters of the dissertation to guide readers to the content most interesting and relevant to them.

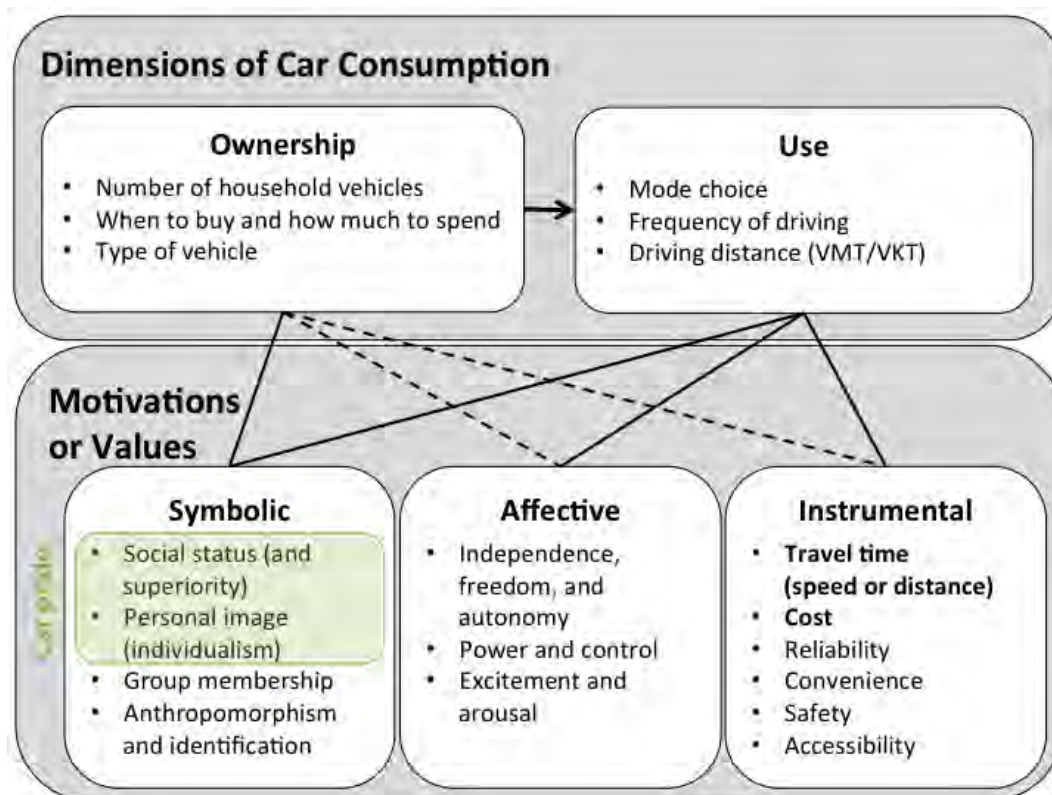
1.1 Symbolic and Affective Motivations of Car Consumption: Theoretical Models

The dominance of the car is an issue that has captured the attention of multidisciplinary researchers and policymakers for decades. The car has undeniable appeal as the most flexible and personalized form of motorized mobility. However, there is still no consensus about what informs people’s travel choices or what makes them prefer the automobile over other modes of transportation in most situations (Schwanen and Lucas, 2011). There is a complex combination of factors at play, including those which predominantly rest with the individual—such as personal values, intentions, and attitudes—and those that are largely outside the individual’s sphere of influence—such as price and availability of different modes; location of services and other physical attributions of the built environment; as well as culturally inflected social norms and moral values (Schwanen and Lucas, 2011). These factors interact with one another and their environment. This high degree of complexity warrants an overarching framework that organizes the many relations among different motivating factors for different car-related behaviors.

1.1.1 The Car as a Material Possession

In this section, we draw from existing theories of material consumption (Dittmar, 1992) to provide a framework for thinking about the different motivations of and values attributed to car consumption (Diekstra and Kroon, 2003; Gärling and Loukopoulos, 2008; Gatersleben, 2007; Steg, 2005). Consumption of the private car involves decisions regarding two dimensions—ownership and use—which are distinct but strongly linked. These two dimensions of car consumption can be motivated by the instrumental (functional) values of a car as well as its affective (emotional) and symbolic values (as depicted in Figure 1.1).

Figure 1.1: Dimensions of car consumption and their related values



Car ownership decisions—such as how many vehicles to buy, when to buy, how much to spend, and what type of vehicle to purchase—are often multi-year decisions that involve complex feedbacks among multiple household decision makers and other life decisions such as residential choice (Anowar et al., 2014; Gatersleben, 2011). Car ownership enables car use, which involves multiple decisions—such as what mode to use, how frequently to use a car, or how long (time or distance) to drive—made on a day-to-day or trip-by-trip basis. Both of these dimensions can vary over time, over space, and across individuals or groups, and decisions regarding use can additionally vary by trip purpose.¹

¹There is a third dimension of car consumption, namely second-to-second driving behavior—such as braking and acceleration, speed, and lane changing—that is beyond the scope of this dissertation.

The instrumental value of a car is related to its functionality as a means of mobility (and accessibility). This value is realized through car use, but can be anticipated when making decisions of ownership. Affective value is derived from connections with deeper, non-instrumental needs and desires, such as feelings of independence, freedom, and autonomy; power and control; personal security; or excitement and arousal (Anable and Gatersleben, 2005; Diekstra and Kroon, 2003; Steg, 2005). Affective value is linked to emotions evoked by driving a car, but these again may be anticipated when making choices related to car ownership (Sheller, 2004).

The symbolic value of car consumption sees the car as a means to express individual identity and social position or group membership. As mobile symbols, the car ‘materializes personality’ and projects how we like to see ourselves, and how we would like others to see us (Gössling, 2017; Sheller, 2004). The symbolic value of a car is derived from the fact that people can express themselves (personal image) and their social position (status) by owning or using a car; they can compare their (use of a) car with others and to social norms (Steg, 2005). This symbolic value may be particularly important to study in relation to resistance to change of car consumption; if a car plays an important role in defining an individual’s status, identity, and self-worth, then attempts to change car use or ownership may be strenuously resisted (Gatersleben, 2011).

Car Pride

For any given individual or household, the car is often the second largest item of consumption after housing (Urry, 2004). Therefore, cars convey and connote images of status, wealth, and social standing in public spaces in a manner in which few other commodities can (Gössling, 2017; Litman, 2011; Nielsen and Wilhite, 2014). Cars are also highly visible statements of personal identity (Glennie and Thrift, 1992). In turn, the attribution of personal success and social status to owning and using a vehicle can elicit feelings of ‘car pride’ (Zhao and Zhao, 2018). In this dissertation, we focus on this symbolic value of a car as a reflection of social status and personal image.

1.1.2 Theories of Transportation Choice

Equipped with an understanding of the different motivations for car consumption, we next turn our attention to the theories that explain how these ownership and use decisions are made. For decades, the transportation domain has relied on economic theories, such as the Random Utility Theory (RUT) to explain and model travel behavior. However, in recent years the domain has embraced more general models of human behavior developed in social psychology, contextualizing these theories to the transportation context.

Random Utility Theory

Random Utility Theory (RUT) assumes that people compare different alternatives according to the logic of the allocation of scarce resources and the principle of least effort (McFadden, 2001). Each alternative is assigned a utility, which is an abstract measure of the degree to which the alternative satisfies the needs and matches the preferences of the individual. Utility is composed of an observable or deterministic component modeled by the researcher and an unobservable stochastic, or random, component that accounts for uncertainty. The deterministic component of each alternative's utility is often derived from three sets of variables: characteristics of the alternatives (for example, the travel times, costs, reliability, and other characteristics of different travel modes), sociodemographic characteristics of the decision-maker, and characteristics of the situation (for example, the type of trip) (Ben-Akiva and Lerman, 1985). The alternatives are then ranked on the basis of their relative utilities and the alternative with the highest utility is selected. Thus, RUT assumes that decision-makers are fully informed and can perfectly discriminate between, and rank, different alternatives. In other words, a choice in RUT reflects a rational process of maximization of benefits to the user.

Some researchers have criticized the RUT for being overly instrumentalist, valuing aspects of car ownership and use—such as cost, speed, reliability, comfort, and safety—and ignoring the importance of symbolic and affective motivations (e.g., Steg et al., 2001a). However, a small but growing number of studies exist within the RUT tradition that account for symbolic, and affective motivations for car ownership and use. One way of accounting for such factors extends the deterministic component of a choice alternative's utility through the inclusion of observed attitudinal variables (e.g., Domarchi et al., 2008; Koppelman and Lyon, 1981; Schwanen and Mokhtarian, 2005). A second approach involves a variant of the hybrid choice model (Ben-Akiva et al., 2002) in which latent attitudinal factors are modeled endogenously as a function of measured variables (e.g., Johansson et al., 2006). Despite the diversification and increasing sophistication of utility-based research, others have turned to generalized models of human behavior developed in social psychology for new approaches to examining transportation choice (Schwanen and Lucas, 2011).

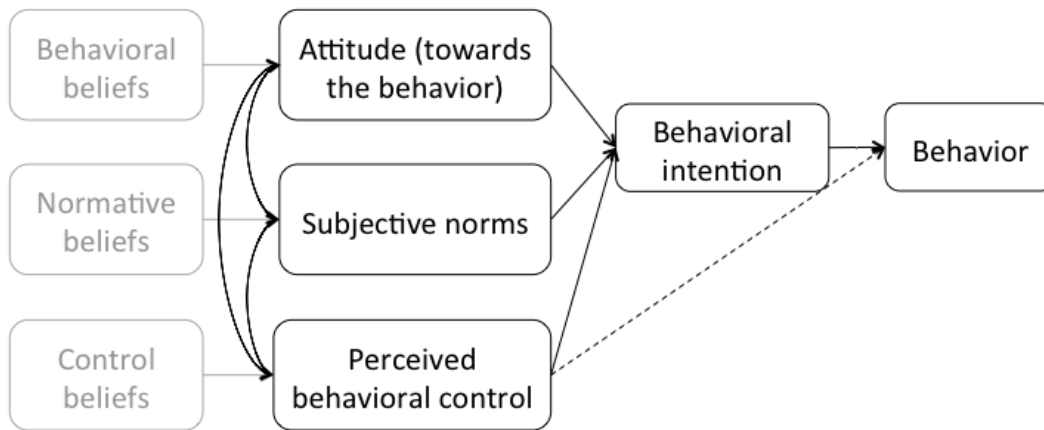
Theory of Planned Behavior and its Alternatives

Many studies of car consumption and transportation decision-making more generally integrate and hybridize generalized models of human behavior developed in social psychology (Schwanen and Lucas, 2011). Of these theories, the most often cited are the Theory of Planned Behavior (TPB) (Ajzen, 1991) and the Theory of Interpersonal Behavior (TIB) (Triandis, 1977).

The TPB assumes that behavioral intention is the most immediate predictor of behavior, and that intention is a function of a person's attitudes, subjective norms, and perceived behavioral control with regard to that behavior (see Figure 1.3) (Ajzen, 1991, 2015; Ajzen

and Fishbein, 2005).² In many ways, the TPB is a psychological variant of rational choice theory. According to the TPB, individuals make rational decisions, but these decisions are informed by the wider social context and practices of the society in which they live rather than made in complete isolation (Schwanen and Lucas, 2011). However, many applications of the TPB in transportation have found its structure to be too reductive. Therefore, researchers have looked to other theories to extend the TBP to include habits (Aarts and Dijksterhuis, 2000; Bamberg and Schmidt, 2003; Gardner, 2009; Gardner and Abraham, 2008; Verplanken et al., 1994) and personal norms (Bamberg et al., 2007; Harland et al., 1999; Heath and Gifford, 2002).

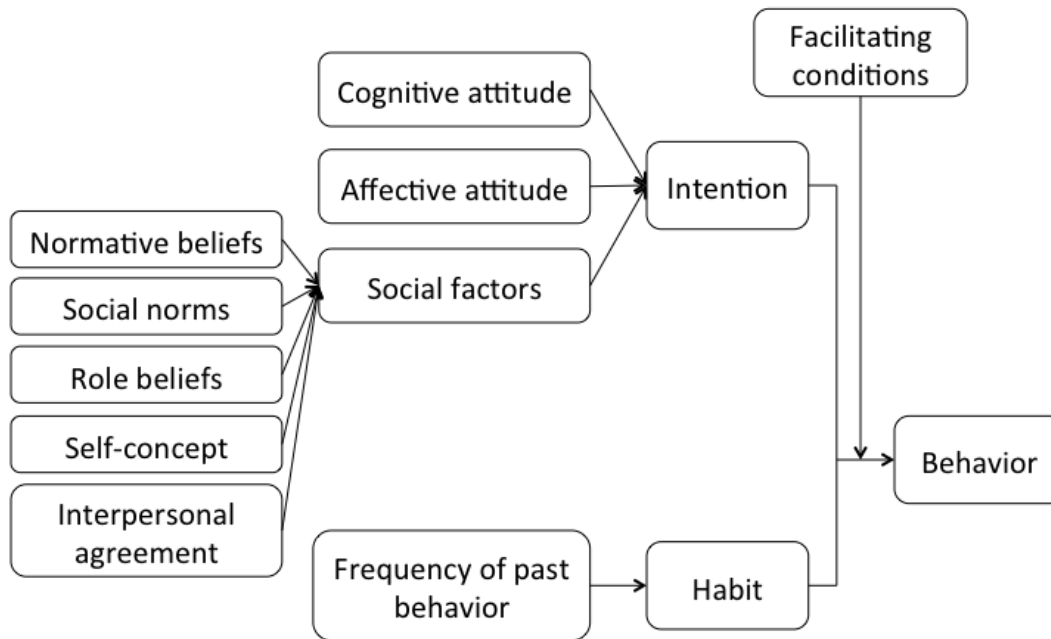
Figure 1.2: Diagram of the Theory of Planned Behavior



An alternative to the TPB relevant for transportation research is the Theory of Interpersonal Behavior (TIB), which postulates that habit plays as important a role as intention when predicting behavior (Triandis, 1977). In this theory, behaviors that are implemented on a regular basis (such as car use), become largely unpremeditated. The TIB differentiates itself from the TPB in two other respects (see Figure 1.3). First, it conceptualizes social influences on behavior much more broadly. Second, it incorporates physical constraints, such as conditions of the built environment and availability of different travel options, as facilitating conditions that mediate the links of habit and intention with behavior (Bamberg and Schmidt, 2003).

²Attitudes, subjective norms, and perceived behavioral control are themselves influenced by more general beliefs, which tend not to be measured explicitly in TPB studies.

Figure 1.3: Diagram of the Theory of Interpersonal Behavior



1.2 Symbolic and Affective Motivations of Car Consumption: Empirical Evidence

While a complete review of all studies considering the symbolic and affective aspects of car consumption is beyond the scope of this dissertation, a growing body of multi-disciplinary literature suggests that symbolic and affective values of the car (and other travel modes) are associated with travel decisions.

1.2.1 Car Use

Research shows that status aspects are important to (some) car users, but that it is not straightforward to study their relative importance and some people may underestimate or even downplay their importance. Studies drawing from diverse theoretical and methodological foundations have consistently shown that attitudes correlate with mode choice and other metrics of car use. In fact, many of these studies suggest that incorporating attitudinal variables significantly improve the explanatory power of regression and other models of actual car use containing sociodemographic and infrastructure factors traditionally used in utility-based theories (Hunecke et al., 2007).

Many studies have shown that symbolic and affective values are associated with the choice to use a car over other modes, particularly public transit (e.g., Beirão and Cabral, 2007;

Bergstad et al., 2011; Domarchi et al., 2008; Haustein and Hunecke, 2007; Miralles-Guasch et al., 2014; Van et al., 2014). Other studies have demonstrated that symbolic and affective values are related to frequency of car use (e.g., Lois and López-Sáez, 2009; Nilsson and Küller, 2000) and intentions to use cars in the future (e.g., Pojani et al., 2018; Stradling et al., 1999). Considering 'car pride' specifically, one previous study in Shanghai, China suggests that higher car pride is associated with a higher probability of choosing a car as the primary commute mode, more frequent car use, greater distance traveled, and higher share of car trips among car-owners (Zhao and Zhao, 2018).

1.2.2 Car Ownership

Despite clear links with car use, the symbolic and affective values of car ownership have been studied less frequently and from fewer theoretical perspectives (Schwanen and Lucas, 2011). While symbolic and affective values are often compared across car-owners and non-car-owners (e.g., Gatersleben, 2011; Hiscock et al., 2002), few studies have explored how attitudes might influence car ownership.

Recent studies suggest that intention to purchase a vehicle is related to symbolic and affective attitudes towards cars, particularly among individuals in developing countries (Belgiawan et al., 2014). One study among 408 households in Xi'an, China found that attitudes towards cars are significantly predictive of intention of owning a vehicle in the future and incorporating these symbolic and affective values improved the accuracy of vehicle ownership choice models (Wu et al., 1999). A survey among university students—consumers with significant future purchasing power—in Shanghai and Zhenjiang, China found that symbolic and affective values dominated the aspiration for car ownership at a level greater than the instrumental valuation of car ownership based on convenience, even after controlling for current household car ownership (Zhu et al., 2012). Another study of non-car-owners in Guangzhou, China found that attitudinal factors are strongly associated with the intention to buy a car, even after controlling for other personal and situational factors (He and Thøgersen, 2017). When it comes to 'car pride' specifically, this symbolic value of a car has been shown to be significantly and positively correlated with car ownership in a cross-sectional sample of residents in Shanghai, China, even after controlling for socioeconomic and location variables (Zhao and Zhao, 2018).

Limited empirical research also suggests that symbolic and affective values of cars relate to household and individual choices to own specific types of cars (Baltas and Saridakis, 2013; Choo and Mokhtarian, 2004). In particular, symbolic and affective values may play a role when buying expensive or luxury cars. In Xi'an, China, more expensive vehicles were found to offer more symbolic meaning and consumers exhibited willingness to pay a higher price for vehicles which have more symbolic meaning (Wu et al., 1999). Symbolic and affective values may also influence the actual and intended purchase of environmentally-friendly vehicles over other types of vehicles (Ashmore et al., 2018a; Griskevicius et al., 2010; Nayum and Klöckner, 2014; White and Sintov, 2017).

1.3 Limitations of Existing Studies

While evidence is mounting that symbolic and affective values of cars relate to people's current and future car consumption, many existing studies share some critical limitations that make it difficult to compare findings across studies and draw general conclusions regarding the order of importance of different symbolic or affective values and how they relate to car consumption behaviors.

First, 'attitudes' are often measured as a simple shaping of good and bad or pleasant and unpleasant, without differentiating between types of symbolic or affective values. Such composite measures of 'car positivity' are often difficult to interpret in applied settings and can be hard to connect with actionable recommendations for policy and practice. Even when specific symbolic or affective values of driving or owning a car are defined and measured separately (as in [Haustein and Hunecke, 2007](#); [Steg et al., 2001a,b](#)), comparing results among studies is difficult; each study uses different survey instruments, often providing very little evaluation of the validity and reliability of these ad-hoc measures.

Furthermore, the direction of causality of these associations of symbolic and affective values and travel behavior is often left unexplored. If bidirectional relations exist and are not adequately modeled, endogeneity can introduce bias in estimated parameters and call into question the veracity of the resulting conclusions. Thus there remains a heated debate on the topic of causality between attitudes and behaviors in transportation research.

Finally, most studies are conducted in specific cities or regions, particularly in developed countries. Thus, findings about the symbolic and affective motivations for car use are contingent on sample composition and research context ([Wall et al., 2007](#)). Therefore, research has yet to systematically demonstrate how attitudes as well as their relations with travel behavior will differ according to an individual's personal circumstances and in different geographical and physical contexts.

1.4 Our Contributions

In this dissertation, we address, in part, each of the limitations in the existing literature summarized above. First, we narrow the scope of our investigation to one specific symbolic value of owning and using a car—pride. By focusing on one symbolic value, we can provide a clear definition of our construct and evaluate different ways to measure it. We establish two standard survey measures of car pride and demonstrate their reliability and validity.

We also consider the invariance of our car pride measures across key sociodemographic groups, cities, and countries, providing the foundation for comparisons across multiple populations of interest. Acknowledging that attitudes and their relation with travel behavior may differ across individuals and contexts, this dissertation measures and compares car

pride and its relations with car ownership and use across individuals in two very different metropolitan areas in the United States and across individuals in 51 countries.

Equipped with standardized and validated measures of car pride in heterogeneous samples, we explore how car pride relates to car consumption behaviors. We use instrumental variable techniques to explicitly capture the bidirectional relation between car pride and car ownership and use among individuals and across cities in the United States. We then international variation in car pride and its relations with car consumption across individuals in 51 countries around the world.

We deliberately narrow the focus of our investigation to one specific symbolic motive of car consumption: car pride. This allows us to clearly define our construct, develop and evaluate how to measure it, model its relations with specific car-related behaviors, and compare it across cultures. However, this narrowing of focus is not without its tradeoffs. By defining only one of the many potential symbolic and affective values of a car, additional research would be needed to understand car pride's relation with other symbolic and affective values of cars that may amplify or dampen the relations that we see here. Further research would be needed to develop measures for other symbolic and affective motives of car ownership and use and to understand their relations with car pride as measured here.

1.5 Dissertation Structure

To explore car pride and its relations with travel behavior quantitatively, this dissertation relies on the design and implementation of surveys to collect primary data. Chapter 2 describes the collection of the data used throughout this dissertation. We introduce the samples from two separate surveys: the U.S. city sample of 1,236 commuters in the New York City, NY and Houston, TX metropolitan areas in the United States and the international sample of 41,932 individuals across 51 countries.

Using these data, we embark on a series of empirical analyses evaluating different measures of car pride (Chapters 3 and 4) and exploring their relation with car ownership and use across individuals, cities, and countries (Chapters 5 and 6). Table 1.1 summarizes the main research aim, data source, and method applied in each of these empirical chapters, which are explained in more detail below. Each empirical chapter begins with a brief review of the relevant methodological literature before presenting and discussing the modeling results. For researchers interested in replicating the results of this study, and/or using it a model for other applications, all model code is saved to a public GitHub repository: <https://github.com/jcmoody6/Dissertation/>.

Chapters 3 and 4 develop multiple measures of car pride. Chapter 3 presents the evaluation of two survey measures of car pride: a polytomous (7-point Likert-scale) measure estimated across individuals in the U.S. city sample and a dichotomous (binary) measure estimated for the international sample. This chapter applies confirmatory factor analysis to demonstrate

the psychometric properties—reliability, validity, and invariance—of these two measurement scales. Chapter 4 discusses the potential limitations of explicit survey measures and presents the design and evaluation of an alternative measure of car pride (relative to bus shame) using an Implicit Association Test. Comparing the performance of our explicit and implicit measures, we find that our survey scales are more valid and interpretable; thus, we carry these measures through the analysis in the remaining chapters.

Table 1.1: Summary of empirical chapters

#	Research aim	Data source	Method
3	Evaluation of (explicit) survey measures of car pride		
	Polytomous scale	U.S. city sample	Confirmatory factor analysis (CFA)
	Dichotomous scale	International sample	Multilevel confirmatory factor analysis (MCFA)
4	Evaluation of implicit measure of car pride	U.S. city sample	Scoring algorithm
5	Model the bidirectional relations between car pride and car ownership and use for individuals; explore differences between cities	U.S. city sample	Structural equation modeling (SEM) with instrumental variables
6	Explore variations in car pride across countries and its relations with car ownership and use	International sample	Multilevel structural equation modeling (MSEM)

Chapters 5 and 6 explore the behavioral implications of car pride. Chapter 5 uses structural equation modeling with instrumental variables to simultaneously estimate the bidirectional relations between car pride and car ownership and use among individuals in the U.S. city sample. Chapter 5 highlights the importance of addressing simultaneity (and resulting endogeneity) when measuring attitude-behavior relations as well as the importance of context (city) in interpreting these results. Chapter 6 demonstrates how multilevel modeling techniques can be used for cross-cultural comparison of attitude-behavior relations. This chapter investigates variations in car pride and its associations with car ownership and use across individuals in our international sample, demonstrating variations at the country level.

Finally, Chapter 7 presents a summary of our findings across all of the empirical chapters. We present the a discussions of limitations and areas for future research that could extend the understanding developed in this dissertation. We reflect on our experience, providing more general recommendations for research on attitude-behavior relations in transportation. Finally, we deliberate on what these findings mean for policymakers promoting sustainable transportation behavior at the urban and national levels and potential next steps in translating this research into practical action.

Chapter 2

Data Collection

While car pride and its association with car consumption is understood anecdotally and has been demonstrated by ad-hoc empirical studies, no systematic data source is available to explore these relations quantitatively. Therefore, this dissertation includes the design and implementation of purpose-built questionnaires to collect primary data on car pride and travel behavior across individuals, cities, and countries. In order to achieve both depth of understanding and breadth of cross-cultural coverage, this research involves two major data collection efforts:

1. U.S. cities survey – a detailed, computer-based questionnaire about car pride and commuting behavior among residents in two targeted metropolitan areas in the United States (see Appendix A).
2. International survey – a short, mobile phone-based questionnaire about mobility culture deployed across individuals in 51 countries (see Appendix B).

Data collected from these questionnaires is complemented with data collected from other publicly-available sources. For the U.S. cities survey, data are collected from the U.S. Census’s American Community Survey and matched with our survey respondents’ home and work locations. For the international survey, systematic keyword searches are conducted across multiple international databases to collect indicators of national economic development and motorization. These complementary datasets are used throughout the dissertation to explore how context might influence car pride and its relations with car consumption.

This chapter describes the implementation of our two surveys (including respondent recruitment), discusses the representativeness of our survey samples, and presents the collection of complementary data from other publicly-available sources. The primary data collection associated with this dissertation are themselves important contributions to the literature and provide the necessary foundation for the empirical measurement validation presented in Chapters 3 and 4 and the behavioral modeling presented in Chapters 5 and 6.

2.1 U.S. Cities Survey

The U.S. cities survey is an in-depth survey designed to gather multiple measures of car pride, current commute behavior, and sociodemographic information for each respondent (see Appendix A).¹ The first measure of car pride included in the U.S. cities survey is the polytomous car pride scale—a set of Likert-format, Likert-scale questions that related different dimensions of social status, and personal image to owning and using a car (see Chapter 3). The second measure of car pride is derived from an Implicit Association Test (see Chapter 4). In addition to these explicit and implicit measures of car pride, the survey also asks respondents about their household car ownership and to complete a basic commute travel diary. Standard information about individual sociodemographics—including age, gender, race or origin, household composition, income level, employment, and education—are also collected.

2.1.1 City Selection

The U.S. cities survey was deployed in two metropolitan statistical areas (MSAs) in the United States defined by the U.S. Census Bureau: the New York-Newark-Jersey City, NY-NJ-PA (NYC) and Houston-The Woodlands-Sugar Land, TX metro area (HOU). The two metropolitan areas were selected for their contrasting urban and transportation contexts. In terms of population, the New York City MSA is the largest metropolitan area in the U.S. having over 20 million residents in 2017; whereas the Houston MSA was home to fewer than 7 million people. In terms of their transportation contexts, New York City has the highest share of trips made by public transit, particularly rail, of any U.S. metropolitan area. In contrast, Houston is selected as a city with decidedly auto-oriented travel patterns despite some public transit service, primarily by bus.

Public Transit Infrastructure and Service

The New York City MSA is served by the largest public transit network in the U.S., consisting of 2,080 track miles of subway and commuter rail. In addition, a fleet of 5,710 buses (2016) service a network of bus routes covering around 2,900 miles (MTA). This public transit system consistently reports the highest annual ridership (2.7 billion) and average weekday ridership (8.6 million) of any system in the U.S. (APTA, 2018). Of these annual (unlinked) trips, about 65% are made by subway, 7% by commuter rail, and 27% by bus in 2016 (Hudson, 2017). Therefore, public transit trips in New York City are served primarily by rail.

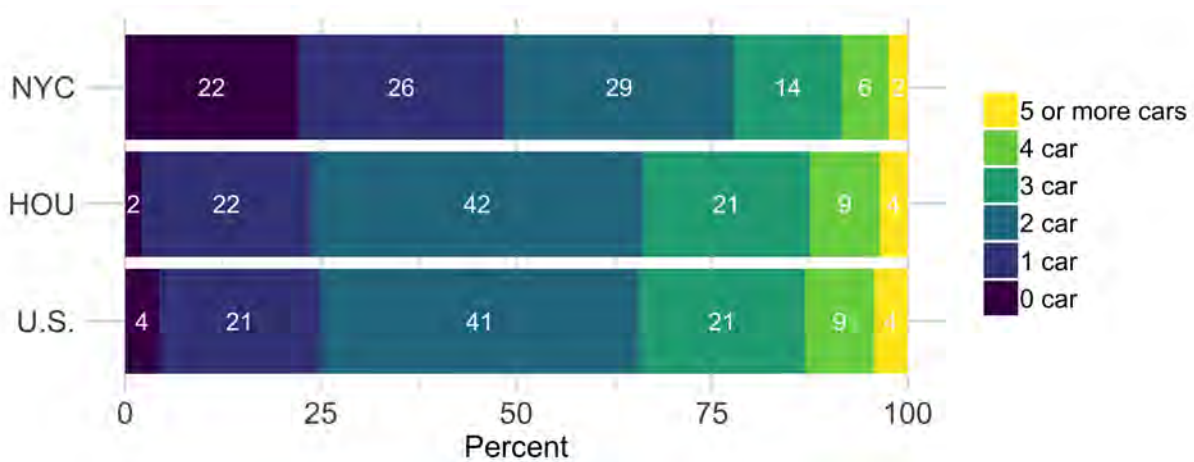
¹Study approved by MIT’s Committee on the Use of Humans as Experimental Subjects under protocol #1605575817.

On the other hand, the Houston MSA is served by a public transit system consisting of only 22.9 miles of light rail transit and a modest bus network with a fleet of 1,230 buses. This public transit system serves an annual ridership of around 89 million, with average weekday ridership of 297,000 (APTA, 2018). Of all trips, almost 75% are made by bus and only 20% by light rail (APTA, 2018). Therefore, unlike in New York City, in Houston public transit trips are served primarily by bus.

Household Car Ownership

Figure 2.1 plots the share of households by numbers of vehicles owned for the New York City and Houston MSAs compared to the U.S. national average. Household vehicle ownership in the NYC MSA is lower than the national average, despite higher median household incomes. In particular, New York City MSA has a much larger share of zero-car households (22%) than in the U.S. as a whole (4%) (Data USA, 2018b); whereas, household vehicle ownership in the Houston MSA is slightly higher than the national average (Data USA, 2018a), with an even lower share of zero-car households (2.1%) than in the U.S. as a whole.

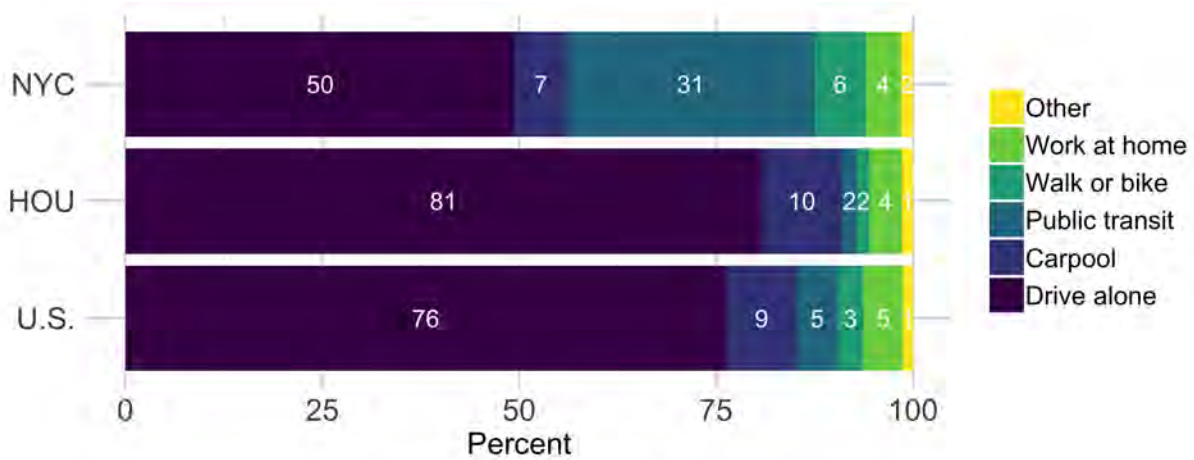
Figure 2.1: Share of households by vehicle ownership in the U.S., NYC, and HOU



Commute Trip Mode Share

Figure 2.2 shows the share of commute trips by mode for the New York City and Houston MSAs compared to the U.S. national average. In the New York City MSA, 30% of commute trips are taken by public transit compared to 5% in the U.S. as a whole; and the drive alone share is around 50% compared with 76% in the U.S. (Data USA, 2018b). On the other hand, only 1.9% of commute trips are taken by public transit in the Houston MSA, with a drive alone share of 80.8% (Data USA, 2018a).

Figure 2.2: Share of commute to work trips by mode in the U.S., NYC, and HOU



2.1.2 Respondent Recruitment and Sample

The U.S. cities surveys were deployed electronically in Spring 2016. Participants were recruited by Qualtrics (<https://www.qualtrics.com/>), a professional panel and survey company. Respondents completed the entire survey online and were compensated with a monetary reward for their time.

Home zip codes were screened to ensure that respondents resided in one of the two target MSAs. Each respondent is at least 18 years of age and self-identified as a commuter (traveling from home to work at least three days out of a work week). Data collection was controlled for representativeness of the MSA populations using response quotas for age, gender, and household income, but these quotas were relaxed towards the end of data collection due to a lagging response rate.

1,251 complete responses were collected, but respondents who failed to answer three attention checks throughout the survey were removed. This yielded a final sample size of 1,236 responses, with 766 responses in New York City and 470 responses in Houston. Comparison of the sociodemographic characteristics of the sample with those of the populations in the two metropolitan areas based on data from the 2016 American Community Survey, show that our samples in both cities are reasonably representative of the target population. However, our sample does underrepresent Black and Hispanic residents, those without high school or college educations, and very high-income households (see Table 2.1).

Table 2.1: Comparison of sample representativeness against U.S. metropolitan area populations

Variable	New York City MSA		Houston MSA	
	Sample (%)	Pop (%)	Sample (%)	Pop (%)
Age ^a				
18-29	28.1	20	29.3	22
30-39	25.5	18	22.3	21
40-49	15.6	17	15.4	19
50-59	16.4	18	17.1	16
60+	14.3	27	15.8	21
Female	52.3	52	61.9	50
Race/ethnicity				
White	66.9	47	64.5	37
Black	10.7	16	12.2	17
Hispanic	7.9	24	9.9	37
Asian	9.9	11	9.0	8
Other	4.6	3	4.5	1
Educational attainment				
No degree	1.0	14	0.4	17
High school	11.7	25	13.9	24
Some college	20.3	22	21.6	28
Bachelor's degree	7.5	23	13.1	20
Post-grad	59.4	16	51.0	12
Household income				
Under \$50,000	41.0	37	42.2	41
\$50,000-\$99,999	42.5	26	40.9	29
\$100,000-\$199,999	13.2	25	13.1	22
Over \$200,000	3.4	12	3.9	9
Average HH size	2.85	2.8	2.83	2.9
Commute mode share ^b				
Drive alone	37.8	52.6	77.8	84.3
Carpool	6.1	7.4	9.3	10.4
Public transit	37.7	32.6	9.3	2.1
Bike	2.5	1	1.9	0
Walk	15.9	6.2	1.7	1
Other	0	1	0	1

Notes: ^a Sample and population age proportions calculated for those greater than 18 years of age.

^b Population data for workers ages 16 and older, excluding those who work at home (5% in NYC and 4% in HOU); sample respondents (commuters ages 18 and older) were allowed to specify multimodal commutes, so sample mode shares are estimated as if each commute leg is its own trip.

2.1.3 Complementary Data

Our U.S. cities survey asks individuals to report their home and work locations by census block, the smallest geographical area defined by the U.S. Census Bureau. By asking this question in the survey, we are able to merge our survey responses with data about their home and work locations from the U.S. census. In particular, we gather measures of average vehicle ownership and share of transportation to work by mode for all census blocks in both target metropolitan areas from the NHGIS Data Finder (Manson et al., 2018). These measures are chosen first as potential instruments for individual car ownership and use (see Chapter 5), but also to enable potential exploration of an individual’s car pride relative to the car consumption of their peers.

2.2 International Survey

While the U.S. cities survey discussed above is designed for in-depth understanding of car pride and its relation to individual sociodemographics and car consumption, our international survey is designed for breadth rather than depth. A micro survey consisting of only 20 questions was administered electronically using mobile phones for participants in 51 countries during December 2016 and January 2017.²

Using mobile phone based data collection provides unprecedented global coverage. Worldwide, more people have access to the internet through mobile devices than through desktop computers (Statistica.com, a). This is even more true in developing countries, where the rapid adoption of smartphones makes mobile sampling particularly effective (Statistica.com, b). However, the mobile phone based platform involves tradeoffs in terms of the length, format, and difficulty of survey questions that can be asked. In particular, the polytomous car pride scale—a matrix format question including a series of statements rated on a 7-point Likert-format from “strongly agree” to “strongly disagree”—does not display easily on smaller screen devices. Therefore, our international survey includes a dichotomous modification of the car pride scale—a similar series of statements for which respondents agree (1) or not (0). Our survey also collects information about each individual’s car ownership, typical mode choice, and frequency of driving (see Appendix B for the English language questionnaire).

In countries where English is not the local language, surveys were translated by a professional company. At least two translators performed independent translations, which were checked against one another for consistency. Once revised, the translated survey underwent a “soft launch” with 100 respondents each asked to fill out the survey and to report any language issues. If a high number of complaints were registered, translations were re-done.

²Study approved by MIT’s Committee on the Use of Humans as Experimental Subjects under protocol #1610719971.

2.2.1 Respondent Recruitment

Dalia Research (<https://daliaresearch.com/>) performed all sampling, recruitment, and survey implementation. Sample respondents were recruited through a variety of ad-exchanges, demand-side platforms (DSPs), apps and mobile websites. All responses are voluntary and compensated. While browsing this content on their mobile device, individuals were prompted to take a short survey. Those who complete the survey are then rewarded in the form of virtual currencies, prepaid credits, access to premium content, and other rewards depending on the specific recruitment channel.

TrustScore

Since respondents are recruited within apps, attention spans may be short and this may raise concerns over quality of responses. However, Dalia research pre-screens respondents to ensure data quality based on individual “TrustScores.” This tool identifies bad respondent behavior, assigns each respondent a trustworthiness score, and prevents respondents from completing surveys if their scores are too low, all in real-time.

The first time a respondent enters the Dalia system, they are asked several questions to help measure their trustworthiness. Their answers to these questions are then coded as 0 (not trustworthy) or 1 (trustworthy) for each of 7 markers:

1. Answer consistency: respondents are asked two variations of the same question (for example, “What is your age?” and “What is your birth year?”) and their answers are compared.
2. Consistency with passive device data: passive device data from browser information is checked against a respondent’s answer to a question about their device.
3. Checks against location data: respondents are asked about the time of day in their current location, and these data are matched against their IP-based geolocation, mapped to possible time zones.
4. Attentiveness check: respondents are asked a tricky question that is easy to answer incorrectly if the content is not read carefully.
5. Speeding: respondents who go through the survey exceptionally quickly compared to the overall distribution of respondents are flagged.
6. Zero incidence check: to detect a respondent’s tendency to pick as many options as possible in screening questions to qualify for surveys, respondents are flagged who answer “yes” to a question that contain a very low/close to zero incidence in the actual population.

Since none of the markers defined above are powerful enough to serve as a standalone criterion to exclude respondents from taking surveys, TrustScores are assigned to each individual by taking the average across all markers. Users who answer fewer than 5 out of 7 markers

correctly (receiving a TrustScore of less than 0.71) are excluded from taking additional surveys. These TrustScores are dynamically updated as each user completes additional surveys. Therefore, only high-quality, verified users of the Dalia platform were asked to complete the survey for research purposes.

2.2.2 Sample of Individuals

The final sample consists of 41,932 voluntary survey participants from 51 countries. Within-country sample sizes are around 1000 respondents for larger countries and 500 for smaller countries, with the smallest sample size of 208 for Hong Kong (see Table 2.2). Quota sampling was used to ensure that survey respondents represent the entire population. Quotas were enforced to ensure reasonable sample representativeness for age and gender for each of the 51 countries sampled based on population statistics available through the U.S. Census Bureau’s International Data Base, adjusted to match the internet-connected population. Therefore, any inference on our sample can only extend to internet-connected, mobile-phone users in each of the countries of interest.

Because population statistics are adjusted to match the internet-connected population we expect, and see, an overrepresentation of younger people and an underrepresentation of the elderly in most of the countries in our sample compared to the national population (see Table 2.2).

Table 2.2: Sample size and comparison of sample representativeness by gender and age against national populations, by country

Country	<i>n</i>	Female (%)		Age 15-24 (%)		Age 25-54 (%)		Age 55+ (%)	
		P	S	P	S	P	S	P	S
Algeria	528	49.5	57.6	21.6	25.9	60.7	70.5	17.6	3.6
Argentina	522	51.1	49.6	20.3	24.7	52.2	70.3	27.5	5.0
Australia	1020	50.2	49.4	15.6	22.0	50.4	68.0	34.0	10.0
Austria	517	51.0	53.0	12.9	20.3	49.3	71.4	37.8	8.3
Bahrain	345	37.9	51.6	19.3	37.4	69.3	62.6	11.4	0.0
Belgium	1027	50.8	58.5	13.7	23.1	48.3	70.1	38.0	6.8
Brazil	1025	50.8	50.1	21.1	22.9	56.5	70.1	22.5	6.9
Canada	1040	50.4	49.8	14.0	17.7	47.3	62.6	38.7	19.7
Chile	507	50.5	51.5	18.8	25.0	53.9	66.7	27.2	8.3
China	1080	48.5	55.2	15.4	19.9	58.6	76.1	26.0	4.0
Colombia	1038	50.8	53.4	22.8	28.7	55.3	65.8	21.9	5.5
Denmark	1051	50.3	53.7	15.6	25.7	46.4	68.4	38.0	5.9
Ecuador	516	50.0	51.0	25.2	30.6	54.3	63.6	20.5	5.8
Egypt	500	49.4	52.6	28.4	28.2	56.4	69.2	15.2	2.6
France	1064	50.8	45.6	14.5	18.5	46.4	69.5	39.2	12.0
Germany	1008	50.8	54.3	11.6	17.5	46.4	69.4	42.0	13.1
Greece	1036	50.8	54.9	11.2	15.3	49.3	79.8	39.5	4.8
Hong Kong	208	53.9	50.5	11.9	34.1	50.9	65.9	37.2	0.0

Table 2.2: Sample size and comparison of sample representativeness by gender and age, by country (*continued*)

Country	<i>n</i>	Female (%)		Age 15-24 (%)		Age 25-54 (%)		Age 55+ (%)	
		P	S	P	S	P	S	P	S
India	1003	48.2	54.4	24.6	25.5	56.5	69.9	18.8	4.6
Indonesia	535	49.6	54.6	22.7	23.4	56.5	75.1	20.8	1.5
Ireland	529	50.4	52.2	15.1	21.4	55.0	71.3	29.9	7.4
Israel	521	50.4	56.4	21.4	30.5	51.3	66.4	27.3	3.1
Italy	1010	51.3	49.7	11.2	14.5	48.8	72.4	40.0	13.2
Japan	1029	51.2	49.7	11.1	16.0	43.0	76.3	45.9	7.7
Kenya	521	50.3	51.8	31.9	34.2	56.5	65.1	11.5	0.8
Malaysia	1027	48.3	53.7	23.3	26.6	56.8	67.8	19.9	5.6
Mexico	1016	50.2	49.5	24.0	27.8	55.8	67.1	20.2	5.1
Morocco	519	50.5	53.0	23.0	28.3	57.0	65.3	20.0	6.4
Netherlands	1000	50.3	55.8	14.4	19.5	47.3	70.2	38.3	10.3
Norway	1056	49.6	54.5	15.3	23.7	50.0	72.8	34.7	3.5
Pakistan	773	48.6	52.5	30.8	43.5	54.6	56.5	14.6	0.0
Peru	1022	50.1	53.2	24.8	33.3	54.5	61.7	20.6	5.0
Philippines	504	49.7	48.4	28.8	26.8	55.5	67.3	15.7	6.0
Poland	1005	51.7	50.5	12.6	16.8	51.0	68.6	36.4	14.6
Portugal	1020	52.7	55.6	13.4	19.8	49.3	75.2	37.3	5.0
Russia	1004	53.5	49.3	11.4	13.3	53.9	75.5	34.6	11.2
Saudi Arabia	1003	43.1	58.8	25.1	26.8	63.4	70.3	11.5	2.9
Singapore	1017	50.6	52.7	19.0	26.1	58.0	69.1	23.0	4.8
South Africa	1035	50.9	53.4	24.6	26.5	58.2	67.1	17.2	6.5
South Korea	1049	50.0	49.9	14.6	15.9	52.4	78.4	33.0	5.7
Spain	1016	51.0	50.8	11.3	15.0	53.1	75.9	35.6	9.2
Sweden	1055	50.0	56.5	13.7	21.0	47.7	69.9	38.6	9.1
Switzerland	521	50.5	55.9	12.8	21.9	50.9	69.7	36.2	8.4
Thailand	1001	51.2	54.5	17.1	23.8	55.8	72.4	27.2	3.8
Turkey	1002	50.8	51.3	21.2	24.6	57.4	73.0	21.4	2.5
Ukraine	507	53.8	56.4	11.7	16.4	52.6	79.1	35.7	4.5
U.A.E.	535	27.2	69.5	17.1	18.7	77.4	79.8	5.5	1.5
U.K.	1024	50.7	57.0	14.4	23.3	49.2	66.2	36.4	10.4
U.S.A.	993	50.5	44.1	16.3	22.5	48.5	63.8	35.1	13.7
Venezuela	523	50.2	50.1	23.4	26.2	55.8	66.5	20.7	7.3
Vietnam	525	50.5	56.8	21.2	27.0	59.6	70.5	19.2	2.5

Notes: S = sample; P = population; U.A.E. = United Arab Emirates; U.K. = United Kingdom; and U.S.A. = United States of America.

Population statistics for gender are from the [World Bank \(2016\)](#) and for age categories are from the [CIA World Factbook \(2017\)](#).

Furthermore, our sample is not necessarily representative of other individual sociodemographics that are not controlled by response quotas. For example, we might expect that mobile phone-based populations, particularly in developing countries, could be higher income, more urban, and/or more likely to be car owners than the national population. However, finding comparable population statistics across our large set of countries and for our population of interest (mobile phone users) is challenging. At best, we can use results from other large, international polls to compare our sample to national populations, but not to national populations of mobile phone users (see Table 2.3). For countries where data are available, we find that our samples contains significantly more car-owners than the population in lower and upper middle income countries, but underrepresent car-owners in high income countries. We also find that our sample similarly overrepresents the population living in urban agglomerations with over one million people in lower middle income countries, but underrepresents these urban residents in high income countries.

Table 2.3: Comparison of sample representativeness of household car ownership and urban populations, by country

Country	HH owns car (%)		In urban area > 1 million (%)	
	P	S	P	S
High income countries				
Australia	–	70	42.9	34.7
Austria	–	57	21.3	30.2
Bahrain	–	72	–	11.9
Belgium	–	57	26.9	11.3
Canada	–	65	45.7	21.7
Chile	49	36	36.7	40.6
Denmark	–	51	22.6	8.2
France	83	70	22.6	9.0
Germany	85	57	9.5	10.9
Greece	76	52	29.3	36.8
Hong Kong	–	21	99.6	65.9
Ireland	–	51	24.7	12.7
Israel	71	45	57.7	4.8
Italy	89	74	18.6	11.5
Japan	81	59	64.4	37.1
Netherlands	–	57	12.4	5.8
Norway	–	62	18.9	9.0
Poland	64	62	4.6	9.5
Portugal	–	65	41.0	10.2
Saudi Arabia	–	70	46.8	47.1
Singapore	–	28	100.0	67.2
South Korea	83	44	50.1	58.1
Spain	79	62	25.4	19.2
Sweden	–	51	15.4	13.5
Switzerland	–	49	16.0	3.1
United Arab Emirates	–	63	58.1	34.0

Table 2.3: Comparison of sample representativeness of household car ownership and urban populations, by country (*continued*)

Country	HH owns car (%)		Living in urban area (%)	
	P	S	P	S
United Kingdom	74	40	26.7	14.3
United States of America	88	55	45.9	19.2
Upper middle income countries				
Algeria	–	31	6.4	18.0
Argentina	43	40	42.9	33.5
Brazil	47	57	41.4	43.7
China	17	45	27.3	56.9
Colombia	17	28	43.4	51.4
Ecuador	–	24	27.9	40.9
Malaysia	82	62	23.1	11.4
Mexico	35	44	39.3	42.0
Peru	11	18	31.7	44.5
Russia	55	39	23.0	34.8
South Africa	31	55	35.0	32.6
Thailand	51	46	19.7	40.2
Turkey	42	39	37.0	64.5
Venezuela	36	32	28.9	39.4
Lower middle income countries				
Egypt	20	41	25.3	53.0
India	6	43	15.2	45.6
Indonesia	4	33	13.3	42.8
Kenya	5	18	10.9	49.5
Morocco	–	26	21.6	28.5
Pakistan	3	15	21.0	34.2
Philippines	6	28	14.3	25.4
Ukraine	29	25	12.0	19.7
Vietnam	2	25	16.2	61.5

Notes: S = sample; P = population; – = data not available. Countries are organized according to income classification by the [World Bank \(2017\)](#).

Population statistics for household car ownership are estimates from [Pew Research Center \(2015\)](#) and those for population living in urban agglomerations greater than one million people are estimates from [United Nations, World Urbanization Prospects \(2017\)](#).

2.2.3 Sample of Countries

Due to the nested or hierarchical nature of the data—with individuals within countries—we must consider sample representativeness not only of individuals within countries, but also of

countries (Lucas, 2014). In this study, the 51 countries are a simple convenience sample and therefore are not intended to be representative of all countries in the world. In particular, our sample contains none of the 34 countries designated as “low income” by the World Bank (2017). Therefore, our sample of countries is much wealthier than the world average (see Table 2.4). However, if we compare only to high and middle income countries, we find that our sample is reasonably representative when it comes to average GDP per capita adjusted by purchasing power parity (World Bank International Comparison Program database, 2016).

Because our sample of countries excludes the lowest income countries and we are not sure how it compares to the world average in terms of other national characteristics that may influence car pride and car consumption—such as income inequality or motorization rate—it is safest to limit any inference across countries to the specific countries included in the sample and not to generalize to a wider population of countries.

Table 2.4: Representativeness of sample national wealth, by type of country

	Number of countries		GDP per capita, PPP (1000)	
	World	Sample	World	Sample
Total	218	51	15.067	30.467
High income	81	28	43.351	44.474
Upper middle income	56	14	15.793	16.542
Lower middle income	47	9	6.306	6.998
Low income	34	–	1.578	–

2.2.4 Complementary Data

This international survey is designed for measuring and visualizing car pride and car consumption across countries. However, in order to explain any observed variations, we must complement our survey data with the collection of standardized national indicators that may relate directly to car pride at the country level. We begin by identifying key categories of indicators that theory and previous empirical analysis might suggest are related to car pride: macroeconomic conditions, vehicle ownership, and vehicle use. For each category, we create a list of keywords to search. Because the indicators have to be available and comparable across a large and diverse set of countries, we focus the keyword search on publicly-available databases of international organizations.

Where applicable, we collect data for the year 2016—the year preceding the international survey deployment—or the next most recently available year. Where historical data are available we also calculate percent growth over recent year(s). This allows us to explore whether recent changes in (as well as current levels of) economic and motorization conditions might be related to country car pride.

Macroeconomic Conditions

We begin by collecting indicators of macroeconomic conditions, including standard measures of national wealth and income inequality that are commonly used to characterize the economic development of a country. We might hypothesize that both national wealth and income inequality help represent the context of economic consumption in a given country, which might be related to car pride. In addition, we collect information on prices that might influence consumption behavior and related attitudes within each country (see Table 2.5).

For national wealth, we collect gross domestic product (GDP) per capita in current US dollars from [World Bank and OECD national accounts data](#) as well as GDP per capita adjusted by purchasing power parity (PPP) in current international dollars from the [World Bank International Comparison Program database](#). Unadjusted GDP is a measure of national economic productivity while GDP adjusted by purchasing power parity is a more comparable measure of standards of living between countries. For unadjusted GDP per capita, annual percent growth is also collected directly from [World Bank and OECD national accounts data](#). For income inequality, we use Gini index. The most complete source identified for these data is the [World Bank Development Research Group](#), however due to data sparsity in any given year, we collect the most recently available number for each country from 2010-2015.

For prices, we are interested in measures of household expenditure on car consumption. While our search did not yield a systematic dataset for vehicle prices across countries, we are able to collect data on average national gas and diesel prices from [German Agency for International Cooperation \(GIZ\)](#). This may be a useful national covariate since fuel is often the most salient cost of car use to consumers and therefore may relate to their general attitudes.

Table 2.5: List of national macroeconomic indicators collected and calculated, with years and number of sampled countries covered

Indicator	Year(s)	N
GDP per capita (current US\$)	2016	50
GDP per capita growth (annual %)	2016	50
GDP per capita, PPP adjusted (current international \$)	2016	50
Gini index	2010-2015	41
Pump price for gasoline (US\$/liter)	2016	51
2-yr change in gas price	2014-2016	50
6-yr change in gas price	2010-2016	51
Pump price for diesel (US\$/liter)	2016	49
2-yr change in diesel price	2014-2016	48
6-yr change in diesel price	2010-2016	49

Vehicle Ownership

We hypothesize that a country’s level of motorization may be related to general attitudes towards car consumption, like car pride. Therefore, we search for comprehensive indicators of car ownership across countries. The [World Health Organization](#) publishes a dataset on the number of registered vehicles by country, but does not differentiate by type of vehicle. Alternatively, the [International Organization of Motor Vehicle Manufacturers \(OICA\)](#) publishes data on vehicle stock and sales, as totals and disaggregated by commercial vs. personal vehicles. Given that our international survey probes car pride among individual consumers, we might want to test whether personal car (rather than total vehicle) stock and sales is more strongly related to country attitudes. Therefore, we opt to use the OICA data for both total and personal vehicles (see Table 2.6). In all cases, measures of vehicle stock and sales were divided by total population estimates in the corresponding year ([United Nations Population Division, et al.](#)) to obtain per capita measures that control for differences in population size across countries.

Table 2.6: List of national motorization indicators collected and calculated, with years and number of sampled countries covered

Indicator	Year(s)	N
Motorization rate (vehicles/1000 people)	2015	51
1-yr change in motorization rate	2014-2015	51
Personal cars as share of total stock (%)	2015	51
Personal car stock per 1000 people	2015	51
1-yr change in personal car stock per 1000 people	2014-2015	
5-yr change in personal car stock per 1000 people	2010-2015	
Personal car sales per 1000 people	2016	51
1-yr change in personal car sales per 1000 people	2015-2016	51
6-yr change in personal car sales per 1000 people	2010-2016	51

Vehicle Use and Road Infrastructure

Indicators of car use proved the most difficult to find. A search of keywords such as “vehicle,” “car,” “kilometers (km) traveled,” and “(road) traffic” in international databases of organizations including the World Bank, the United Nations, and the International Road Federation did not yield many useful results. The only potential indicator that we could find covering all of the countries in our sample is an estimation of passenger kilometers by road transport by country published by the [United Nations Department of Economic and Social Affairs, Statistics Division](#). However, passenger kilometers is a poor proxy for vehicle use because it confounds vehicle use with the number of occupants (which is notoriously difficult to measure).

A more appropriate measure of national vehicle use would be vehicle kilometers traveled. While such a measure is not available for all of our 51 sampled countries, we do find this and other relevant information regarding road density and road infrastructure investment published for a subset of countries by the [International Transport Forum \(ITF\)](#), an inter-governmental organization within the [Organization for Economic Co-Operation and Development \(OECD\)](#) (see Table 2.7). The subset of countries for which these data are available represent mostly developed countries, covering only a few of the larger developing countries in our sample such as China and India. Therefore, while gathering these data will allow us to look at how car pride at the country level may relate to national indicators of vehicle use and provision of road infrastructure, these results will be even more limited in their generalizability across countries.

Table 2.7: List of national vehicle use and road infrastructure indicators collected, with years and number of sampled countries covered

Indicator	Year	N
Passenger km by road per 1000 vehicles	2015	51
Vehicle-km (1000) per road motor vehicle	2014	20
Vehicle-km per GDP (1000 current US\$)	2014	20
Density of road (km per 100 square km)	2015	21
Road infrastructure investment (US\$) per capita	2014	25
Road infrastructure investment per GDP	2014	25

2.3 Conclusions

This dissertation represents the first time that car pride and its relations with car consumption are measured systematically and compared across individuals, cities, and cultures. The foundations for the empirical analyses presented in the following chapters lie in the carefully designed and implemented data collection discussed here. When interpreting the results in any of the subsequent chapters, it is important to keep in mind the limitations of our samples as presented here. Furthermore, measurement and structural modeling on these data must account for their unique sampling frames and control for key individual sociodemographic characteristics that were not used as quotas for sample representativeness.

Data from our U.S. cities survey are used in Chapter 3 to derive the polytomous car pride scale and in Chapter 4 to derive an implicit measure of social status association for cars versus buses. Our data are combined with data from the U.S. Census in Chapter 5 to estimate the bidirectional relations between car pride and car consumption. The sampling frame of our U.S. cities survey is limited to commuters, aged 18 and older, living in the two metropolitan statistical areas of New York City and Houston. Modeling of these data must account for potential differences between these two cities, which were selected because of their contrasting urban and transportation contexts. Within these two cities, our samples

underrepresent key segments of the population, particularly Black and Hispanic residents, those with low educational attainment, and those living in households with very high incomes and more than three vehicles. Therefore, care should be taken in generalizing any results beyond middle class, Caucasian residents of these two metropolitan regions.

Data from our international survey is used in Chapter 3 to derive the dichotomous car pride scale. Our data are combined with national indicators of economic development, car ownership, and car use from our complementary systematic search of international databases in Chapter 6 to explore associations between car pride and car consumption across individuals and countries. The hierarchical structure of our international survey data—with individuals nested within countries—require consideration of sampling frame at both the individual and country levels. Inference from our international survey should be limited to mobile phone users in 51 specific high and middle income countries, keeping in mind that mobile phone users may not be representative of national populations particularly when it comes to income, urbanization, and household car ownership and that the differences between our sampling frame and national populations may vary by country. Therefore, modeling of these data should adopt multilevel modeling techniques to properly address its nested structure and to properly differentiate variance in the data attributable to individuals and to countries.

While every care was taken to design and collect quality data, our samples may not be representative of all individuals in our cities and countries of interest. Sampling error is a natural part of survey-based research, and it is difficult to understand and control for all of the potential bias that sample non-representativeness may introduce into our results in the following empirical chapters. Therefore, results based on these data should not be generalized beyond their sampling frames and future research should work to replicate and extend these studies in similar and new populations. The discussion presented in this chapter and the questionnaires included in the Appendices should provide a solid platform for such future research.

Chapter 3

Survey Measure Development

Measurement—the assignment of numbers to attributes, traits, constructs, or features (Lord and Novick, 1968)—is a key exercise in psychological and behavioral research. The measurement instruments used to evaluate research data must be of high quality, or else the study risks making biased or flawed conclusions, potentially doing more harm than good (Kline, 2016).

In this chapter, we present the development and evaluation of two survey measures of car pride. The first is a polytomous (7-point Likert-scale) measure of car pride estimated for individuals in cities. The second is a dichotomous (binary) measure of car pride that is estimated in a multilevel setting with individuals nested within countries. The collection of these data are described in Chapter 2.

This chapter starts with a brief overview of confirmatory factor analysis (CFA), the method we employ throughout the chapter to demonstrate the psychometric properties of the two measurement scales. Section 3.2 then discuss key psychometric properties of measures and how they can be evaluated in a CFA framework. Section 3.3 presents the evaluation of the polytomous measure of car pride within multiple city samples. The scale is developed from items piloted in a survey of respondents in New York City and Houston in the United States. Then the English version of the scale is evaluated in a separate sample of respondents in Singapore. Section 3.4 concludes the chapter with the evaluation of the dichotomous measure of car pride within an international sample of individuals living in 51 countries.

3.1 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a powerful and flexible statistical technique that models the relations between observed indicators (or items) and underlying latent variables (factors). The goal of CFA is to estimate a latent or unobserved factor using a set

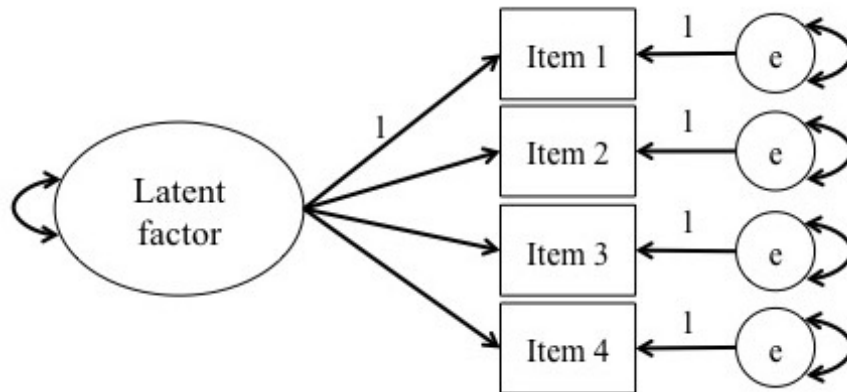
of observed indicators. Based on the common factor model, each observed indicator is expressed as a function of one or more common latent factors and a unique indicator variance (Thurstone, 1947). CFA techniques attempt to partition the variance of an indicator into common variance—the proportion of variance that is due to the latent variable—and unique variance—a combination of random error variance (measurement error) and reliable variance that is specific to a particular item.

Mathematically, a general CFA model for a set of n observed indicators and k latent factors can be expressed as:

$$Y = \nu + \lambda F + \epsilon \quad (3.1)$$

where Y is an $n \times 1$ vector of observed indicators, F is a $k \times 1$ vector of unobserved latent factors, ν is a vector of intercepts, λ is an $n \times k$ matrix of factor loadings, and ϵ is an $n \times 1$ vector of unique indicator errors. CFA models are often expressed graphically using path diagrams, such as the example in Figure 3.1.

Figure 3.1: Path diagram of a conceptual confirmatory factor analysis model - example of a single latent factor with 4 observed indicators



Note: Following path diagram convention, observed variables are represented as rectangles; latent variables (including error terms) are represented as circles or ellipses; directed functional relations (or paths) are expressed as straight, single-headed arrows; and variances are represented as curved, double-headed arrows that connect a variable to itself (Kline, 2016).

CFA models apply estimation techniques, such as maximum likelihood, to minimize the difference between the variance-covariance matrix implied by the proposed factor model and the observed variance-covariance matrix in the data. The estimated functional relation from the factor to the indicator is called the factor loading. For continuous indicators, unstandardized factor loadings are interpreted as linear regression coefficients. For dichotomous indicators, unstandardized factor loadings are logistic or probit regression coefficients depending on the estimation method used.

3.1.1 Indices of Model Fit

CFA provides a rigorous evaluation of how a theoretical model represents the observed data. Assessing goodness of model fit—the extent to which the hypothesized model reproduces the multivariate covariance structure underlying the set of observed indicators—is a key exercise in CFA. In CFA there are two types of model fit statistics: model test statistics and approximate fit indices.

In CFA, the chi-square statistic is used to test the exact-fit hypothesis that there is no difference between the covariances predicted by the model (given the parameter estimates) and the population covariance matrix. This chi-square test is an accept-support test where the null hypothesis represents the belief that the model is correct; thus, it is failure to reject the null hypothesis, or the absence of statistical significance (e.g., $p \geq .05$), that supports the model (Kline, 2016).

The binary decision of whether or not to reject the exact-fit null hypothesis does not by itself determine whether to reject or retain the model (Kline, 2016). One reason for this is statistical power since χ^2 is overly sensitive to sample size: appreciable differences between model and data can be missed in small samples, but, more commonly, trivial differences can be flagged in large samples (Gallagher and Brown, 2013; Kline, 2016). Therefore, χ^2 model test statistics are often complemented by approximate (or relative) fit indices that compare the fit of the hypothesized CFA model to a baseline model (usually an independence or null model), often incorporating adjustments for sample size and model parsimony (number of parameters).

The most widely accepted approximate fit indices are the root mean square error of approximation (RMSEA) (Browne and Cudeck, 1992; Steiger, 1990), the comparative fit index (CFI) (Bentler, 1990), the Tucker-Lewis index (TLI) (Tucker and Lewis, 1973), and the standardized root mean square residual (SRMR). These indices are intended as continuous measures of model-data correspondence, usually ranging from 0 to 1. RMSEA and SRMR are considered “badness-of-fit” indices, where lower values (closer to 0) indicate better model fit. On the other hand, CFI and TLI are considered “goodness-of-fit” indices, where higher values (closer to 1) indicate better model fit.

Recommendations vary in terms of what values of these fit statistics should be considered acceptable. Early guidelines for model fit suggested that CFI and TLI values greater than 0.9, and RMSEA values less than 0.1 should be considered acceptable (Bentler, 1990; MacCallum et al., 1996). More recently, guidelines have been tightened based on the results of simulation studies (Hu and Bentler, 1999): SRMR values below 0.08, RMSEA values below 0.06, and CFI and TLI values above 0.95. Rather than rigid guidelines, these thresholds should be approached as general recommendations. Furthermore, model fit should always be evaluated in terms of multiple fit indices rather than just a single fit statistic (Gallagher and Brown, 2013; Kline, 2016)

3.1.2 Multilevel CFA

Multilevel (or hierarchical) models are characterized by a nested data structure in which there are multiple levels of analysis (e.g., individuals nested within countries). A nested data structure breaks the general assumption that individual observations are independently and identically distributed that underlies traditional, single-level CFA. This is because it is reasonable to expect that observations from one group (e.g., individuals from the same country) may share common variance due to similar circumstances or environment. Incorrectly applying a single-level approach to multilevel data can lead to underestimated standard errors due to violation of the independence assumption and improper inferences of the findings from one level to another, such as the atomistic fallacy that incorrectly extrapolates the effects found at the individual level to the group-level and the ecological fallacy that falsely infers the effects at the individual level on the basis of results across groups (Kim et al., 2016). Therefore, appropriate multilevel modeling that relaxes the assumption of identically distributed observations must be applied (Muthén, 1994).

In multilevel CFA, one factor model is estimated for the within-group variation at the individual level and another is simultaneously estimated for the between-group variation in the parameters of the individual-level model. With such a formulation, model parameters may vary across groups and are treated as random effects (Muthén, 1994; Muthén and Asparouhov, 2011). For an vector of observed variables Y across individuals, i , nested within groups g , a general MCFA model can be expressed as:

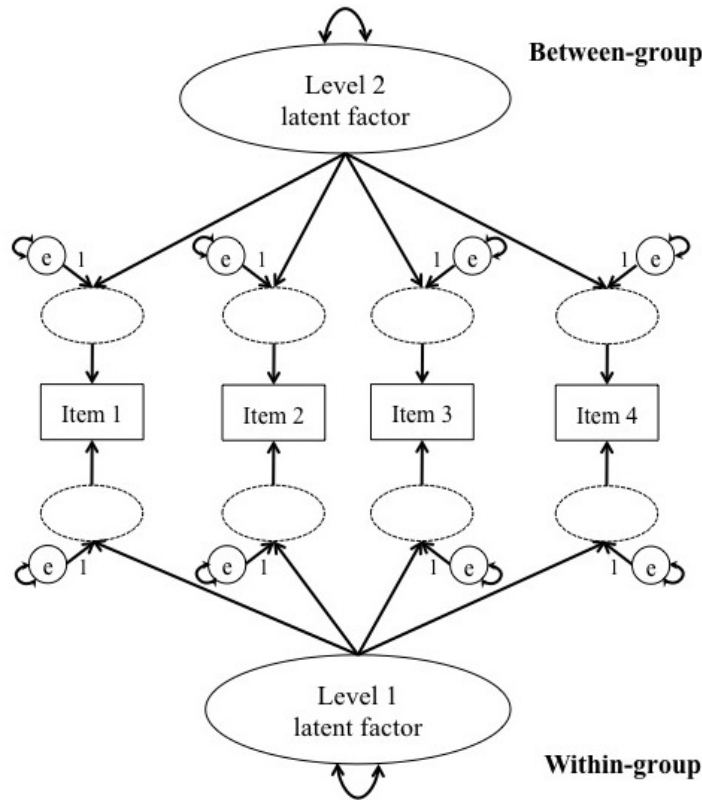
$$Y_{gi} = \nu + \lambda_B F_{Bg} + \epsilon_{Bg} + \lambda_W F_{Wgi} + \epsilon_{Wgi} \quad (3.2)$$

where ν is the vector of intercepts, λ_B and λ_W are the between- and within-level vectors of factor loadings, F_{Bg} is the vector of factors across groups g at the between level, F_{Wgi} is the vector of factors within groups g and individuals i , and ϵ_{Bg} and ϵ_{Wgi} are the between- and within-level residuals, respectively (Muthén, 1994). It can be shown that the variance of the observed indicators can be decomposed into between-group and within-group covariance matrices, Σ :

$$Var(Y_{gi}) = \Sigma_B + \Sigma_W \quad (3.3)$$

In estimation of MCFA models, the variance in each observed indicator or item is first decomposed into two latent variables: a within-group estimate as a deviation score from the group mean at the within (individual) level, and the estimated group mean or intercept at the between (country) level (Kim et al., 2016). The decomposed estimate of the observed variable at each level is then predicted by a latent factor with an error or residual at the corresponding level (Kim et al., 2016). This can be represented graphically as in Figure 3.2.

Figure 3.2: Path diagram of a conceptual multilevel CFA model - example of a single latent factor with 4 observed indicators



Note: Following emerging standards for MCFA diagrams, observed indicators are represented as rectangles, the latent variable decomposition of the indicators at the within- and between-group levels are represented as dotted circles, and latent factors (as well as errors) are represented by solid circles or ellipses (Kim et al., 2016; Stapleton et al., 2016)

Types of Multilevel Latent Constructs

When data are collected in a multilevel setting, latent constructs of interest may exist at multiple levels, which has important implications for construct meaning and validation (Stapleton et al., 2016). There are four types of multilevel constructs based on the level(s) of analysis at which the constructs are conceptually meaningful. Each type of construct requires different MCFA model specifications (Kim et al., 2016; Stapleton et al., 2016):

1. *Individual construct:* When individuals are the unit of analysis and the construct is only conceptually meaningful at the within-group level, then any between-level variance is assumed to be spurious and specifying a latent variable at the between-level may not be appropriate. To estimate this type of construct in an MCFA framework, the latent factor is defined on the within-level, and a simple saturated variance-covariance model is specified at the between-level.

2. *Shared construct*: While an individual construct is meaningful only at the individual- or within-level, a shared construct is only meaningful at the group level. While measured from item responses from individuals, shared (or reflective or composition constructs) (e.g., teacher instructional quality perceived by students). In an MCFA framework, a shared construct is estimated with a latent factor defined on the between-level and a saturated variance-covariance model specified among the items on the within-level.¹
3. *Configural construct*: A configural construct is an aggregate of individual characteristics. A configural construct has meaning at both the individual- and group-levels. In an MCFA framework, a configural construct is defined by the same latent factor on both the within- and between-levels, with identical factor structure and factor loadings constrained to be equal across levels.²
4. *Shared and configural constructs*: Shared and configural constructs can exist simultaneously. This is usually the case when more than one construct is required to adequately model significant between-group variance.

Because of their meaningful constructs at both levels of analysis, configural and shared configural constructs can be used for both within-group comparisons of individuals and for the study of between-group contextual effects.

Depending on the type of multilevel construct, the interpretation of the measure's psychometric properties and the MCFA's estimated parameters is more meaningful at a certain level than the other. Thus construct validation with multilevel models must be conducted so as to be consistent with the multilevel conceptualization of the construct (Kim et al., 2016).

Intraclass Correlation Coefficient (ICC)

The intraclass correlation coefficient is a measure of data dependency defined as the proportion of a variable's variance that is attributed to between-group differences. Therefore, low ICCs suggest that the construct is mainly a within-group (generally individual) construct, while high ICCs suggest that the construct may be more strongly shared at the between-group level.

Under an MCFA framework, ICCs can be calculated for each of the observed indicators as well as for the latent factor. For observed indicators, ICCs can be calculated as:

$$\text{Observed variable ICC} = \frac{b}{b + w} \quad (3.4)$$

where b is the total between-level variance of the observed indicator, equal to the square of the between-level factor loading times the between-level factor variance plus the between-

¹Shared constructs have also been referred to as climate (Marsh et al., 2012), reflective (Lüdtke et al., 2008), or composition (Bliese, 2000) constructs.

²Configural constructs have also been referred to as contextual (Marsh et al., 2012), formative (Lüdtke et al., 2008), or compilation (Bliese, 2000) constructs.

level residual variance; and w is the total within-level variance of the observed indicator, equal to the square of the within-level factor loading times the within-level factor variance plus the within-level residual variance (Snijders and Bosker, 2012).

For a latent factor, the ICC is:

$$\text{Latent factor ICC} = \frac{B}{B + W} \quad (3.5)$$

where B is the latent factor variance at the between-level and W is the latent factor variance at the within-level (Heck and Thomas, 2009; Muthén, 1994). The computation of factor ICCs requires the equality of factor loadings across levels because the metric used at the within- and between-levels should be consistent in order to take a ratio of between-level factor variance to the total factor variance (Kim et al., 2016).

Multilevel Indices of Model Fit

During the early development of multilevel CFA, the standard approach was to evaluate the goodness of fit for the entire model across all levels simultaneously using similar overall and relative fit statistics as are applied in a single-level CFA. However, in multilevel settings this standard approach to evaluating the goodness of model fit may not adequately detect misfit in the between-level model, particularly when the number of groups (effective between-level sample size) is small (Ryu, 2014). Furthermore, when this standard approach does detect poor model fit, it is not clear at which level the model does not fit the data. Two alternative approaches have been proposed to overcome these limitations by calculating level-specific fit indices. One approach—the segregating procedure—is a two-step procedure which first produces estimates of saturated covariance matrices at each level and then performs single-level analysis at each level with the estimated covariance matrices as input (Schweig, 2014; Yuan and Bentler, 2007). The other approach—the partially saturated model method—utilizes partially saturated models to obtain test statistics and fit indices for each level separately (Ryu, 2011; Ryu and West, 2009; Schermelleh-Engel et al., 2014). Simulation studies have consistently shown that both alternative approaches perform better than the standard approach in detecting lack of fit at any level, but the partially saturated model method outperforms the segregating procedure in terms of convergence rates and Type I error rates (Ryu and West, 2009).

In the partially saturated model approach, a saturated model at a particular data level can be obtained by correlating all the observed variables and allowing all the covariances to be freely estimated. A saturated model can be treated as a just-identified model with zero degrees of freedom and the χ^2 test statistic equals zero. Therefore a saturated within-level or between-level model contributes nothing to the fitting function (Hox, 2010). This feature allows us to compute different fit indices at each level. To evaluate the hypothesized between-level model, a saturated within-level model can be specified so that any misfit can be attributed to possible misspecification at the between-level (Hsu et al., 2016). In the same way, χ^2_W for the

within-level model can be obtained by specifying the hypothesized within-level model and a saturated between-level model. Using the partially saturated model approach, level-specific fit indices can also be calculated for RMSEA, CFI, and TLI (Hsu et al., 2016; Ryu and West, 2009).

Because SRMR is not a function of the χ^2 statistic and is derived from the deviation between the sample variance-covariance matrix and the model-implied variance-covariance matrix, it can be computed for the within- and between-levels separately without requiring any special procedure (Hsu et al., 2016).

3.1.3 Primary Advantages and Uses of CFA

CFA has several key advantages over traditional statistical techniques such as correlation and regression. The primary advantage of CFA is that it estimates the relations among variables while explicitly accounting for measurement error. Traditional statistical techniques impose the assumption that variables have been measured with no error. This assumption of error-free measurement is rarely appropriate in psychological applications and results in parameter estimates that are biased to an unknown degree. By specifying a latent variable model that estimates measurement error, relations among observed and latent constructs in the model can be estimated more accurately and reliably. This can also result in increased statistical power (Gallagher and Brown, 2013).

Due to CFA's robust framework for the rigorous evaluation of how a theoretical model represents observed data and its explicit handling of measurement error, CFA provides a superior method of evaluating psychometric properties of measurement scales. In fact, conducting a series of CFA models is now considered standard practice when developing a new measure. Common uses of CFA include scale validation and evaluating measurement invariance (Gallagher and Brown, 2013).

3.2 Psychometric Properties of a Measurement Scale

Psychometrics is the science of quantitatively measuring (unobservable) constructs in psychology, education, and the social sciences. Psychometrics provide the statistical theories and applications necessary to develop and evaluate measurements. These measurements, usually derived from responses to questionnaires, must demonstrate both reliability and validity before they can be used to explore relevant research questions. Furthermore, when comparing measures across groups, measurement invariance (or the absence of measurement bias) must also be demonstrated to ensure that differences in means are attributable to differences in the true construct rather than differences in the performance of the measurement instrument across groups.

Reliability and validity can be likened to precision and accuracy, respectively. A measurement is reliable if it consistently measures the same construct across individuals (or across multiple administrations or settings). A measurement scale is valid if it measures what it says it is going to measure. If a measure is valid, it is always reliable; however a measure can be reliable without being valid. It is important to remember that reliability and validity are attributes of measures (scores) rather than immutable properties of the measurement scale (test). Therefore reliability and validity are functions not only of the properties of the underlying construct being measured and the scale itself, but also of the sample being assessed and the purpose of the assessment (intended inference) (Kline, 2016).

Ideally, measures would demonstrate strong validity, reliability, and measurement invariance; however, in practice there are often tradeoffs among these different properties. The development and evaluation of measures must carefully weigh the importance of these different psychometric properties according to the needs of the specific research question or application of interest. While consideration of theory is paramount, empirical analysis can help inform these decisions. Therefore, in this section we introduce how to assess measurement reliability, validity, and invariance in the CFA framework discussed above.

3.2.1 Reliability

Reliability is the degree to which scores in a particular sample are precise. In classical theory, reliability (for positive observed score variance) has two alternative, but mathematically equivalent definitions: the squared correlation between true and observed scores (Lord and Novick, 1968) or the ratio of the true score variance over the total variance (e.g., McDonald, 1999). In factor models, the common factor variance is used as an estimate of the true score variance. The remaining variance in an indicator stems from a residual factor that consists of two components: a component that is stable over persons, but not shared with other indicators; and a truly random component (Bollen, 1989). In the SEM definition of reliability, the regressions of the indicator variables on the common factors represent the systematic components of the indicators, and all else represents error. So, the reliability of a single indicator can be evaluated based on the size of the factor loading (Kim et al., 2016). Indices that focus on the reliability of scales with multiple indicators usually represent some form of the ratio of common indicator variance over total indicator variance. While a CFA framework provides various ways to estimate reliability, three of the most commonly utilized measures are Cronbach’s alpha (α), composite reliability (ω), and maximal reliability (H).

Because reliability is a proportion of variance, its theoretical range is $[0, 1]$. While there is no gold standard as to how high reliability indices should be, general guidelines suggest that coefficients around .90 are “very good,” values around .80 are “good,” and values around .70 are “adequate” (Kline, 2016). Even lower levels of score reliability can be tolerated in latent variable methods compared with observed variable methods, especially if the sample size is large (Little et al., 1999).

Cronbach's Alpha (α)

By far the most commonly cited measure of reliability is Cronbach's alpha (α) (Cronbach, 1951). Alpha is a measure of internal consistency reliability, or the degree to which responses are consistent across the items of the scale. Cronbach's alpha is expressed as a function of the average inter-item covariance within a scale ($\bar{\sigma}_{ij}$), the variance of the scale score (σ^2), and the number of items included in the scale (n):

$$\alpha = \frac{n^2 \bar{\sigma}_{ij}}{\sigma^2} \quad (3.6)$$

Alpha can be estimated by specifying a fully saturated covariance structure CFA model that has no latent variables (Geldhof et al., 2014).

In general, α is only a consistent estimate of reliability when all items load on a single underlying construct and when all items represent that construct equally well (Novick and Lewis, 1967). While adjustments exist for calculating alpha with multiple correlated, unique factors, the assumption of equal factor loadings remains. In most applications of factor analysis, the model allows for heterogeneous factor loadings between indicators and their underlying factor(s). For this reason, researchers working with factor analysis have suggested composite reliability (ω) as a measure of reliability analogous to α , but more precise when item-construct relations are heterogeneous.

Composite Reliability (ω)

Composite reliability (ω) calculates true score variances as a function of factor loadings. Assuming a congeneric scale with a standardized latent construct (with variance fixed to 1), ω is estimated as:

$$\omega = \frac{\left(\sum_{i=1}^k \lambda_i\right)^2}{\left(\sum_{i=1}^k \lambda_i\right)^2 + \sum_{i=1}^k \sigma_i^2} \quad (3.7)$$

where λ_i is the factor loading of item i onto a single common factor and σ_i^2 represents the unique variance of item i .

Composite reliability represents the relation between a scale's underlying latent factor and its unit-weighted composite, but a unit-weighted composite may not optimally reflect its underlying latent structure (Geldhof et al., 2014). Given that factor analysis allows for heterogeneous indicator weights, it is reasonable to also incorporate heterogeneous weights when creating a scale's composite score. One alternative to comparing true score variance to the variance of a unit-weighted scale is to compare it to the variance of a scale's optimally weighted composite using maximal reliability (e.g., Bentler, 2007).

Maximal Reliability (H)

Maximal reliability (H) can be expressed as:

$$H = \left(1 + \frac{1}{\sum_{i=1}^k \frac{l_i^2}{1-l_i^2}} \right) \quad (3.8)$$

where l_i^2 represents the squared standardized factor loading of indicator i onto a single factor (Hancock and Mueller, 2001).

Reliability in a Multilevel Context

Estimating reliability with multilevel data is complex because variances are decomposed into within- and between-group components. Early research explored measures that combined both within and between group variability to estimate reliability in MCFA (Raykov and Toit, 2005). However, these procedures did not differentiate whether the scale was sufficiently reliable for use at a specific level of analysis. Recent work advocates separate estimation of reliability at each level of analysis (Geldhof et al., 2014). In particular, the single-level definitions of alpha (α), composite reliability (ω), and maximal reliability (H) can be directly and separably applied to the within- and between-level results to estimate level-specific indicators of reliability (Geldhof et al., 2014).

Level-specific α 's can be estimated in multilevel models by specifying fully saturated indicator covariance matrices in both levels of an MCFA and then separately applying Equation 3.6 to the within- and between-level parameters. The numerator of each level-specific α is therefore the squared number of indicators present at a given level of analysis multiplied by the average covariance at that same level. The denominator of each level-specific α similarly represents the sum of all elements in the full level-specific covariance matrix and can be obtained by summing all level-specific indicator variances and two times each unique level-specific covariance (Geldhof et al., 2014).

Estimating level-specific ω and H in MCFA requires specification of a unidimensional factor structure at both the within- and between group levels that freely estimates within- and between-level factor loadings and residual variances for the indicators (with the within- and between-level residual variance for the latent variables fixed at 1 for identification purposes). Equations 3.7 and 3.8 can then be applied to the level-specific parameter estimates so that within-level factor loadings and within-level residual variances are used to estimate ω_{within} and H_{within} while between-level factor loadings and between-level residual variances are used for $\omega_{between}$ and $H_{between}$.

3.2.2 Validity

Validity is concerned with the soundness of a given inference based on the measure and is therefore relative to the proposed interpretation and intended uses of the score (Kane, 2013; Kline, 2016). Validity has multiple dimensions related to the measure's representativeness of the target domain and construct (content validity) and the measure's relation to other variables (convergent and divergent validity).

Content Validity

Content validity deals with whether scale items are representative of the domain(s) or hypothetical latent construct(s) they are supposed to measure. Content validity is not established by statistical analysis, but instead by careful and well-grounded design of the survey instrument from which the measure will be derived (Kline, 2016). From the outset, careful review of relevant theoretical and empirical literature can help ensure that all dimensions or facets of the target concept are covered by the indicators in the scale.

Convergent and Divergent Validity

Convergent and divergent (or discriminant) validity involve the evaluation of measures against each other instead of against an external standard (Kline, 2016). In general, variables presumed to measure the same or highly-related constructs show convergent validity if their correlations are large in magnitude; variables presumed to measure different constructs show divergent validity if their correlations are small in magnitude.

Standard CFA models with observed indicators that each depend on just a single factor with independent errors are an ideal framework for testing convergent and divergent validity. Correlations between indicators of the same factor should be greater than cross-factor correlations with indicators that are supposed to measure different factors. Empirically, convergent validity is demonstrated if the majority of the variance of each indicator is explained by its underlying factor. Ideally, this is demonstrated by showing that all items have standardized factor loadings greater than 0.7 and R^2 values greater than 0.50 (Kline, 2016) (although, in real-world applications the cutoff for acceptable standardized factor loadings is often around 0.40). Divergent validity between factors is demonstrated if the correlation between factors is less than 0.90 (Kline, 2016). Given that researchers rarely test factors together that are completely unrelated, a small to moderate correlation is usually fine.³

³When indicators simultaneously load onto more than one factor, determining divergent validity becomes more complicated. However, this is beyond the scope of this dissertation as all of the measurement models in this dissertation avoid any cross-loading.

3.2.3 Measurement Invariance

Measurement invariance is the absence of measurement bias across groups. Measurement invariance evaluates whether items measure the same attributes for different (groups of) respondents. Measurement invariance is a necessary condition for the comparisons of a given (latent) measure across groups. The importance of measurement invariance is widely recognized (e.g., Meredith, 1993; Vandenberg and Lance, 2000).

The most common method used to investigate measurement invariance is multigroup factor analysis (MGFA). This method involves testing the equality of measurement parameters—namely, factor loadings, intercepts, and residual variances—across groups and is applicable for both continuous and ordinal items (Millsap and Yun-Tein, 2004; Reise et al., 1993). With MGFA, a series of increasingly restrictive models can be fitted to test different levels of measurement invariance across groups (Meredith, 1993; Meredith and Teresi, 2006):

1. *Configural invariance*: the same factor structures (i.e. the number of factors and the specific items that correspond to them)
2. *Weak factorial (or metric) invariance*: constrains both the factor structure and factor loadings to be equal across groups
3. *Strong factorial (or scalar) invariance*: constrains the factor structure, factor loadings, and item intercepts to be equal across groups
4. *Strict factorial (or residual) invariance*: additionally constrains item residual variances to be equal across groups

In general, strong factorial invariance suffices for meaningful comparison of common factor means. In MGFA, violations of strong factorial invariance suggest uniform bias and violations of weak factorial invariance suggest nonuniform bias (Mellenbergh, 1989, 1994).

While much of the literature focuses on measurement bias with respect to the latent variable estimated from multiple observed indicators, there might also be measurement bias with respect to some but not all indicators, referred to as partial invariance (or differential item functioning, DIF) (Byrne et al., 1989).

Measurement Invariance in a Multilevel Context

When research questions involve differences between large numbers of groups—common in cross-cultural research (Byrne and van de Vijver, 2010)—it becomes infeasible to apply MGFA. In these cases, a multilevel approach can be applied to investigate measurement invariance (Jak et al., 2013). This method circumvents the limitations of standard MGFA by treating group membership as a random rather than a fixed variable (Muthén and Asparouhov, 2011).

In a multilevel context, invariance across levels of analysis is viewed as evidence of invariance across groups (Jak et al., 2013; Kim et al., 2016). In other words, if within-level factor loadings are equal across groups (metric invariance holds), then the factor loadings at the between-level should be identical to those at the within-level. Therefore, corollaries to configural invariance, weak factorial invariance, and strong factorial invariance across groups can be defined and tested by three increasingly restrictive assumptions across levels in an MCFA framework (Jak et al., 2013). Testing for strong factorial invariance is equivalent to testing a model in which factor loadings are constrained to be equal across levels and the covariance matrix at the between-level is constrained to be zero (Jak et al., 2013). Testing for weak factorial invariance is equivalent to testing the hypothesis that the factor loadings are equal across levels (with the between-level covariance matrix freely estimated) (Jak et al., 2013).

Such tests for invariance can be applied for the latent construct or for each individual item. These tests are often conducted with a constrained (or “fixed”) baseline approach, which first evaluates the overall fit of the fully constrained model and then tests it against an alternative model that frees item parameters using a test such as a likelihood ratio or chi-square difference test (Jak et al., 2013). Statistical significance indicates that the model with constraints fits significantly worse than the model without constraints, and the model exhibits measurement bias (Guenole, 2018; Jak et al., 2013).

An alternative approach to the constrained baseline strategy begins with a free baseline where minimal constraints are imposed and compares it to an alternative model that constrains only the parameters (factor loadings and residual variances) of the items being tested across groups, leaving all other parameters free across groups. An evaluation of the difference in fit between the constrained and unconstrained models is then made using a test such as the likelihood ratio test. Statistical non-significance in a free baseline strategy indicates that fixing the item parameters to be equal across groups does not yield a statistically significant decrement in model fit, and that the item does not exhibit bias (Guenole, 2018). Simulation studies indicate that when the referent item is unbiased, the constrained baseline approach leads to similar true positive (power) rates but much higher false positive (Type I error) rates compared to the free baseline approach (Guenole, 2018). Therefore, the free baseline approach should be preferred when the referent indicator is unbiased.⁴

Options for Handling Non-invariance

In practice, it is difficult to create measurement scales that demonstrate strong factorial (or scalar) invariance as a whole and across each item. If weak or partial non-invariance is identified, researchers can investigate the source of non-invariance by sequentially removing or adding item intercept constraints and retesting the model until a partially invariant model is achieved. Non-invariance can be informative and may lead researchers to important con-

⁴When the referent indicator is biased, neither the free nor the constrained baseline approaches performed well, with both exhibiting unacceptably high false positive rates and poor true positive rates (Guenole, 2018).

clusions about how different groups interpret the same construct (Putnick and Bornstein, 2016).

If particular items appear problematic, the researcher can omit items with non-invariant intercepts and retest the models; however, this should be done with caution since removing items can reduce the coverage (i.e., content validity) of the scale. Therefore, it is common practice to accept some violations of measurement invariance as long as these are states as potential limitations of the study and group differences are interpreted accordingly. Therefore, a failure to demonstrate invariance should not necessarily preclude all further analyses of group or developmental differences (Putnick and Bornstein, 2016).

Therefore, in either a multigroup or a multilevel setting, consideration of measurement invariance is a tradeoff between standardization of the measure (to allow for comparisons across groups on the same measurement scale) and contextualization of the measure (to capture how each group differentially interprets the item). Researchers must find the right balance for their specific application of interest.

3.3 The Polytomous Car Pride Scale within U.S. Cities

In this section, we discuss the development and evaluation of a polytomous (7-point Likert-scale) measure of individual car pride. Many potential survey items were first piloted in a survey of $N = 1,236$ residents in New York City and Houston metropolitan statistical areas in the United States (see Chapter 2). Using a standard CFA approach, we investigate the psychometric properties of a polytomous measure of individual car pride in this U.S. city sample.

All CFA models presented in this section are estimated using maximum likelihood with robust standard errors (MLR) estimation to correct for the non-normality of the Likert-format survey items in Mplus version 8.1 (Muthén and Muthén, 1998-2018).⁵ By applying MLR estimation, we treat as continuous our polytomous items measured on a 7-point Likert scale. This is a common practice given that most literature suggests that maximum likelihood performs reasonably well with five (or more) response categories whereas weighted least squares with mean and variance adjustment (WLSMV) is recommended with two or three response categories (Beauducel and Herzberg, 2006; Dolan, 1994).

3.3.1 Content Validity

The U.S.-city survey contained 20 items designed to assess the degree to which an individual attributes social status and personal image to driving and using a car. Items were scored on a

⁵MLR estimation in Mplus provides a test statistic that is asymptotically equivalent to the Yuan-Bentler test statistic (Yuan and Bentler, 2000).

7-point Likert scale from “strongly disagree” (-3) to “strongly agree” (3). In order to ensure that our measure encompasses the full construct of car pride, items relate both to driving and owning a car with two facets of pride that are well established in the social psychology literature. Alpha or hubristic pride is pride related to subjective feelings of superiority in relation to others (for example, “Driving a car makes me feel superior to those who don’t”), whereas beta or authentic pride is related to genuine feelings of self-esteem and self-worth (for example, “Driving a car positively affects my perception of myself”) (Tracy and Robins, 2007a,b). Synonyms for social status and personal image used throughout the items are taken from semantic studies conducted by (Tracy and Robins, 2007a,b). The items in this survey include and expand upon those statements used in previous studies to measure car pride using survey instruments (Zhao and Zhao, 2018).

3.3.2 Convergent Validity

We estimate a series of CFA models to identify a subset of the 20 observed survey items that show high correlations with one another and the hypothesized latent construct of car pride. We start by estimating a CFA model with all 20 items loading onto a single factor. From this 20-item model, we identify the items for which the majority of the item variance is explained by the single factor (standardized factor loading greater than 0.70 and an R^2 greater than 0.5) to ensure convergent validity (Kline, 2016). This leaves us with a subset of 12 items (see Table 3.1).

Table 3.1: Results for the 20-item car pride CFA in in New York City and Houston

Item#	Statement	b	$S.E.$	β	R^2
Q28.2	I feel more accepted in my community when I drive a car	1.000 ^a		0.695	0.483
Q28.3	Driving meets my self esteem or personal image	1.080	0.031	0.753	0.567
Q28.4	Driving a car makes me feel superior to those who don’t	1.201	0.050	0.729	0.532
Q28.5	I feel like I don’t belong driving a car [rev]	0.369	0.064	0.227	0.051
Q28.6	Driving a car positively affects my perception of myself	1.088	0.039	0.735	0.540
Q28.8	Driving to work suits my job/position	0.778	0.043	0.517	0.268
Q51.1	A car is a sign of social status	1.000	0.051	0.677	0.458
Q51.2	I would be ashamed if future financial circumstances prevented me from driving	0.791	0.045	0.506	0.256
Q51.3	I would love to be seen more often driving	1.100	0.050	0.727	0.528
Q51.4	If more people saw me in/with my car, I would drive more	1.163	0.054	0.726	0.527
Q51.5	I gain respect from my peers because I drive a car	1.202	0.052	0.754	0.569
Q31.1	Having a car is connected with one’s social image	1.133	0.048	0.790	0.624
Q31.2	I deserve to own and express myself with a great car	1.134	0.049	0.803	0.645
Q31.3	Others would see me as more successful if I owned a better car or more cars	1.144	0.051	0.757	0.574
Q31.4	I have achieved in life and therefore I deserve a good car	1.099	0.050	0.786	0.617
Q31.5	I feel proud of owning my car	0.688	0.046	0.594	0.353
Q53.6	I feel owning a car is a positive component of my identity	1.119	0.044	0.824	0.680

Table 3.1: Results for the 20-item car pride CFA in NYC and Houston (*continued*)

Item#	Statement	<i>b</i>	<i>S.E.</i>	β	R^2
Q53_7	Having a car makes me feel superior to those who don't	1.123	0.054	0.698	0.487
Q53_8	I have a sense of accomplishment after buying a car	0.943	0.045	0.711	0.505
Q53_9	I want to have a successful life and that includes owning a nicer car or more cars	1.115	0.050	0.764	0.584

Notes: *b* = unstandardized factor loading; *S.E.* = standard error; β = standardized factor loading; [rev] = reverse-coded; ^a = value fixed to one for model identification and scaling.

Overidentified model fit: $\chi^2(60, N = 1,236) = 2808, p < .01, CFI = 0.773, TLI = 0.747, RMSEA = 0.113$ with 90% confidence interval of [0.109, 0.116], *SRMR* = 0.075.

Shaded items were removed from the final car pride measure due to standardized factor loadings < 0.7 and R-squared values < 0.5.

All factor loadings are statistically different from zero with two-tailed $p < 0.001$.

We reconsider the content validity of this subset of 12 items to ensure that together they continue to provide adequate coverage over the construct of interest—including statements relating both facets of pride to both car ownership and car use. Satisfied that content validity remains, we run a subsequent CFA on this subset of 12 items. We find that the 12-item factor structure demonstrates strong convergent validity (see Table 3.2). However, the global model fit indices do not meet established standards. An investigation of Lagrangian Multiplier modification indices suggests that adding correlations among error terms of some of the items can significantly improve model fit.

Table 3.2: Results for the 12-item car pride CFA without correlated errors

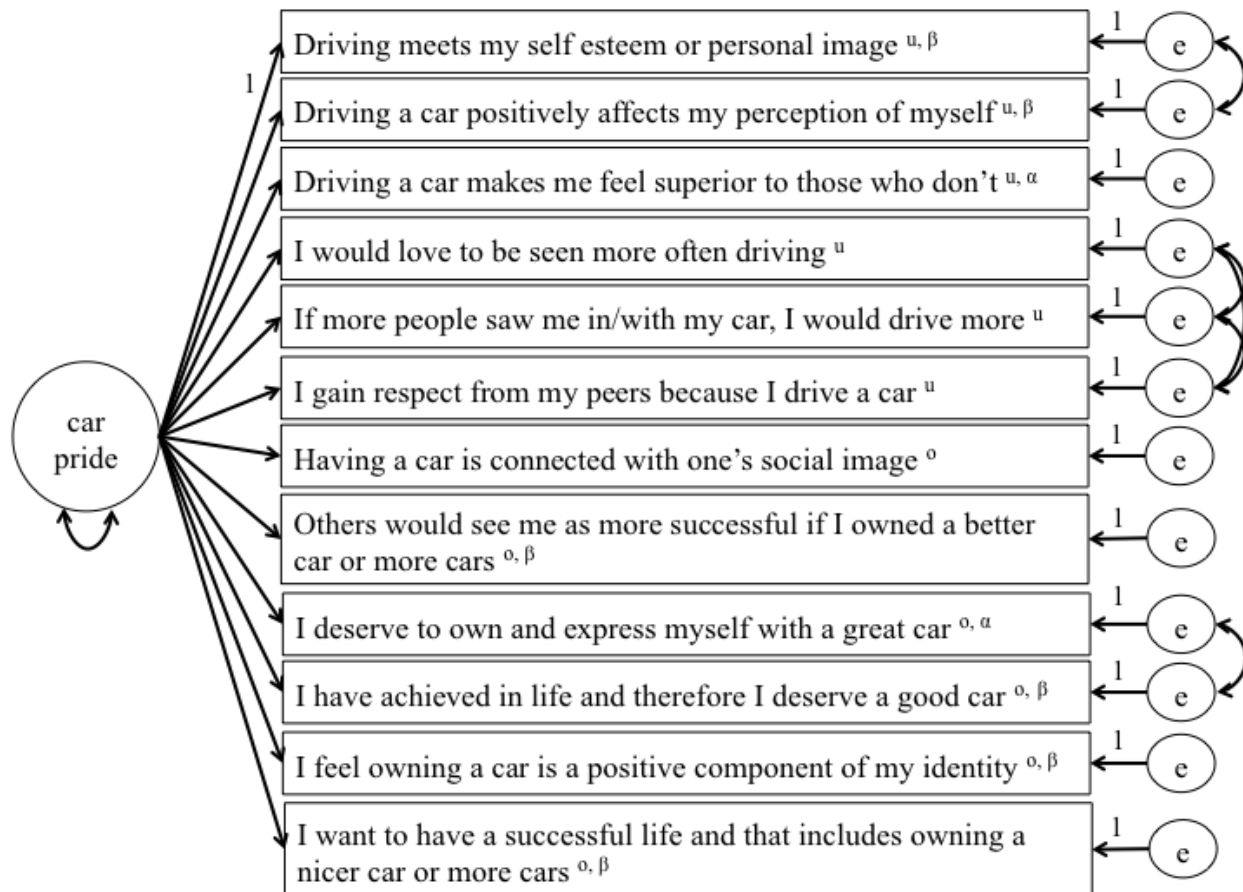
Statement	<i>b</i>	<i>S.E.</i>	β	R^2
Driving meets my self esteem or personal image	1.000 ^a		0.731	0.534
Driving a car makes me feel superior to those who don't	1.138	0.045	0.724	0.524
Driving a car positively affects my perception of myself	1.019	0.034	0.721	0.519
I would love to be seen more often driving	1.074	0.045	0.743	0.553
If more people saw me in/with my car, I would drive more	1.141	0.052	0.746	0.557
I gain respect from my peers because I drive a car	1.166	0.050	0.766	0.587
Having a car is connected with one's social image	1.076	0.044	0.786	0.618
I deserve to own and express myself with a great car	1.094	0.041	0.812	0.660
Others would see me as more successful if I owned a better car or more cars	1.094	0.047	0.759	0.576
I have achieved in life and therefore I deserve a good car	1.050	0.043	0.787	0.619
I feel owning a car is a positive component of my identity	1.051	0.036	0.812	0.660
I want to have a successful life and that includes owning a nicer car or more cars	1.058	0.041	0.759	0.577

Notes: Overidentified model fit: $\chi^2(54, N = 1,236) = 1168, p < .01, CFI = 0.833, TLI = 0.796, RMSEA = 0.129$ with 90% confidence interval of [0.123, 0.136], *SRMR* = 0.063.

All factor loadings are statistically different from zero with two-tailed $p < 0.001$.

We review each pair of statements for which modification indices suggest that introducing a correlation term could improve the chi-square of the model by at least 100. We introduce a total of 5 correlations among statements that share similar wording or are probing the same specific facet of car pride. We propose a final 12-item CFA model of car pride with correlated error terms as depicted in Figure 3.3.

Figure 3.3: Path diagram for the 12-item polytomous car pride CFA



Notes: u = use; o = ownership; β = authentic pride; α = hubristic pride. Variances of the item error terms are estimated but not shown.

The CFA model results for the factor structure depicted in Figure 3.3 are given in Table 3.3. We find that this 12-item single-factor measure of car pride with correlated error terms fits the data well: $\chi^2(49, N = 1,236) = 346, p < .01, CFI = 0.955, TLI = 0.940, RMSEA = 0.070$ with 90% confidence interval of $[0.063, 0.077], SRMR = 0.040$. Given the large sample size, we overlook the statistically significant chi-square test statistic and note that the CFI and TLI are well above the established threshold of 0.90 for moderate model fit and that RMSEA and SRMR are well below 0.08 (Kline, 2016). The convergent validity of the measure is well-established, with all items having standardized factor loadings close to or greater than 0.7 and R^2 values close to or greater than 0.50.

Table 3.3: Results for the 12-item car pride CFA with correlated errors

Statement	<i>b</i>	<i>S.E.</i>	β	R^2
Driving meets my self esteem or personal image	1.000 ^a		0.717	0.515
Driving a car makes me feel superior to those who don't	1.119	0.046	0.698	0.488
Driving a car positively affects my perception of myself	1.018	0.036	0.706	0.499
I would love to be seen more often driving	1.009	0.043	0.685	0.469
If more people saw me in/with my car, I would drive more	1.047	0.048	0.673	0.453
I gain respect from my peers because I drive a car	1.091	0.047	0.706	0.498
Having a car is connected with one's social image	1.117	0.049	0.800	0.640
I deserve to own and express myself with a great car	1.118	0.044	0.814	0.662
Others would see me as more successful if I owned a better car or more cars	1.130	0.051	0.768	0.590
I have achieved in life and therefore I deserve a good car	1.077	0.047	0.791	0.626
I feel owning a car is a positive component of my identity	1.102	0.040	0.834	0.696
I want to have a successful life and that includes owning a nicer car or more cars	1.105	0.045	0.778	0.605

Notes: Overidentified model fit: $\chi^2(49, N = 1,236) = 346, p < .01, CFI = 0.955, TLI = 0.940, RMSEA = 0.070$ with 90% confidence interval of [0.063, 0.077], and $SRMR = 0.040$.

All factor loadings are statistically different from zero with two-tailed $p < 0.001$.

3.3.3 Divergent Validity

Having established the convergent validity of our 12-item measure of car pride, we can demonstrate its divergent validity against a measure of general pride.

Our general pride factor is estimated from 6 indicators related to the facet of authentic pride associated with genuine feelings of self-esteem and self-worth based on specific accomplishments as depicted in Figure 3.4. Other than a significant chi-square test statistic due to large sample size, the model meets all criteria for reasonable model fit. Convergent validity is confirmed by standardized factor loadings of close to 0.70 or above (see Table 3.4). Furthermore, these six items have a Cronbach's alpha of 0.91, demonstrating adequate internal consistency.

Figure 3.4: Path diagram for the 6-item general authentic pride CFA

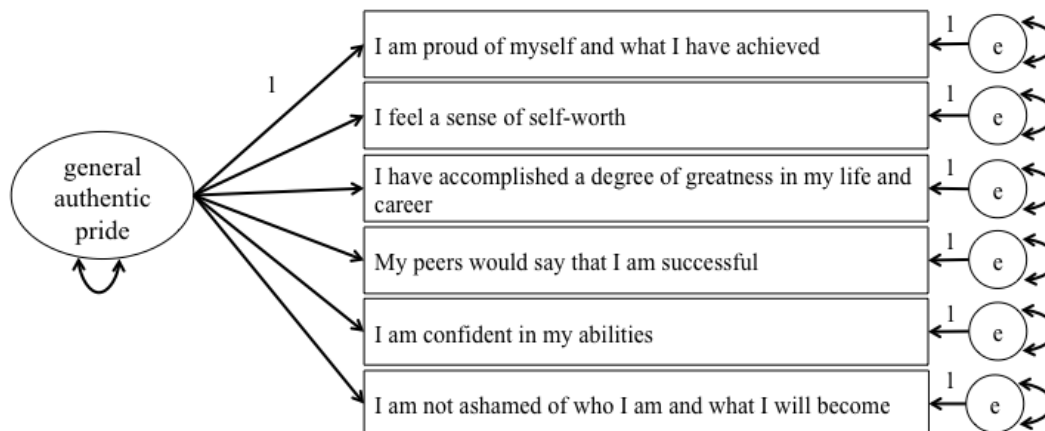


Table 3.4: Results for the 6-item general pride CFA in New York City and Houston

Item#	Statement	b	$S.E.$	β	R^2
Q54.1	I am proud of myself and what I have achieved	1.000 ^a		0.864	0.747
Q54.2	I feel a sense of self-worth	0.971	0.032	0.866	0.750
Q54.3	I have accomplished a degree of greatness in my life and career	1.052	0.036	0.791	0.625
Q54.4	My peers would say that I am successful	1.034	0.038	0.808	0.652
Q54.6	I am confident in my abilities	0.783	0.043	0.730	0.533
Q54.8	I am not ashamed of who I am and what I will become	0.827	0.041	0.683	0.466

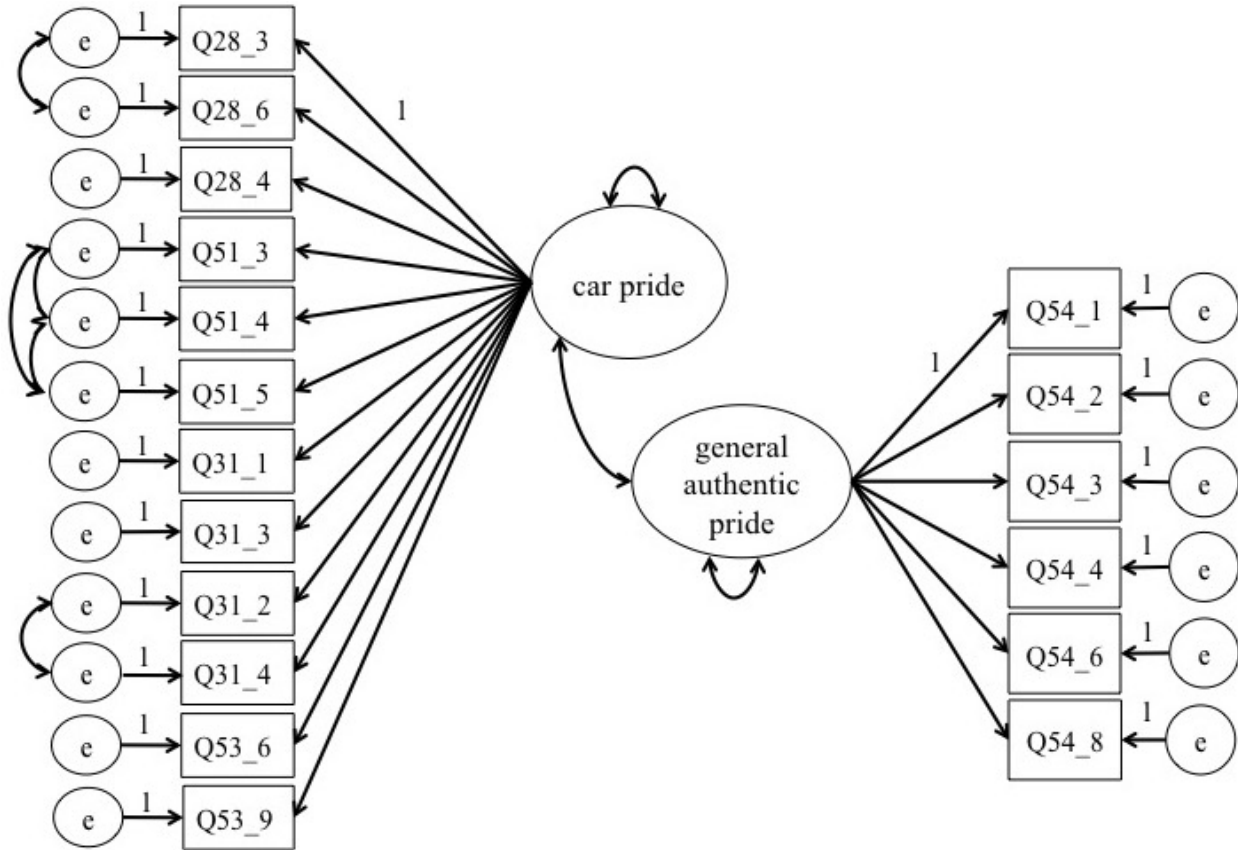
Notes: Overidentified model fit: $\chi^2(9, N = 1,236) = 84.055$, $p < .01$, CFI = 0.963, TLI = 0.938, RMSEA = 0.082 with 90% confidence interval of [0.066, 0.098], and SRMR = 0.029.

All factor loadings are statistically different from zero with two-tailed $p < 0.001$.

We run a CFA model that simultaneously estimates the two latent constructs of car pride and general authentic pride while allowing them to correlate (as in Figure 3.5). This model demonstrates adequate model fit: $\chi^2(129, N = 1,236) = 748.309$, $p < .01$, CFI = 0.941, TLI = 0.930, RMSEA = 0.062 with 90% confidence interval of [0.058, 0.066], SRMR = 0.0255. Factor loadings for the 12 car pride items and the 6 general authentic pride items are consistent with those estimated in the individual measurement models for car pride and general authentic pride presented in Table 3.3 and Table 3.4, respectively.

Of particular interest for divergent validity is the correlation of car pride with general authentic pride. We find that this correlation is statistically significant, small to moderate in magnitude, and positive ($b = 0.345$, $S.E. = 0.045$, $p < .01$, $\beta = 0.271$). This positive correlation suggests that those with higher values of general authentic pride also have higher values of pride attributed to driving or owning a car. The low magnitude of the correlation between these measures suggests that our measure of car pride, while related to general authentic pride, captures a specific association of social status and personal image with driving and using a car.

Figure 3.5: Path diagram for the simultaneous estimation of the 12-item car pride and 6-item general authentic pride measures



Note: Variances of the item error terms are estimated but not shown.

3.3.4 Measurement Invariance

Next, we analyze measurement invariance to determine whether observed differences across subsamples represent true differences in car pride or are merely indicative of item bias (an indicator functioning differently across groups). We perform a series of multigroup analyses to determine whether our car pride measure is invariant across respondents in the two cities (NYC and HOU), who are car-owners or non-car-owners, and who are drive alone commuters or commuters by other modes.

For each multigroup analysis, we adopt a free baseline approach. First we estimate the car pride CFA depicted in Figure 3.3 allowing all estimated parameters to differ across groups. We then compare this free baseline model to that of the weak factorial invariance model (constraining factor loadings to be equal across groups) and the strong factorial invariance model (constraining both factor loadings and item intercepts to be equal across groups). We compare the overall fit of the models using a Satorra-Bentler scaled chi-square difference test with a correction factor for MLR estimation (Satorra and Bentler, 2001, 2011). A statistically significant result indicates that the constrained (invariant) model fits significantly worse

than the baseline, suggesting the presence of bias. Due to the sensitivity of chi-square difference testing to large sample sizes, we also assess changes in approximate fit indices using recommended benchmarks of $\Delta\text{RMSEA} > 0.01$ and $\Delta\text{CFI} > 0.015$ as indicative of problematic variance across groups (Chen, 2007; Cheung and Rensvold, 2002).

Invariance between New York City and Houston

First, we consider the invariance of our car pride scale across the two city subsamples. The χ^2 difference tests suggest that the car pride scale demonstrates weak factorial invariance, but fails to hold strong factorial invariance across the two cities (see Table 3.5). However, constraining to strong factorial invariance across cities does not lead to substantial loss of fit according to approximate fit indices, with $\Delta\text{RMSEA} = 0.000$ and $\Delta\text{CFI} = -0.01$ within recommended bounds for concluding invariance. Given that the factorial invariance model meets basic recommended thresholds across all approximate fit indices, we adopt the strong factorial invariance model to enable consistent comparison of car pride across cities.

Table 3.5: Multigroup analysis of the invariance of the 12-item polytomous car pride scale between cities

	Unconstrained MGFA	Weak factorial invariance	Strong factorial invariance
χ^2 value (degrees of freedom)	400.984 (98)	420.055 (109)	489.331 (120)
MLR correction factor	1.4150	1.3838	1.3466
RMSEA	0.071	0.068	0.071
CFI	0.956	0.954	0.945
TLI	0.940	0.945	0.940
SRMR	0.042	0.045	0.053
Weak invariance vs. unconstrained: $\chi_D^2(11) = 12.55, p = .324$			
Strong invariance vs. unconstrained: $\chi_D^2(22) = 87.86, p < .01$			
Strong invariance vs. weak invariance: $\chi_D^2(11) = 79.41, p < .01$			

While the polytomous car pride scale failed the χ^2 difference test of strong measurement invariance across the two city subsamples, we want to explore which of the 12 survey items contribute to this invariance. We estimate weak and strong invariance constrained models for each of the 12 indicators (allowing all others to be freely estimated). We then compare this to a free baseline model using MLR-corrected scaled χ^2 -difference tests to detect partial or indicator-specific invariance (see Table 3.6). We find that only two items—Q31_2 and Q53_9—show statistically significant weak invariance, while 8 of the 12 items show statistically significant strong factorial invariance.

Table 3.6: Detection of partial or indicator-specific invariance between cities using a free baseline MLR-corrected scaled χ^2 difference test

Item#	Weak factorial invariance		Strong factorial invariance	
	$\chi_D^2(1)$	p	$\chi_D^2(2)$	p
Q28_3	0.97	.353	18.75	.000***
Q28_4	0.086	.353	0.87	.648
Q28_6	1.72	.190	8.87	.012**
Q51_3	0.01	.925	7.00	.030**
Q51_4	0.30	.585	9.30	.010**
Q51_5	0.00	.948	1.84	.398
Q31_1	1.87	.172	4.56	.102
Q31_2	5.27	.022**	8.89	.012**
Q31_3	1.23	.266	2.35	.309
Q31_4	1.10	.294	9.98	.007***
Q53_6	1.11	.291	13.06	.001***
Q53_9	3.17	.075*	11.08	.004***

Note: Significant bias detected at the * = 10% level, ** = 5% level, and *** = 1% level.

Invariance between Car-Owners and Non-Car-Owners

We follow a similar multigroup analysis procedure to evaluate the invariance of our car pride measure between those respondents whose household owns one or more cars (car-owners) and those whose household does not own a car (non-car-owners). We find that the 12-item polytomous car pride scale fails to pass the χ^2 difference test for both weak and strong measurement variance across car owners and non-car-owners (see Table 3.7). However, constraining factor loadings and item intercepts to be equal across car-owners and non-car owners (strong factorial invariance) leads to only a moderate loss of fit according to some approximate fit indices, with $\Delta CFI = -0.012$ just within the recommended threshold of 0.015 and $\Delta RMSEA = 0.001$ well below the recommended 0.01. These results suggest that the car pride factor may behave differently across car-owners and non-car-owners. However, we can accept the reduced model fit of the strong factorial invariance model as a reasonable tradeoff for comparability of car pride scores across car-owners and non-car-owners.

Given this significant scale-level variance, we can test for partial or indicator-specific invariance to determine which items in the car pride scale demonstrate the greatest bias across car-owners and non-car-owners (see Table 3.8). We find that all 12 survey items show significant variation in the item intercepts across car-owners and non-car-owners, but only items Q28_3, Q28_4, Q51_4, Q51_5 and Q31_1 show significant variation in factor loadings. Curiously, these all but one of these items that differ in factor loadings across car-owners and non-car-owners are related to using (rather than owning) a vehicle, which suggests that while car-owners and non-car-owners attribute social status and personal image to owning a car in the same way, these two groups think about the symbolic value of driving a car differently.

Table 3.7: Multigroup analysis of the invariance of the 12-item polytomous car pride scale between car-owners and non-car-owners

	Unconstrained MGFA	Weak factorial invariance	Strong factorial invariance
χ^2 value (degrees of freedom)	424.654 (98)	465.684 (109)	523.026 (120)
MLR correction factor	1.3841	1.3357	1.3058
RMSEA	0.073	0.073	0.074
CFI	0.951	0.946	0.939
TLI	0.934	0.935	0.933
SRMR	0.043	0.052	0.055
Weak invariance vs. unconstrained: $\chi_D^2(11) = 37.87, p < .01$			
Strong invariance vs. unconstrained: $\chi_D^2(22) = 99.48, p < .01$			
Strong invariance vs. weak invariance: $\chi_D^2(11) = 60.38, p < .01$			

Table 3.8: Detection of partial or indicator-specific invariance between car-owners and non-car-owners using a free baseline MLR-corrected scaled χ^2 difference test

Item#	Weak factorial invariance		Strong factorial invariance	
	$\chi_D^2(1)$	p	$\chi_D^2(2)$	p
Q28_3	6.00	.014**	86.23	.000***
Q28_4	6.01	.014**	26.09	.000***
Q28_6	0.33	.564	19.48	.000***
Q51_3	2.55	.111	12.00	.002***
Q51_4	5.88	.015**	19.28	.000***
Q51_5	9.73	.002***	25.29	.000***
Q31_1	5.44	.020**	28.66	.000***
Q31_2	1.85	.174	44.74	.000***
Q31_3	0.01	.934	29.16	.000***
Q31_4	0.23	.630	49.39	.000***
Q53_6	0.02	.889	77.92	.000***
Q53_9	0.07	.792	27.91	.000***

Invariance between Drive Alone Commuters and Others

We again follow a similar multigroup analysis procedure to evaluate the invariance of our car pride measure between those respondents who indicate that their most typical commute mode is “drive alone” (drive alone commuters) and those who commute by other modes (others). Given the significant overlap between individuals who are car owners and car users, we expect and do see similar patterns to what was observed above for car-owners and non-car-owners across drive alone commuters and others (see Table 3.9). Again, these results suggest that the car pride factor may behave differently across drive alone commuters and

others, but imposing strong factorial invariance (to allow comparability) does not result in substantial loss of model fit.

Given this significant scale-level variance, we again test for partial or indicator-specific invariance to determine which items in the car pride scale demonstrate the greatest bias across drive alone commuters and others (see Table 3.8). We find that all 12 survey items show significant variation in the item intercepts across car commuters and others, and that most of the items relating social status and personal image to using (rather than owning) a car show weak invariance (variation in the factor loadings).

Table 3.9: Multigroup analysis of the invariance of the 12-item polytomous car pride scale between drive alone commuters and others

	Unconstrained MGFA	Weak factorial invariance	Strong factorial invariance
χ^2 value (degrees of freedom)	412.100 (98)	440.867 (109)	512.265 (120)
MLR correction factor	1.4028	1.3628	1.3292
RMSEA	0.072	0.070	0.073
CFI	0.954	0.951	0.942
TLI	0.937	0.941	0.936
SRMR	0.044	0.050	0.054
Weak invariance vs. unconstrained: $\chi_D^2(11) = 22.57, p = .020$			
Strong invariance vs. unconstrained: $\chi_D^2(22) = 102.67, p < .01$			
Strong invariance vs. weak invariance: $\chi_D^2(11) = 80.39, p < .01$			

Table 3.10: Detection of partial or indicator-specific invariance between drive alone commuters and others using a free baseline MLR-corrected scaled χ^2 difference test

Item#	Weak factorial invariance		Strong factorial invariance	
	$\chi_D^2(1)$	p	$\chi_D^2(2)$	p
Q28_3	5.84	.016**	94.37	.000***
Q28_4	5.82	.016**	47.52	.000***
Q28_6	0.87	.350	38.75	.000***
Q51_3	5.24	.022**	12.68	.002***
Q51_4	11.08	.001***	38.03	.000***
Q51_5	8.93	.003***	28.41	.000***
Q31_1	5.82	.016**	34.57	.000***
Q31_2	2.11	.147	44.14	.000***
Q31_3	0.29	.593	17.68	.000***
Q31_4	0.27	.601	65.40	.000***
Q53_6	0.79	.375	93.47	.000***
Q53_9	0.51	.472	38.28	.000***

3.3.5 Reliability

Finally, we estimate three common reliability indicators for the 12-item polytomous car pride scale using the pooled sample of respondents from both U.S. cities (see Table 3.11). We find that the car pride scores show very good internal consistency, composite reliability, and maximal reliability, with all indices greater than 0.9.

Table 3.11: Single-level reliability indices for the polytomous car pride scale for two U.S. cities

Reliability index	Estimate	<i>S.E.</i>
Cronbach's alpha (α)	0.942	0.003
Composite reliability (ω)	0.937	0.003
Maximal reliability (H)	0.942	0.003

3.3.6 Discussion

In this section, we present the development and evaluation of a 12-item, 7-point Likert-scale survey measure of car pride for a sample of commuters in two U.S. metropolitan areas. This polytomous scale measures the attribution of both social status and personal image (two facets of pride) to both owning and using a car. Using a CFA framework, we demonstrate this measure's strong reliability, convergent validity, and divergent validity against a measure of general pride. Using multigroup CFA, we also demonstrate its weak (or metric) invariance between individuals in New York City and Houston, between car-owners and non-car-owners, and between car-users and non-car-users. While our car pride indicates some loss of model fit when imposing strong (or scalar) invariance, the overall effect is minimal and therefore judged to be an appropriate tradeoff to allow for standardized comparisons between these groups. Making this judgment, we overlook the fact that individuals in different cities and with different car ownership and use patterns may systematically respond to certain items slightly differently.

3.4 The Multilevel Dichotomous Car Pride Scale across Countries

Based on data from our international survey of $N = 41,932$ individuals in $n = 51$ countries (see Chapter 2), we investigate the psychometric properties of a multilevel, dichotomous car pride scale. The development and evaluation of this scale must account for two key features that differentiate it from the polytomous car pride scale: the categorical nature of its indicators and the multilevel structure of the data in the international sample. First,

we must employ a model estimation method that treats the observed indicators not as continuous (as in the polytomous car pride scale), but as binary. Second, we must adopt a multilevel confirmatory factor analysis (MCFA) approach that captures the nested structure of the data allowing individuals residing within the same country to have correlated error terms.

All models in this section are estimated using weighted least squares with mean and variance adjustment (WLSMV) and theta parameterization in Mplus version 8.1 (Muthén and Muthén, 1998-2018). Using this estimation method, loadings between the latent car pride factor and the binary observed indicators are estimated as probit regression coefficients. Furthermore, because the χ^2 value for WLSMV cannot be used for chi-square difference tests, when comparing models we use χ^2 values and correction factors from identical model runs estimated with weighted least squares with mean adjustment (WLSM) (Muthén and Muthén, 1998-2018).

3.4.1 Content Validity

The international survey contained 9 binary items designed to assess whether an individual attributes social status and personal image to driving and using a car, with 0 indicating disagreement and 1 indicating agreement. In order to ensure that our measure encompasses the full construct of car pride, items relate both driving and owning a car with two facets of pride (see Table 3.12). Synonyms for social status and personal image used in the items are taken from semantic studies of the two facets of pride (Tracy and Robins, 2007a,b). The items in this survey include and expand upon those statements used in previous studies to measure car pride using survey instruments (Zhao and Zhao, 2018). Therefore, we conclude that our survey items cover the full construct of car pride.

Table 3.12: Content covered by the 9 items in the dichotomous car pride scale

Item#	Statement	Type of Pride	Use or Ownership
Q14A	A car is a sign of social status		
Q14B	Driving meets my self esteem or personal image	Authentic	Use
Q14F	I gain respect from my peers because I drive a car	Hubristic	Use
Q14K	If more people saw me in/with my car, I would drive more	Hubristic	Use
Q15A	Having a car is connected with my social image		Ownership
Q15B	I feel proud of owning a car		Ownership
Q15C	I have a sense of accomplishment after buying a car		Ownership
Q15D	I have achieved in life and therefore I deserve to own a good car	Authentic	Ownership
Q15F	Others would see me as more successful if I owned a better or more cars	Hubristic	Ownership

3.4.2 Multilevel Construct Conceptualization

In formulating our multilevel conceptualization of the car pride construct, we first verify the necessity of multilevel analysis of the nested data structure. Prior to specifying any factor structure, we calculate the intraclass correlation coefficients (ICCs) of the 9 observed indicators. The item ICCs range from 0.022 to 0.086 (see Table 3.13). These are relatively small, but consistent with those found in other empirical studies with similar multilevel factor structures: minimum ICCs between 0.01 and 0.31 (mean = 0.09, standard deviation = 0.07) and maximum between 0.04 and 0.70 (mean = 0.30, standard deviation = 0.14) (Kim et al., 2016).

Table 3.13: Intraclass correlation coefficients (ICCs) for the 9 dichotomous car pride items

Item#	Statement	ICC
Q14A	A car is a sign of social status	0.046
Q14B	Driving meets my self esteem or personal image	0.038
Q14F	I gain respect from my peers because I drive a car	0.050
Q14K	If more people saw me in/with my car, I would drive more	0.022
Q15A	Having a car is connected with my social image	0.031
Q15B	I feel proud of owning a car	0.059
Q15C	I have a sense of accomplishment after buying a car	0.072
Q15D	I have achieved in life and therefore I deserve to own a good car	0.086
Q15F	Others would see me as more successful if I owned a better or more cars	0.032

Next we fit a null model with a saturated within-level model and no variances and covariances at the between-level. We find that this null model does not fit the data, particularly at the between-level: $\chi^2(45) = 192.406$, $p < .01$, RMSEA = 0.009, CFI = 0.996, TLI = 0.993, SRMR_W = 0.000, SRMR_B = 0.582. This indicates that there is significant between-level variance. Finally, we fit an independence model with a saturated within-level model and freely estimated variances, but no covariances at the between level. We find that this independence model does not fit the data either: $\chi^2(36) = 134.237$, $p < .01$, RMSEA = 0.008, CFI = 0.997, TLI = 0.994, SRMR_W = 0.000, SRMR_B = 0.443. This indicates that there are significant covariances at the between level. Therefore, we conclude that these data require multilevel modeling.

To evaluate the goodness of fit of our MCFA models, we use model fit indices— χ^2 , CFI, TLI, and RMSEA—estimated from the combined variance across both the within- and between-levels in MCFA. This standard approach to evaluating the goodness of model fit may not adequately detect misfit in the between-level model, particularly when the number of groups (effective between-level sample size) is small, as is the case with our sample of only 51 countries (Ryu, 2014). While literature recommends the calculation of model fit indices estimated from the combined variance across both the within- and between-levels in MCFA, the two methods available for calculating these level-specific fit indices (Ryu and West, 2009;

Yuan and Bentler, 2007) do not allow specification of models with invariance constraints across levels, which is needed to ensure comparisons of our car pride measure across countries. Given the central importance of specifying a measure of car pride that allows for cross-country comparisons, we opt for a rigorous investigation of invariance and accept a less rigorous approach to model fit evaluation. We do report level-specific SRMR, which can be easily computed for the within- and between-levels separately because it is derived from the deviation between the sample variance-covariance matrix and the model-implied variance-covariance matrix (Hsu et al., 2016).

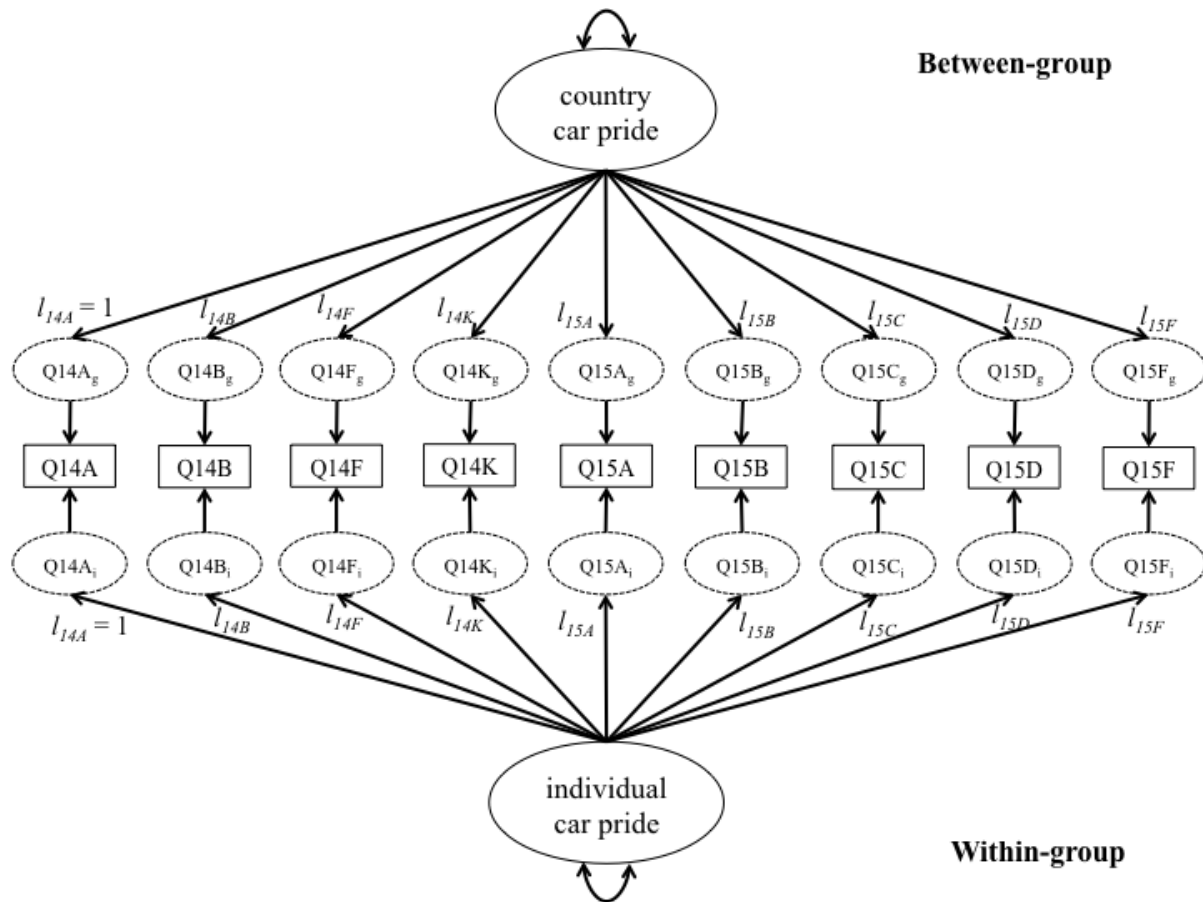
Having confirmed that these data require multilevel modeling, we must next consider the type of multilevel construct that we purport to measure. We conceptualize car pride as a *configural construct* that exists at the within-level as an individual construct and exists at the between-level as a country average (Stapleton et al., 2016). In other words, the between-level model in our MCFA represents country-level mean differences in the latent car pride, and the within-level model represents differences in individual deviations from the respective country means (Jak and Jorgensen, 2017). For such a construct, it is not expected that individuals within a group respond in the same way to the item measures, and their responses are not interchangeable (Kim et al., 2016; Stapleton et al., 2016). This conforms with our conceptualization of car pride, which we expect would differ among individuals within a country.

To correctly model configural constructs, the same factor structure (number of factors and their associated indicators) has to apply at both levels of analysis and factor loadings should be equal across the two levels (Stapleton et al., 2016) (see Figure 3.6). Specifying factor loadings to be equal across the within- (individual) and between- (country) levels is equivalent to imposing weak factorial invariance, a constraint called isomorphism in cross-cultural research (Jak et al., 2013; Tay et al., 2014). Across-level invariance ensures that the factors at different levels can be interpreted as the within-level and between-level components of the same latent variable (van de Vijver and Poortinga, 2002).

3.4.3 Measurement Invariance

Measurement invariance (or the absence of measurement bias) is a necessary condition for the comparison across groups (Jak et al., 2013). Furthermore, cross-level invariance is essential for the validity of a configural construct because the construct at the between-group level merely reflects the cluster aggregate of the construct at the within-group (individual) level (Kim et al., 2016; Stapleton et al., 2016). Therefore, we perform statistical tests of measurement invariance using a WLSM-corrected Satorra-Bentler scaled chi-square difference test (Satorra and Bentler, 2001, 2011). We adopt a free baseline approach and then compare the difference in model fit between an unconstrained MCFA model and the weak and strong factorial invariance models that constrain factor loadings and between-level variances across groups (Guenole, 2018; Jak et al., 2013) (see Table 3.14). Adopting the free baseline approach means that statistical non-significance indicates that fixing parameters to

Figure 3.6: Path diagram for the 9-item car pride MCFA modeled as a configural construct



Note: Imposing weak measurement invariance equates the factor loadings at the within- and between-group levels as depicted here, but allows the variances of the error terms of each indicator to be freely measure. Imposing strong measurement invariance also sets the error terms of each indicator at the between-group level to zero.

be equal across groups does not yield a statistically significant decrement in model fit so there is no bias (Guenole, 2018). Due to the sensitivity of chi-square difference testing to large sample sizes, we also assess changes in CFI and RMSEA (Cheung and Rensvold, 2002). In general, a change of more than .01 for CFI and .015 for RMSEA indicates problematic variance across groups (Chen, 2007).

We find that the 9-item dichotomous car pride scale exhibits statistically significant measurement bias across countries by a χ^2 difference test. While the unconstrained model has the least discrepancy between the model-implied and sample variance-covariance matrices. This statistical significance is unsurprising given our large sample size ($N = 41,932$), which can inflate χ^2 values based on trivial discrepancies between model and data. Considering additional indices of relative fit for each of the models in Table 3.14, we find that the strong

factorial invariance model provides the lowest RMSEA and within-level SRMR and the most consistently high CFI and TLI. In fact, the difference in approximate fit indices between the free baseline and strong invariance models ($\Delta\text{RMSEA} = -0.006$, $\Delta\text{CFI} = 0.004$) are well within recommended bounds for concluding invariance. However, imposing the constraints across countries increases the between-level SRMR to above recommended thresholds. Given that between-level SRMR has been shown to perform poorly in low ICC conditions such as those in our data (see Table 3.13) (Hsu et al., 2016), we overlook this poor SRMR_B and adopt the strong factorial invariance model to enable the consistent comparison of car pride across both individuals and countries.

Table 3.14: 9-item dichotomous car pride scale: model fit indices for invariance testing

	Unconstrained MCFA	Weak factorial invariance	Strong factorial invariance
χ^2 value (<i>d.f.</i>)	2130.561 (54)	1667.995 (62)	1731.651 (71)
WLSM correction factor	0.5077	0.6654	0.6686
RMSEA	0.030	0.025	0.024
CFI	0.977	0.982	0.981
TLI	0.969	0.979	0.981
SRMR_W	0.050	0.050	0.049
SRMR_B	0.075	0.166	0.404
Weak invariance vs. unconstrained: $\chi_D^2(8) = 16.23$, $p = .04$			
Strong invariance vs. unconstrained: $\chi_D^2(17) = 64.48$, $p < .01$			
Strong invariance vs. weak invariance: $\chi_D^2(9) = 69.36$, $p < .01$			

Partial Invariance

While the 9-item dichotomous car pride scale overall demonstrates (weak and) strong invariance across countries, we may be interested in which of the individual indicators exhibit bias across the 51 countries in our sample. To explore partial or indicator-specific invariance, we estimate models that constrain the factor loading to be equal across levels (weak invariance) and between-level variance to be zero (strong invariance) for each of the 9 dichotomous indicators. We compare this to a free baseline model by performing a WLSM-corrected scaled χ^2 -difference tests to detect partial invariance (see Table 3.15).

We find that items Q15C and Q15D violate the tests for both weak and strong factorial invariance, while items Q14K and Q15B violate only the test for strong factorial invariance. These item-specific invariance test results might suggest removing Q15C and Q15D from the scale, but the consideration of item bias must be balanced with consideration of other psychometric properties, such as validity and reliability.

Table 3.15: WLSM-corrected scaled χ^2 difference tests against free baseline model for partial or indicator-specific invariance

Item#	Weak factorial invariance		Strong factorial invariance	
	$\chi^2_D(1)$	p	$\chi^2_D(2)$	p
Q14A	1.030	.310	4.290	.117
Q14B	0.990	.320	2.847	.241
Q14F	0.934	.334	4.615	.100
Q14K	1.074	.300	5.352	.069*
Q15A	1.086	.297	2.853	.240
Q15B	0.977	.323	9.976	.007***
Q15C	3.106	.078*	13.325	.001***
Q15D	4.417	.036**	17.557	.000***
Q15F	0.075	.785	0.975	.614

Note: Significant bias detected at the * = 10% level, ** = 5% level, and *** = 1% level.

3.4.4 Convergent Validity

Having established car pride as a multilevel configural construct and having explored our scale's measurement invariance, we now consider our scale's convergent validity. We estimate the MCFA model specified in Figure 3.6 imposing strong measurement invariance. The estimated factor loadings are provided in Table 3.16.

Table 3.16: Multilevel confirmatory factor analysis results for the 9-item car pride scale enforcing strong measurement invariance

Item#	b	$S.E.$	β	R^2
Q14A	1.000		0.799	0.638
Q14B	0.863	0.026	0.753	0.568
Q14F	0.752	0.015	0.707	0.500
Q14K	0.439	0.012	0.504	0.254
Q15A	0.746	0.014	0.704	0.495
Q15B	0.534	0.012	0.578	0.335
Q15C	0.472	0.007	0.531	0.282
Q15D	0.429	0.008	0.495	0.245
Q15F	0.646	0.015	0.651	0.424

Notes: Overidentified model fit: $\chi^2(71) = 748.640$, $p < .01$, CFI = 0.980, TLI = 0.979, RMSEA = 0.015, SRMR_W = 0.049, SRMR_B = 0.404.

All factor loadings are statistically significant at $p < 0.001$.

We find that all survey items have standardized factor loadings close to, or greater than, 0.5, suggesting high correlations between the indicators and the hypothesized latent configural construct of car pride. While for many items, the standardized factor loadings are below

the ideal value of 0.7 and the $R^2 < 0.5$ suggest that the latent construct does not explain the majority of the item variance, these factor loadings are above the minimum reported in empirical studies: level 1 minimum (mean = 0.41, standard deviation = 0.20) and level 2 minimum (mean = 0.47, standard deviation = 0.25) (Kim et al., 2016). Therefore we suggest that our 9-item dichotomous car pride scale demonstrates reasonable convergent validity.

From this MCFA model, we can also calculate the ICC for our latent car pride factor. With within-level variance of 1.765 and between-level variance of 0.109, our latent factor has an ICC of 0.058, suggesting that the majority of variation in car pride is attributable to individuals, with only 5.8% of its variance occurring at the country-level.

3.4.5 Reliability

Finally, we want to consider the reliability of our multilevel, dichotomous measure of car pride. We calculate level-specific reliability measures for α , ω , and H (Geldhof et al., 2014). While these multilevel reliability measures have been derived for continuous indicators, we must introduce approximations to estimate analogous reliability measures for our dichotomous car pride scale. For dichotomous indicators residual variances at the within-level are not freely estimated. When the link function between the latent variable and the dichotomous indicators is logistic (as is the case with MLR estimation), the within- and between-level residual variances for each indicator are fixed at $\frac{\pi^2}{3}$. When the link function between the latent variable and the dichotomous indicator is probit (as is the case with WLSMV estimation and theta parameterization), the within-level residual variances for each indicator are fixed at 1 and the between-level variance is freely estimated. Using WLSMV estimation, we plug in the fixed value of 1 for each of the within-level item variances and use all other freely estimated parameters to calculate our level-specific α , ω , and H . In estimating level-specific ω and H , we additionally constrain the factor loadings to be equal across the within- and between-levels to be consistent with our conceptualization of car pride as a configural construct and impose zero between-level item residual variances to ensure strong factorial invariance.

Our approximate level-specific reliability indices and their standard errors are given in Table 3.17. We find that the multilevel 9-item dichotomous car pride scale demonstrates very good reliability at the between-level, with all reliability indices greater than 0.9. At the within-level, the scale demonstrates good reliability according to Cronbach's alpha and adequate reliability based on ω and H even with strong factorial invariance constraints.

Table 3.17: Approximate level-specific reliability indices (and standard errors) for the 9-item dichotomous car pride scale for the international sample

Reliability index	Within-level		Between-level	
	Estimate	<i>S.E.</i>	Estimate	<i>S.E.</i>
Cronbach’s alpha (α)	0.858	0.002	0.910	0.018
Composite reliability (ω)				
Unconstrained	0.872	0.002	0.925	0.016
Strong invariance	0.724	0.004	1.000 ^a	–
Maximal reliability (H)				
Unconstrained	0.880	0.002	0.945	0.013
Strong invariance	0.741	0.004	–	–

Note: ^a = fixed; – = not defined

3.4.6 Discussion

In this section, we present the development and evaluation of a 9-item, dichotomous (binary) survey measure of car pride across an international sample of 41,932 individuals in 51 countries. This dichotomous survey measure shares many of the same survey statements as the polytomous survey scale discussed in Section 3.3, and similarly covers the attribution of both social status and personal image (two facets of pride) to both owning and using a car.

The hierarchical structure of these international data as well as the binary nature of the survey responses make the evaluation of the dichotomous car pride scale particularly challenging. We use an MCFA framework that is only recently available in commercial software and for which best practice is established in the literature mainly for continuous indicators. Given our categorical indicators, we must make reasonable approximations of existing best practice when evaluating model fit, measurement invariance, and reliability.

In addition to their binary nature, our car pride indicators have low ICCs. While this is consistent with our conceptualization of car pride as a configural construct—consisting primarily at the individual-level, but with an aggregate, cultural effect at the country-level—research does suggest that MCFA estimators and model fit indices may not perform as well in low-ICC conditions, particularly when combined with small between-group sample size (such as our 51 countries).⁶ However, all existing studies exploring the effect of low-ICC conditions have been carried out for continuous indicators, so there is very little empirical evidence on how these issue may play out with categorical (in our case, binary) indicators.

⁶The association between lower ICC and greater biased parameter estimates in the between-level model are well documented in the literature (Hox and Maas, 2001; Lai and man Kwok, 2015; Lüdtke et al., 2008; Preacher et al., 2011). Lower ICCs have also been associated with lower convergence rates (Kim et al., 2012; Lüdtke et al., 2008). While early studies suggest that ICCs have no substantial impact on the effectiveness of traditional fit indices (Hsu et al., 2016), these traditional single-level fit indices are in general overpowered by the within-level model misspecification. Level-specific fit indices have been shown to be sensitive to low ICC conditions, particularly when the group size is low (Hsu et al., 2016).

With these caveats in mind, we estimate car pride factor scores for both individuals and countries, demonstrating their convergent validity and reliability at both levels of analysis. We also explore the invariance of our car pride measure across countries. While we find statistically significant differences in the interpretation of some of our items across countries, we impose strong (or scalar) invariance to enable us to compare car pride scores on the same scale across all individuals in all countries in our sample. This choice preferences standardization of our dichotomous car pride scale over contextualization, which is warranted given the global approach we plan to take with this measure in Chapter 6; however, if research questions were to probe further into the heterogeneity of individuals within any one country it may be more appropriate to relax this constraint.

3.5 Conclusions

This chapter presents the development of two survey measures of car pride—the attribution of social status and personal image to owning and using a car. The first survey measure is a 12-item, polytomous (7-point Likert-scale) measure of car pride piloted in our U.S. cities survey. Using CFA, we demonstrate this measure’s convergent and divergent validity and reliability and impose strong measurement invariance for individuals in different cities, with different household car ownership, and with different car use patterns. The second survey measure is a 9-item, dichotomous (binary) measure of car pride piloted in our international survey. Using MCFA, we estimate car pride factor scores for both individuals and countries and demonstrate their convergent validity and reliability. We impose strong measurement invariance across countries to allow for standardized international comparison.

Empowered with these well-validated measures for car pride, Chapters 5 and 6 of this dissertation can explore variations in car pride across individuals, cities, and countries and car pride’s relations with car ownership and use.

3.5.1 Limitations and Future Work

As a strong first step towards establishing standard measures for car pride, this chapter establishes key psychometric properties of two survey scales. However, the results presented here fail to address to areas that are addressed in the following chapters—namely, potential vulnerabilities of explicit measures and the establishment of predictive validity.

Vulnerabilities of Explicit Measures

While survey scales are the main method for measuring attitudes and other latent constructs in transportation and many other domains, these self-report (or explicit) measures have a few, well-documented vulnerabilities. First, individuals may respond to survey questions

based not on their actual attitudes, but instead on what they think others expect of them (social desirability bias) or what they want themselves to be (self-enhancement) (e.g., Greenwald, 1980; Steenkamp et al., 2010). In addition, respondents may not be able to identify or articulate their own attitudes (self-ignorance) (Wilson, 2002). Because of these vulnerabilities, researchers in the field of social psychology have developed implicit measures that try to capture attitudes that exist outside awareness that may differ from conscious or expressed survey responses.

When it comes to symbolic and affective motivations of car consumption (such as car pride), one might hypothesize that there is pressure to conform to social norms or a lack of self-awareness that might manifest in explicit, survey measures such as the car pride scales developed here. Therefore, in Chapter 4, we design and evaluate an alternative implicit measure of social status bias in car vs. bus choice.

Predictive Validity

While this chapter concerned itself with the content, convergent, and divergent validity of our survey measures, an additional form of validity—predictive validity—is also critical to establish. Rather than focusing on the internal measure structure, predictive validity focuses on the usefulness of the resulting score for explaining or predicting behaviors or other performance measures of consequence. In our case, we are interested in whether our measure of car pride is related to car ownership and use. Chapters 5 and 6 model the relations between car pride and car consumption for our U.S. cities sample and international sample, respectively. While these chapters focus on the behavioral implications of these models, the models also provide evidence of the predictive validity of our car pride scales (and therefore can be considered part of our measurement evaluation).

3.5.2 Reflections

Despite the prevalence of CFA studies in the transportation literature, there is still significant room to improve the current state of methodological and reporting practice. This chapter provides a review of both traditional and multilevel CFA and highlights the many psychometric properties that should be established for any measure of attitudes or other latent construct. We hope that this chapter will serve as a useful reference of “good practice” for future applications of CFA in transportation. In this section, we reflect on a few key considerations for researchers as they approach the measurement of attitudes and other latent constructs in the transportation domain.

First, good measure development starts from careful and systematic survey design, informed by existing theory and empirical evidence. In particular, survey statements should be designed to collectively cover the entire construct of interest; and if piloting the survey scale for the first time, redundancy of coverage across multiple statements may be wanted in case

certain items are later removed from the scale. This is how the measure’s content validity is established.

Once data is collected, measurement evaluation is carried out in a CFA framework. This evaluation goes far beyond the current practice of citing established thresholds for factor loadings and overall model fit (which speak to convergent validity); it should consider multiple indicators of measure reliability and should compare the measure to other related constructs (to establish divergent validity). In models where multiple latent constructs are used, this measurement evaluation should be carried out for each individual latent variable and their successive combinations.

All survey items (both used and discarded), as well as the CFA testing results should be reported to enable cross-study comparisons, replications, and standardization. In particular, unstandardized factor loadings can be used for score linking (or equating) to allow comparisons on the same scale across different samples (without needing access to the raw data) (e.g., Lee and Lee, 2018). This chapter demonstrates how a more systematic and transparent approach to measurement development and evaluation can help the transportation discipline build comprehensive theories of the interrelations among different attitudes and travel behavior, across people and place.

Simple Scoring of the Car Pride Scales

While factor analysis is the most rigorous way to score the polytomous and dichotomous car pride survey scales developed in this chapter and should be used by researchers to capture potential measurement error, this approach requires technical expertise that may be outside the capacity of many existing policymaking agencies. For policymakers, advocates, and others outside of the academic community, simpler scoring methods are available for our car pride scale. These simpler scoring methods allow our scale to be deployed and interpreted across individuals without advanced statistical methods; however, this comes at the cost of assuming no measurement error—in other words, little information on the measure’s reliability, validity, and invariance in the given context.

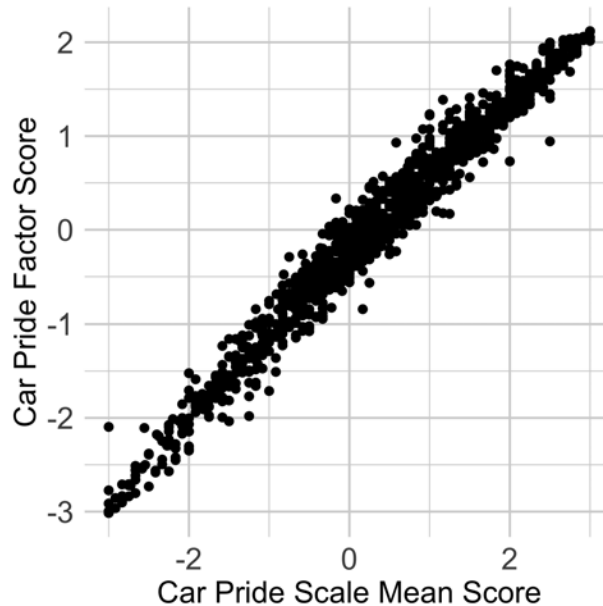
For the polytomous scale, responses to each of the 12 survey items can be scored from “strongly disagree” = -3 to “strongly agree” = $+3$ and then the mean can be calculated. For respondents missing responses to a few items, these items can be omitted from the calculation of the mean.⁷ This average has the additional advantage of being on a directly interpretable scale (as opposed to the normally-distributed, mean-centered factor scores output from the CFA). The resulting car pride average score would have a hypothetical minimum value of -3 , a hypothetical maximum value of $+3$, and a zero point indicating neutral.

For the individuals in our U.S. sample, we can compare the simple mean score across the 12 items of the polytomous scale with our factor scores estimated from the CFA (see Figure

⁷Missing items should not be coded as 0, because this would fail to differentiate between neutral responses and missing responses and could artificially pull the average score towards neutral.

3.7). We find that these measures are highly correlated ($r = 0.985$), suggesting that the mean score could be an appropriate substitute for the estimated factor scores in this sample.

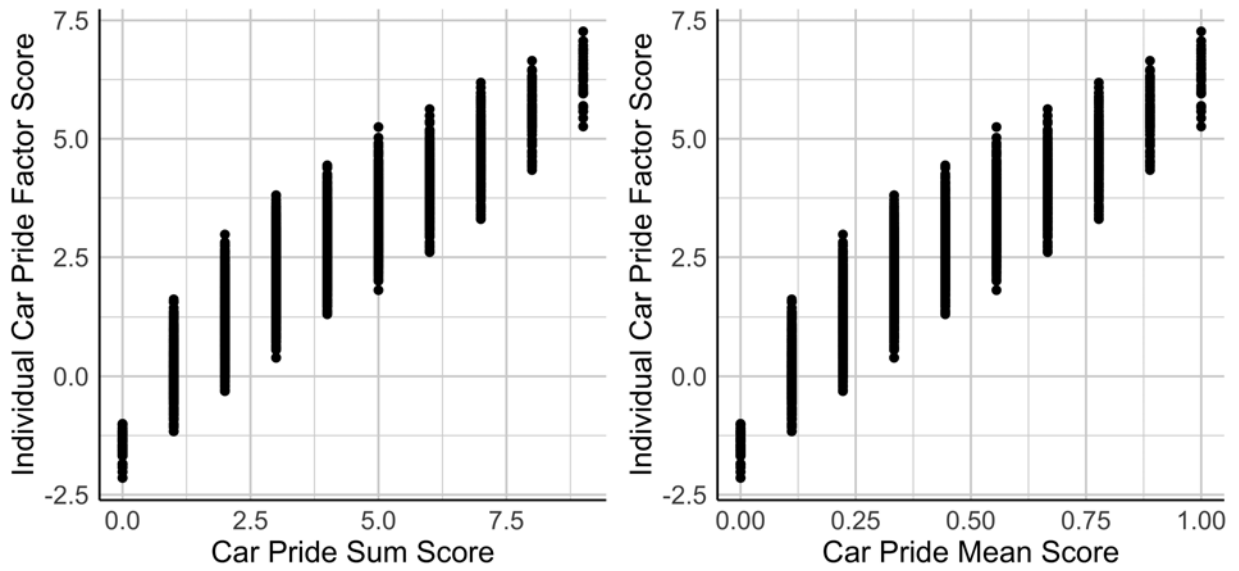
Figure 3.7: Comparison of factor scores with mean scores for the polytomous car pride scale in the U.S.



For the dichotomous scale, responses across the 9 survey items would be scored as “agree” = 1 and “disagree” = 0 then scored according to one of two methods. If there is no missing data across all statements and all individuals (hard to achieve in practice) responses across the 9 items can be summed together. The resulting sum car pride score would have a hypothetical minimum value of 0 (indicating disagreement to all statements) and a hypothetical maximum value of 9 (indicating agreement to all statements). If there are missing data, then an average score can be calculated across the 9 binary items. This mean dichotomous car pride score would have a hypothetical minimum value of 0 and a hypothetical maximum value of 1. In the absence of missing data, this sum score and this mean score will be perfectly correlated.

For our international sample (without missing data), we compare our individual-level factor scores estimated from the MCFA and the sum and mean scores calculated as outlined above (see Figure 3.8). While it is clear that our car pride factor scores provide greater differentiation among individuals than either of the simpler scoring methods, our car pride factor scores and these simple measures are highly correlated ($r = 0.952$). This suggests that either simpler scoring method could be used in lieu of the factor analysis results depending on the application.

Figure 3.8: Comparison of individual factor scores with simple sum and mean scores for the dichotomous car pride scale for our international sample



Chapter 4

Implicit Measure Development

The human mind can be divided into two general systems: one that processes information in a relatively conscious, controlled, deliberate, rule-based, reflective, rational, and logical fashion, and another that processes in a subconscious, habitual, spontaneous, automatic, effortless, associative, impulsive, emotional, and intuitive fashion (Greenwald and Banaji, 1995; Gregg and Klymowsky, 2013; Kahneman, 2011; Searle, 1992). While research on attitudes and behaviors has relied heavily on theory and measurement of the conscious (or explicit) side of cognition, a growing body of literature is investigating the subconscious (or implicit) pathways that can underlie certain behaviors. This literature suggests that it is not just factors inside awareness, but also those working outside awareness that help shape attitudes and drive behavior (Eagelman, 2011; Hassin et al., 2005).

In the transportation domain, theories of explicit cognition dominate. For example, much of the literature explaining travel behavior is based on rational utility-maximization. Even when exploring the relations between attitudes and travel behavior, many researchers cite the Theory of Planned Behavior, which posits that attitudes, subjective norms, and perceived behavioral control help determine intentions and behavior (Ajzen, 2005). By definition, however the Theory of Planned Behavior explains only consciously-made, or “planned” behaviors and may not be directly applicable to behaviors that are reactive, that are made without forethought, happen with a high degree of automaticity or by default, or which may be guided by subconscious attitudes (Fazio, 1990; Triandis, 1977). When it comes to car consumption, one might reasonably postulate that implicit (as well as explicit) cognitive pathways are at play. For example, habit may play a key role in mode choice and regular car use, while impulse may dominate split-second driving decisions. These behaviors may be governed more by automatic, subconscious processes than by conscious decisions. Therefore, when trying to understand how attitudes interact with these behaviors, it is important to match the type of measure to the cognitive pathway that governs the behavior of interest (Greenwald and Banaji, 1995).

Because of the dominance of theories of explicit cognition, the transportation domain relies on explicit measurement. Surveys or other self-report measurement techniques are the

workhorse of research into travel behavior and attitudes. While self-report is a flexible and economical means of eliciting useful information, three common reactions by respondents can compromise the validity of these results. First, if the attitudes or preferences being measured are controversial, respondents may respond to questions so as to please the researcher rather than truthfully representing their preferences and actions (Fisher, 1993; King and Bruner, 2000; Steenkamp et al., 2010). This is often referred to as social desirability bias. Second, respondents may deceive themselves with regard to their true attitudes, sometimes called self-enhancement or self-deception (Greenwald, 1980; Sedikides and Gregg, 2008). Third, respondents may simply not be able to identify or articulate their own attitudes—what scholars term self-ignorance (Wilson, 2002). All three of these vulnerabilities of self-report measures are manifestations of the same underlying fact: that respondents may hold attitudes outside awareness that differ from their conscious or expressed attitudes. When it comes to symbolic and affective motivations of car consumption (such as car pride), there may be pressures to conform to social norms or a lack of self-awareness that make it difficult for traditional stated and revealed preference survey methods to capture these attitudes.

Many existing methods help circumvent these limitations of self-report measures by modifying the design of survey instruments. These include techniques that encourage respondents to be honest (Lensvelt-Mulders et al., 2005; Tourangeau and Yan, 2007; Tourangeau et al., 1997) or subjective methods that gather qualitative data, such as laddering, projective techniques, or phenomenological interviews (Horeni et al., 2014; Mariampolski, 2001). Other techniques use respondent’s reaction time as an implicit measure of the strength of subconscious association or attitude. These quantitative measures can get around the vulnerabilities of self-report measures by being covert—meaning that respondents are unaware of how or what is being assessed—and robust—meaning that respondents are unable to modify their responses. These reaction time-based measures can also be relatively easily incorporated into existing statistical analysis or policy benchmarking. In particular, the Implicit Association Test (IAT) is the most scrutinized, validated, and commonly used implicit measure technique.

Given this motivation for considering implicit, as well as explicit measures in the context of car consumption, this chapter presents the development and evaluation of an implicit measure of the attribution of social status to cars vs. buses using our U.S. city sample (see Chapter 2). Section 4.1 introduces the Implicit Association Test (IAT) as the most commonly used method for capturing implicit associations and attitudes. This section reviews the literature on the psychometric properties of IAT scores and some practical and theoretical constraints to their interpretation and use. Section 4.2 briefly summarizes previous applications of the IAT (and its variants) in the transportation field. Section 4.3 presents the experimental design and scoring algorithm used for our car vs. bus social status IAT. In this section, we also evaluate the psychometric properties—reliability and validity—of our implicit measure of car pride compared to our explicit measure. Finally, Section 4.4 concludes with a discussion of the limitations of our IAT and lessons-learned for future IAT studies in the transportation domain.

4.1 The Implicit Association Test

The IAT is a computer-based measure in which users rapidly match two opposing concepts (such as car vs. bus) with two levels of an attribute (such as positive vs. negative social status). Each respondent is taken through a series of experimental blocks, consisting of multiple trials. In each trial, the respondent matches the item—word or image representing the concept or attribute—that appears at the middle of the screen in each trial to the pairing of concept and attribute at the upper left and right corners. If the item matches the pairing at the upper left corner, the respondent presses the E key; whereas the I key is used to match to the upper right corner. or the category on the right upper corner (see Figure 4.1). The category combination of concept and attribute on the upper right and left would remain on the screen for all matching trials in a block and then switch.

Figure 4.1: Example of an IAT experimental interface.



The IAT uses response times (from key strokes) to assess the degree to which the implicit association between the concept and attribute are jointly stronger or weaker than the implicit association between the opposite pairing. Those pairings that are easier for the respondent, manifested in faster responses, are interpreted as more strongly associated in memory than more difficult pairings, manifested in slower responses. From the difference in average response latency among different pairings of concept and attribute, one can derive a measure of the strength and direction of implicit association. This means that the IAT ranks or scales the two concepts relative to one another along the dimension of the specified attribute.

4.1.1 Psychometric Properties of the IAT

It is important to consider whether or not the implicit measure from the IAT is reliable and valid. As discussed in Chapter 3, reliability concerns the precision or consistency of the measure whereas validity concerns its accuracy. In this section we discuss the general evidence for the reliability, validity, and usefulness of the IAT as an additional method for trying to understand the attitudes, biases, and perceptions underlying behavior.

Reliability

Implicit measures from the IAT have been shown to be generally reliable and reproducible. Meta-analyses of IAT studies suggest that IAT scores (of various adaptations) usually reach internal consistency estimates (split-half correlations or Cronbach's alphas) between 0.70 and 0.90 (Hofmann et al., 2005; Schnabel et al., 2008). On the other hand, test-retest reliabilities obtained from the same respondents on different occasions are only moderate for the IAT (Nosek et al., 2007; Schnabel et al., 2008). In general, the reliability of IAT measures are not quite as high as those typically obtained for explicit measures because of the IAT's reliance on reaction times, which are inherently a "noisy" index (Gregg and Klymowsky, 2013). Even so, results from the IAT psychometrically outperform alternative implicit measures based on reaction times (de Houwer and de Bruycker, 2007). Furthermore, the internal consistency of the IAT can approach that of standard explicit measures if the IAT is lengthened (by increasing the number of trials) and administered under optimal conditions that improve respondents' attentiveness to the task (Gregg and Klymowsky, 2013).

Validity

When it comes to the IAT, content validity is established through careful experimental design and the informed choice of items used to represent the concepts and attributes. The validity of the resulting scores is often assessed by demonstrating that the implicit measure is related to (but distinct from) existing explicit measures (convergent validity) and predictive of behaviors of interest.

The motivation to supplement standard self-report measures with the IAT is based on the premise that the IAT can capture implicit or subconscious preferences, biases, or attitudes that traditional techniques cannot. Therefore, it is important to consider whether explicit survey measures and implicit (IAT) measures are really distinct. For the same construct, if the IAT and an explicit measure had near perfect correlation, this would suggest that the IAT is redundant. However, if there is zero correlation between the IAT measure and the explicit measure, one might distrust the validity of what the IAT is measuring. Meta-analysis across multiple disciplines and applications has shown that there is a nonzero, but small correlation (average $\rho = 0.19$) between the implicit measure from the IAT and explicit self-report measures of similar constructs (Hofmann et al., 2005). This modest correlation

suggests that the IAT and explicit measures typically assess different aspects of people's attitudes (Gregg and Klymowsky, 2013).

Furthermore, the IAT has been shown to predict outcomes of interest. A meta-analysis found that the overall predictive correlation of IAT is slightly smaller, but similar to that of self-report measures (Greenwald et al., 2009). This relative predictive validity of the IAT and self-report varies by application. When that application is such that responses to survey questions are most likely to be biased, the IAT outperforms self-report (Greenwald et al., 2009). In addition, several studies suggest that the IAT possesses incremental predictive validity, meaning that even when self-report measures are used as controls the IAT provides additional explanatory power (Richetin et al., 2007).

A Note on Cheating

Whereas explicit measures, such as self-report, probe the factors inside awareness, implicit measures, such as the IAT, probe and therefore tend to reflect factors outside awareness. As a first approximation, the consequence of this mapping is that explicit (self-reported) measures of attitude are susceptible to the biases of social desirability, self-deception, and self-ignorance because respondents are aware of and have control over their responses (Gregg et al., 2006). However, implicit measures of attitude, particularly the IAT, are shown to be more covert and are therefore relatively resistant to these same biases.

While IAT results can still be fabricated, they are more difficult to fake than self-report measures (Steffens, 2004). When simply instructed to fake their responses, respondents typically fail (Kim, 2003); they can only fabricate IAT results when they are coached about the IAT's modus operandi or have prior experience taking IATs (Fiedler and Bluemke, 2005; Steiger et al., 1990). This suggests that faking will rarely be successful, except among extremely motivated respondents who would be equally if not more likely to misreport on a survey (Czellar, 2006). Moreover, processing algorithms can now identify deliberate fakers on the IAT up to 75% of the time (Cvencek et al., 2010).

Invariance

The IAT has been applied extensively in comparative studies across people, cultural contexts, and time (e.g., Dunham et al., 2006). In such studies, respondents from different populations are typically asked to take the same IAT with identical stimuli, scores are determined from the pooled sample of all respondents, then means are compared across subsamples. However, in most of these studies it is assumed that the contrasting concepts and the attribute category used are equivalent across cultures (Szeto et al., 2009). This assumption must be informed by theory at the outset of experimental design; it is difficult to verify the IAT's invariance empirically after data is collected.

Therefore, one of the most important methodological issues for cross-cultural applications of the IAT is to establish construct equivalence to ensure that concepts, attributes, and the items used to represent them all have the same meaning and significance in their different contexts (Buil et al., 2012). For the IAT, this means considering whether different populations might view the IAT concepts differently as a function of their different cultural contexts. Much of this justification must be provided by theory and qualitative studies, but one way to test the invariance of concepts empirically is to pilot and compare scores across multiple IATs with different concepts compared against a known neutral or invariant category (e.g., Pinter and Greenwald, 2005). The items (words, images, or other stimuli) used to represent these concepts must also be instantaneously recognizable and interpreted equivalently across all experimental populations.

In addition to considering the equivalent representation of the IAT concepts across cultures, researchers must also consider equivalence of the IAT attribute dimension. This is particularly relevant for the most traditional IAT designs that match concepts along oppositional emotions (e.g., good and bad or pleasant and unpleasant). Some have argued that the experience of oppositional emotions differs between cultural groups, with some cultures experiencing higher co-occurrence of positive and negative affect (Goetz et al., 2008). Respondents from these cultures that exhibit emotional complexity may have less consistent association across these bidirectional attribute dimensions (Kim et al., 2008; Spencer-Rodgers et al., 2004). While this issue of invariant emotional complexity can also affect explicit measures using bipolar scales, such as Likert-format questions (Larsen et al., 2001, 2004), it is often unaddressed in cross-cultural applications of the IAT (Szeto et al., 2009).

4.1.2 When Might the IAT Outperform Traditional Self-Report Measures

Certain areas of behavioral research can gain insight from the IAT’s distinct investigation of implicit cognitive pathways. The IAT has particular predictive strength when trying to capture attitudes that are outside awareness or behaviors that are habitual or impulsive. These three strengths capitalize on the IAT’s relative resistance to the social desirability bias, self-deception, and self-ignorance that trouble self-report measures.

First, the IAT appears to “know” things about people they do not know themselves. In other words, even for respondents who would answer neutrally or as “undecided” on a survey, the IAT can capture implicit preferences that predict actual outcomes (Galdi et al., 2008). Second, the IAT appears to capture people’s propensity to engage in routine behaviors (without deliberately considering alternatives or consequences) (Conner et al., 2007). When it comes to car consumption, car use is often repetitive—such as commuting to school or work—so these behaviors may be thoughtless or automatic and therefore sustained outside awareness. Accordingly, the IAT, which accesses this less-conscious part of the mind, may predict these habitual behaviors better than self-report measures.

Third, the IAT appears to capture impulses that people usually, but not always, restrain (Gregg and Klymowsky, 2013). One might expect that mental processes outside of awareness are faster and more efficient than conscious ones, requiring fewer cognitive resources. Therefore, if people are mentally busy, deliberate and conscious thinking processes will be disrupted more than those outside of awareness (Gilbert, 1991). Under such conditions, human decisions become more impulsive and may be driven more by the symbolic or affective appeal of an alternative than by its rational merits (Shiv and Fedorikhin, 2002; Vohs and Faber, 2007). For example, driving a car requires many split-second decisions that are made impulsively. Particularly in complex and congested urban environments where driving is mentally taxing, these decisions—such as when to accelerate or decelerate, change lanes, or stop for a pedestrians at a crosswalk—may be made through implicit cognitive pathways. Evidence suggests that implicit measures may outperform self-report measures in predicting these impulsive behaviors (Hofmann et al., 2007).

4.1.3 Addressing Practical Challenges with the IAT

While the IAT has been shown to complement and even out-perform explicit measures in certain applications, its experimental design comes with a few practical challenges. In particular, the traditional IAT has two interrelated structural limitations:

1. The IAT makes pairwise comparison of two target concepts along an attribute dimension, so all associations are pairwise-relative.
2. The IAT score is not a standard or absolute metric, so it only permits the calculation of implicit associations relative to others in the study sample.

Comparative Assessment

The traditional IAT is a comparative assessment: matching two target concepts along an attribute dimension. For example, consider an IAT intended to measure social status associations for cars vs. buses. This IAT does not assess whether cars alone are more implicitly associated with positive or negative social status. Instead, it assesses whether the balance of positive-negative social status implicit associations differs for buses versus cars. Hence, implicit attitudes towards buses and towards cars both contribute to the IAT effect and cannot be distinguished. Furthermore, if a car vs. bus social status IAT yields a significant effect, this might be because (a) one mode was implicitly linked with positive social status and the other linked with negative social status, (b) both modes were implicitly linked with positive social status, with one more strongly than the other, or (c) both modes were implicitly linked with negative social status, with one more strongly than the other. Large effects would make possibility (a) most probable, but moderate effects would remain ambiguous (Gregg and Klymowsky, 2013).

The upshot is that the IAT is optimized for head-to-head comparisons, where the relative standing of a few key concepts—such as two different travel options—along a few key associative dimensions—such as comfort or social status—needs to be established. This makes IAT potentially useful to planners who want to assess the relative impact of a small number of possible alternatives.

To overcome the structural drawback of pairwise comparisons, researchers have devised variants of the IAT. While these variants may reduce reliability and sensitivity, they serve as means to circumvent the limitation of comparative assessment imposed by the original IAT. The most straightforward is the Single-Category IAT (SC-IAT), which simply omits one of the target categories from the original (Bluemke and Friese, 2008; Karpinski and Steinman, 2006). Using the SC-IAT allows a researcher or planner to understand how a single policy or concept lies along the attribute dimension. One might use this to assess general opinion on how fair or just is a single intervention. Another IAT variant, the Simple IAT (Blanton et al., 2006), features two neutral dummy categories, which are associatively independent of one another and of the two target categories. In this way, one might decompose the comparative association of the two concepts into individual associations; however, this approach has been criticized since it relies on what many see as a faulty assumption—that comparative preferences reduce to component attitudes (Nosek and Sriram, 2007).

The Go No-Go Association Test or GNAT (Nosek and Banaji, 2001), matches a single concept (car) along an attribute (positive-negative social status). In GNAT, respondents are tasked with pressing a key (“go”) if an item belongs to either category but to refrain from doing so (“no-go”) if it belongs to neither category. The go versus no-go decision on each trial is made within a tight timeframe (e.g., 600ms), and the block performance index is overall accuracy rather than average reaction time (Gregg and Klymowsky, 2013). Although a little more taxing than the original IAT, the GNAT nonetheless shows predictive validity above and beyond explicit measures (Eastwick et al., 2011).

Sample-Relative Metric

Another challenge to interpreting IAT results is the issue of a reference point or standard metric. Despite a well-established experimental framework that recommends a standard number of trials, presence of practice blocks, and so forth, different IATs often include slightly different sets of stimuli. Furthermore, even for identical IATs, scores are assigned relative to the study’s sample, which may be small and purpose-specific. As a consequence, there is no standard metric along which an individual IAT score can be interpreted (Blanton and Jaccard, 2006) and comparisons across samples would require access to raw (unscored) data.

The meaning of any individual IAT score is imprecise, but opinions differ on how much of a limitation this is given that the IAT successfully predicts “consequential” outcomes (Greenwald et al., 2006). It is generally accepted that larger scores point to stronger implicit preferences and are likely more diagnostic of behavior while smaller scores point to weaker

ones. It is possible to make rough interpretations of the meaning of individual scores by comparing them to natural or empirically established reference points. The most obvious reference point is zero, indicating that the individual has no implicit preference for one concept over another. A logical contrasting reference point could be the maximal score achievable on a reference IAT. Accordingly, a particular score on a comparable IAT could be scaled as a percentage of this maximal value. While one must make the simplifying assumption that the intervening metric is linear, this is also common practice for linking scores on conventional Likert-scales (Wright, 1999).

4.1.4 Addressing Theoretical Critiques to the IAT

While the above section discusses practical limitations of the IAT, in this section we address theoretical critiques to the IAT. Many have argued that, despite its name, the IAT is neither implicit nor does it measure implicit associations (e.g., Fiedler et al., 2006).

Self-report is generally taken to be an index of explicit attitudes while the IAT is generally taken to be an index of implicit attitudes. However, the distinction between explicit and implicit is not one-to-one, but instead is a matter of degree. Both self-report and the IAT can reflect the operation of conscious (foreground) and subconscious (background) processes; self-report just reflects the former more whereas the IAT reflects the latter more. In fact, explicit and implicit attitudes sometimes correlate substantially, in which case respondents cannot be said to be unaware of their implicit attitudes (Gawronski, 2009; Nosek, 2007). Despite this correlation, the IAT still could be implicit in the sense that it is a bias-resistant measure that provides information beyond self-report.

Some have claimed that the implicit associations underlying IAT results are not personal links in respondents' subconscious minds, but are merely passive reflections of social values (Han et al., 2006). Although an important consideration, these extrapersonal associations do not explain many IAT effects. For example, cultural knowledge does not correlate with IAT-assessed implicit preferences independently of self-reported explicit preferences (Nosek and Hansen, 2008a). To eliminate the confounding of social values on individual associations, there exist modified versions of the IAT that replace impersonal categories like "good" and "bad" with personal categories like "I like" and "I don't like." These personalized IATs have been shown to resist social manipulations. However, other studies suggests that personalized IATs may be somewhat more affected by foreground processes—required for judgments of truth and falsity (Gawronski and Bodenhausen, 2006)—than the standard IAT (Nosek and Hansen, 2008b). In other words, the more familiar respondents were with the concepts in the IAT, the greater the correlation between self-reports and a personalized IAT, but not between self-report and a standard IAT.

One confounding factor in interpreting IAT results may be that the concepts and attribute dimensions are mentally grouped together, not only by virtue of their shared meanings (the implicit association of interest), but also by virtue of their shared noticeability or familiarity. Such salience asymmetries are a sufficient basis for perceiving similarities between category

pairs (de Houwer et al., 2005). The concern arises that standard IAT effects are driven by salience rather than by associative effects (Rothermund et al., 2005). However, evidence suggests that IATs detect meaning above and beyond salience (Greenwald et al., 2005). Nevertheless, a few methodological improvements can be implemented to help eliminate this confounding factor. First, unnecessary sources of salience asymmetry should be eliminated by using marked rather than unmarked terms as attribute categories—for example, “safe” vs. “unsafe” should be avoided in favor of the use of contrasting terms like “safe” vs. “risky” (Gregg and Klymowsky, 2013). Second, if a salience asymmetry is suspected or unavoidable, then two parallel IATs should be run, with one incorporating the attribute categories of interest (e.g., “equitable” vs. “inequitable”) and the other incorporating asymmetrically salient control categories so that effects can be compared.

4.2 Previous Applications of the IAT in Transportation

While implicit methods such as the IAT have been used in psychology for decades to explore attitudes that are outside of respondent awareness or may be difficult for respondents to explicitly acknowledge, only recently have they been applied to understand travel behavior, particularly driver behavior and road safety (Fulcher et al., 2014). In particular, different variants of the IAT—particularly the Go No-Go IAT (GNAT)—have been recently applied to understand attitudes towards drunk driving (Martinussen et al., 2018), risk-taking behavior for pilots (Molesworth and Chang, 2009), drivers (Hatfield et al., 2008; Martinussen et al., 2015), and cyclists (Ledesma et al., 2015). In particular, Hatfield et. al. developed an IAT to measure implicit attitudes toward speeding and assessed the implicit measures compared to explicit measures in predicting behavior in a driving simulator (Hatfield et al., 2008). They concluded that the IAT could be a valuable tool in assessing driver attitudes and behaviors. Another published use of the IAT found that drivers hold both distinct explicit and implicit self-evaluations of driving ability, but the implicit associations are stronger; a surprising finding that they attribute to social desirability bias of explicit reporting on driver ability and risk-taking (Harré and Sibley, 2007; Sibley and Harré, 2009a,b).

Perhaps the most closely related to the current study is a recent investigation of drivers’ implicit attitudes towards other motorists and cyclists using a traditional pairwise comparative IAT design (Goddard, 2017). This study found that the implicit bias measured through an IAT added value to traditional survey methods. The implicit bias was found to have additional explanatory power in predicting intergroup attitudes, even after controlling for sociodemographics, individual travel behavior, and the built environment (Goddard, 2017).

While the GNAT has been applied to understand risk-taking behavior and aggression among pilots, drivers, and cyclists and the traditional IAT has been used to explore attitudes of drivers towards other road users, the use of implicit measures of attitudes have yet to become a mainstream tool for understanding attitudes and travel behavior. In the next section, we

partially address this research gap by presenting the experimental design and psychometric assessment of a traditional IAT purpose-built to measure social status for cars vs. buses.

4.3 The Car vs. Bus Social Status IAT

4.3.1 Experimental Design

Traditional IATs compare two target concepts along an attribute dimension. Designed to capture implicit car pride, our IAT compares cars and buses along the attribute dimension of positive-negative social status. The concepts and attributes are represented by items (usually words or images) that appear at the center of the screen and are matched to different concept-attribute pairings. When taking the IAT, respondents are encouraged to match the target concept and attribute as quickly as possible. Therefore, concepts, attributes, and the items used to represent them must be chosen to be instantaneously recognizable to the population of interest. Following best practice in clarifying the matching task (Nosek et al., 2007), we represent our concepts and attributes by different types of items: with images used for cars and buses and words used for positive and negative social status. These design choices are discussed in more detail below.

Concepts: Cars vs. Buses

While automobile travel is often considered prestigious, alternative modes such as walking, cycling, and mass transit are often stigmatized (Beirão and Cabral, 2007). Therefore, there were many potential options when choosing the comparator for car in our social status IAT. The comparator mode is an important experimental choice, as we would expect results comparing cars to buses to differ from results comparing cars to other modes, such as trains or walking. Ultimately, we choose to compare cars against (local) buses for our implicit measure of social status bias based on a number of considerations.

We decide not to compare cars to walking, because walking does not involve any material possession (other than the self) to which to attribute social status or personal image. Given previous research that suggests implicit associations exist between self and ownership (LeBarr and Shedden, 2017), comparison with walking might confound implicit associations with ownership of an object more generally with associations of the car specifically.

We additionally decide not to compare cars to bicycles because in many U.S. cities, travel distances and lack of bicycle infrastructure limit the types of trips that are served by bicycles. Given our focus on social status associations between modes, this asymmetry in instrumental value between car and bicycle could be problematic. This suggests that we should compare the car to another motorized form of transport that can serve a (more) comparable set of transportation needs.

Having decided to compare cars to a motorized mode, a natural comparison to the personalized mobility of a car would be fixed-route mass transit (rail or bus). In choosing fixed-route mass transit as the comparator, there may still be lingering confounding effects due to ownership, but at least both cars and their alternative involve the association of social status and personal image with an object rather than self.

From the mass transit modes, we choose to compare the car to local bus rather than rail. This choice is made for three reasons. First, anecdotal evidence suggests that the bus may be the most extreme foil to the car in terms of associations with social status. Buses, or “loser cruisers,” are more often portrayed as undesirable or inferior travel modes than rail (Litman, 2011). Of forms of mass transit, buses are generally thought to reflect most poorly on the social standing and personal image of their users.

Second, we choose bus rather than rail because of its equivalency as a concept and recognizability across our two target cities. Houston and New York City have vastly different mass transit infrastructure provision and use patterns (see Chapter 2). In particular, while Houston does have a small light rail system, it is not comparable to the vast commuter rail and subway system serving New York City. This raises concerns over whether the concept of rail is understood equivalently across our two city samples. On the other hand, local buses operate throughout both metropolitan areas. While neither system serves a significant portion of all trips in the metropolitan region, they are a common sight on the city’s streets (similar to cars). Therefore, we determine that buses are more likely to be a recognizable concept that does not vary in its interpretation and associations between our two target cities.

Third, choosing bus as the comparator to car widens the applicability of our social status IAT beyond the current sample. In the U.S. and around the world, rail transit is reserved to the largest and densest urban areas. Buses, on the other hand, are a much more common form of mass transit.

Having chosen to compare cars and buses based on the discussion above, the next design consideration is how to represent these modes as precise and distinctive concepts using a set of homogenous items. The authors choose to use black and white images to represent the concepts of cars and buses in the IAT trials (see Figure 4.2). These images are carefully selected and cropped to reduce variation and to eliminate any background or other salient features that would confound the association of the mode (such as a car on an open road vs. a bus stuck in traffic). To exclude associations related to specific car attributes, car images are selected for mid-priced and mid-sized vehicles in good condition photographed on a neutral background. In addition, we choose to use a standard 4-door sedan as the image of the car as opposed to an SUV, truck, minivan, or other type or luxury brand of vehicle. Similarly, to exclude associations related to specific bus attributes, bus images are selected to represent the typical 40-ft buses used for mass transit service in U.S. metropolitan areas, excluding articulated buses or intercity coaches.

Figure 4.2: Images selected to represent cars and buses in the IAT



While choosing the bus as the comparator to car provides wider applicability of our social status IAT to cities in the U.S. and elsewhere, it is important to recognize that the form of a “bus” may be different in different contexts. While the 40-ft bus (such as those pictured in Figure 4.2) is the standard across most U.S. cities and is easily recognizable to respondents in both of our target metropolitan areas of New York City and Houston, these images may not translate to other contexts. For example, our IAT may not be applicable to cities in Africa where minibus taxis are the dominant form of mass transit. These minibus taxis not only look different (suggesting the need for different images) but may also have different service characteristics (and therefore potentially different social status associations) than the 40-ft bus used in our IAT. Similarly, we might find that “buses” operating in protected, well-branded bus rapid transit (BRT) systems may have very different social status associations than the local buses operating in mixed traffic in New York City and Houston. Therefore, the choice of concept and how it is represented must be informed by the intended sampling frame.

Attribute Dimension: Positive to Negative Social Status

The attribute dimension that we explore spans from positive social status to negative social status. Positive and negative social status are represented by words for the IAT trials. An initial list of words was developed from published results of semantic studies and word association exercises for pride carried out in U.S. samples (Tracy and Robins, 2007a,b). This initial list was split into positive and negative columns, then each word was input into an online thesaurus and other synonyms and related words were collected. Unmarked terms (such as “unsuccessful”) were eliminated to avoid salience asymmetry. The words on both lists were then reviewed and critiqued by multiple researchers in the U.S., with specific care to involve reviewers who were both native English and English-as-a-second-language speakers. Words that were not immediately associated with positive or negative social status in either group were eliminated. From the remaining words, the most cohesive set of 8 were chosen for both positive and negative social status (see Table 4.1).

Table 4.1: Words selected to represent positive and negative social status in the IAT

Positive Social Status	Negative Social Status
Winner	Loser
Fame	Nobody
Success	Failure
Rich	Poor
Powerful	Loner
Pride	Shame
Respect	Creepy
Popular	Outcast

Again, the choice of attribute and its representing items is specific to our sampling frame. While research suggests that pride and its social valuation translate across cultures (Sznycer et al., 2017), the words used to represent this construct may vary across contexts. Therefore, if applying the car vs. bus social status IAT to a population outside the U.S., the list of words representing positive and negative social status in Table 4.1 should be appropriately translated and re-evaluated for use in the population of interest.

Having determined the concepts, attributes, and their representative items for our application, we next set-up the IAT experimental framework: a series of experimental blocks, each consisting of matching or association trials.

Blocks and Trials

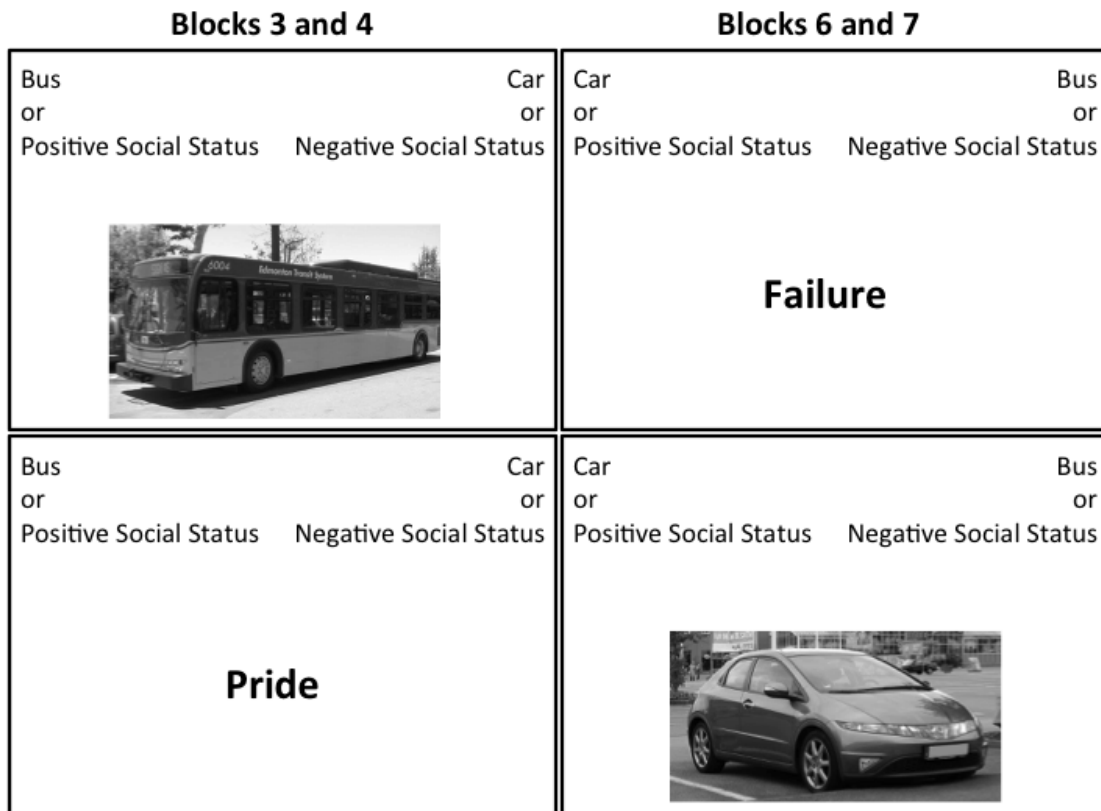
There are established best practices for the number and sequence of blocks and trials in an IAT (Nosek et al., 2007). In line with these standards, we implement a 7-block IAT that matches the concepts (car vs bus) with the attribute of social status. The first two blocks are training blocks during which the respondent familiarizes him/herself with the concept images and attribute words. For the experimental blocks 3, 4, 6 and 7, respondents are prompted to simultaneously classify a pairing of concept and attribute (see Figure 4.3). Table 4.2 summarizes this experimental process.

Table 4.2: Experimental process for the car vs. bus social status IAT

Block	# Trials	Items assigned to the Left	Items assigned to the Right
1	20	Bus	Car
2	20	Positive Social Status	Negative Social Status
3	20	Bus + Positive Social Status	Car + Negative Social Status
4	40	Bus + Positive Social Status	Car + Negative Social Status
5	40	Car	Bus
6	20	Car + Positive Social Status	Bus + Negative Social Status
7	40	Car + Positive Social Status	Bus + Negative Social Status

Previous studies have demonstrated that the order in which each concept is associated with the attribute dimension can result in some degree of bias in the measured association. For example, if car is associated with positive social status first (in blocks 3 and 4), the strength of the association between positive status and car is more likely to be over-estimated as respondents get used to the first side on which concepts are classified. Two methodological improvements can help to mitigate this effect (Nosek et al., 2005). First, the number of trials in the re-training block 5 can be set to 40 to provide respondents with additional practice for the switched classification side. Second, the order of blocks 3-4 and 6-7 can be randomly alternated across respondents to explicitly identify task order biases. We implement both of these methodological improvements in our IAT design.

Figure 4.3: Representation of the experimental blocks of the car vs. bus social status IAT



We implemented the IAT using an open source, web-based platform with a built-in error penalty (Mason et al., 2014). This platform automatically records the response times (in ms) of each trial in each block. In taking the test, if a respondent mistakenly matches the image or word at the center of the screen with the incorrect category, a red *X* indicates the error on the screen and they must correctly re-categorize the trial. The total time from when the item is displayed in the center to when the respondent makes the correct match is recorded. In contrast to common practice in other studies using response time measures, these mistake trials are not excluded from the calculation of the test score. In calculating the implicit measure, the conventional IAT algorithm uses error times together with those for correct responses—with the error times including the time required to produce the second correct response. In effect, this means that the error times contain a built-in error penalty that has been shown to improve scoring performance (Greenwald et al., 2003).

Scoring

From these raw response times, we can calculate the degree of implicit association between each concept (mode) and the attribute (social status). Traditionally, this degree is measured using the D-score algorithm (Greenwald and Banaji, 1995; Greenwald et al., 2003):

1. Use data from all experimental blocks (3, 4, 6, and 7)
2. Eliminate both correct and error trials with response times greater than or equal to 10,000 ms; eliminate subjects for whom more than 10% of trials have response times less than 300 ms
3. No additional extreme value treatment (beyond Step 2)
4. Compute mean of correct response times for all experimental blocks; replace each error response time with the block mean plus 600 ms
5. Compute a pooled standard deviation for all trials in blocks 3 and 6 ($SD_{3,6}$) and another for all trials in blocks 4 and 7 ($SD_{4,7}$)
6. Re-compute the means for each block including both correct and error response times; take the mean differences: $\mu_6 - \mu_3$ and $\mu_7 - \mu_4$
7. Divide each mean difference from Step 5 by their associated pooled standard deviations from Step 6; average the two quotients:

$$D = \frac{1}{2} \left(\frac{\mu_6 - \mu_3}{SD_{3,6}} + \frac{\mu_7 - \mu_4}{SD_{4,7}} \right)$$

This algorithm was chosen and updated based on tests considering different formulas to compute the difference between the mean, median, or logarithm transformed mean of the experimental blocks divided by the standard deviation; error treatments; criteria for respondent exclusion (i.e., outliers at the level of the sample); treatments of extreme latencies (i.e., outliers at the level of the participant); and the inclusion or exclusion of trials from different experimental blocks. The performance of the different algorithms was compared based on the correlations of the resulting IAT score with explicit measures of the same construct (convergent validity) or behavioral outcomes of interest (predictive validity) (Glashouwer et al., 2013; Greenwald et al., 2003). However, they did not examine systematically the effects of each of the different variations they included in each scoring method in terms of reliability. Recent studies have suggested minor modifications to the scoring algorithm that incorporate robust statistical practices to improve reliability and predictive validity (Chevance et al., 2017; Richetin et al., 2015). Based on these results, we implement the newly recommended DW-score algorithm to calculate our measure of implicit social status bias for cars vs. buses. The steps of the algorithm are as follows:

1. Use data from all experimental blocks (3, 4, 6, and 7)
2. Eliminate both correct and error trials with response times greater than or equal to 10,000 ms
3. Perform “statistical winsorizing”: replace the 10% fastest and slowest response times by the last untrimmed maximum or minimum response times for both error and correct responses
4. Compute mean response times for blocks 3 and 4 ($\mu_{3,4}$) and blocks 6 and 7 ($\mu_{6,7}$).
5. Compute one pooled standard deviation (SD) for all trials in blocks 3, 4, 6, and 7
6. Compute the mean difference: $\mu_{6,7} - \mu_{3,4}$

7. Divide the mean difference by the pooled standard deviation:

$$DW = \frac{\mu_{6,7} - \mu_{3,4}}{SD}$$

When calculating the mean response times in Step 4 of the scoring algorithm, we expect that those with higher car pride will be able to match the pairing of car and positive social status (and bus and negative social status) in blocks 6 and 7—the congruent pairing—faster than the incongruent association in blocks 3 and 4. Therefore, if an individual has an implicit association of positive social status and personal image for car and against bus, the mean difference in Step 6 will yield a positive result (and hence DW-score). On the other hand, a negative result corresponds to a positive social status bias towards bus and against car. This mean difference is divided by the standard deviation of response times across all testing blocks to account for underlying variability in the individual’s response times (Cai et al., 2004; Greenwald et al., 2003). The resulting DW-score can vary between -2 and 2, with zero indicating a neutral response or lack of any social status bias for one mode over the other.

4.3.2 Reliability

Having estimated the IAT DW-score for each individual in our U.S. city sample, we next consider the psychometric properties of this implicit measure for our specific application. First, we estimate the split-half reliability of our IAT measure. We randomly split the trails in each experimental block (3, 4, 6, and 7) into two halves. We then calculate the DW-score separately for each half and calculate their correlation. We find that our car vs. bus IAT has a split-half reliability of 0.82 across all individuals in the sample.

4.3.3 Validity

As is common practice with the IAT, we assess the validity of our implicit measure by comparing it first with our explicit measure of car pride and then with car ownership and use behaviors of interest.

Correlation with our Explicit Measure

To assess the convergent validity of our implicit measure, we estimate the correlation between our polytomous car pride survey measures and the IAT DW-score using a confirmatory factor analysis model.¹ We find that the correlation is positive, but not significantly different from zero by a two-tailed t-test: $\beta = 0.030$ ($p = .301$). This very small correlation suggests that

¹Model estimated using MLR; overall model fit of $\chi^2(60) = 502.206$, $p < .01$, RMSEA = 0.077, CFI = 0.944, TLI = 0.927, and SRMR = 0.043.

the implicit measure of social status for cars vs. buses measures something distinct from our explicit measure of car pride. This low correlation is likely partially explained by the fact that our IAT measure is comparative (car vs. bus), whereas our explicit measure only captures the attribution of social status and personal image to cars (ignoring any potential associations with buses).

This parallels findings in other applications of IAT in transportation, with the most similar study concluding that implicit attitudes towards cyclists relative to motorists are related to, but distinct from, explicit or stated attitudes (Goddard, 2017). This is further corroborated by extensive research into implicit biases in other domains in which the mean explicit-implicit correlation was 0.19 (Banaji and Greenwald, 2013; Hofmann et al., 2005; Lane et al., 2007). Even on issues where there is little social desirability or other effects that might call into question the validity of explicit measures, implicit methods have been shown to capture related, but distinct cognitions (Greenwald et al., 2009).

Correlations with Behavioral Outcomes

Next we consider the predictive validity of our implicit measure by investigating its correlation with respondents' self-reported car consumption (see Table 4.3). We again use confirmatory factor analysis, incorporating additional correlations among observed IAT DW-scores and car ownership and frequency of use.²

Table 4.3: Estimated correlations among implicit and explicit car pride measures and car consumption

	HH owns car (0/1)	Frequency of drive alone commute (days/month)
Implicit DW-score	0.039	0.058**
Explicit car pride scale	0.552***	0.367***

Note: Statistical significance of the two-tailed t-test against 0 at * = 10% level, ** = 5% level, *** = 1% level.

We find that the implicit DW-score is not significantly correlated with the binary indicator of household car ownership, but is positively and significantly correlated with the frequency of an individual's commuting by car. The fact that our implicit measure is correlated with use but not ownership may be a reflection of the type of cognition underlying these different dimensions of car consumption. This might suggest that car ownership is largely a conscious or considered decision, whereas car use may be more automatic, instinctive, or habitual.

By comparison, the explicit polytomous car pride scale shows much stronger correlation with both outcomes. Our explicit measure is even more strongly related to car ownership than

²Model estimated using WLSMV due to correlations specified with a categorical observed outcome variable; overall model fit of $\chi^2(82) = 517.565$, $p < .01$, RMSEA = 0.065, CFI = 0.848, TLI = 0.806, and SRMR = 0.040.

car use, again suggesting that ownership decisions may be more related to explicit cognition (involving detailed tradeoffs among costs and vehicle attributes) than use (involving less consequential day-to-day, habitual decisions).

4.4 Conclusions

This chapter motivates and introduces an Implicit Association Test (IAT) designed to measure social status associations between cars and buses. Applying a standard scoring algorithm, we derive an implicit measure and explore its psychometric properties within our sample of commuters in New York City and Houston. While the score demonstrates strong split-half reliability, low correlations between our implicit measure and our explicit measure of car pride established in Chapter 3 suggests very weak convergent validity. One reason for this low convergent validity could be the IAT's comparative assessment. Unlike our explicit, polytomous survey measure derived from Likert scale statements that relate only cars to social status and personal image, the IAT DW-score compares both cars and buses to positive and negative social status. Therefore, our implicit measure does not distinguish between a positive association for one mode and a negative association for the other.

Furthermore, our implicit measure demonstrates lower predictive validity than our explicit measure when it comes to car ownership and use decisions. This may suggest that car consumption, particularly car ownership, involves explicit rather than implicit cognitive pathways. However, simple correlations can be misleading in the context of bidirectional (or simultaneous) attitude-behavior relations. Therefore, in the next chapter, we explore in more depth the relation of our explicit and implicit measures with car ownership and use outcomes.

Overall, this chapter suggests that our polytomous survey measure of car pride is a more reliable and valid predictor of actual travel behavior compared to our implicit measure derived from the car vs. bus social status IAT. As Chapter 5 continues to explore the relations between car pride and car consumption in our sample of U.S. metropolitan commuters, this chapter suggests a healthy amount of skepticism when interpreting results from our implicit measure.

4.4.1 Limitations and Future Work

The results of the car vs. bus social status IAT presented here are discouraging. Low convergent and predictive validity call into question its interpretation as an implicit measure of car pride among our sample of commuters in New York City and Houston. While these results might suggest that car pride and its relations with car consumption are more explicit than implicit, they could also be due to experimental limitations. Future research could test alternative IAT designs for capturing the attribution of social status and personal im-

age to owning and using a car as well as the generalizability of these designs across more heterogeneous populations than the two U.S. cities included in this study.

Alternative IAT Designs

One potential explanation for the low validity of our car vs. bus social status IAT is the comparative nature of the measure. While the choice of bus as the comparator to car was purposeful, we might expect different results had we compared the car to other forms of mass transit, such as rail, or non-motorized modes, such as walking or biking. The performance of our car vs. bus social status IAT could be compared against alternative IAT designs that compare the car to other modes, particularly rail. This extension of existing work may be particularly important in the context of our U.S. sample, since the metropolitan areas of New York City and Houston have significantly different availability and use of different (mass transit) modes (see Chapter 2).

Future research may also consider variants of the traditional IAT experimental design that relax the constraint of comparative assessment. An implicit measure of association of social status and car could potentially be derived from a Single Category IAT (SC-IAT) or the Go No-Go IAT (GNAT). Such a measure may be more easily interpreted and modeled as car pride in the same way that we treat our explicit measure throughout the rest of this dissertation.

Generalizability

Additionally, future work is needed to explore the generalizability of the car (vs. bus) social status IAT (in its current or alternative form) to other populations. The choices of bus as the comparator mode, of images to represent cars and buses, and of words to represent positive and negative social status were all made to allow for generalization of our experimental design to most other medium and large cities within the U.S. Extending to populations outside the U.S., all of these parameters must be re-considered to ensure that the constructs and their stimuli are immediately recognizable and form clear associations for the individuals being studied.

4.4.2 Reflections

While the IAT has its critics, decades of research has shown it to be a well-validated and useful tool for capturing implicit associations and biases that are difficult to capture using traditional survey techniques. Despite its popularity, the IAT has seen only limited application within the transportation field. This chapter provides a review of the IAT method that may serve as a reference for future IAT applications in transportation. Throughout the chapter, we synthesize a large body of literature on the psychometric properties and design

parameters of the IAT. In this section, we reflect upon the experience of developing and evaluating one of the first traditional IAT applications in transportation. We highlight key considerations for researchers as they go through the process of deciding whether or not to apply an IAT and, if applying it, how to design it.

From the outset, researchers must consider which type of measure (explicit vs. implicit) and therefore which measurement tool (survey vs. IAT) is appropriate for their specific research question. Only when theory and professional judgment suggest that explicit measures may be biased or behaviors of interest are determined through implicit cognitive pathways should an IAT (or alternative implicit assessment) be used.

If the application suggests the use of an IAT, researchers should carefully consider whether a traditional IAT (limited by its comparative assessment) or a variant is most appropriate. In either case, the choice of concept(s), attribute, and the items (words or images) used to represent them must be made to evoke immediate and clear associations with the construct of interest. It is through this experimental design process, before any data is collected, that content validity of the IAT measure is established.

When choosing the concept, attribute, and their items, it is critical to consider the sampling frame. How people interpret concepts, attributes, and their representative items may vary based on the cultural and social context. Therefore, experimental design choices should be piloted to ensure that all constructs in the IAT are easily recognizable and clearly defined within the population of interest. When conducting cross-cultural studies, researchers must pay additional attention to potential invariance in the interpretation of the constructs in different populations.

Our experience from the development and evaluation of the car vs. bus social status IAT makes it clear that careful consideration of the above is a necessary, but perhaps not sufficient condition for achieving valid and interpretable results from an IAT study. While our experience is a cautionary tale, we want it to inform rather than discourage future research applying the IAT to better understand attitude-behavior relations in transportation.

Potential Applications of the IAT in Transportation Research

There are many areas of transportation research that might benefit from application of the IAT. Some of these applications may require the development and evaluation of purpose-built IAT designs to capture transportation-specific attitudes (such as the car vs. bus social status IAT). Others might leverage existing and well-validated IAT designs for capturing implicit associations of race, gender, or age to explore how these general biases influence transportation-related behaviors.

When it comes to development of new, transportation-specific IATs, the most promising applications are those in which behaviors of interest are likely determined through implicit cognitive pathways and/or explicit measures may be biased. A purpose-built IAT may be

useful for predicting travel behaviors that are likely to result from implicit (rather than explicit) cognitive pathways. This includes travel behaviors that are habitual (such as commuting behavior and default mode choice) or impulsive (such as split-second or risk-taking driving decisions). This line of research is a continuation of most of the existing applications of the IAT in the transportation domain.

A purpose-built IAT may also be useful for capturing transportation-related attitudes in certain populations where individuals may feel significant pressure to conform to social norms. In these cases, self-report measures of attitudes may be most vulnerable to social desirability bias and/or self-enhancement, whereas implicit measures may be more likely to capture the underlying attitude held by the individual. One such example could be an investigation of explicit vs. implicit pro-environmental attitudes and their relation to support for transportation policies, particularly in places such as California where public discourse values sustainability.

Alternatively, transportation researchers could leverage existing IATs to explore how general biases—such as racism, sexism, or ageism—influence transportation behavior. For example, implicit measures of racial bias may be used to explain differential yielding behavior of drivers to pedestrians of different races at crosswalks (Goddard et al., 2015) or wait times and cancellations for passengers of taxis or ride-hailing services (Brown, 2018). Implicit measures of gender- or age-related bias may be used to explain denied boardings or differential levels of service for women or the elderly in mass transit. This type of application is perhaps the easiest way to bring the study of implicit biases into the field of transportation, because it requires that researchers understand the IAT well enough to appropriately apply and interpret its results, but does not require the level of understanding needed to design and evaluate a new, purpose-built IAT design. This type of study could help build familiarity with the IAT as a research tool and help bridge existing gaps in the study of discrimination and equity between the fields of transportation and social psychology.

Chapter 5

Car Pride and its Bidirectional Relations with Car Ownership and Use Across Individuals in U.S. Cities

Car consumption—owning and using a car—has clear instrumental value, by providing flexible and private motorized mobility. However, the appeal of the automobile goes beyond instrumental transportation functions; the car holds important symbolic and affective meaning for its owners and users. One such symbolic meaning afforded to cars is that of social status and personal image—or pride. Many studies have demonstrated correlations between symbolic and affective meanings of cars (collectively referred to as ‘attitudes’) and car consumption, however current literature often fails to answer the causal question of whether attitude causes car consumption or vice versa. Understanding the relative strengths of the bidirectional relations between attitude and behavior has important implications for planning and policy, determining whether interventions should target the attitudes (car pride) through informational campaigns and marketing, or the behavior itself through interventions such as car ownership and use restrictions or fees.

With this motivation, this chapter investigates variations in car pride and their relation with car ownership and use behaviors. We build up from simple bivariate correlations and comparisons to a multivariate modeling approach that probes the bidirectionality of these attitude-behavior relations. We start by exploring variations in car pride across individuals and between cities in our U.S. sample (see Chapter 2). We compare two different ways of measuring car pride in this sample: the explicit polytomous car pride survey scale developed in Chapter 3 and the implicit DW-score measure presented in Chapter 4. We then compare these measures between car-owners and non-car-owners and between car-commuters and others to expose whether bivariate relations between car pride and car consumption warrant further exploration.

We then incorporate our car pride measures into structural equation models that explore bidirectional relations between car pride and car ownership and car use, respectively, in a

multivariate framework. Incorporating instrumental variables into our SEM, we demonstrate a practical way to probe the bidirectional relations between car pride (attitude) and car consumption (behavior) despite having only cross-sectional data. This approach allows us to quantitatively compare the relative strengths of the attitude-to-behavior and behavior-to-attitude relations, which has important implications for transportation research and practice.

5.1 Bidirectionality of Attitude-Behavior Relations in Transportation

As early as the 1970s, transportation research acknowledged that non-instrumental factors (such as attitudes) might play an important role in determining people’s travel behavior. Initial studies investigating the attitude-behavior relationship in transportation focused on assessing the direction of causation. Studies from this period used cross-sectional data in combination with two-stage least squares estimation (Dobson et al., 1978; Reibstein et al., 1980; Tardiff, 1977) or panel data (Tischer and Phillips, 1979). Without exception, these studies found reciprocal relationships between attitudes and travel behavior.

After this initial interest, research into attitude-behavior relations in the transportation domain declined until the late 1990s (Gärling et al., 1998). Since then, theoretical frameworks have been developed to study the effects of attitudes on behavior through the lens of psychological action models (Ajzen and Fishbein, 1980, 2005). The most prominent and influential framework is the Theory of Planned Behavior, which models behavior as a function of “behavioral intention”—a combination of “attitude toward the behavior,” “subjective norm,” and “perceived behavioral control” (Ajzen, 1991, 2005). This model, and extensions thereof, have been extensively applied in the transportation domain (Bamberg, 2006; Bamberg et al., 2003; Donald et al., 2014; Groot and Steg, 2007; Haustein and Hunecke, 2007; Heath and Gifford, 2002; Verplanken et al., 1994). It has also become popular to include attitudes in discrete choice models (Ben-Akiva et al., 2002). However, all of these approaches generally assume that attitudes influence behavior and not the other way around. While researchers typically acknowledge that a reverse relationship—from behavior to attitudes—may also exist (Ajzen, 2015), these possible reciprocal effects are rarely explored, even when panel data are available (e.g., Bamberg et al. (2003), with the exception of Thøgersen (2006)).

Recent work presents a new framework (in line with the Theory of Cognitive Dissonance) to study attitude-behavior (in)consistency over time and to assess the direction of causality between attitudes and behavior (Kroesen et al., 2017). Using data from a two-wave mobility panel, they estimate cross-lagged panel models and latent transition models. Their results corroborate the existence of a bidirectional attitude-behavior relationship, indicating that use of a mode and the attitude towards using that mode mutually influence each other over time. Contrary to conventional wisdom and commonly used modeling frameworks, however, they find that the effects of behavior on attitude are much larger than vice versa in their case study.

While cross-lagged panel models incorporating latent variables provide a powerful framework for exploring the bidirectionality of the attitude-behavior relationship, it requires longitudinal data (Kroesen et al., 2017). In this paper, we explore the bidirectional relations between attitudes and behavior using an alternative approach that does not rely on panel data. Using cross-sectional data in a commonly applied Structural Equation Modeling (SEM) framework (e.g., Golob, 2003), we introduce instrumental variables for our latent (attitudinal) construct and behavioral outcome, enabling us to simultaneously estimate and compare bidirectional attitude-behavior relations.

5.2 Structural Equation Modeling

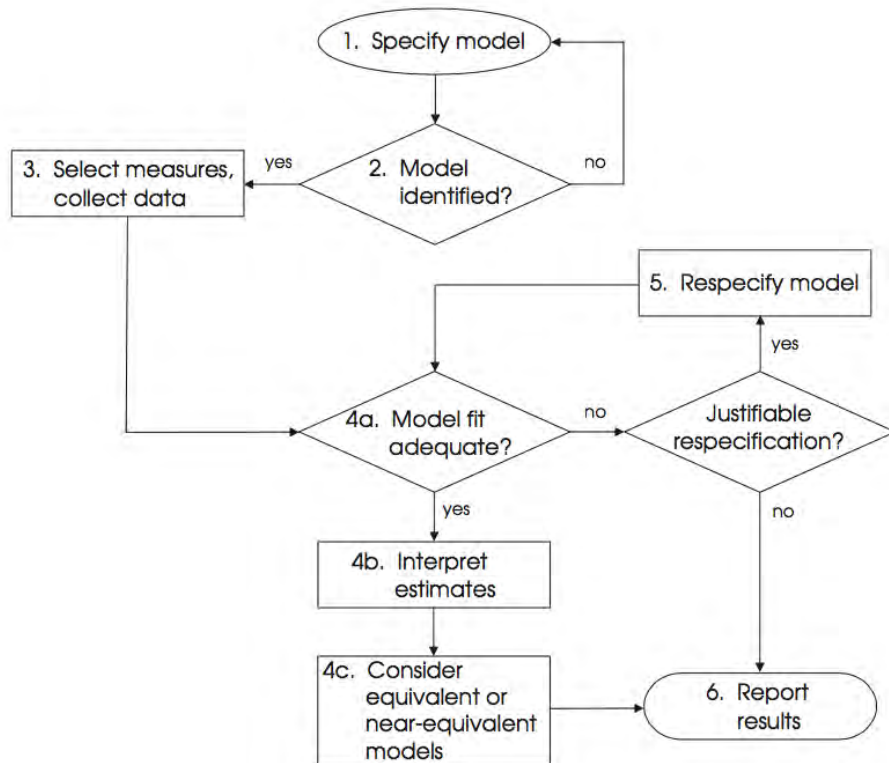
Structural equation modeling (SEM; also known as covariance structure analysis) describes a family of statistical models used to evaluate the validity of theories with empirical data. SEM takes a confirmatory approach, which determines whether a hypothesized theoretical model is consistent with the data collected to reflect this theory. The consistency is evaluated through model-data fit, which indicates the extent to which the postulated network of relations among variables is plausible.

In simple terms, SEM involves the evaluation of two models: a *measurement model* and a *path model* (Lei and Wu, 2007). The measurement model in SEM is used to measure unobserved latent variables from responses to a number of observed indicators using confirmatory factor analysis (CFA) (see Chapter 3). The path model is an extension of multiple regression that can simultaneously estimated a series of equations representing directed relations among multiple variables (either observed or latent). The pattern of inter-variable relations (and thus the equations to be estimated) is specified a priori based on theory, research design, prior studies, scientific knowledge, logical arguments, temporal priorities, and other evidence that the researcher can identify (Bollen and Pearl, 2013). In other words, the research incorporates directional assumptions as part of the model. Assumptions are often made in the form of what values a parameter can take, for instance setting the relation between two variables to zero if it is assumed there is no relation.

5.2.1 SEM Process

In general, every SEM analysis goes through a logical sequence of steps, including model specification (and identification), model estimation, model evaluation or testing, and (possibly) model modification (Kline, 2016; Lei and Wu, 2007). These steps are usually iterative because problems at a later step may require the researcher to return to an earlier step (see Figure 5.1). The goal of this process is to “discover” a model that makes theoretical sense, is reasonably parsimonious, and has acceptably close correspondence to the data (Kline, 2016). Only then can the researcher comfortably interpret the estimated parameter coefficients and whether or not they support the researcher’s hypotheses.

Figure 5.1: Flowchart of the basic steps of structural equation modeling



Notes: Justifiable respecification has a basis in theory or prior empirical results. Step 5 assumes that the respecified model is identified.

Entire textbooks are dedicated to explaining the nuances and specific issues arising at each step of the SEM process (e.g., Kline, 2016; Schumacker and Lomax, 2010). Here, we briefly review the most critical steps to provide context for interpreting the results presented later in the chapter.

Model Specification

Specification is the most important step in SEM, because results from later steps assume that the model—representing the researcher’s hypotheses—is basically correct (Kline, 2016). Specification of a model consists of identifying the variables that should (and should not) be included as well as how they each relate to one another, which is often conceptualized and communicated in graphical form. A sound model is based on theory, domain knowledge, and previous empirical research. Due to the flexibility in model specification, a variety of models can be conceived. However, these models must generally respect certain restrictions. In particular, the model must be identified; in other words, it must be theoretically possible to derive a unique estimate of every model parameter.

Model Estimation

This step involves using SEM computer software to estimate free parameters in the specified model from the data. Free parameters are estimated through iterative procedures to minimize a certain discrepancy or fit function between the observed covariance matrix from the data and the model-implied covariance matrix (Lei and Wu, 2007). Definitions of the discrepancy function depend on specific methods used to estimate the model parameters. The default estimation method for most SEM software is maximum likelihood, which relies on a normal theory discrepancy function (Bollen, 1989). While this works well in many applications, alternative estimators are available when dealing with continuous outcome variables with severely non-normal distributions or for categorical (including ordinal or nominal) outcome variables (Kline, 2016).

Model Evaluation

Once estimated, the researcher begins model evaluation by considering model fit to determine how well the model explains the data.¹ If the initial SEM does not fit the data very well, the researcher must skip the rest of this step and consider whether a respecification of the model is justified (see Figure 5.1). If the SEM does fit the data, then the researcher can begin to interpret the parameter estimates.

Fitting the data does not “prove” the relational assumptions in the model, but it makes them more plausible (Bollen and Pearl, 2013; Lei and Wu, 2007). Any such positive results need to be replicated and to withstand the criticism of researchers who suggest other models for the same data. This is because a well-fitting SEM may exist among many other models that are not tested but which may produce the same (or better) level of fit.

A Note on Causal Interpretations for SEM

Although SEM allows the testing of directed hypotheses, a well-fitting SEM model does not and cannot prove causal relations without satisfying the necessary conditions for causal inference, such as time precedence and robust relationship in the presence or absence of other variables (Bollen and Pearl, 2013; Pearl, 2000). However, SEM can be used with experimental data (including randomized treatments), longitudinal data, and other techniques developed for making causal inference from statistical models.

¹Established standards exist for goodness of overall model fit indices: a chi-square test statistic that is not statistically different from zero, CFI and TLI greater than 0.90 (moderate) or 0.95 (strong), RMSEA less than 0.06 and SRMR less than 0.08 (Gallagher and Brown, 2013; Hu and Bentler, 1999; Kline, 2016).

5.2.2 Reciprocal Relations in SEM

The flexibility of structural equation modeling allows researchers to specify and simultaneously evaluate bidirectional relations (or feedback loops) between variables. However, bidirectional or reciprocal relations between variables leads to endogeneity, which if ignored, could lead to parameter estimates that are biased (Antonakis et al., 2010, 2014). For cross-sectional data, the most common approach to the endogeneity issue is the use of “instrumental variables” to purge the endogenous predictor variable of bias (Bollen, 2012; Bollen and Noble, 2011).

Instrumental Variable Specification and Estimation

An instrumental variable represents exogenous sources of variance in the explanatory variable that are not correlated with the error term of the outcome. For a variable to be a good instrument, neither the explanatory variable nor the outcome variable has a direct or indirect effect on the instrument; nor does any other variable in the model affect both the instrument and the outcome variable (Mulaik, 2009).

In specifying any instrumental variable SEM model, consistency of parameter estimates can only occur if the cross-equation disturbances are estimated. One must build into the model the very correlation that we are trying to correct for with the instrumental variable: the correlation between the error term of the predictor variable (x) and the outcome variable (y) (Allison, 2018). This specification makes sense because if variables mutually influence each other, then it is plausible that they may share unmeasured causes. Estimating this correlation acknowledges any unmodeled common cause of x and y , which must be included in the model; failing to estimate it suggests that x is exogenous and does not require instrumenting (Antonakis et al., 2010).

Limited information estimators, such as two-stage least squares (2SLS) or instrumental-variable estimation, is recommended for simultaneous equations where one or more predictors are endogenous (Antonakis et al., 2010, 2014). This estimator is recommended because, if there is a misspecification in one part of a complicated model, this misspecification will not bias estimates in other parts of the model as would occur when using full-information estimators such as maximum likelihood (the usual estimator in most structural-equation modeling programs) (Bollen, 1996; Bollen et al., 2007). 2SLS estimation incorporating latent variables is available in Stata and R;² however, these programs cannot handle categorical outcomes with observed predictors. In such cases, applied researchers must settle for using full information estimators, such as maximum likelihood or weighted least squares. While more sensitive to model misspecification, these full information approaches have been shown to provide parameters equivalent to those produced by 2SLS for models with a single instrument for each endogenous variable (Allison, 2018; Burgess et al., 2014).

²See the MIIVsem package (Fisher et al., 2019) that builds on the popular `lavaan` package (Rosseel, 2018)

Reciprocal Causation

Controversy has arisen over estimating reciprocal causation in SEM models with concurrent measurement (cross-sectional data) due to the absence of temporal precedence in such designs (Wong and Law, 1999). Without temporal precedence, some argue that reciprocal relations represent an instantaneous cycling process that does not reflect a causal mechanism in reality (Hunter and Gerbing, 1982). But the absence of temporal precedence may not always be a liability when estimating reciprocal causation (Kline, 2016). In particular, it may be justifiable when the time lag between the relations is very short or when the bidirectional relations of interest meet the assumptions of equilibrium and stationarity.

Estimation of bidirectional relations with cross-sectional data relies on the fact that equilibrium has been achieved—that changes in the system underlying reciprocal causation have already manifested their effects and that the system is in a steady state (Kline, 2016). If the equilibrium assumption is violated, computer simulation studies suggest parameter estimates can be severely biased (Kaplan et al., 2001). The equilibrium assumption cannot be evaluated statistically, but must instead be substantively argued (Kaplan et al., 2001). Another requirement is that of stationarity—that the basic causal structure does not change over time (Kline, 2016).

5.3 Variations in Car Pride across Individuals and U.S. Cities

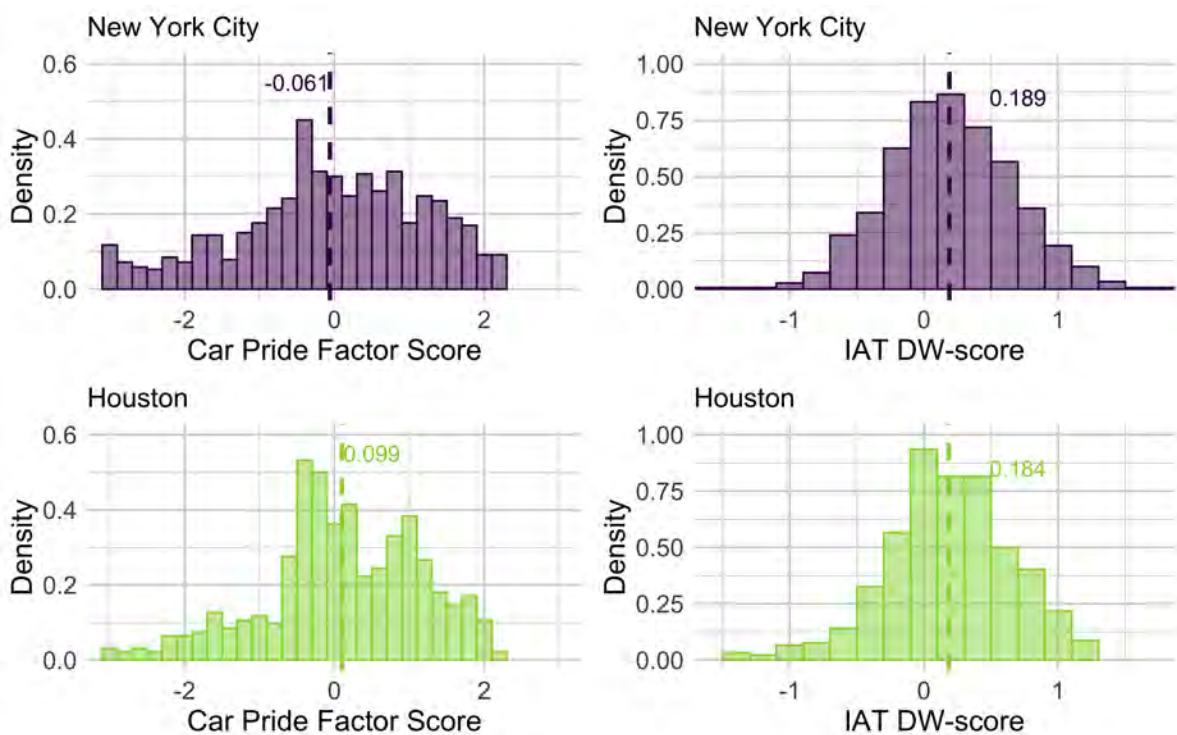
For our sample of commuters in New York City and Houston (see Chapter 2), we have validated both a polytomous survey measure of car pride and an implicit measure of social status associations for cars versus buses (see Chapter 3). In this section, we look at variation in these two measures across individuals and cities. First, we compare the means of our car pride scores between residents of New York City and Houston.³ Next, we estimate two structural equation models that regress our polytomous car pride score and IAT DW-score, respectively, on a set of individual and household sociodemographic variables. This multivariate approach provides us with a more nuanced picture of what types of individuals exhibit stronger car pride across our two measures and allows us to test whether observed city effects remain after controlling for the individuals that make up our subsamples.

³We can compare the polytomous car pride scale scores across cities because we have shown the scale to be invariant in Chapter 3). Estimated factor scores for each individual are exported from the CFA and then treated as observed for descriptive analysis.

5.3.1 Mean Car Pride Scores across Cities

First we consider how our explicit and implicit measures of car pride vary between individuals residing in the New York City or Houston metropolitan statistical areas (see Figure 5.2). Comparing the average car pride measures across cities, we find that respondents in New York City have a lower explicit car pride ($\mu_{\text{NYC}} = -0.061$) than respondents in Houston ($\mu_{\text{HOU}} = 0.099$) and that this difference is statistically significant by a two-tailed t-test: $t = -2.41, p = .016$. However, we find no statistically significant difference in mean IAT DW-scores across the two cities: $t = 0.188, p = .851$.

Figure 5.2: Distributions of explicit and implicit measures of car pride across individuals in New York City ($n = 779$) and Houston ($n = 471$)



Note: Car pride factor scores are standardized around a mean of zero across all individuals in the sample.

The difference in our polytomous car pride scale across the two cities might suggest that the different urban and transportation contexts of New York City and Houston contribute to differences in attitudes and social norms among their residents. It also underscores the importance of exploring city-to-city differences in car pride and its relations to car consumption. However, a simple comparison of means does not tell us whether observed differences across cities are due to contextual factors or are simply artifacts of differences in the individuals living in these two cities. To help answer this question, the next section adopts a multivariate approach that includes a city indicator after controlling for other individual and household sociodemographic variables.

5.3.2 Regressions on Sociodemographic Variables

Given the limitations of bivariate relations such as mean comparisons, we next run two structural equation models that regress each of our car pride measures on all of the individual and household sociodemographics included in our survey, allowing all observed variables to correlate.⁴ We include a binary city indicator (1 for New York City; 0 otherwise) to capture any city contextual effects not explained by the sociodemographic variables of the individuals in the two city subsamples.

Explicit Car Pride Factor Score

First we consider how sociodemographic characteristics relate to our explicit car pride factor. We find that age, gender, student status, household size, and household income are all significantly predictive of an individual's level of car pride (see Table 5.1). Interpreting the sign of the estimated coefficients, we find that those who are younger, male, students, and from larger households with higher incomes report higher car pride.

Considering the city indicator, we find that being from New York City is predictive of lower car pride than being from Houston, even after controlling for individual and household sociodemographics of the subsamples ($b = -0.218$, $S.E. = 0.069$, $p = .002$, $\beta = -0.087$). This parallels and reinforces the results of the comparison in mean car pride scores across the two city subsamples seen in Figure 5.2. While it is possible that other characteristics of the individuals residing in the two cities not captured by our sociodemographic variables explain the differences observed across cities, this result suggests that car pride may be related to city contextual effects. Car pride may be lower in New York City because the more robust rail-based public transit network allow individuals to be less car-dependent. Houston, on the other hand, provides few alternatives to owning and using a car, so individuals in this more car-dependent context may create greater symbolic attachment to their vehicles (in line with the Theory of Cognitive Dissonance).

While the effects discussed above are statistically significant, we find that all of the variables in the model combined only explain about 16% of the variance in explicit car pride scores across all individuals in the sample ($R^2 = 0.164$, $S.E. = 0.021$, $p < .01$). This suggests that there is room for future research into other factors (not captured in our set of individual sociodemographic and city effect) that explain an individual's car pride. This might suggest that an individual's car pride is related more to an individual's environment and general personality than their sociodemographic characteristics. For example, an individual's social networks or other attitudes may relate to an individual's car pride. In fact, adding our explicit measure of each individual's general (authentic) pride derived in Chapter 3 as an additional predictor increases the R^2 value to 0.233.

⁴For the explicit measure, the latent car pride factor and the structural regression relations are estimated simultaneously to control for potential measurement error. For the implicit measure, the DW-scores are treated as observed and is therefore assumed to be measured without error.

Table 5.1: Regression of the polytomous survey measure of car pride on individual and household sociodemographics

Predictor	<i>b</i>	<i>S.E.</i>	<i>p</i>	β
Age (yrs)	-0.026	0.003	.000***	-0.327
Female (0/1)	-0.276	0.070	.000***	-0.112
Caucasian (0/1)	0.121	0.075	.107	0.046
Education (yrs after HS)	0.012	0.013	.340	0.030
Full time employed (0/1)	-0.024	0.079	.761	-0.010
Student (0/1)	-0.510	0.147	.001***	-0.105
Number of people in HH	0.127	0.032	.000***	0.151
Number of HH working adults	-0.052	0.058	.371	-0.045
HH income (\$1000)	0.002	0.001	.002***	0.091
New York City (0/1)	-0.218	0.069	.002***	-0.087

Notes: HH = household; *b* = unstandardized coefficient; *S.E.* = standard error; *p* = p-value of two-tailed t-test against $b = 0$; β = standardized coefficient.

Statistical significance at * = 10% level, ** = 5% level, *** = 1% level.

Overidentified model fit: $\chi^2(159, N = 1, 250) = 797.423$, $p < .01$, CFI = 0.930, TLI = 0.918, RMSEA = 0.057 with 90% confidence interval = [0.053, 0.061], SRMR = 0.042.

Implicit DW-score

We repeat the same modeling procedure for our implicit measure derived from the car vs. bus social status IAT. We find that only 1.3% of the variance in individual IAT DW-scores is explained by the individual and household sociodemographics included in our survey ($R^2 = 0.013$, $S.E. = 0.006$, $p = .051$). Of these sociodemographics, we find that only gender, the number of working people in the household, and student status are statistically significant in predicting the individual's DW-score. In particular, we find that being female, being a student, and having more working adults in the household predict higher implicit association of car with positive social status and bus with negative social status. We find that an individual's IAT DW-score is not significantly related to their age, educational attainment, employment status, their household income, or their resident city. The insignificance of the city fixed effect is unsurprising given the lack of statistical significance in the average IAT DW-score between the two city subsamples. Furthermore, we caution against detailed interpretations of these findings given our concerns over the implicit measure's validity expressed in Chapter 4.

Table 5.2: Regression of the car vs. bus social status IAT DW-score on individual and household sociodemographics

Predictor	<i>b</i>	<i>S.E.</i>	<i>p</i>	β
Age	0.002	0.001	.148	0.049
Female (0/1)	0.053	0.029	.062*	0.056
Caucasian (0/1)	0.057	0.032	.070*	0.056
Education (yrs after HS)	0.001	0.005	.784	0.009
Full time employed (0/1)	0.025	0.033	.444	0.026
Student (0/1)	0.115	0.052	.027**	0.062
Number of people in HH	-0.005	0.010	.632	-0.016
Number of HH working adults	0.024	0.010	.015**	0.054
HH income (\$1000)	0.000	0.000	.757	0.010
New York City (0/1)	0.006	0.028	.830	0.006

Note: Completely saturated model: does not allow for estimation of model fit.

5.4 Car Pride of Car Owners and Car Users

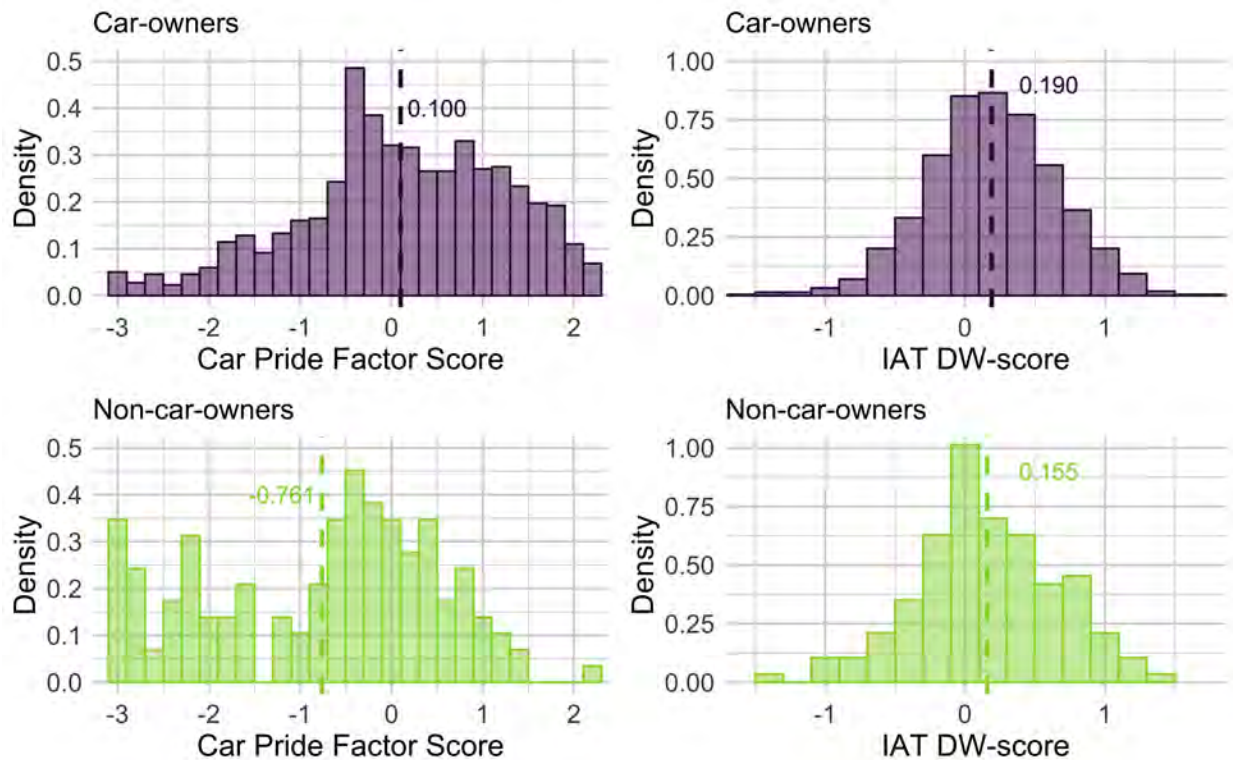
Having explored variation in car pride across cities and individuals, we now turn our attention to the relations between our measures of car pride and car consumption—car ownership and use. We start from basic descriptive statistics, considering whether our explicit and implicit measures of car pride show significant differences across key car consumption groups: between car-owners and non-car-owners and between those who drive alone as their most typical commute versus those who commute by other modes. These descriptive statistics allow us to see whether relations between car pride and car ownership and use warrant further exploration.

5.4.1 Car-Owners vs. Non-Car-Owners

We first consider the distribution of explicit and implicit car pride between individuals whose households do own cars (car-owners, $n = 1029$) and those whose households do not own cars (non-car-owners, $n = 144$) in the full sample of residents in both New York City and Houston (see Figure 5.3).⁵ Looking at our explicit measure, we find that car-owners ($\mu_{\text{car-owner}} = 0.100$) have a higher average car pride than non-car-owners ($\mu_{\text{non-car-owner}} = -0.761$) and that this difference is statistically significant by a two-tailed t-test: $t = 7.70$, $p < .01$. This parallels findings from a sample of individuals in Shanghai, China that used a related, but different survey to measure car pride (Zhao and Zhao, 2018). However, we find no statistically significant difference in mean IAT DW-scores between car-owners and non-car-owners: $t = 0.844$, $p = .399$.

⁵Subsetting car-owners and non-car-owners further by city produces sample sizes too small for meaningful comparisons.

Figure 5.3: Distributions of explicit and implicit measures of car pride across individuals whose households do ($n = 1029$) and do not own cars ($n = 144$)

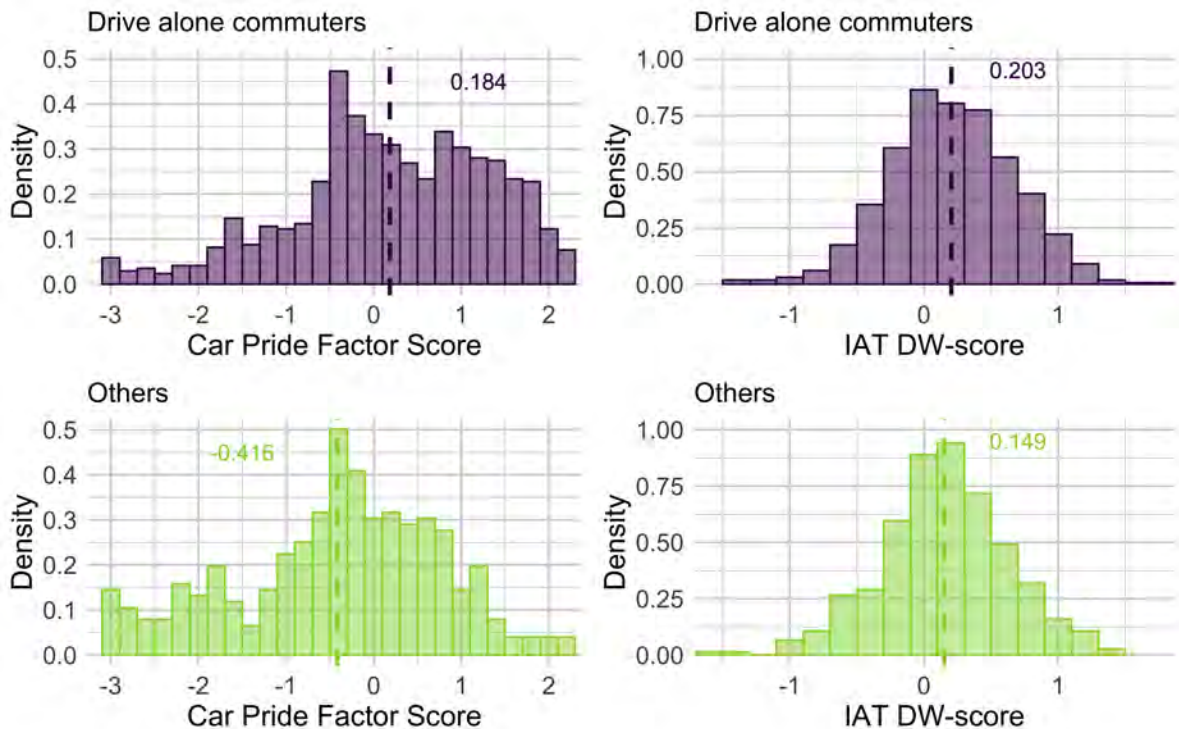


5.4.2 Drive Alone Commuters vs. Others

We next consider the distribution of explicit and implicit car pride between individuals who select drive alone as their primary commute mode ($n = 859$) and those who select some other mode ($n = 391$) in the full sample of individuals in both New York City and Houston (see Figure 5.4). We use commute mode choice as one way of differentiating car-users from non-car-users. Looking at our explicit measure, we find that drive alone commuters ($\mu_{\text{drive alone commuters}} = 0.184$) have a significantly higher average car pride than commuters by other modes ($\mu_{\text{others}} = -0.416$): $t = 8.38$, $p < .01$.

We also find a marginally statistically significant difference in mean IAT DW-scores between drive alone commuters: $t = 1.890$, $p = .059$. We find that drive alone commuters hold higher associations of positive social status with car and negative social status with bus ($\mu_{\text{drive alone commuters}} = 0.203$) compared with commuters by other modes ($\mu_{\text{others}} = 0.149$).

Figure 5.4: Distributions of explicit and implicit measures of car pride across individuals who do ($n = 859$) and do not ($n = 391$) drive alone as their primary commute mode



5.4.3 Discussion

The fact that we see significant differences in the implicit DW-score across car-users but not car-owners parallels the findings in Chapter 4, which showed that our implicit measure is correlated with use but not ownership. This result may be a reflection of the type of cognition underlying different types of car consumption, suggesting that car ownership is largely a conscious or considered decision, whereas car use may be more automatic, instinctive, or habitual. On a more practical level, it suggests that our implicit measures of social status association of cars versus buses may only be a relevant predictor in models of car use behavior, but not car ownership. This parallels findings from Chapter 4.

Considering our polytomous car pride survey measure, these simple subsample comparisons demonstrate that explicit car pride is positively related to an individual's car consumption—both ownership and use. However, they cannot tell us whether these relations persist after controlling for other related and potentially confounding variables (such as household income) nor can they tell us how the attitude and behavior might reinforce one another. Therefore, in the next two sections, we adopt a multivariate structural equation modeling approach incorporating instrumental variables to estimate and compare the bidirectional relations between car pride and car consumption: first car ownership and then car use (controlling for car ownership).

5.5 Bidirectional Relations between Car Pride and Car Ownership

In this section, we use our polytomous car pride scale (explicit measure) to explore the relations between an individual's level of car pride and whether or not their household owns a vehicle. Here we might reasonably expect bidirectional relations, with higher car pride contributing to a greater likelihood of car ownership, and, conversely, owning a car reinforcing car pride.

5.5.1 Analytic Plan

We apply structural equation modeling techniques with instrumental variables as a practical way to probe the bidirectional relation between car pride (attitude) and car ownership (behavior) in cross-sectional data. We estimate the model in Figure 5.5, which simultaneously estimates the direct path from car pride to household car ownership and the reverse path from household car ownership to car pride while controlling for individual and household sociodemographic characteristics. This approach allows us to quantitatively compare the relative strengths of the attitude-to-behavior and behavior-to-attitude relations.

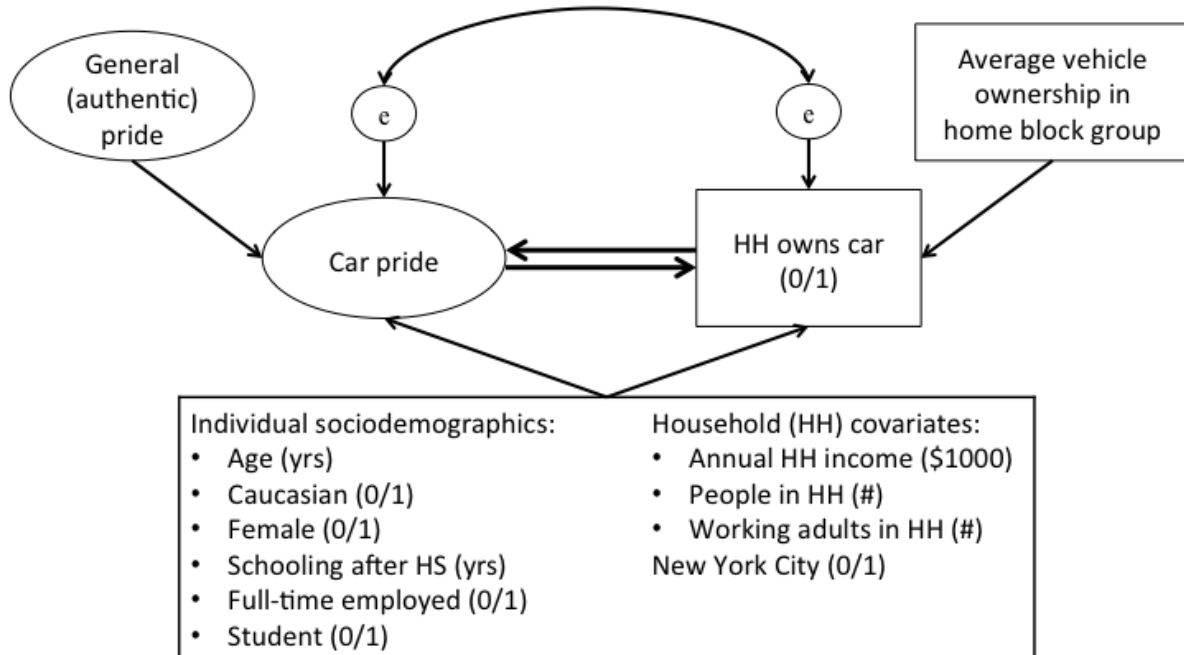
Instrumental Variables

Our model must incorporate instrumental variables for both car pride and household car ownership in order to address endogeneity from the bidirectional relations. For the direct path from car pride to household car ownership, we use a measure of an individual's general authentic pride as an imperfect instrumental variable. This measure of general pride is estimated from response patterns on six 7-point Likert-format items designed to capture the respondent's pride in their life and achievements (see Chapter 3). These statements were designed with synonyms of pride taken from the same source as was used to construct the car pride scale (Tracy and Robins, 2007a,b), but without specific relation of social status or personal image to the car (for example, "My peers would say that I am successful" or "I feel a sense of self-worth"). However, unlike the car pride measure, the final measure of general pride did not contain statements covering both facets of pride, but only the authentic pride related to one's genuine feelings of self-esteem and self-worth. Although it is reasonable to assume that general pride only predicts household car ownership through its manifestation as car pride, general pride may be correlated with some of the other individual sociodemographics in the model that are also used to explain the outcome of interest. This makes it an imperfect instrumental variable.

For the direct path in the opposite direction from household car ownership to car pride, the average household vehicle ownership in the respondent's home census block group from the 2016 American Community Survey was merged with their individual responses based

on their self-reported home location. The average vehicle ownership in the home census block group is highly correlated with whether or not the respondent's household owns a car. But it may also be an imperfect instrumental variable if an individual's car pride is directly related to the average vehicle ownership in their home census block group (perhaps by way of self-selection of home location or social comparison).

Figure 5.5: Path diagram for the structural equation model simultaneously estimating the bidirectional relationship between car pride and household car ownership



Notes: Car pride and general authentic pride are estimated using the measurement models presented in Chapter 3. Variances and covariances among all observed sociodemographic variables are also estimated.

Estimation Method

While limited information estimators, such as two-stage least squares (2SLS) or instrumental variable estimation, are recommended for structural equation models of bidirectional relations, these methods cannot currently handle categorical outcomes (such as our binary household car ownership indicator) with observed predictors. Therefore, for our models, we must settle for using a full information estimator. We estimate our bidirectional model using the weighted least square mean and variance adjusted (WLSMV) estimator with theta parameterization using a probit link function in Mplus version 8.1 (Asparouhov, 2016; Muthén and Muthén, 1998-2018). As recommended when applying full information estimators, we explicitly model the correlation among the error terms of car pride and car ownership where we expect endogeneity from the existence of the bidirectional relation.

City Multigroup Analysis

We might reasonably expect differences in the bidirectional relations between car pride and car ownership across our two cities given their different urban and transport contexts. Therefore, after estimating the average model on the pooled sample of survey respondents, we conduct a multigroup analysis that allows the reciprocal paths between car pride and household car ownership to differ across the two city subsamples.⁶ First we estimate an unconstrained multigroup model that allows all structural relations to differ across the two city subsamples (while imposing strong invariance constraints on the car pride and general pride measurement models). Then we estimate a model that constrains both of the directed paths between car pride and car ownership to be equal across groups. Because these models are hierarchically nested, we can use a χ^2 difference test to determine whether there are statistically significant differences in these paths across groups.

5.5.2 General Results

The estimated structural parameters for the model pictured in Figure 5.5 are presented in Table 5.3. We are particularly interested in the sign, statistical significance, and relative magnitudes of the bidirectional relations between car pride and car ownership. We find that the path from car pride to car ownership is positive and statistically significant ($b = 0.673$, $S.E. = 0.090$, $p < .01$, $\beta = 0.661$). In fact, an individual's car pride is a stronger predictor of household car ownership compared to the individual and household sociodemographic characteristics captured in our survey and used in traditional ownership forecasting, including household income.

Considering the opposite path from car ownership to car pride, we find it is not statistically different from zero ($b = -0.050$, $S.E. = 0.071$, $p = .481$, $\beta = -0.051$). Comparing the statistical significance and relative magnitudes of the standardized regression coefficients for the car pride to car ownership and car ownership to car pride relations, we conclude that car pride (attitude) influences car ownership (behavior) much more strongly than the reverse (behavior reinforcing attitude). This suggests that, the overall effect between car pride and car ownership is positive, following the direction traditionally assumed by the Theory of Planned Behavior—from attitude to behavior.

⁶Multigroup analysis is the recommended approach when considering moderation by discrete variables (Baron and Kenny, 1986; Sauer and Dick, 1993).

Table 5.3: Direct path parameter estimates for simultaneous estimation of the bidirectional relation between car pride and car ownership

Dependent variable	Predictor	<i>b</i>	<i>S.E.</i>	<i>p</i>	β
Car pride	Age	-0.028	0.003	.000***	-0.338
	Female (0/1)	-0.352	0.079	.000***	-0.139
	Caucasian (0/1)	0.115	0.081	.157	0.042
	Education (yrs after HS)	0.006	0.013	.628	0.015
	Full time employed (0/1)	-0.038	0.083	.652	-0.014
	Student (0/1)	-0.557	0.158	.000***	-0.111
	Number of people in HH	0.147	0.032	.000***	0.171
	Number of HH working adults	-0.070	0.032	.026**	-0.060
	HH income (\$1000)	0.002	0.001	.019**	0.096
	New York City (0/1)	-0.216	0.096	.024**	-0.084
	General authentic pride	0.322	0.038	.000***	0.253
	Car owner (0/1)	-0.050	0.071	.481	-0.051
		<i>R</i> ²	0.218	0.031	.000***
Car owner (0/1)	Age	0.015	0.005	.003***	0.180
	Female (0/1)	-0.114	0.127	.371	-0.044
	Caucasian (0/1)	0.140	0.118	.232	0.051
	Education (yrs after HS)	0.018	0.020	.370	0.043
	Full time employed (0/1)	0.085	0.133	.522	0.032
	Student (0/1)	0.114	0.219	.603	0.022
	Number of people in HH	0.138	0.056	.013**	0.158
	Number of HH working adults	0.044	0.070	.535	0.037
	HH income (\$1000)	0.007	0.002	.000***	0.259
	New York City (0/1)	-0.172	0.174	.323	-0.065
	Average vehicle ownership in home block group	0.888	0.137	.000***	0.494
	Car pride	0.673	0.090	.000***	0.661
		Threshold	0.562	0.269	.037**
	Pseudo- <i>R</i> ²	0.390	0.123	.002***	–

Notes: Overidentified model fit: $\chi^2(332, N = 1,236) = 1084.086$, $p < .01$, CFI = 0.877, TLI = 0.859, RMSEA = 0.043 with 90% confidence interval = [0.040, 0.046], SRMR = 0.095.

Correlation between error terms: car pride with car owner ($b = -0.577$, $S.E. = 0.153$, $p = .000$, $\beta = -0.519$).

5.5.3 City-Specific Results

The bidirectional relation measured in the model above represents the average across all respondents in both U.S. cities. However, given the different mobility patterns and infrastructure in New York City and Houston, we might expect to see different relations between

car pride and car ownership across the two cities. Therefore, we test whether city differences exist in the bidirectional relations between car pride and car ownership using multigroup analysis. We test two separate models of the data, one where the bidirectional relations between car ownership and car pride are fit independently in the two city subsamples (“free”), and one where these relations are constrained to have the same coefficients across the entire sample (“constrained”) (see Table 5.4).

With the free model as the baseline, we can compare whether constraining the coefficients to be the same in both cities leads to significantly worse fit between the model-implied variance-covariance matrix and the variance-covariance matrix observed in our data. Using a chi-square difference test, we find that constraining the paths between car pride and car ownership to be equal across the two city subsamples does not result in statistically significant worsening of model fit: $\chi^2_D = 2.198$, $p = .333$. This suggests that there are no significant differences in the bidirectional relations between car pride and car ownership between our subsamples of New York City and of Houston commuters.

Table 5.4: Bidirectional relations between car pride and household car ownership by U.S. city subsample

Dependent variable	Predictor	Model	b_{NYC}	b_{HOU}	β_{NYC}	β_{HOU}
Car pride	Car owner (0/1)	Free	-0.017	-0.317	-0.018	-0.201
		Constrained		-0.027	-0.025	-0.019
Car owner (0/1)	Car pride	Free	0.596***	0.802***	0.560	1.263
		Constrained		0.750***	0.815	1.091

Note: Coefficients are standardized separately for the two city groups.

Even if we treat the two cities separately (as in the free model in Table 5.4), our finding about the relative magnitudes of the relations between car pride and car ownership do not change. In both New York City and Houston, the path from car pride (attitude) to car ownership (behavior) is much stronger and more statistically significant than the reverse path from car ownership (behavior) to car pride (attitude). Therefore, the general conclusions from the average model presented above hold across both cities.

5.5.4 Discussion

Using structural equation modeling with instrumental variables allows us to explore the bidirectionality of the relation between car pride and car ownership in cross-sectional data. In our combined sample of commuters in two U.S. cities, we find that a positive and statistically significant relation exists from car pride to car ownership, but that no significant relation exists in the reverse direction. This suggests that, when it comes to car pride and car ownership, it is the attitude that drives behavior rather than the behavior that reinforces

the attitude. Thus, these results support the direction of the attitude-behavior relation assumed in the Theory of Planned Behavior.

We also consider whether there are differences in car pride and its relations with car ownership between our two case study cities. First, we consider average car pride scores between the two cities. Second, we consider whether the bidirectional relations between car pride and car ownership differ between the two cities.

Comparing average car pride between the two cities, we find that commuters in New York City report significantly lower car pride than commuters in Houston, even after controlling for individual and household sociodemographics of the two city samples. This suggests that the lower car pride observed among commuters in New York City cannot be fully explained by differing individual characteristics in the city subsamples. In other words, an individual's car pride is related to the urban and transportation contexts in which they live. In particular, individuals living in the Houston metropolitan area, where urban form and transportation infrastructure provide little alternative to car ownership and use, have higher car pride than the similar individuals (by sociodemographics) living in the New York City metropolitan area. Thus, we find distinct differences in car pride between the two cities and speculate that individual car pride may be positively related to car dependence (as a function of the metropolitan context in which the individual lives).

We also consider whether the relations between car pride and car ownership differ between our two cities. We find no statistically significant difference in the bidirectional relations between car pride and car ownership between the two cities, despite the cities' different average levels of car pride. This suggests that car pride is positively predictive of household car ownership despite different baseline levels of car pride in our two cities. It also suggests that our findings from the combined sample hold across both cities: when it comes to the relations between car pride and car ownership, attitude predicts behavior.

5.6 Bidirectional Relations between Car Pride and Car Use

Having explored the relations between car pride and car ownership, we now turn our attention to the relations between an individual's car pride and car use, which we operationalize as the frequency (number of days) of drive alone commutes in a typical month. In this section, we build on the modeling framework developed in the previous section to explore potential bidirectionality—having higher car pride might contribute to more frequent use of a car, and conversely, using a car may reinforce one's symbolic attachment to it.

5.6.1 Analytic Plan

Again, we apply structural equation modeling techniques with instrumental variables to simultaneously estimate the bidirectional relation between car pride (attitude) and car use (behavior). This simultaneous estimation allows for direct comparison of the relative strengths of the relations from attitude to behavior and vice versa.

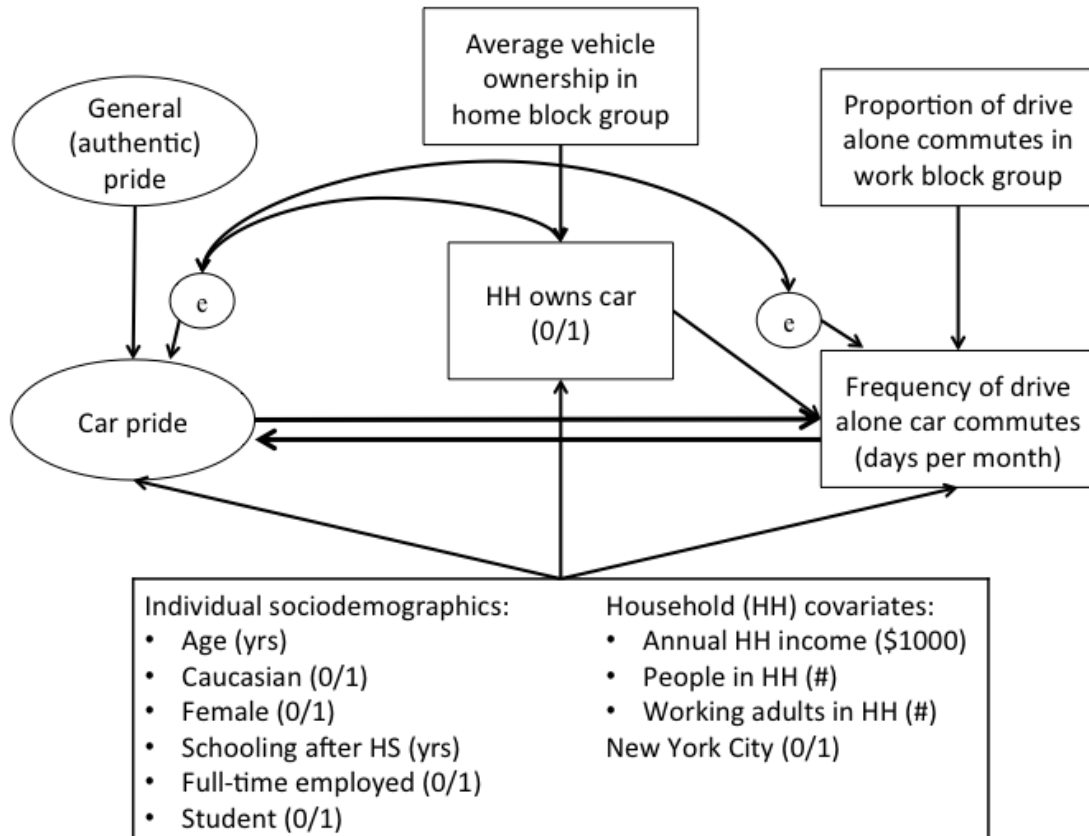
It is well established that car ownership is one of the most important factors that may lead to driving (Dargay, 2001; de Palma and Rochat, 2000; Train, 1980). Therefore, we plan to build our car pride and car use model as an extension of our car pride and car ownership model given in Figure 5.5. As we extend the model, we find that there are multiple ways in which car pride, car ownership, and car use could relate to one another and there remains disagreement in the literature as to the best way to specify these attitude and joint behavior relations. Therefore, we test two potential model specifications to determine which model best fits the relations observed in the data.

Hypothesized and Alternative Model Specifications

Most empirical studies treat car ownership simply as an additional predictor (in addition to sociodemographic variables, characteristics of the built environment, etc) to explain travel behavior (e.g., Bagley and Mokhtarian, 2002). Adopting such an approach for our model would mean replacing the bidirectional relations between car pride and car ownership with an undirected correlation, and allowing both car pride and car ownership to predict car use as in Figure 5.6. In this model, car pride is only related to car use directly.

However, other studies have treated car ownership as both an endogenous and exogenous variable, mediating the relation between predictors (such as individual sociodemographics and characteristics of the built environment) with car use. In this specification, car use is directly determined by car ownership and other predictors, and car ownership itself is influenced by these same predictors. It was found that this mediating model best described the observed travel patterns of households in the metropolitan area of Ghent, Belgium (Acker and Witlox, 2010) and it has been extended to include attitudes for a sample of respondents in Guangzhou, China (He and Thøgersen, 2017). Adopting this specification, car pride can influence car use directly or indirectly via the mediated relation through car ownership (see Figure 5.7). We hypothesize this model that includes both direct and indirect relations between car pride and car use and test its fit against the alternative model in Figure 5.6.

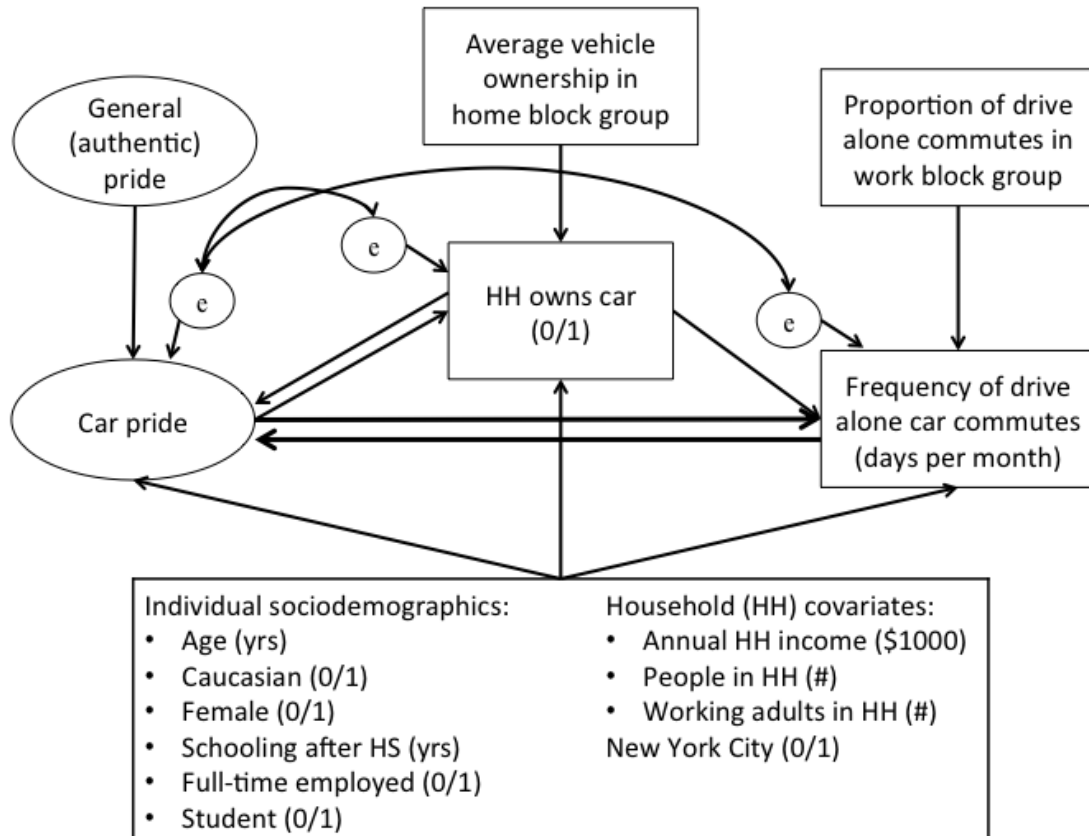
Figure 5.6: Path diagram for the alternative structural equation model simultaneously estimating the bidirectional relationship between car pride and car use, with household car ownership as a correlated predictor



Instrumental Variables

Both our hypothesized and alternative car use models maintain the same instrumental variables for the bidirectional relations between car pride and car ownership used in the previous section: general (authentic) pride for car pride and average vehicle ownership in the home census block group for household car ownership. In addition, we must incorporate an instrumental variable for our measure of car use in order to address endogeneity from its potential bidirectional relation with car pride. We take as our instrument for frequency of drive alone commuting the proportion of drive alone commute trips in the respondent's work census block group from the 2016 American Community Survey. These values were merged based on the respondent's self-reported work location. The proportion of drive alone commutes in the respondent's work census block group is a reasonable instrument given its moderately high correlation with the frequency with which he/she drives alone to work and limited theoretical justification for why it would be related directly to an individual's car pride.

Figure 5.7: Path diagram for the hypothesized structural equation model simultaneously estimating the bidirectional relationship between car pride and car use, mediated by household car ownership



Estimation Method

Due to the inclusion of the binary household car ownership variable as a mediator in Figure 5.7, we must settle for using the weighted least square mean and variance adjusted (WLSMV) estimator with theta parameterization using a probit link function in Mplus version 8.1 to implement our model (Asparouhov, 2016; Muthén and Muthén, 1998-2018). As recommended when applying full information estimators, we explicitly model the correlation between the error terms of car pride and car ownership and between the error terms of car pride and frequency of drive alone commuting where we expect endogeneity from the existence of bidirectional relations.

Addition of the Implicit Measure

Given that there are significant differences in the DW-score between drive alone commuters and others (see Section 5.4), we want to test whether our implicit measure of car vs. bus social status associations may help explain car use in addition to our explicit survey measure of car pride. Therefore, we estimate an additional model, adding each individual's IAT DW-score as a predictor of car pride, household car ownership, and frequency of drive alone car commute.

5.6.2 General Results

Comparison of Hypothesized and Alternative Models

First we compare our hypothesized model—with household car ownership mediating the relation from car pride to car use (Figure 5.7)—against our alternative model—which incorporates car ownership as a simple predictor of car use (Figure 5.6). Given that these models are not nested, we cannot use a χ^2 difference test and must rely on comparison of other approximate fit statistics (see Table 5.5). We find that our hypothesized mediation model outperforms our alternative model on all fit indices. This parallels similar findings from a study in Ghent, Belgium, which found that car ownership partially mediates the relation of car use with sociodemographics and the built environment (Acker and Witlox, 2010). From these results, we conclude that the hypothesized mediation model is an improvement over the simple correlated predictor model and we retain this hypothesized model for further analysis.

Table 5.5: Comparison of the overall fit of the hypothesized and alternative models

	Correlated predictor model (alternative)	Mediated model (hypothesized)
χ^2 value (degrees of freedom)	1187.520 (369)	1088.043 (367)
RMSEA	0.043	0.040
CFI	0.874	0.889
TLI	0.853	0.870
SRMR	0.112	0.097

Direct and Indirect Effects

Having determined that the hypothesized mediation model depicted in Figure 5.7 fits the data better than the alternative, we present the mediation model's estimated parameters in Table 5.6. We are particularly interested in the bidirectional relations between car pride and

car use (measured as frequency of drive alone commutes). Because car ownership mediates the relation between car pride and car use, the influence of car pride on car use can either be direct or indirect (through car ownership).

When considering how car pride (attitude) influences car use (behavior), we find that there is no statistically significant direct effect from car pride to frequency of drive alone commutes. However, the indirect effect of car pride on car use through car ownership is positive and statistically significant ($b = 3.099$, $S.E. = 0.505$, $p < .01$, $\beta = .373$). This yields a positive and statistically significant total effect of car pride on frequency of drive alone commutes. Together these estimated direct and indirect effects suggest that car pride positively influences frequency of drive alone commutes, but that the majority of this influence is mediated by car ownership. In other words, individuals with higher car pride are more likely to own a car and thus use it more frequently.

In the opposite direction, we find that frequency of car use is positively and significantly predictive of car pride ($b = 0.077$, $S.E. = 0.037$, $p = .038$, $\beta = 0.637$). In fact, we find that this reinforcing path from car use to car pride is greater in magnitude than the direct and indirect paths from car pride to car use. Therefore, when it comes to car pride and car use (modeled as frequency of drive alone commute trips), we find that the behavior influences the attitude more strongly than the attitude influences the behavior, contradicting the Theory of Planned Behavior. Our finding parallels findings from a longitudinal study of Dutch households that found positive and statistically significant bidirectional relations between car use (in terms of kilometers driven in a week) and general attitudes towards car use, but concluded that use influenced attitudes more strongly than the reverse (Kroesen et al., 2017).

Table 5.6: Estimated path parameters for the simultaneous estimation of the bidirectional relation between car pride and car use

Dependent variable	Predictor	b	$S.E.$	p	β
Car pride	Age	-0.027	0.005	.000***	-0.328
	Female (0/1)	-0.423	0.141	.003***	-0.168
	Caucasian (0/1)	0.023	0.132	.860	0.009
	Education (yrs after HS)	-0.003	0.021	.899	-0.007
	Full time employed (0/1)	-0.350	0.197	.075*	-0.135
	Student (0/1)	-0.446	0.223	.045**	-0.089
	Number of people in HH	0.237	0.074	.001***	0.277
	Number of HH working adults	-0.033	0.063	.598	-0.029
	HH income (\$1000)	0.008	0.003	.014**	0.331
	New York City (0/1)	-0.028	0.191	.885	-0.011
	General authentic pride	0.413	0.073	.000***	0.326
	Car owner (0/1)	-0.826	0.402	.040**	-0.730
	Frequency of drive alone commutes	0.077	0.037	.038**	0.637

Table 5.6: Estimated path parameters for the simultaneous estimation of the bidirectional relation between car pride and car use (*continued*)

Dependent variable	Predictor	<i>b</i>	<i>S.E.</i>	<i>p</i>	β
Car owner (0/1)	Age	0.016	0.005	.001***	0.215
	Female (0/1)	-0.103	0.126	.415	-0.046
	Caucasian (0/1)	0.124	0.116	.286	0.052
	Education (yrs after HS)	0.021	0.020	.304	0.057
	Full time employed (0/1)	0.082	0.131	.529	0.036
	Student (0/1)	0.165	0.219	.451	0.037
	Number of people in HH	0.128	0.055	.021**	0.170
	Number of HH working adults	0.042	0.070	.548	0.041
	HH income (\$1000)	0.007	0.002	.000***	0.294
	New York City (0/1)	0.063	0.195	.746	0.028
	Average vehicle ownership in home block group	0.453	0.102	.000***	0.305
	Car pride	0.699	0.082	.000***	0.791
	Frequency of drive alone commutes	Age	-0.053	0.027	.047**
Female (0/1)		-1.242	0.658	.059*	-0.059
Caucasian (0/1)		1.860	0.612	.002***	0.083
Education (yrs after HS)		0.270	0.105	.011**	0.078
Full time employed (0/1)		4.296	0.691	.000***	0.199
Student (0/1)		-2.581	1.344	.055*	-0.062
Number of people in HH		0.107	0.286	.709	0.015
Number of HH working adults		-0.557	0.314	.076*	-0.057
HH income (\$1000)		-0.027	0.010	.005***	-0.129
New York City (0/1)		-0.474	0.931	.611	-0.022
Car owner (0/1)		4.436	0.583	.000***	0.471
Proportion of drive alone commutes in work block group		9.276	1.405	.000***	0.309
Car pride: direct effect		-0.190	0.463	.681	-0.023
Car pride: indirect effect through car ownership	3.099	0.535	.000***	0.373	
<i>R</i> ²		0.537	0.035	.000***	–

Note: Covariances between error terms: car pride with car owner ($b = -0.404$, $S.E. = 0.232$, $p = .083$, $\beta = -0.320$) and car pride with frequency of drive alone commute ($b = -2.068$, $S.E. = 1.855$, $p = .265$, $\beta = -0.231$).

5.6.3 Addition of the Implicit Measure

We rerun our hypothesized mediated model in Figure 5.7 adding the individual's DW-score as a predictor of car pride, car ownership, and car use to test whether car use is additionally influenced by people's implicit associations of social status with cars versus buses. We find that the IAT

DW-score, while positively related to frequency of drive alone commuting, is barely a marginally statistically significant predictor having controlled for other sociodemographic characteristics as well as our explicit measure of car pride.

Table 5.7: Estimated path parameters for implicit association of social status with cars versus buses in the bidirectional car pride and car use SEM

Dependent variable	Predictor	<i>b</i>	<i>S.E.</i>	<i>p</i>	β
Car pride	IAT DW-score	0.025	0.114	.825	0.009
Car owner (0/1)	IAT DW-score	0.000	0.114	.998	0.000
Frequency of drive alone commute	IAT DW-score	0.944	0.570	.098*	0.043

Note: Overidentified model fit: $\chi^2(384) = 1086.819$, RMSEA = 0.039 with 90% confidence interval [0.036, 0.042], CFI = 0.891, TLI = 0.873, SRMR = 0.097.

5.6.4 Discussion

Exploring the bidirectional relation between car pride and car use (operationalized as frequency of drive alone commute trips), we find that the relation between car pride and car use is mediated by car ownership. In fact, car pride does not appear to influence car use directly, but instead only influences frequency of use indirectly via car ownership. Even stronger than this indirect path from attitude to behavior is the reverse path from behavior to attitude. We find that there is a strong positive feedback path from car use to car pride, suggesting that individuals who more frequently commute alone by car reinforce their car pride.

5.7 Conclusions

In this chapter, we explore variations in both explicit and implicit measures of car pride—the attribution of social status and personal image to owning and using a car—across individuals in two U.S. cities: New York City and Houston. We find that the explicit measure of car pride shows clear differences across individuals and between cities. For individuals, we find that being younger, male, a student, and from larger households with higher incomes predicts higher car pride. We also find that being from New York City is predictive of lower car pride than being from Houston, even after controlling for individual and household sociodemographics of the subsamples. On the other hand, we do not find clear differences in our implicit measure of social status associations with cars versus buses across individuals or between cities.

Next we consider whether our explicit and implicit measures of car pride show significant differences across key car consumption groups: car-owners versus non-car-owners and those who drive alone as their most typical commute versus those who commute by other modes. We find that our explicit measure of car pride shows significant differences between these groups, suggesting that there is a positive relation between car pride and car ownership and use.

In the final two sections of this chapter, we examine in more depth the relations between car pride and household car ownership and frequency of car use using structural equation modeling. Our use of instrumental variables allows us to explore the bidirectionality of these attitude-behavior relations in cross-sectional data. We find that the relative strength of these bidirectional relations depend on the type of car consumption.

When it comes to car ownership, we find that a positive and statistically significant relations exists from car pride to car ownership, but not in the reverse direction. This suggests that it is the attitude that drives behavior more than the behavior reinforces the attitude. These findings regarding the direction and relative magnitude of the attitude-behavior relations hold on average in the full sample as well as in each of the two cities.

When it comes to car use, we find that car pride does not influence frequency of drive alone commuting directly, but that it has a positive and statistically significant influence through car ownership. We also find that a positive and statistically significant feedback exists from car use to car pride, suggesting that individuals who drive more frequently reinforce their symbolic attachment to their vehicle. Comparing the relative magnitudes of these relations, we find that the reverse path from car use (behavior) to car pride (attitude) is stronger than the indirect path from attitude to behavior, the opposite of the findings for car ownership.

Together these results suggest that car pride is strongly related to car consumption, with significant and positive bidirectional relations existing between car pride and car ownership as well as between car pride and car use. However, the relative strength of these attitude-behavior relations depends on the type of car consumption. We find that car pride more strongly predicts car ownership, but car use more strongly reinforces car pride.

5.7.1 Contributions

This chapter demonstrates how commonly applied structural equation modeling techniques can incorporate instrumental variables to answer causal questions regarding attitude-behavior relations in cross-sectional data, with a particular application to the relations between car pride and car consumption. Answering the causal question of whether attitude causes behavior or vice versa has important implications for behavioral research, model development, and policy intervention—particularly those intended to reduce car ownership and use and promote sustainable travel behaviors (Chorus and Kroesen, 2014).

When it comes to behavioral research, our results add to a small body of literature that demonstrates the limitations of correlational analyses when dealing with attitude-behavior relations that are likely bidirectional. When it comes to model development, we add to a large and diverse body of literature that demonstrates how incorporating attitudinal factors into models of car consumption improve model fit and predictive power above traditional sociodemographic and instrumental factors, such as travel time and travel cost.

When it comes to policy interventions, our results provide only preliminary insights. Current efforts to reduce car ownership and use often focus on regulations targeting individual's travel behavior, such as license restrictions or congestion charging, that have proved politically difficult

to implement. However, our results suggest that cheaper and less politically-fraught marketing and communications interventions that target attitudes such as car pride may also be effective in influencing behavior through attitude change. However, our results also suggest that the relations between car pride and car consumption are complex, involving direct and indirect effects from attitude to behavior as well as feedback from behavior to attitude. In addition, we find that the same attitude towards cars (car pride) interacts differently with car ownership and with car use behaviors. These complexities mean that policy interventions aimed at any one of car attitudes, car ownership behavior, and car use behavior can have secondary impacts on the others. Therefore, extreme care is needed in crafting policy interventions so as to minimize unintended consequences. Furthermore, with our well-validated measure of car pride, the impact of such interventions could be evaluated in accordance with evidence-based policy-making frameworks using pre- and post-studies to understand how these attitude-behavior dynamics play once manipulated.

5.7.2 Limitations and Future Work

While this chapter provides substantial insight into car pride among individuals in U.S. cities and its relation to current car ownership and use, the results are limited in their operationalization of car ownership and use, the quality of the instrumental variables used, the inability of cross-sectional data to capture dynamics over time, and their generalizability to other populations. Here we discuss these remaining limitations and propose ways that future research could address them.

Operationalization of Car Ownership and Use

In this chapter, we look at the relations of car pride with car ownership and use decisions. However, we are limited in how we operationalize car consumption. Car ownership decisions do not just involve the binary decision of whether or not a household owns a vehicle—the outcome in our models—but also decisions such as how many cars to own and what type(s) of vehicle(s) to purchase that could be related to car pride. Similarly, car use is not limited to the frequency of drive alone commuting—the outcome in our models—but could also include the choice of car over other modes, frequency of car travel, and distance of car travel all for different types of trips. Therefore, future research could build on the measurement and modeling approaches outlined here to explore car pride’s relation with other car ownership and use decisions not measured in this dissertation.

Quality of Instrumental Variables

In general, the robustness of instrumental variable techniques depends on the quality of the instruments available for the given application. As previously discussed, an instrument must meet two general requirements: first, it is correlated with the explanatory variable it instrumenting (x), and second, it is uncorrelated with the error term of the dependent variable (y). When it comes to reciprocal attitudes and travel behavior relations, identifying quality IVs that meet the second requirement (the “exclusion restriction”) may be particularly difficult due to the many individual and social dynamics at play.

In our car pride and car consumption models, we use the average vehicle ownership in the individual's home census block group as the instrument for whether or not the individual owns a car and the proportion of drive alone commute trips in the individual's work census block group as the instrument for the individual's frequency of drive alone commuting. While we argue that an individual's car pride is not directly related to the average vehicle ownership in their home census block group or the proportion of drive alone commute trips in their work census block group (meeting the exclusion restriction), this assumption would be invalidated if car pride is related to an individual's self-selection into certain neighborhoods and workplaces. Furthermore, since one facet of pride is related to social comparison, an individual's car pride may be directly related to their relative standing compared to the car ownership and use of their peers at home or at work. This social comparative facet of pride may also call into question our choice of neighborhood or workplace average as an instrumental variable for individual car ownership and commute driving frequency. Future work into the relations between car pride and car consumption can consider other instrumental variables that more robustly meet the exclusion restriction. And in general, research into bidirectional attitude-behavior relations should pay particular attention to the quality of instrumental variables used and, when possible, should employ multiple instruments to support more rigorous econometric testing of their quality.

Dynamics over Time

While our use of instrumental variables allows us to estimate bidirectional relations with cross-sectional data, these results present only a single snapshot in time and rely on assumptions of equilibrium and stationarity of the relations between car pride and car consumption behaviors. Future research using longitudinal or panel data could add to the insights developed here by exploring the dynamics of car pride and its relations with car consumption behaviors over time. These longitudinal studies could also add weight to the causal claims suggested in this chapter by adding time precedence.

Generalizability

The results and conclusions presented here are for a limited sample of commuters in two cities in the United States. Even within these two cities, our sample underrepresents key segments of the population, particularly Black and Hispanic residents, those with low educational attainment, and those living in households with very high incomes and more than three vehicles (see Chapter 2). Therefore, care should be taken in generalizing the results beyond middle class, Caucasian residents of these two metropolitan regions.

While the two cities in this study were selected specifically for their different transportation and urban contexts in order to test the invariance and sensitivity of our car pride measure across different groups of people, future research should continue to evaluate the performance of the car pride scale in other samples of individuals and cities both within and outside the U.S. Such studies could also extend the structural understanding presented in this paper to explore car pride's relation with other travel behaviors such as commute mode choice, frequency of car use or vehicle miles traveled, price and type of car purchased, or propensity to use new transportation technologies and services. For each type of behavior, it will be important to continue to consider the bidirectionality of attitude-

behavior relationships and to address this reciprocity using instrumental variables, longitudinal data, or other experimental techniques appropriate for causal inference.

Furthermore, while the focus of this study was on the attitudes and behaviors of individuals, the symbolic and affective values of car consumption extend beyond individuals through flows, circulations, distributions, intensifications, and interferences among people, things, and places (Sheller, 2004). Therefore, a more thorough study of car pride and other symbolic and affective values of car consumption could also consider meso-level aggregation of specifically located car cultures and macro-level patterns of regional, national, and transnational emotional, cultural, and material geographies around car consumption (Ashmore et al., 2018b; Gössling, 2017; Sheller, 2004). Cross-cultural studies of attitudes and their impact on travel behavior come with their own methodological challenges (Ashmore et al., 2017), but would help clarify the extent to which the results in this chapter generalize to other populations. In the following chapter, we partially address this limitation of generalizability by exploring car pride and its associations with car ownership and use across individuals in 51 countries.

Recognizing these and other limitations that stress the need for continued research, this chapter provides a solid foundation for the continued exploration of the bidirectional relations between an individual's car pride and their car consumption behavior and reinforces the need for proper methodologies to handle simultaneity when studying attitudes and behaviors.

Chapter 6

Car Pride and its Associations with Car Ownership and Use Across Individuals and Countries

Social psychological studies of car consumption have begun to emphasize the complex determinants of transportation choices, including the different instrumental, affective, and symbolic motivations of car use and ownership. However, many of these studies are performed in relatively homogeneous populations, failing to account for the fact that these individual attitudes are generated by collective cultural patterns (or emotional geographies) which may reinforce cultures of automobility (Sheller, 2004). In this chapter, we consider the connections between car pride and its relation to car consumption at the individual-level and macro-level patterns of national emotional, cultural, and material geographies. While we do not model the flows, circulations, distributions, intensifications, and interferences of attitudes between and among people and places, we do measure and visualize the resulting geographies of car consumption across countries. Therefore, this chapter represents one of the first cross-cultural studies of attitudes and their impact on travel behavior.

Using data from our international survey (see Chapter 2), this chapter explores the individual and country car pride factor scores estimated in Chapter 3 from the 9-item dichotomous survey scale. This international comparison of attitudes and their relations to car consumption across 41,932 individual in 51 country is at a scale unprecedented in existing literature (Ashmore et al., 2017). Throughout this chapter, we adopt a multilevel structural equation modeling (MSEM) approach, which recognizes the hierarchical structure of the data and apportion variance observed in our sample to individual- and country-levels separately. This allows us to explore variations in car pride and car consumption across individuals, accounting for potential similarities of individuals within the same country, and across countries, controlling for effects due to different types of individuals living in different countries. Therefore, our analysis is an improvement on most existing international comparisons in terms of both sample size and method.

This chapter begins with an introduction to the MSEM method in Section 6.1. Three sections dedicated to variations in car pride and its relation with car consumption across individuals then follow. Section 6.2 summarizes and visualizes variation in our car pride scores across individuals.

Then, Sections 6.3 and 6.4 consider relations of individual car pride with car ownership and car use, respectively. In our international data, we do not have the instrumental variables needed to explore bidirectional relations between car ownership and car consumption; instead, we specify our models based on the results from the U.S. sample (in Chapter 5) without correcting for potential endogeneity.

Then, in Section 6.5 we move away from individual-level results, exploring variation in car pride scores across our 51 countries. Our multilevel framework allows us to demonstrate variance in car pride across countries, without the confounding effect of different individuals living in different countries. We then consider whether national indicators of macroeconomic conditions, vehicle ownership and vehicle use help explain this variation in country car pride. However, this analysis is limited to bivariate correlations due to insufficient statistical power at the country level.

We conclude in Section 6.6 with a discussion of the general findings from this chapter, limitations of our approach, and areas for future work.

6.1 Multilevel Structural Equation Modeling

Social and behavioral research often investigates relations between individuals and the larger context in which they live, such as neighborhoods, cities, or countries. Multilevel regression models handle such hierarchically-structured data—with individuals nested within groups—in a statistically sound way. In general, these models relax assumptions of general linear regression to allow for individuals within the same group to be related to one another through shared experience and context (modeled as correlated error terms) (Hox, 2010).

Multilevel structural equation modeling (MSEM) is a more recent development, which adopts multilevel structures in the more flexible SEM framework that models the complete covariance structure of the data rather than just the mean-variance structures. MSEM has two main advantages over traditional multilevel regression models. First, multilevel regression models assume covariates are measured without error. While this may be acceptable for variables that can be accurately and reliably measured, when measurement error may be large (as in the case of measuring attitudes) regression estimates can be significantly biased. MSEMs can relax this assumption, because they can include a measurement model for the predictor or outcome variables (Hox, 2010; Muthén and Asparouhov, 2011). Second, MSEM models can estimate more complicated structures, such as models with multiple outcomes or those with indirect effects (such as mediation analysis) Hox (2010). It is particularly for this second reason that we choose to apply MSEM in this work.

Modifying notation from Muthén (1994), we specify a generalized two-level SEM with a system of equations. A vector of continuous, observed variables Y_{gi} across individuals i in groups g is specified as a linear combination of latent and observed factors, each decomposed into within-group (W)

and between-group (B) components:

$$Y_{ig} = \overbrace{\Lambda_W \eta_{W,ig} + \epsilon_{W,ig}}^{Y_{W,ig}} + \overbrace{\nu_B + \Lambda_B \eta_{B,g} + \epsilon_{B,g}}^{Y_{B,g}} \quad (6.1)$$

$$\eta_{W,ig} = V_W \eta_{W,ig} + X_W x_{W,ig} + \zeta_{W,ig} \quad (6.2)$$

$$\eta_{B,g} = \beta_B + V_B \eta_{B,g} + X_B x_{B,g} + \zeta_{B,g} \quad (6.3)$$

where $x_{W,ig}$ and $x_{B,g}$ are the vectors of predictor variables observed at the two levels; $\eta_{W,ig}$ and $\eta_{B,g}$ are vectors of latent variables given by Equations (6.2) and (6.3), respectively; and $\epsilon_{W,ig}$, $\zeta_{W,ig}$, $\epsilon_{B,g}$, $\zeta_{B,g}$ are residual variables normally distributed with mean zero and variance-covariance matrices freely estimated. The parameters of the structural and measurement models to be estimated are Λ , V , and X at both the within and between levels as well as the intercepts at the between-level, ν_B and β_B (Asparouhov and Muthén, 2014).

Multilevel regression models can include random regression intercepts, slopes, and error terms, which allow coefficients at the within-level to vary by group. In multilevel SEM, $Y_{B,g}$ is equivalent to the random intercepts in a linear multilevel regression. Random slopes and residuals can be modeled as between-level latent variables, capturing the variation in the means of the observed individual level variables across groups. In other words, the parameters Λ_W , V_W , and X_W can be specified as group-specific random effects instead of fixed parameters by including them in the vector of between-level latent variables $\eta_{B,g}$ (Asparouhov and Muthén, 2014).

Additionally, the above model can be extended to categorical observed variables Y_{gi} by defining an underlying continuous variable Y_{gi}^* using the probit link function with threshold parameters $\tau_{l-1,p}$ and $\tau_{l,p}$ such that:

$$Y_{gi} = l \Leftrightarrow \tau_{l-1,p} < Y_{gi}^* < \tau_{l,p}$$

and then substituting Y_{gi}^* for Y_{gi} in Equation 6.1. In such models, the variance of $\epsilon_{W,gi}$ must also be fixed to 1.

Given Equation 6.1, latent and observed variables in an MSEM can be specified at the within or between group level. Within-group variables are measured at the individual-level. Therefore, they may include variation due to individual characteristics as well as residual variation due to group context, which must be carefully disentangled. Between-level variables may be random coefficients drawn from the within-level model, but other between-level variables may be variables defined only at the group level (Hox, 2010). For example, when considering a multilevel model of individuals nested within neighborhoods, between-level variables may include characteristics of the built environment or amenities provided in each neighborhood.

6.1.1 Variable Centering

Given that variables measured across individuals in hierarchical data are necessarily a blend of within- and between-level variance, one of the key considerations when specifying any multilevel model is whether and how to center data, particularly at the within level.

Within-Level Variables

In general, within-level variables can be centered at the grand mean (the mean across all individuals in all groups) or they can be group mean centered (i.e., deviated around the mean of the group to which they belong). These different centering methods produce parameter estimates that differ in value and in meaning. In particular, grand-mean centered variables contain both within- and between-group variation, resulting in regression coefficients at the within-level that are an ambiguous mixture of individual and group level associations. On the other hand, group mean centered variables are uncorrelated with group-level variables, resulting in regression coefficients that are a pure estimate of the within-level association of interest (Enders and Tofighi, 2007).

The choice of centering method depends on the research question of interest. If a relation at the within-level is of substantive interest, group mean centering is the most appropriate because it removes all between-group variation from the predictor and yields a “pure” estimate of the within-cluster (i.e., individual-level) regression coefficient (Enders and Tofighi, 2007). This specification implies that an individual’s relative position within a group is an important determinant of attitude, behavior, or other construct of interest. If, instead, a relation at the between level is of substantive interest, grand mean centering of within-level variables (and between-level variables) is preferred (Enders and Tofighi, 2007). Furthermore, while it may seem unnatural to center binary predictors, the previous recommendations also extend to dummy variables (e.g., gender) that appear in the within-level model (Enders and Tofighi, 2007).

Finally, in situations in which it is of interest to determine whether a relation is the same at both levels of the model, it is necessary to decompose the predictor and outcome into within- and a between-level component. In traditional multilevel regression, this is accomplished by using both the group mean centered individual scores in the within-level model and the group means in the between-level intercept equation and then testing whether the coefficients at each level are statistically different from one another. However, this approach is limited by the fact that the mean score at the between-level is an aggregate of the individual scores within each group, which may be an unreliable measure of the true group-level effect. In multilevel SEM, this issue can be avoided by using latent variable decomposition that apportions observed variation in a predictor variable to separate individual and country components while accounting for potential measurement error (Muthén and Asparouhov, 2011).

Between-Level Variables and Interaction Terms

Centering at the between-level is typically far less complex than the decision required at the within-level. In general, raw metrics are used for their direct interpretability in the between-level equation unless higher-order terms, such as a power series or a between-level interaction term, are included, in which case, grand mean centering is preferred (Enders and Tofighi, 2007).

The centering method chosen also affects the interpretation and estimation of interaction terms at the within-level or across levels (e.g., when a between-level variable moderates the magnitude of a within-level relation). When including an interaction term between two within-level variables, requires an unbiased estimate of a within-level relation, making group mean centering the natural choice (Enders and Tofighi, 2007). In fact, simulation studies have shown that group mean center-

ing produces unbiased estimates of regression coefficients for within-level interaction terms, while grand mean centering produces biased estimates (Ryu, 2015). For cross-level interactions, simulation studies have shown that grand mean centered variables produce unbiased estimates at both the within and between levels (Ryu, 2015) despite some researchers suggesting that grand mean centering can produce a significant interaction effect when no such effect exists in the population (Enders and Tofghi, 2007).

6.1.2 Sample Size and Statistical Power

In multilevel models, researchers must consider sample size and statistical power at all levels of analysis. As a general rule, it is usually desirable to have as many units as possible at the top level of the multilevel hierarchy, whereas sample size at the within-group level(s) can be smaller (Snijders, 2005). While sample size requirements depend on many factors, including the size of the model, distribution of the variables, amount of missing data, reliability of the variables, and strength of the relations among the variables at each level (Muthén and Muthén, 2009), rules of thumb exist in the literature.

For continuous variable models, simulation studies suggest at least 100 between-level observations are needed with at least 4 observations within each group for both maximum likelihood (ML) (Julian, 2001; Koch et al., 2014) or Bayesian estimation (Holtmann et al., 2016). These recommendations correspond to a ratio of 10 or more observations per parameter in the model, a number in line with the findings of previous simulation studies on continuous variable, single-level and multi-level SEMs (Bentler and Chou; Koch et al., 2014). For ordered categorical variable models, simulation studies suggest a minimum number of 100 between-level and 4 observations per group when using weighted least squares (WLS) or a minimum of 150 between-level and 6 observations per group when using Bayesian estimation without informative priors (Holtmann et al., 2016).

While these guidelines are a good starting point, studies contemplating multilevel experimental designs should strongly consider using a Monte Carlo simulation of the intended model and potential estimates to determine appropriate sample size prior to data collection (Snijders, 2005). In Monte Carlo studies, data are generated from a population with hypothesized parameter values. A large number of samples (replications) are drawn, and a model is estimated for each sample. Parameter values and standard errors are averaged over the samples (Muthén and Muthén, 2009). The number of replications (analogous to sample size) is increased until stability of the results is achieved.

6.1.3 Bayesian Estimation

While traditional estimation methods such as ML and WLS can be applied to multilevel structural equation models with observed (but not latent) outcomes, in practice they often result in convergence issues—such as non-positive definite or singular variance-covariance matrices or negative residual variances (Asparouhov and Muthén, 2014; Muthén and Muthén, 1998-2018). Particularly difficult with these traditional estimators is the specification of random slopes at the between-level. WLS cannot estimate such models, while ML requires numerical integration that becomes intractable with increasing model complexity (in practice, 3 or 4 group-specific variables is the

maximum possible) (Asparouhov and Muthén, 2007). Bayesian estimation can greatly expand the set of structural equation models that can be estimated (Asparouhov and Muthén, 2010a,b). Bayesian methodology can be used to easily estimate MSEM with any number of random intercepts, slopes, and factor loadings with categorical and continuous, observed or latent dependent variables (Asparouhov and Muthén, 2014).

While a Bayesian approach can greatly expand the set of MSEM models available to researchers, it comes with its unique set of challenges and modeling considerations: the specification of prior distributions, determination of convergence of the simulation algorithm, and alternative assessment of model fit.

Specification of Prior Distributions

Bayesian analysis differs from traditional estimation methods by viewing parameters as variables rather than constants. Bayesian inference combines prior distributions for parameters with the data likelihood to form posterior distributions of the parameter estimates. Therefore, one of the key decisions when specifying a model for Bayesian estimation is the choice of prior distributions for the model parameters. These distributions should be specified by the research according to how much information is available prior to data collection and the accuracy of that information.

In some cases, there may not be enough information to aid in drawing posterior information. In these cases, “noninformative” or “diffuse” priors can be used to quantify existing ignorance of the relation or parameters at hand. The most common noninformative prior distribution is the uniform distribution over some sensible range of values (Kaplan and Depaoli, 2012).¹ In other applications, there may be sufficient prior information on the shape and scale of the distribution of a model parameter that it can be systematically incorporated into the model as an “informative” prior distribution.

For multilevel models in particular, simulation studies have shown that models with categorical items and with small between-level samples demonstrate significant “prior assumption dependence” (Asparouhov and Muthén, 2010b). In other words, the choice of informative prior has a substantial effect on the estimated results (e.g., Depaoli and Clifton, 2015; Holtmann et al., 2016; Lee et al., 2010). Since there is often less empirical information available in data with small sample sizes and categorical indicators, specifying informative but inaccurate priors may have particularly detrimental effects and should be avoided in favor of noninformative priors.

Convergence

When performing Bayesian estimation, researchers must familiarize themselves with Markov chain Monte Carlo (MCMC) simulation and the diagnostics, such as potential scale reduction (PSR) factors and autocorrelation plots, used to assess parameter convergence under this approach (Kaplan and Depaoli, 2012).

¹Mplus uses diffuse priors as the default for Bayesian estimation. For all loadings and intercepts the prior is uniform on the $(-\infty, \infty)$ interval, while priors for the variance parameters are the inverse-gamma (Muthén and Muthén, 1998-2018).

Put simply, Bayesian analysis uses MCMC algorithms to iteratively obtain an approximation to the posterior distribution of the parameters from which the estimates are obtained as means or medians. In general, several chains of these iterations are carried out in parallel using multiple processors (Muthén, 2010). The first half of the iterations in each chain are considered as a “burn in” phase and are not used to represent the posterior distribution. Using PSR, convergence is determined by comparing the parameter variation within each chain to that across chains to check that the different chains converge to the same value (Gelman and Rubin, 1992; Gelman et al., 2004).

Parameter values are drawn from each k^{th} iterations in the chain. Ideally, each draw from the posterior distribution should be independent, so it is important to specify k based on observed autocorrelation, or the correlation of parameter values across iterations. In general an autocorrelation of 0.1 or lower is recommended (Muthén, 2010).

Model Fit and Comparison across Models

A key exercise in SEM is the specification, estimation, and testing of models against underlying data and one another. However, Bayesian estimation is more limited in its handling of model fit and model comparison compared to traditional estimators.

While a wide array of exact and relative model fit statistics have been developed for traditional estimators, such as ML and WLS (see Chapter 5), there are fewer model fit statistics available for Bayesian estimation. The most common method for evaluating the quality of fit of Bayesian models is posterior predictive checking (PPC) Gelman et al. (2004). PPC measures the discrepancy between the data (posterior distributions) generated by the model and the actual data.

While PPC may be sufficient of evaluating model fit in single-level SEMs, it is very limited in its usefulness in the multilevel setting. Current best practice for MSEM using traditional estimators suggests methods for estimating model fit separately at each levels of the model (Hsu et al., 2016; Ryu, 2011; Ryu and West, 2009; Schermelleh-Engel et al., 2014). However, an analogous approaches does not yet exist for Bayesian models, so there is no way to diagnose potential sources of misfit at different levels of the model.

When comparing a set of competing models, the Deviance Information Criteria (DIC) is used (Gelman et al., 2004; Spiegelhalter et al., 2002), with preference given to the model with the smallest DIC among the set.

Our Approach

In this chapter, we adopt what some researchers call a “psuedo-Bayesian” approach, which uses MCMC simulation methods designed for Bayesian inference as just another estimator, allowing us to specify more complex models than could be handled by ML or WLS estimation techniques. As one of the first studies of its kind, we have little empirical evidence to inform the choice of prior distributions for our car pride and car consumption relations, so we specify diffuse priors for all model parameters. This approach, is in line with recommendations given the small sample size and

categorical outcomes included in our multilevel model. However, it does not take full advantage of Bayesian theory, which challenges researchers to bring in prior information on the distribution of model parameters, requiring a deeper understanding of the underlying model (Kaplan and De-paoli, 2012). Thus, there is room for future research to incorporate parameters knowledge of the parameters estimated here to inform Bayesian estimates of related models.

6.2 Individual Car Pride

For our international sample of 41,932 individuals in 51 countries (see Chapter 2), we have validated a 9-item dichotomous (binary) survey measure of car pride at the individual and country levels (see Chapter 3). In this section, we visualize the distribution of our estimated individual car pride factor scores and explore what characteristics of individuals relate to their car pride. In Section 6.5, we visualize and explore the estimated car pride factor scores for countries.

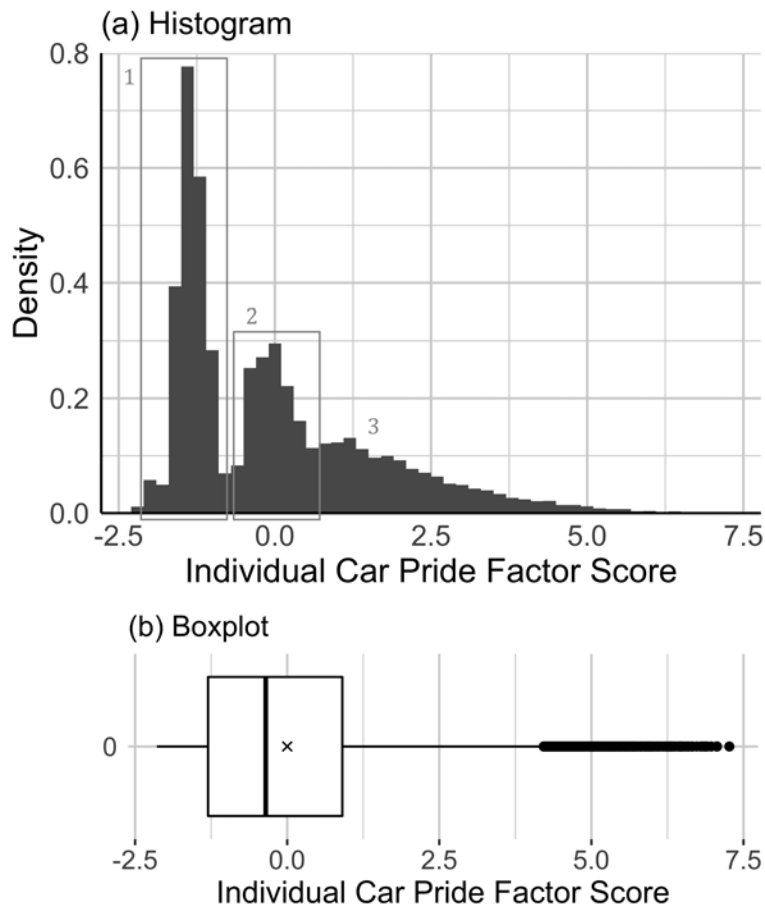
Considering the individual car pride scores, we find that there is significant variability in the estimated factor scores. The distribution across the entire sample has a non-normal distribution with strong positive skew (see Figure 6.1a) and two clear peaks. In general, the right-tailed distribution suggests that, while the majority of individuals in our international sample have moderate-to-low levels of car pride, there are some with extremely high car pride (see Figure 6.1b).

In Figure 6.1a, we potentially see a mixture of three different groups of individuals. Group 1 consists of individuals with below average car pride. Group 2 contains individuals with moderate and positive car pride just around the average (zero). Group 3 comprises all other individuals with a very broad distribution of car pride scores, extending far into the positive score range.

The first group of individuals disagree with all or all but one of the 9 dichotomous items in our scale, indicating little to no positive associations of social status and personal image to the car (car pride). The concentration of individuals within this group is due to the fact that our dichotomous scale is only able to differentiate between levels of positive associations (related to the number and type of survey statement to which individuals agree), but is not able to differentiate between levels of negative associations of social status and personal image to the car (car shame). This is one disadvantage of the dichotomous (short-form) version of the car pride scale compared to the polytomous (long-form) version of the car pride scale used in the U.S. cities sample. Unlike the dichotomous version, the polytomous version is able to differentiate among individuals with below-average and potentially even negative associations of social status and personal image to the car based on the individual's level of disagreement (strong, moderate, weak) to the different survey statements.

The fact that our car pride scale is unable to differentiate among individuals without positive associations of social status and personal image to the car is an important caveat to the modeling results presented throughout the rest of this chapter. All relations measured at the individual-level between sociodemographics and car pride and between car pride and car consumption may only hold for individuals with none or positive associations of social status and personal image to the car, but not those who experience negative associations or car shame.

Figure 6.1: Histogram and box plot distributions of individual car pride factor scores for the full international sample



Note: Individual car pride factor scores are estimated around a mean of zero across all individuals in the international sample. Our box plots show distributions with the thick black line indicating the median, the x indicating the mean, the box spanning from the first quartile to the third quartile, whiskers spanning between the minimum and maximum values, and dots representing outliers.

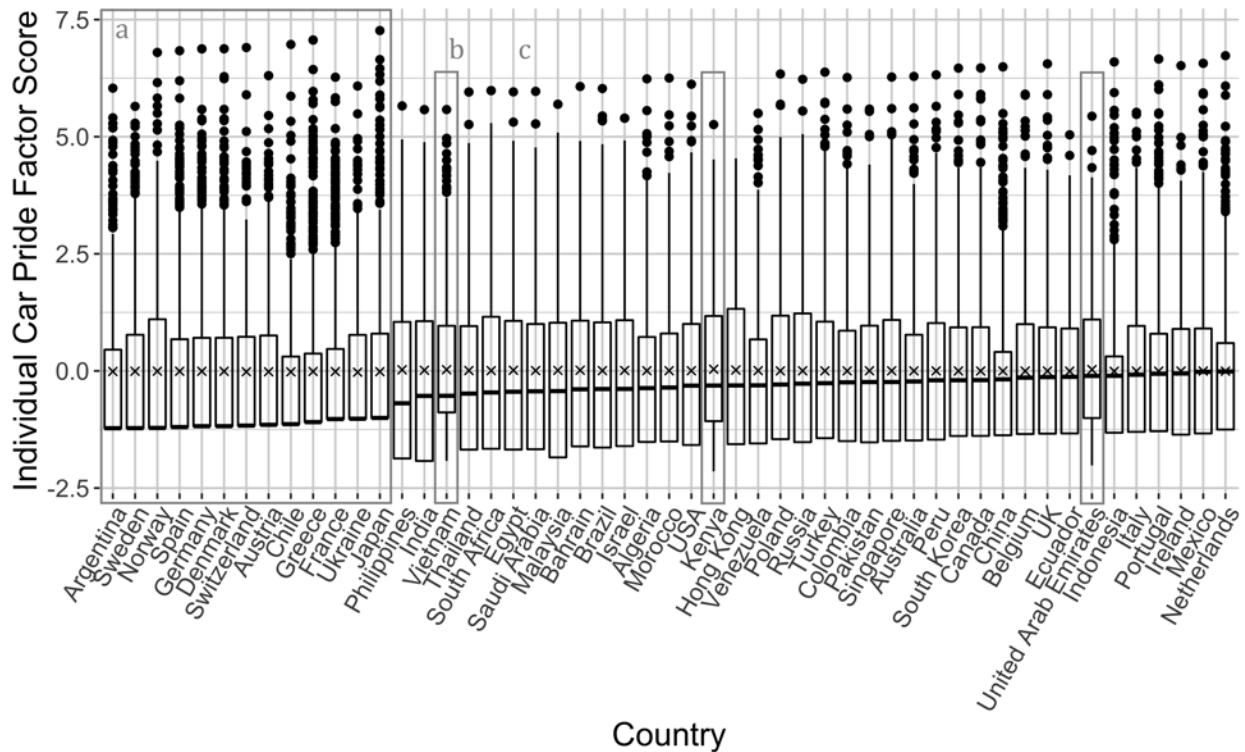
6.2.1 Distributions by Country

Next, we explore whether the same distribution of individual car pride demonstrated in Figure 6.1 is repeated within each country or whether there are differences in the distribution of individual car pride across countries. Visualizing the boxplot distributions of individual car pride by each of the 51 countries in Figure 6.2, we find that, for a majority of countries, individuals exhibit the same positive-skewed distribution of car pride as was observed in the entire international sample. However, there are also some differences in these distributions across groups of countries (see Figure 6.2).

For countries in group *a* at the far left of Figure 6.2, the median and 1st quartile of individual car pride scores are equal to the minimum. In these countries, the majority of individuals disagree

to almost all of the survey statements, indicating no or low car pride (see Figure 6.3a). In other words, these countries contain a much larger proportion of individuals in group 1 of Figure 6.1a compared to the entire international sample. Group *b* is comprised of Vietnam, Kenya, and United Arab Emirates, which are the only countries to show distributions with tails on the negative as well as the positive side of the interquartile range (see Figure 6.2). These countries appear to contain a higher proportion of individuals with average or positive car pride (from groups 2 and 3, respectively) (see Figure 6.3b). Group *c* includes all other countries, which have distributions of car pride with fairly similar mixtures of the three groups seen in Figure 6.1a (see Figure 6.3c).

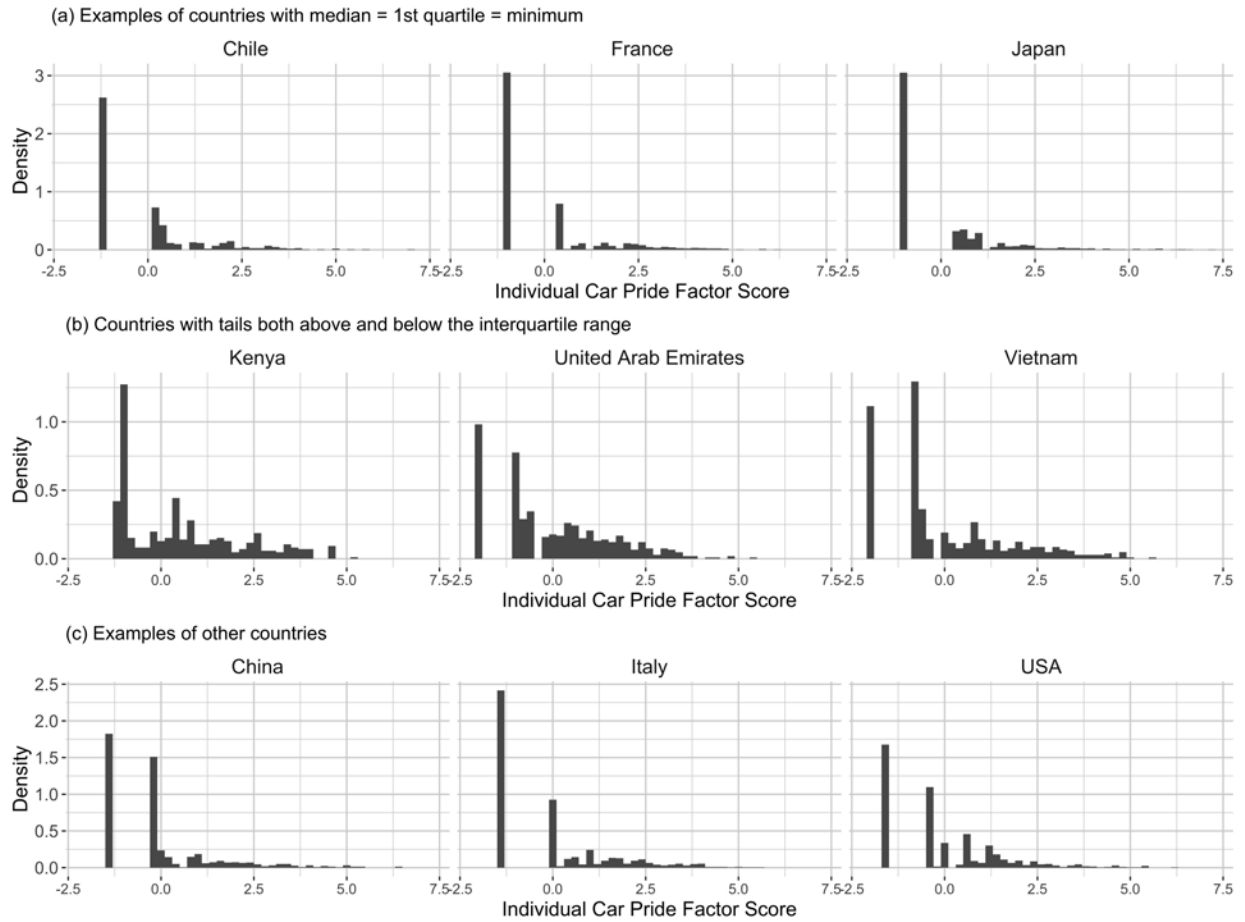
Figure 6.2: Boxplot distributions of individual car pride factor scores for each of the 51 countries sampled



Note: Countries ordered along the x-axis according to their median individual car pride.

Visualizing individual car pride scores suggests that there are three distinct types of individuals across our entire international sample: those with low to no car pride, those with around average car pride, and those with positive car pride. We also find that the distribution of individual car pride scores by country vary based on the proportional mixture of these three different groups within them. Having demonstrated that car pride differs across individuals, we next turn our attention to explaining these individual differences using available sociodemographic characteristics.

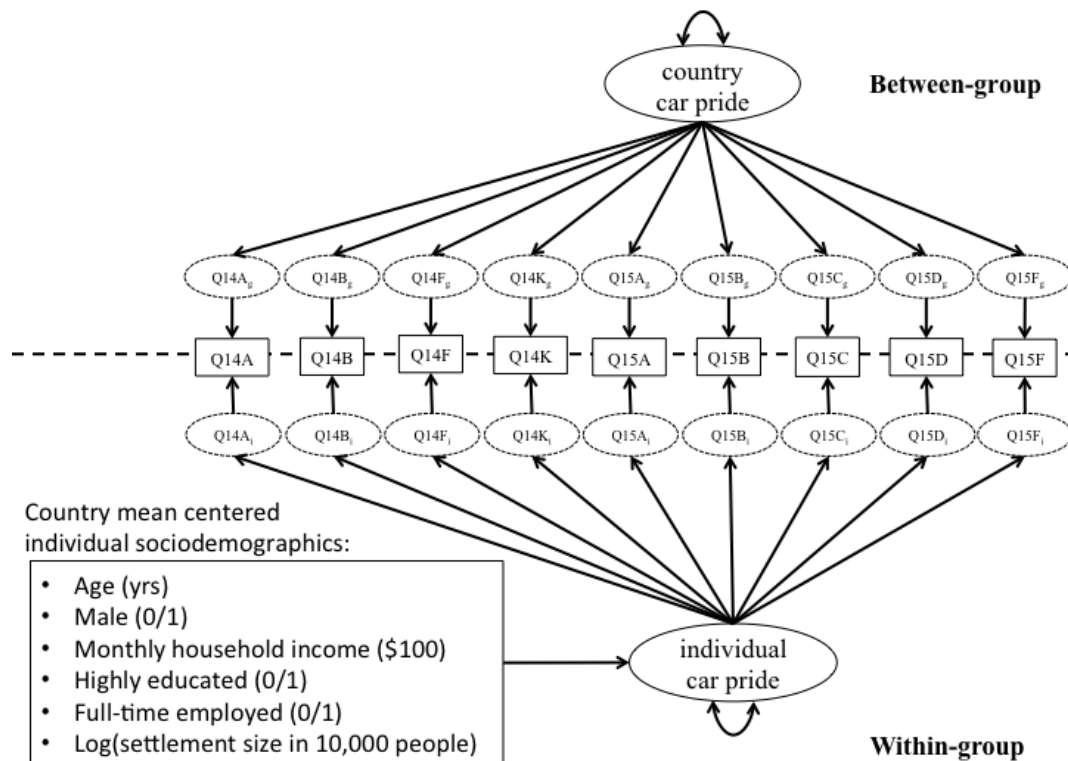
Figure 6.3: Histograms of individual car pride factor scores for select countries



6.2.2 Multilevel Regression of Individual Car Pride on Sociodemographics

In this section, we investigate what sociodemographic characteristics help to explain the variation in individual car pride scores across our entire international sample (visualized in Figure 6.1). We employ a multilevel structural equation model (MSEM) that simultaneously estimates the multilevel confirmatory factor analysis (MCFA) model of car pride and the regression of individual car pride on individual and household sociodemographics (see Figure 6.4).² This approach provides a picture of what types of individuals exhibit stronger car pride, while accounting for potential measurement error in these estimated scores.

Figure 6.4: Analytic path diagram for the MSEM predicting individual car pride with individual and household sociodemographics



Notes: Variances and covariances for all exogenous (observed) variables and disturbance terms for the outcomes are estimated, but not shown. Strong invariances constraints are included in the MCFA as in Chapter 3.

²We estimate this MSEM using the MLR estimator in MPlus version 8.1 to be consistent with the MCFA estimated in Chapter 3. The MLR estimator computes regression coefficient estimates using Full Information Maximum Likelihood (FIML) estimation to handle small amounts of missing data on household income and education level and then computes robust standard errors with the Huber-White sandwich estimator to correct for non-normality (Muthén and Muthén, 1998-2018). In this multilevel setting, the MLR estimator requires numerical integration, which is computationally intensive.

The sociodemographics in our MSEM include the age and gender of respondents as well as binary indicators of whether the individual is “employed, working 30 or more hours per week” and whether the individual is highly educated (has a college or advanced degree). Self-reported monthly household income (in US\$100; converted from national currency) is derived as a quasi-continuous variable from the midpoint of 12 categories. Similarly, the estimated settlement size of the individual’s home location (in units of 10,000 people) is derived from the midpoint of 8 survey categories and then log-transformed to reduce skew and kurtosis. Finally, all sociodemographics are country-mean centered to remove any country-level variance from the estimation of the individual-level parameters (Enders and Tofghi, 2007).

We estimate fixed slopes for these sociodemographic characteristics across the 51 countries. In other words, we use sociodemographic variables to explain the variance observed across the entire international sample (in Figure 6.1) rather than the variances observed in each country (in Figure 6.2). Therefore, the linear regression parameters presented in Table 6.1 are interpreted as the global average relation between sociodemographic and individual car pride. Across our international sample, we find that all sociodemographic characteristics captured in the survey are statistically significant in explaining individual car pride. In particular, those with household incomes higher than average, who live in larger towns or cities, and who are younger, male, highly educated, and full-time employed have higher individual car pride. Comparing the standardized coefficients, we find that age and household income are the sociodemographics most predictive of individual car pride. In general, we find that the sign and relative magnitudes of these relations are consistent with what is found for individuals in the U.S. (see Chapter 5).

Table 6.1: Parameter estimates for MSEM predicting car pride factor scores with individual and household sociodemographics

Predictor	<i>b</i>	<i>S.E.</i>	<i>p</i>	β
Age (yrs)	-0.027	0.003	.000***	-0.143
Male (0/1)	0.379	0.056	.000***	0.086
Monthly household income (\$100)	0.008	0.001	.000***	0.109
Highly educated (0/1)	0.359	0.053	.000***	0.079
Full time employed (0/1)	0.332	0.052	.000***	0.074
Log(settlement size (10,000 people))	0.040	0.007	.000***	0.054

Notes: *b* = unstandardized coefficient; *S.E.* = standard error; *p* = p-value for two-tailed t-test against *b* = 0; β = standardized coefficient.

Significance code: * = 10%; ** = 5%; *** = 1%.

Variance explained in individual car pride: $R^2 = 0.051$, S.E. = 0.005, $p < .01$.

While all the sociodemographic characteristics included in our model are significant (not surprising given our large sample size at the individual level), the overall variance in individual car pride explained by our model is very low ($R^2 = 0.051$). This suggests that factors not captured in this simple linear model contribute to these attitudes and future research should delve further into factors that help explain car pride at the individual level. This research might consider interaction terms among the different sociodemographics, potential non-linear relations, or the estimation of random slopes (a form of mixture model) that allows the impact of sociodemographics on car pride to differ by country. Alternatively one might consider using latent class modeling to try to capture

the different groups of individuals identified in Figure 6.1, and potentially their different mixtures in different countries (see Figure 6.3).

6.3 Association of Car Pride with Car Ownership

Having explored variation in car pride across individuals and countries, we now turn our attention to the relations between car pride and car consumption behaviors. In this section, we consider the association of car pride with car ownership, while the next section considers the association of car pride with car use.

We start by comparing the mean individual car pride scores between car-owners and non-car-owners in our international sample. These descriptive statistics allow us to see whether bivariate relations between car pride and car ownership behavior warrant further exploration. We then employ multilevel structural equation modeling (MSEM) to estimate the association between car pride and car ownership while controlling for the individual sociodemographics of our sample. We estimate both the average relation between individual car pride and car ownership as well as country-specific relations to demonstrate how the relations between car pride and car consumption may change with differing social and cultural contexts.

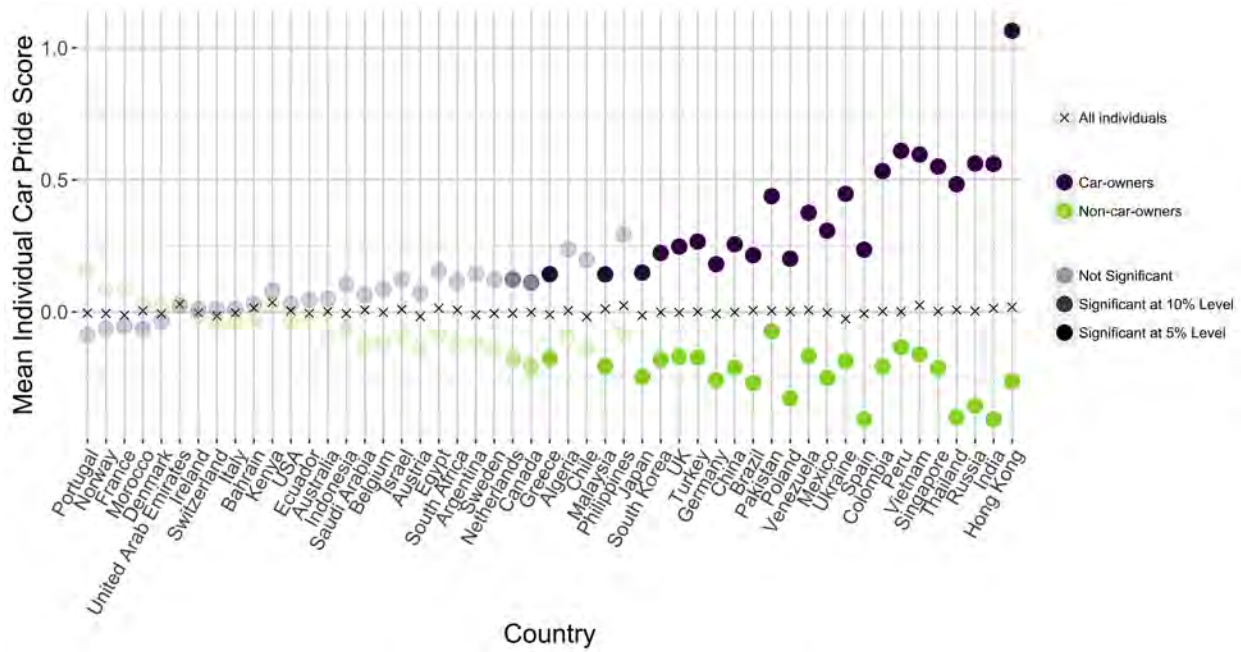
6.3.1 Car Pride of Car-Owners vs. Non-Car-Owners

Comparing the distribution of individual car pride factor scores between individuals whose households do and do not own cars across our entire international sample, we find that car-owners have a higher average car pride ($n = 20,358$; $\mu_{\text{car-owner}} = 0.162$) compared to non-car-owners ($n = 21,574$; $\mu_{\text{non-car-owner}} = -0.152$) and that this difference is statistically significant by a two-tailed t-test: $t = -19.99$, $p < .01$.

In addition to this test across the entire international sample, we can also compare the mean individual car pride scores for car-owners vs. non-car-owners in each of the country subsamples. We perform a series of two-tailed two-sample t-tests, employing the Holm-Bonferroni method to correct the p -value significance level for multiple comparisons. We find that car-owners exhibit higher individual car pride than non-car-owners in nearly every country and that this difference is significant at the 5% level for 45% of the countries in the sample (see Figure 6.5). We find a large and significant difference in the China subsample, which parallels published findings for a sample of individuals in Shanghai, China (Zhao and Zhao, 2018). However, we do not find a statistically significant difference in the U.S. subsample, unlike the result from our polytomous car pride scale in New York City and Houston (see Chapter 5).

These simple comparisons of means demonstrate that individual car pride is positively related to an individual's car ownership behavior. However, they cannot tell us whether these relations persist after controlling for other related and potentially confounding variables (such as income). Therefore, in the next section we adopt a multivariate approach to estimate whether the relation between car pride and car ownership holds after controlling for other sociodemographic characteristics of the individuals in our international sample.

Figure 6.5: Mean car pride scores for car-owners vs. non-car-owners by country



Note: Countries along the x-axis ordered by increasing difference in mean individual car pride of car-owners and non-car-owners.

6.3.2 Multilevel Structural Equation Model

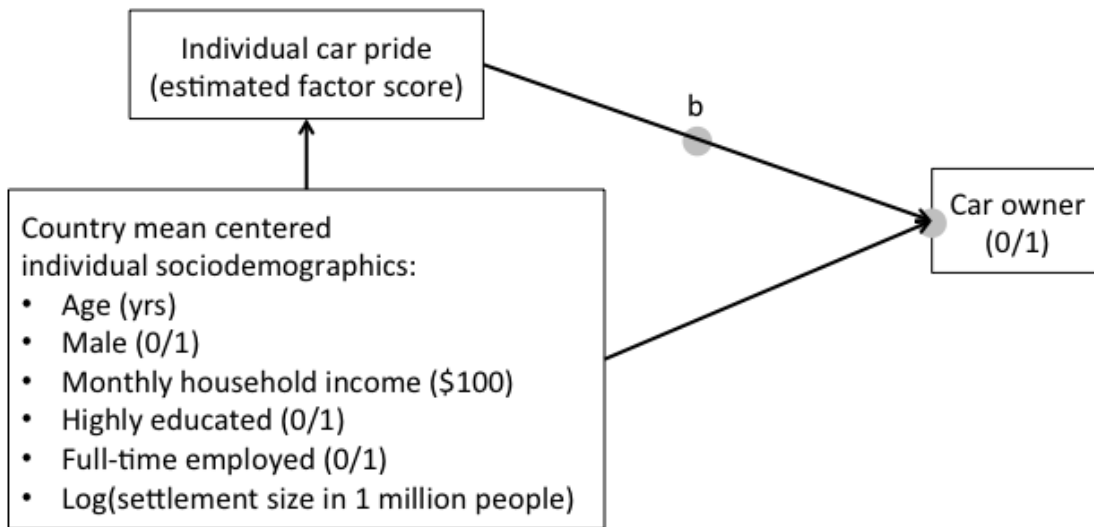
Here we estimate an MSEM to explore the association between car pride and whether or not the individual owns a vehicle while controlling for individual sociodemographics.

Analytic Plan

We estimate the MSEM in Figure 6.6, with a primary focus on the direct path from individual car pride to the binary indicator of whether or not the individual owns a vehicle. While a bidirectional relation exists between car pride and car ownership, our international sample does not enable us to estimate reciprocal paths. Since Chapter 5 has demonstrated that the direct path from car pride to car ownership is much stronger than the reverse for a sample of commuters in U.S. cities, in this model we assume car pride predicts car ownership.

To reduce the complexity of our model to a manageable level, we do not simultaneously estimate the factor scores for individual and country car pride scores and the regression coefficients. Instead, we export the factor scores from the MCFA estimated in Chapter 3 and treat them as observed variables in our model. While this step-wise estimation—first of the factor scores and then of the structural models—allows us to estimate additional multivariate relations of interest, it comes at the price of assuming no measurement error in the exported factor scores. This concern is mitigated by the fact that the standard error of measurement diminishes as the number of indicators for the

Figure 6.6: Analytic path diagram for the within-level of an MSEM predicting car ownership with car pride and sociodemographics



Notes: Grey circles indicate random intercepts or slopes estimated at the country level. Variances and covariances for all observed variables and disturbance terms for all outcomes are estimated, but not shown.

factor increases, so we can be reasonably confident in the estimates from the response patterns across the 9 items of the car pride scale. Furthermore, initial exploration of the factor scores and their standard errors show that the standard errors are much smaller than the individual and country-level variances being modeled in the structural components.

We estimate two versions of the model given in Figure 6.6. First, we estimate a fixed effect model, which estimates a single, average relation between individual car pride and car ownership across the entire international sample. Second, we estimate a random effect model that allows the relation between individual car pride and car ownership to vary by country. For both models, all individual sociodemographic variables are country-mean centered to remove country-to-country variance from the estimation of individual relations and are estimated as fixed effects.

Because our modeling approach combines a multilevel structure, a binary outcome, and random effects, we employ Bayesian estimation using Markov Chain Monte Carlo with the Gibbs algorithm using Mplus version 8.1 (Asparouhov and Muthén, 2010a; Muthén and Muthén, 1998-2018). We use diffuse (non-informative) priors for all estimated parameters. The first half of each MCMC chain is discarded as the burn-in phase, then convergence is assessed using the Gelman-Rubin criterion based on the potential scale reduction factor for each parameter (Gelman and Rubin, 1992; Gelman et al., 2004). To reduce potential auto-correlation (or non-independence) of consecutive draws from the chain, we base our estimation on every 10th iteration. For our binary outcome of car ownership, all paths are estimated using the default probit link function.

Fixed Effect Model Results

First, we estimate the fixed effect model (see Table 6.2). We find that the estimated relations between individual sociodemographics and car pride are consistent in terms of sign and relative magnitudes with those estimated in Table 6.1. In terms of the relations between individual sociodemographics and car ownership, we find that being older, male, highly educated, and fully employed as well as having a higher household income are all significantly and directly predictive of higher likelihood of the individual owning a car. Interestingly, the settlement size of the individuals home is not significantly predictive of car ownership. All of these sociodemographics also have an indirect impact on car ownership through car pride. Of these sociodemographics, we find that age and being fully employed are the most substantively predictive of household car ownership based on standardized regression coefficients.

Even after controlling for these individual sociodemographics, the direct path from individual car pride to whether or not the individual owns a car (0/1) is statistically significant: $b = 0.087$, $p < .01$, $\beta = 0.120$. While statistically significant, the magnitude of the probit regression coefficient is small. It is not as predictive as many of the individual sociodemographics included in the model. A one unit increment in individual car pride (equivalent to moving from the mean to the 76th percentile across the entire international sample in Figure 6.1) predicts only a 4% increment in the probability of owning a car. Thus, on average, we find that higher individual car pride is significantly, but only slightly predictive of higher levels of car ownership across all individuals and countries in our international sample.

Table 6.2: Select parameter estimates for the fixed effect MSEM predicting car ownership

Dependent variable	Predictor	b	95% CI		p	β
			Low	Upp		
Individual car pride	Age (yrs)	-0.014	-0.015	-0.013	.000***	-0.101
	Male (0/1)	0.201	0.169	0.230	.000***	0.062
	Monthly HH income (\$100)	0.004	0.004	0.005	.000***	0.087
	Highly educated (0/1)	0.189	0.156	0.225	.000***	0.057
	Full time employed (0/1)	0.173	0.141	0.206	.000***	0.053
	Log(settlement size)	0.021	0.016	0.026	.000***	0.038
	R^2	0.028	0.025	0.031	.000***	
Car owner (0/1)	Age (yrs)	0.034	0.033	0.035	.000***	0.344
	Male (0/1)	0.103	0.076	0.131	.000***	0.044
	Monthly HH income (\$100)	0.006	0.005	0.006	.000***	0.156
	Highly educated (0/1)	0.382	0.351	0.410	.000***	0.159
	Full time employed (0/1)	0.505	0.479	0.534	.000***	0.213
	Log(settlement size)	-0.002	-0.007	0.003	.196	-0.005
	Individual car pride	0.087	0.078	0.095	.000***	0.120
	Threshold	0.119	-0.027	0.262	.049**	0.228
	R^2	0.262	0.253	0.271	.000***	

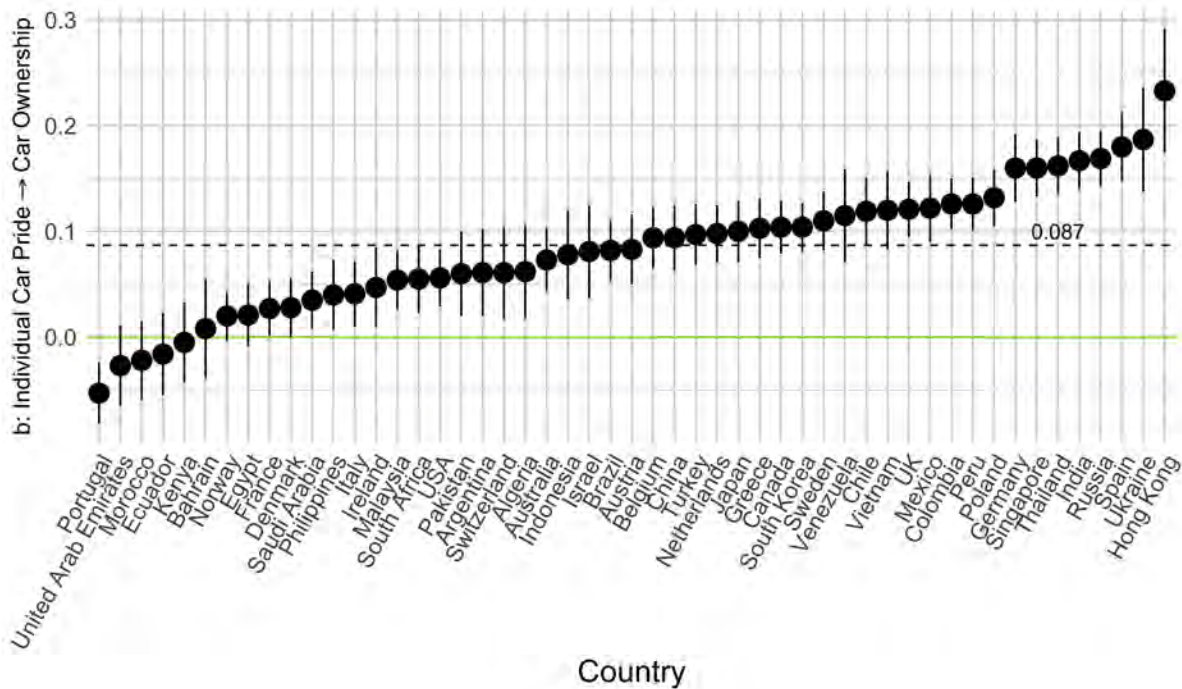
Notes: Model fit by Bayesian Posterior Predictive Checking (PPC): 95% CI for difference between observed and replicated chi-square values = [4537.959, 4715.211], $p < .01$.

Random Effect Model Results

Estimating a random effect rather than a fixed effect for the relation between individual car pride and car ownership, we find that there is significant variation in the magnitude of the probit regression coefficient depending on country (see Figure 6.7). Almost all countries that have a relation between individual car pride and car ownership that is statistically different from zero have a positive relation, indicating that greater individual car pride leads to greater car ownership. In only a few countries, most notably Portugal, do we see a negative relation between individual car pride and car ownership.

Furthermore, in many countries, we estimate a country-specific relation between individual car pride and car ownership greater than the average or fixed effect estimated in the previous model. For example, in India, the probit regression coefficient is estimated to be $b = 0.167$, indicating that a one unit increment in car pride from 0 predicts a 7% increment in the likelihood of the individual owning a vehicle.³

Figure 6.7: Random probit regression coefficient of car ownership (0/1) on individual car pride by country



Note: The purple, dashed line is the estimated fixed effect of $b = 0.087$. The solid green line indicates zero. Error bars show the mean b plus or minus one standard deviation based on 50 draws from the posterior distribution.

³While one unit of car pride is comparable across countries, it is also important to remember that the distributions of individual car pride differ across countries (see Figure 6.2).

6.3.3 Discussion

Our analysis suggests that, on average across all individuals and countries in our international sample, greater car pride is predictive of greater car ownership. We find that this relation remains statistically significant, but with very modest effect after controlling for individual sociodemographics.

While it is inappropriate to make a direct comparison between the results here and those estimated for individuals in New York City and Houston in Chapter 5,⁴ we find that the average impact of car pride on car ownership across individuals in our international sample is somewhat smaller—relative to individual sociodemographics and in terms of the implied increment in likelihood of owning a vehicle attributed to a one unit increment in car pride—than that estimated for individuals in our two U.S. cities. The smaller impact estimated here could be due to unaddressed endogeneity in the model; without instrumental variables to control for bidirectionality of the relations between car pride and car ownership, our single estimate is potentially the combined effect of two opposing relations.

We also see significant country-to-country variation in the relation between car pride and car ownership. This suggests that social and cultural contexts not captured by the sociodemographics of the individuals who make up our country subsamples influence how strongly car pride predicts car ownership. This means that individuals in different countries with the same car pride don't have the same likelihood of owning a car.

6.4 Association of Car Pride with Car Use

Having considered the association of car pride with car ownership, this section considers the association of car pride with car use. We start by comparing mean individual car pride scores between individuals in our international sample who select “car: driver” as one of their typical weekday travel modes (car users) and those who did not (non-car-users). These descriptive statistics allow us to expose whether bivariate relations between car pride and car use (in the form of mode choice) warrant further exploration.

We then employ multilevel structural equation modeling (MSEM) to estimate the association between car pride and car use while controlling for the individual sociodemographics of our international sample. We consider two different measures of car use as outcomes in the model: a binary indicator of whether or not driving a car is the respondent's typical weekday mode (0/1) and the self-reported quasi-continuous number of miles driven on a typical day.

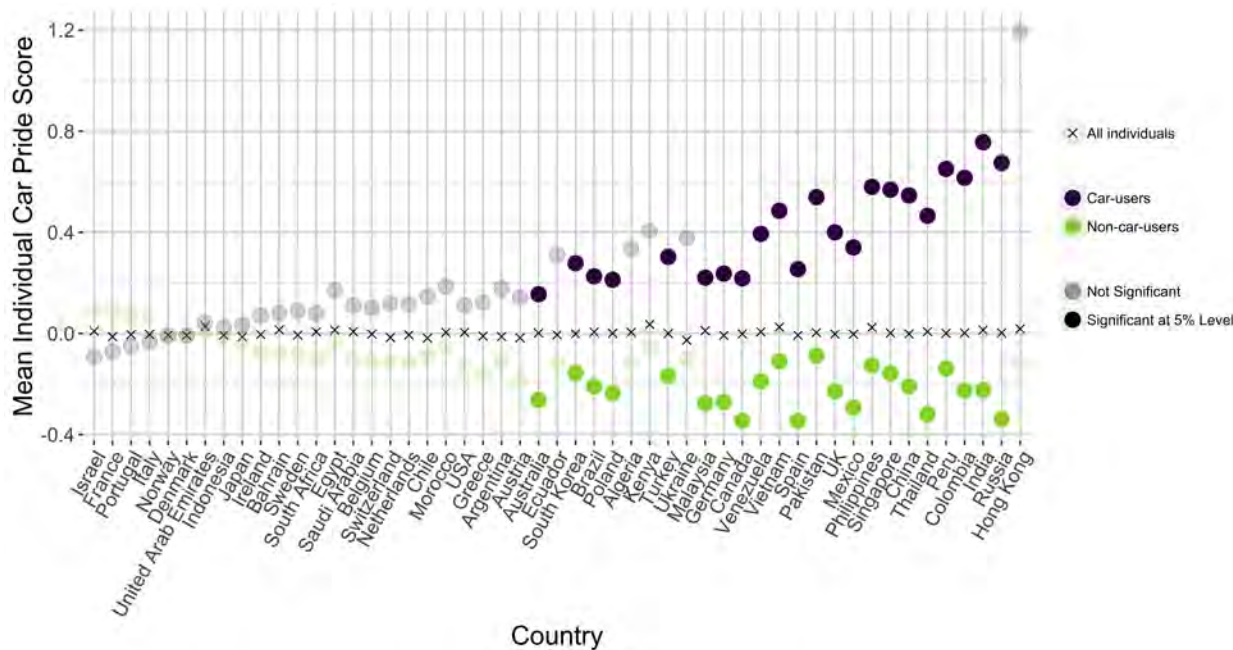
⁴While both models use probit regression, the U.S. city analysis is estimated with our polytomous car pride scale and here we estimate with our dichotomous car pride scale and a different set of sociodemographic covariates.

6.4.1 Car Pride of Car-Users vs. Non-Car-Users

Comparing the distribution of individual car pride factors scores between respondents who state that they drive a car as a typical mode and those who rely on other modes, we find that car users have a higher average car pride ($n = 17,887$; $\mu_{\text{car-users}} = 0.194$) compared to users of other modes ($n = 24,045$; $\mu_{\text{non-car-users}} = -0.144$) and that this difference is statistically significant by a two-tailed t-test across our entire international sample: $t = -21.10$, $df = 36233$, $p < .01$. This agrees with findings from our sample of commuters in New York City and Houston, United States (see Chapter 5).

In addition to this test across the entire international sample, we can also compare the mean individual car pride scores for car-users and non-car-users within each of the country subsamples, again using the Holm-Bonferroni method to correct the p -value significance level for multiple comparisons. We find that car-users exhibit higher individual car pride than non-car-users in most countries, and that this difference is significant at the 5% level for many countries in the sample (see Figure 6.8). We find a large and significant difference in individual car pride between car-users and non-car-users, which parallels findings among car-owners in Shanghai, China (Zhao and Zhao, 2018). However, we do not find a statistically significant difference in the U.S. subsample.

Figure 6.8: Mean car pride scores for car-users vs. non-car-users by country



These simple comparisons of means demonstrate that individual car pride is positively related to whether or not an individual drives a car for their typical weekday trips. However, it cannot tell us whether these relations persist after controlling for other variables, particularly car ownership. Therefore, in the next section we adopt a multivariate approach to estimate whether the relation between car pride and car ownership holds after controlling for other sociodemographic characteristics of the individual respondents.

6.4.2 Multilevel Structural Equation Model

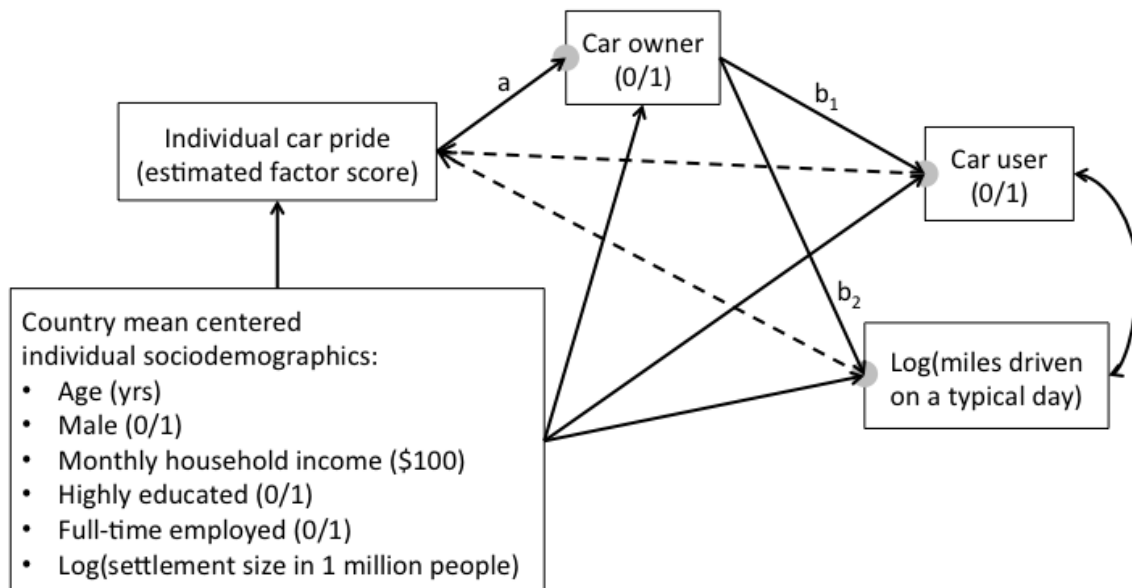
Here we estimate an MSEM to explore the association between car pride and car use while controlling for individual sociodemographic characteristics.

Analytic Plan

We estimate the MSEM in Figure 6.9, with a primary focus on the relations between individual car pride and two correlated car use outcomes. The first outcome is a binary indicator of whether or not the individual selected “car: driver” as one of the modes they typically take to get to work, school, or other regular journey on a weekday. The second outcome is a quasi-continuous variable of miles driven on a typical day. Responses were collected for 5 ordinal categories, which were recoded with the midpoint: 0 = “none/not applicable,” 5 = “up to 10 miles,” 30 = “10-50 miles,” 75 = “50-100 miles,” 110 = “more than 100 miles.” Given significant skew and kurtosis in the distribution of reported daily miles driven, the outcome variable is log-transformed before being included in the model.

Again, our international sample does not enable us to estimate reciprocal paths, so we must rely on our results from Chapter 5 and theory to guide our choice of directed paths. In our U.S. sample, we found that car pride influences car use indirectly (through car ownership), but not directly. We also found that the feedback from car use to car pride was greater than the total effect of car pride on car use. Therefore, in our MSEM we specify an indirect path from car pride to car use (through car ownership) and direct paths from car use back to car pride (see Figure 6.9).

Figure 6.9: Analytic path diagram for the within-level of an MSEM predicting car use with sociodemographics and car pride (through car ownership)



Just as in the previous section, we adopt a step-wise approach that first estimates and exports individual and country car pride scores and then incorporates them as observed variables in the structural model. All individual sociodemographic variables are country-mean centered to remove country-to-country variance from the estimation of individual relations and are estimated as fixed effects. We again use Bayesian estimation with diffuse (non-informative) priors in Mplus version 8.1 (Asparouhov and Muthén, 2010a; Muthén and Muthén, 1998-2018).

Model Results

For the model in Figure 6.9, we estimate only the fixed effects (average across all countries) for the direct and indirect effects between individual car pride and car use. The estimated path parameters are given in Table 6.3. Considering the sociodemographics, we find that being male, fully employed, and living in less populated areas are all significantly and positively predictive of greater likelihood of car use and more miles driven on a typical day. We also find that being highly educated is not statistically predictive of either car use outcome, while household income is not directly predictive of being a car user but is positively related to the number of miles driven on a typical day. As expected, being a car owner is strongly predictive of being a car user and moderately predictive of the number of miles driven on a typical day.

After controlling for these sociodemographics, we find that the indirect paths from individual car pride to both car use outcomes (through car ownership) are positive and statistically significant. While statistically significant, the magnitudes of the path-implied effects are relatively small. A one unit increment in individual car pride (equivalent to moving from the mean to the 76th percentile) predicts an 8% increment in the probability of using a car. When it comes to miles driven in a typical day, we find that the indirect effect from car pride through car ownership ($b = 0.011$, $p < .01$) suggests that a one unit increment in individual car pride predicts only a 1% increment in the number of miles driven in a typical day. Thus, on average, we find that higher individual car pride is significantly, but only slightly predictive of higher levels of car use and miles driven across all individuals and countries in our international sample.

We also find that positive and statistically significant relations exist directly from car use to individual car pride. We find that being a car user predicts a $b = 0.241$ unit increase in individual car pride. In fact, comparing standardized regression coefficients we find that being a car user is more predictive of individual car pride than any of the sociodemographics included in the model. Less substantial is the direct path from miles driven to individual car pride; our model suggests that a dramatic increase in the number of miles driven on a typical day, for example by 100, results in a negligible increment in car pride of $b = 0.016$ units. Together, these paths suggests that using a car strongly reinforces an individual's car pride, but that the number of miles driven are inconsequential.

Table 6.3: Select parameter estimates for the MSEM predicting car use

Dependent variable	Predictor	b	95% CI		p	β
			Low	Upp		
Individual car pride	Age (yrs)	-0.024	-0.025	-0.022	.000***	-0.163
	Male (0/1)	0.132	0.101	0.163	.000***	0.039
	Monthly HH income (\$100)	0.002	0.002	0.003	.000***	0.039
	Highly educated (0/1)	0.052	0.017	0.085	.001***	0.015
	Full time employed (0/1)	-0.009	-0.041	0.025	.292	-0.003
	Log(settlement size)	0.025	0.020	0.031	.000***	0.045
	Car user (0/1)	0.241	0.228	0.252	.000***	0.278
	Log(miles driven)	0.016	-0.003	0.035	.048**	0.009
	R^2	0.183	0.170	0.197	.000***	
Car owner (0/1)	Age (yrs)	0.035	0.034	0.037	.000***	0.337
	Male (0/1)	0.080	0.053	0.106	.000***	0.032
	Monthly HH income (\$100)	0.005	0.005	0.006	.000***	0.134
	Highly educated (0/1)	0.369	0.340	0.399	.000***	0.144
	Full time employed (0/1)	0.502	0.474	0.529	.000***	0.198
	Log(settlement size)	-0.003	-0.008	0.001	.067*	-0.008
	Individual car pride	0.170	0.160	0.179	.000***	0.232
	Threshold	0.136	-0.012	0.284	.035**	0.259
	R^2	0.349	0.338	0.361	.000***	
Car user (0/1)	Age (yrs)	-0.004	-0.006	-0.002	.000***	-0.024
	Male (0/1)	0.125	0.088	0.162	.000***	0.032
	Monthly HH income (\$100)	0.000	0.000	0.001	.102	0.007
	Highly educated (0/1)	0.020	-0.020	0.062	.172	0.005
	Full time employed (0/1)	0.052	0.012	0.091	.006***	0.013
	Log(settlement size)	-0.017	-0.024	-0.011	.000***	-0.026
	Car owner (0/1)	1.330	1.291	1.368	.000***	0.842
	Individual car pride: indirect	0.225	0.211	0.240	.000***	
Threshold	0.498	0.275	0.727	.000***	0.612	
	R^2	0.739	0.728	0.750	.000***	
Log(miles driven on a typical day)	Age (yrs)	0.005	0.003	0.006	.000***	0.053
	Male (0/1)	0.158	0.133	0.184	.000***	0.078
	Monthly HH income (\$100)	0.002	0.001	0.002	.000***	0.048
	Highly educated (0/1)	0.015	-0.013	0.044	.147	0.007
	Full time employed (0/1)	0.079	0.053	0.106	.000***	0.039
	Log(settlement size)	-0.010	-0.014	-0.005	.000***	-0.029
	Car owner (0/1)	0.066	0.048	0.083	.000***	0.082
	Individual car pride: indirect	0.011	0.008	0.014	.000***	
	R^2	0.030	0.025	0.035	.000***	

Notes: Model fit by Bayesian PPC: 95% CI for difference between observed and replicated chi-square values = [6444.930, 7070.190], $p < .01$.

6.4.3 Discussion

In this section, we explore the relation between individual car pride and car use. Informed by the bidirectional models estimated in Chapter 5, we assume that car pride predicts car use only indirectly through car ownership, while car use directly reinforces car pride. Estimating average relations across all individuals and countries in our international sample, we find that the indirect paths from car pride to both car use outcomes are positive and statistically significant. This suggests that greater individual car pride predicts greater likelihood of using a car and higher number of miles driven on a typical day, but this relation is mediated by car ownership. In the reverse direction, we find that being a car user and driving more miles on a typical day are both predictive of greater individual car pride. We find that these relations remain statistically significant after controlling for individual sociodemographics.

Descriptive statistics that compare the mean individual car pride scores of car-users and non-car-users across countries suggest that there is substantial variation across countries in our sample. Therefore, we might expect that the average relations between car pride and car use estimated in this section may vary by social and cultural contexts, which may not be wholly captured by the sociodemographics of the individuals who make up our country subsamples.

6.5 Country Car Pride

While car pride and its relations with car ownership and use primarily exist at the individual level, our international sample also allow for us to explore variation in car pride across countries. Our multilevel modeling framework apportion variance observed in the survey items to individuals and countries, resulting in estimates of country car pride factor scores (see Chapter 3). Unlike simple country mean scores often employed in international comparisons, our country car pride scores represent the “pure” country contextual effects having controlled for differences in the individuals that make up each country.

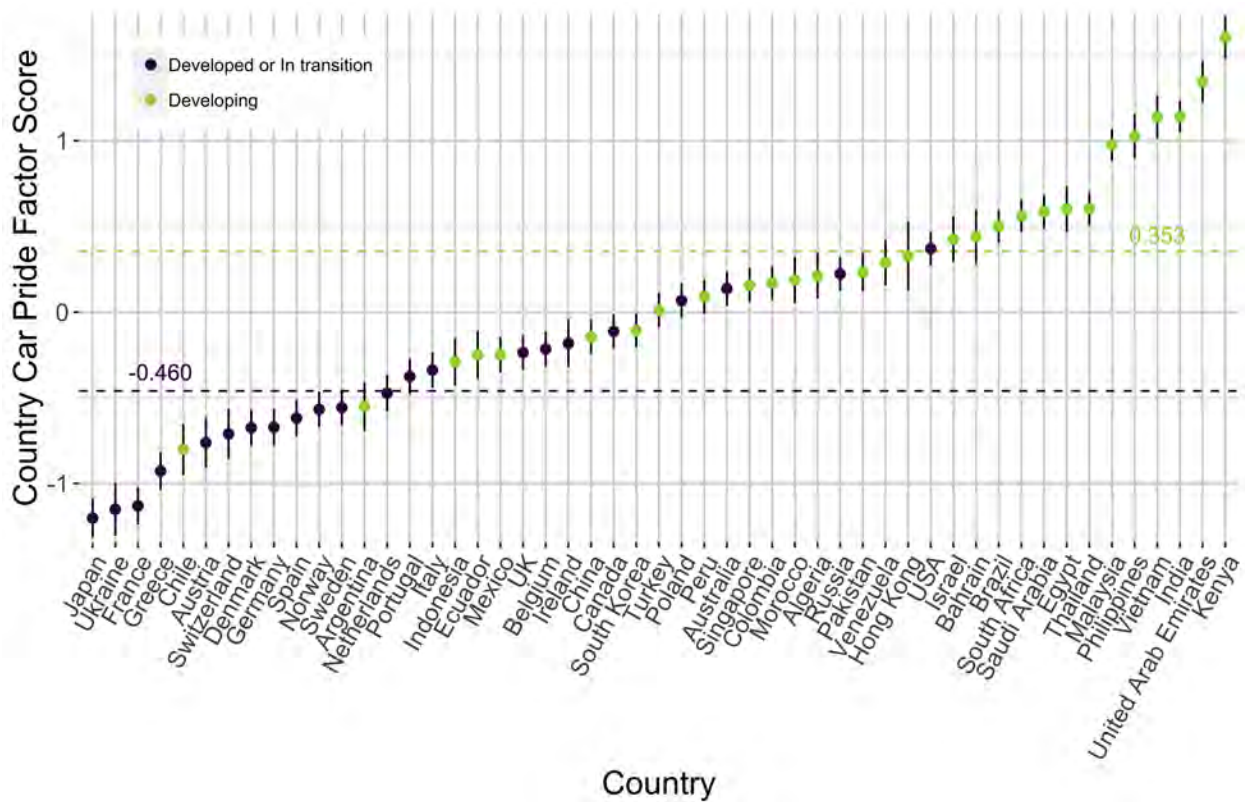
In this section, we use these country car pride factor scores to explore cross-country variation in car pride. We begin by plotting our country car pride scores for developing and developed countries and by region. Then we explore what national characteristics might help to explain the variations we see in our country car pride scores. While the multilevel SEM approach that we have adopted throughout this chapter allow for specification of multiple regression relations at the between-group (country) level as well as the within-group (individual) level, our small sample of countries ($n = 51$) cannot support such a multivariate approach. Therefore, we limit our investigation of country car pride to simple bivariate relations with indicators of national economic development and motorization.

6.5.1 Visualizing Variation Across Countries

We begin by plotting our estimated car pride factor scores for the 51 countries in our international sample (see Figure 6.10). Classifying countries as developing or developed according to the [United](#)

Nations (2017), we see a striking trend. In general, we see that developed countries have low country car pride, whereas developing countries appear to have higher country car pride. We confirm this visual trend by comparing the average country car pride scores of developing and developed countries. We find that developing countries have a higher average country car pride ($\mu_{\text{developing}} = 0.353$) than their developed country counterparts ($\mu_{\text{developed}} = -0.460$) and that this difference is statistically significant by a two-sample t-test: $t = -5.755, p < .01$.

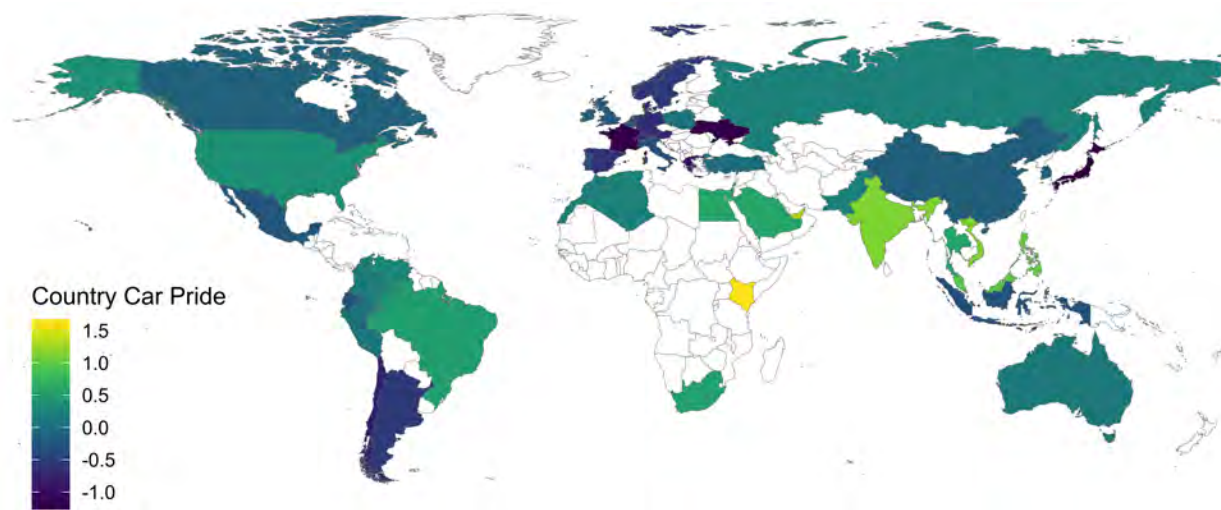
Figure 6.10: Distribution of country car pride factor scores



Note: Bars represent standard errors of estimation.

While there is a clear global trend of higher car pride in developing rather than developed countries, mapping the country car pride scores enables further comparison of car pride among neighboring countries and allows us to discuss additional regional differences. From Figure 6.11, we find that there are indeed clear regional differences, even within the global trend of higher car pride among developing countries and lower car pride among developed countries. Among developing countries, the highest car pride is observed among countries in Southeast Asia, Africa, and the Middle East. On the other hand, we see moderate-to-low car pride among developing countries in Latin America, particularly Chile and Argentina. Among developed countries, we find the lowest car pride scores in Japan and among countries in Europe, whereas the U.S., Russia, and Australia are outliers reporting higher car pride.

Figure 6.11: World map of country car pride factor scores



These differences we observe in country car pride between developing and developed countries and among different regions of the world suggest that national context contributes to differences in car pride at the country-level. Having demonstrated country-to-country variation in car pride, our next step is to try to determine what contextual factors, such as differing levels of economic development and motorization, might contribute to these differences we see in country car pride.

6.5.2 Correlations with National Indicators

To explore how different levels of national economic development and motorization might relate to country car pride, we use a set of complementary national indicators gathered from various publicly available and globally consistent datasets as detailed in Chapter 2. For each category of indicator, we calculate their linear Pearson (r) and Spearman rank (ρ) correlations with country car pride across as many of the 51 countries in the sample for which data are available.

Macroeconomic Conditions

The first set of national indicators that we consider are those selected to represent economic development and macroeconomic conditions surrounding car consumption (see Table 6.4).

We consider the correlation of measures related to national wealth and income inequality with country car pride. We find that two both commonly used GDP per capita measures have a negative relation with country car pride, but that the relation is stronger for unadjusted GDP—a measure of economic production—than for GDP per capita adjusted for purchasing power parity—a more comparable measure of standard of living. We also find that GDP per capita annual growth as well as Gini index—a measure of income inequality—have moderate and positive correlations with car pride. Together these results suggests that countries with lower current economic production,

higher rates of economic growth, and greater income inequality report higher car pride at the country level (see Figure 6.13).

Table 6.4: Correlation matrix of country car pride and national macroeconomic indicators

	0	1	2	3	4	5	6
0 Country car pride		-.385	.264	-.239	.327	.477	-.505
1 GDP per capita (US\$1000)	-.439		-.171	.900	-.443	.568	.596
2 GDP per capita an. growth (%)	.247	-.320		-.198	-.297	-.014	-.026
3 GDP per capita, PPP (I\$1000)	-.304	.952	-.307		-.439	.395	.393
4 Gini index	.337	-.351	-.159	-.412		-.309	-.325
5 Gas pump price (US\$/liter)	-.543	.561	-.046	.430	-.310		.956
6 Diesel pump price (US\$/liter)	-.554	.577	-.068	.443	-.400	.953	

Note: an. = annual; I\$ = current international dollars.

The shaded upper triangle contains linear Pearson correlations and the lower triangle contains Spearman rank correlations.

We also consider correlations of country car pride with national indicators of the price of fuel for consumers. In particular, we find that country car pride is strongly and negatively correlated with pump price for both gas and diesel (see Figure 6.12). Because gas and diesel pump prices at the national level are themselves highly correlated, having both relations is redundant. However, the trend is clear: car pride is higher in countries where fuel is less expensive. There are many potential explanations for this bivariate relation. One might be that countries with lower fuel costs encourage car use at the national scale, which in turn reinforces higher country car pride.

Figure 6.12: Country car pride score vs. pump price for gas and diesel

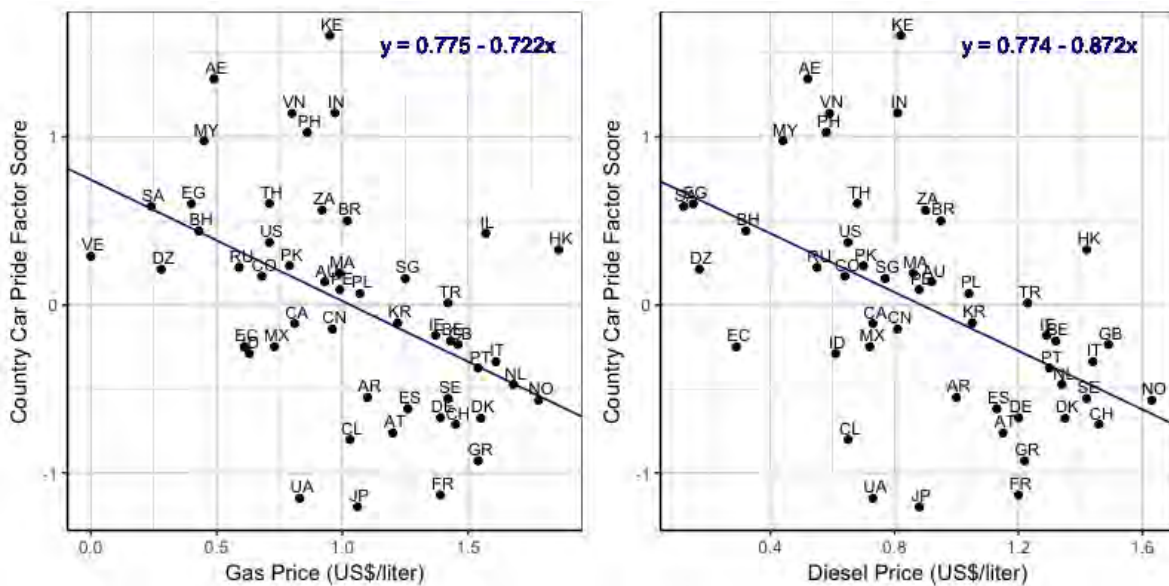
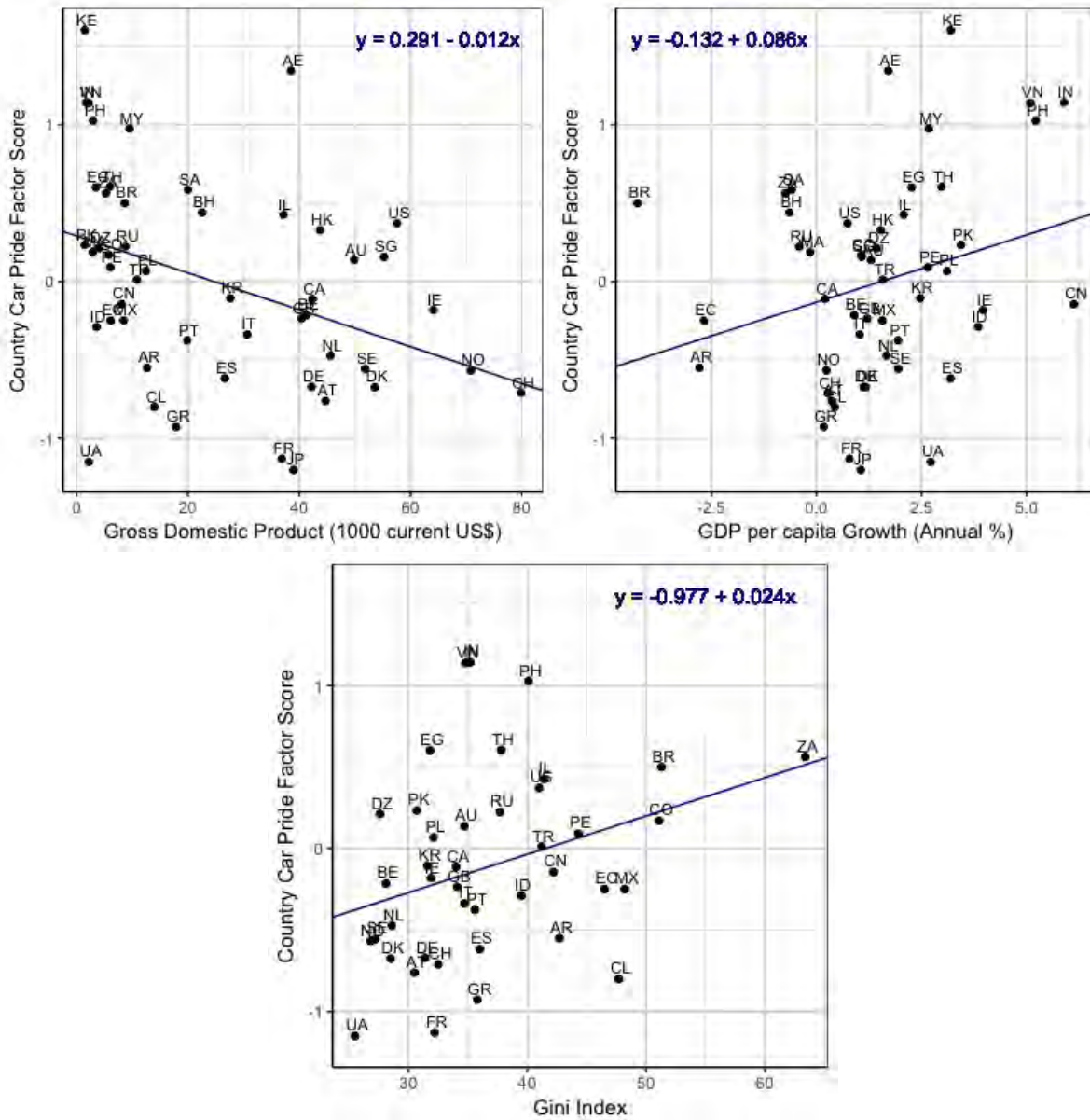


Figure 6.13: Country car pride score vs. GDP per capita, GDP annual percent growth, and Gini index



Motorization

Next we consider the correlations of national car ownership indicators with country car pride (see Table 6.5). We first note that national motorization rate (total vehicles per 1000 people) has a strong, negative correlation with country car pride. However, we find that if we look at the correlation of personal vehicle (car) stock rather than total vehicle stock, the correlation is even stronger. Therefore, we focus our discussion on the correlations of current levels and recent growth in personal vehicle stock and sales with country car pride.

Table 6.5: Correlation matrix of country car pride and national motorization indicators

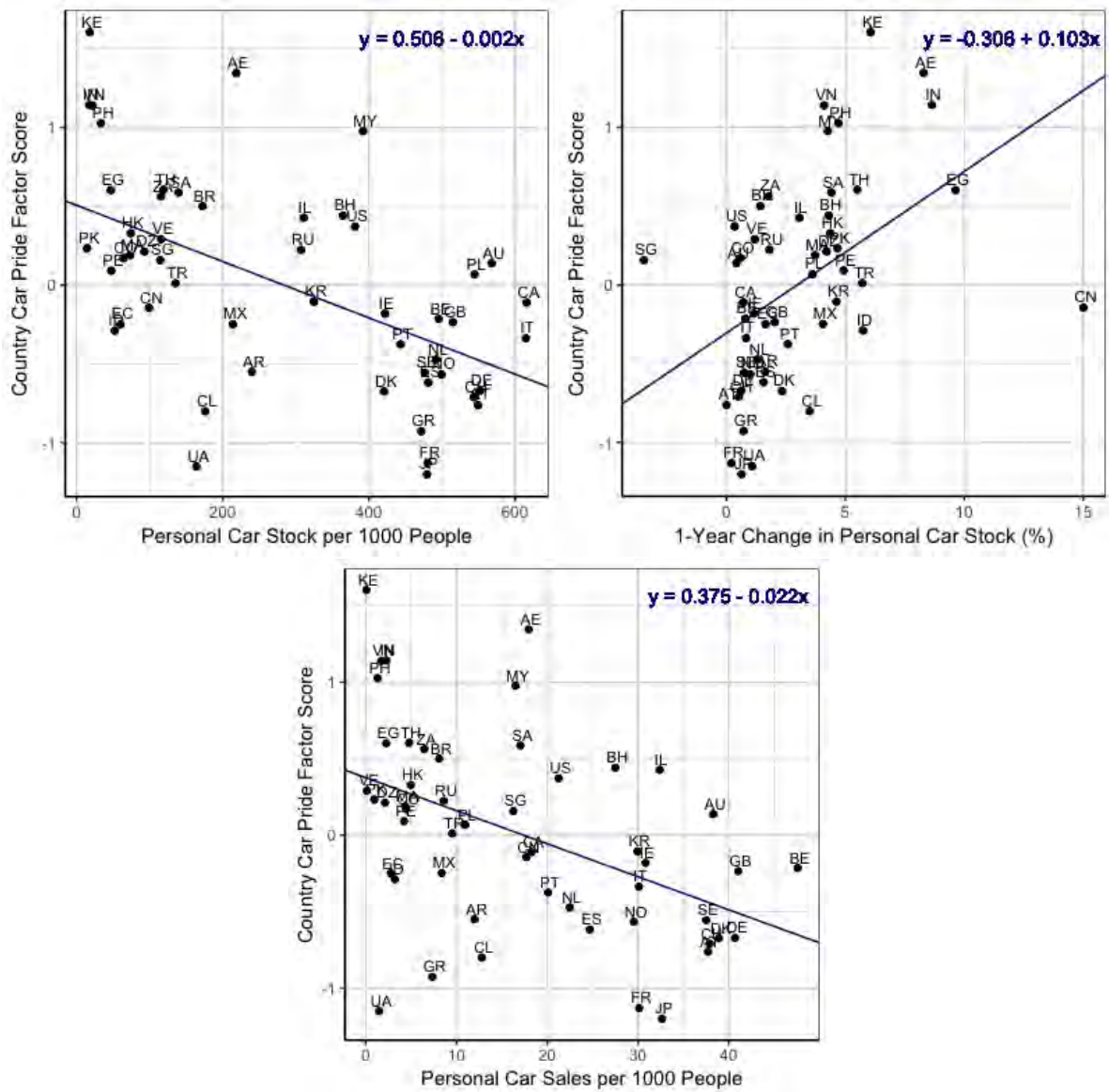
	0	1	2	3	4	5	6
0 Country car pride		-.540	.561	-.550	.473	.337	-.463
1 Motorization rate (veh/1000 ppl)	-.548		-.572	.968	-.540	-.565	.789
2 1-yr change in motorization rate	.631	-.675		-.563	.903	.719	-.397
3 Personal car stock per 1000 ppl	-.575	.967	-.680		-.521	-.550	.819
4 1-yr change in personal car stock	.566	-.666	.875	-.643		.828	-.385
5 5-yr change in personal car stock	.436	-.670	.766	-.652	.774		-.410
6 Personal car sales per 1000 ppl	-.492	.812	-.502	.843	-.512	-.534	

Note: veh = vehicles; ppl = people.

Across our 51 countries, we see higher car pride in countries with less mature personal vehicle markets—markets with lower current personal vehicle ownership levels (in terms of car stock per 1000 people), but higher growth in personal vehicle ownership (see Figure 6.14). When it comes to car sales, we also see moderate, negative correlations with country car pride. This result again points to the fact that less mature car markets—where sales per capita are not yet very high—have higher country car pride (see Figure 6.14).

At first glance, the fact that country car pride is negatively correlated with national indicators of vehicle ownership may appear to contradict our previous finding that, in most countries, individual car pride is positively predictive of individual car ownership (see Section 6.3). Instead, this difference between individual and country level relations of car pride and vehicle ownership is plausible and highlights the importance of using multilevel modeling to appropriately decompose observed variance into individual and country level components. By properly addressing the hierarchical nature of the data, we find that individual car pride is positively predictive of owning a car, but that being in a country where more people own cars is negatively correlated with aggregate attitudes towards car consumption.

Figure 6.14: Country car pride score vs. national personal car stock and sales



Road Density, Expenditure, and Use

Finally, we consider the correlation of national indicators of road density, expenditure, and use with country car pride (see Table 6.6). As discussed in Chapter 2, these indicators proved the most difficult to find for all 51 countries in our international sample. Therefore, the correlations cited in Table 6.6 are only for a subset of 20-25 high and upper-middle income countries. Therefore these results are based on an even smaller sample than the other correlations discussed above, and that sample is less representative of all global countries.

Table 6.6: Correlation matrix of country car pride and national indicators for road density, expenditure, and traffic

	0	1	2	3	4
0 Country car pride		-0.366	-0.225	.592	-.255
1 Road density (km per 100 km ²)	-0.452		-0.252	.018	-.014
2 Road investment (US\$) per capita	-.228	-.096		.093	.241
3 Veh-km (1000) per veh	.664	-.131	-.056		.124
4 Log(pass-km by road per 1000 veh)	-.300	-.001	.254	.039	

Note: veh = vehicle; pass = passenger.

For this smaller sample of mostly developed countries, we find that country car pride is negatively correlated with road density, but positively correlated with vehicle use and road use (see Figure 6.15). In other words, countries with lower road density, but higher vehicle and road use have higher car pride. The finding for vehicle use, in particular, is notable as it might be related to our previous finding that countries with lower fuel costs have higher car pride. Combining these country results, we might posit that countries with lower fuel costs encourage car use at the national scale, which in turn reinforces higher country car pride. In this case, the country level results would parallel the results we see at the individual level in Section 6.4, where car use is positively predictive of car pride.

Figure 6.15: Country car pride score vs. road density, vehicle-km, and passenger-km

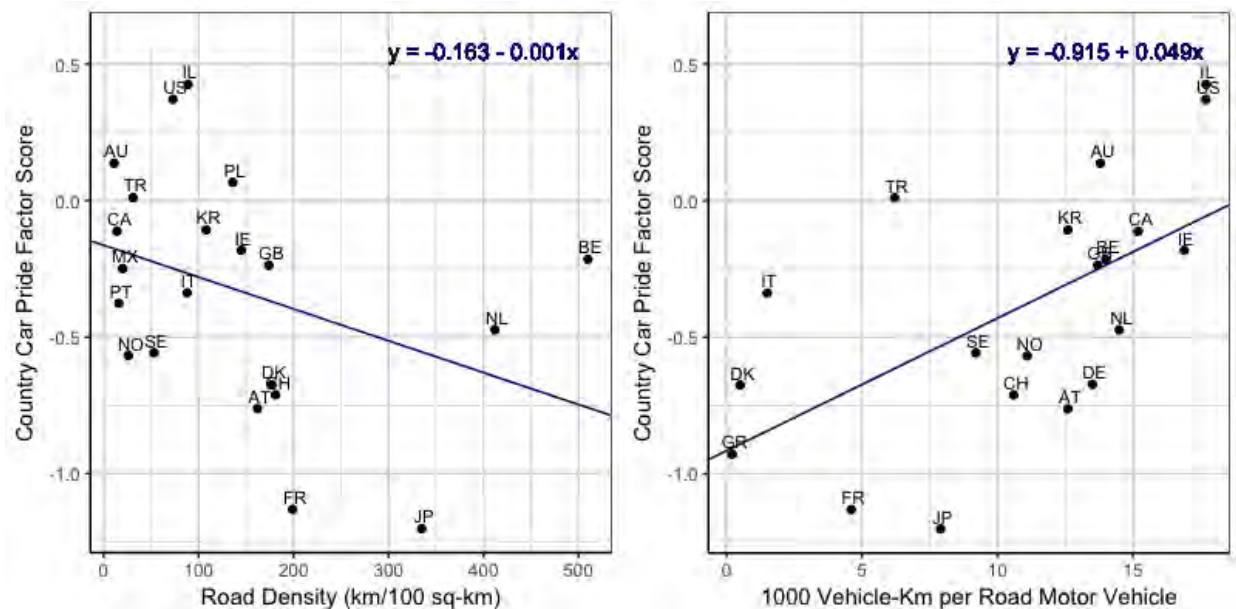
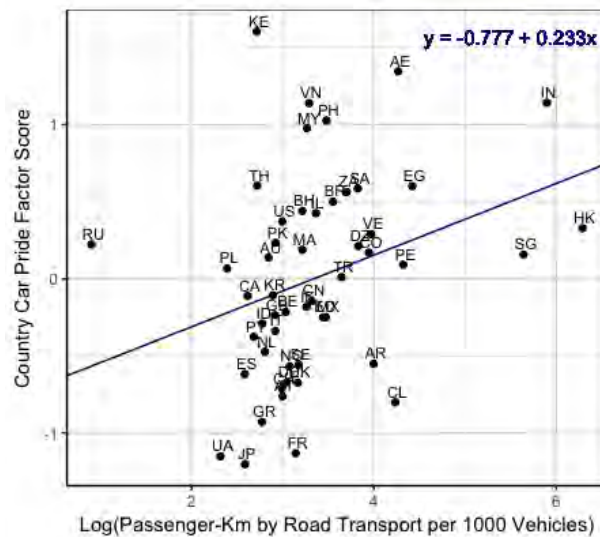


Figure 6.15: Country car pride score vs. road density, vehicle-km, and passenger-km (*continued*)



6.5.3 Discussion

In this section, we explored variation in car pride across countries. Our analysis is an improvement over most international comparisons in the literature because it looks at car pride across a larger and more varied set of countries and because it uses multilevel modeling techniques (rather than simple country mean responses) to capture the “pure” country-level effect. We demonstrated that variation exists in car pride across countries, even after controlling for differences in the individuals that live in these countries. Across the 51 countries in our international sample, we found that developing countries show significantly higher car pride than developed countries, particularly in Southeast Asia, Africa, and the Middle East.

We next explored whether these differences in car pride at the country level could be explained by differences in national macroeconomic conditions, motorization levels, and road density, expenditure, and use. Because our sample of countries is too small to support a multivariate approach, we considered bivariate correlations between car pride and select national indicators. Together, these correlations mirrored the findings that developing countries—countries with lower national production (GDP per capita), higher income inequality (Gini index), lower fuel prices, less mature personal vehicle markets, but greater vehicle use—have higher country car pride.

6.6 Conclusions

In this chapter, we explore variation in car pride and its relations with car consumption across individuals in our international sample. We find that individuals with higher household incomes, who live in larger towns or cities, and who are younger, male, highly educated, and full-time

employed have higher car pride.

Considering how individual car pride relates to car ownership. A simple comparison of mean car pride scores between car-owners and non-car-owners in our sample suggests that car pride is positively related to individual car ownership globally and in almost all country subsamples. Controlling for individual sociodemographic characteristics in an MSEM, we find that greater car pride is significantly, but only modestly predictive of greater car ownership across all individuals in our sample. Allowing these relations to vary by country, we find that individuals in different countries with the same car pride don't have the same likelihood of owning a car. This suggests that social and cultural contexts not captured by the sociodemographics of the individuals who make up our country subsamples influence how much car pride predicts car ownership.

Similarly, we consider how individual car pride relates to car use. A simple comparison of mean car pride scores between car-users and non-car-users in our sample suggests that car pride is positively related to individual car usage globally and in almost all country subsamples. Controlling for individual sociodemographic characteristics in an MSEM, we find that individual car pride is positively and significantly predictive of car use—likelihood of using a car and number of miles driven on a typical day—through car ownership. In the reverse direction, we find that being a car user and driving more miles on a typical day are both predictive of greater individual car pride across all individuals in our sample.

Taken together, these results suggest that, on average, car pride is positively and significantly related to car consumption across a diverse sample of individuals. However, the strength of these relations do vary by country. This variance observed across countries demonstrates the importance of taking macro-level social, cultural, and national context into account when measuring and interpreting symbolic and affective motivations for car consumption, even at the individual-level.

Finally, we explore variation in car pride across countries. Unlike a simple mean scores, our country car pride factor scores measure the “pure” country effect after controlling for the fact that different types of individuals live in different countries. We find that developing countries—countries with lower national wealth, higher income inequality, lower fuel prices, less mature personal vehicle markets, but greater vehicle use—have higher country car pride than developed countries. While our data cannot tell us how car pride will predict car ownership or vice versa at the country level, the fact that we observe higher car pride among developing countries is potentially an alarming trend given that the majority of growth in car ownership and use is projected to occur in these same developing countries. This suggests a bleak future for sustainable transport at the global scale in the absence of early and sustained policy intervention targeting both attitudes and car ownership and use, particularly in developing and motorizing countries (see Chapter 7 for a more thorough discussion of the potential implications of this dissertation for sustainable transportation policy).

6.6.1 Contributions

This chapter visualizes and summarizes variation in car pride and its relations with car consumption across a global sample of unprecedented size and diversity. Using multilevel structural equation modeling techniques, we properly apportion variance in our data to individual and country components. We find that car pride and its associations with car consumption are fundamen-

tally individual-level relations, but there are clear country-level patterns and material geographies around car consumption. This cross-cultural study of car pride and its associations with car ownership and usage clearly shows the importance of taking context into account and demonstrates empirically that car cultures exist at national levels.

While our data is unable to support a deeper dive into the factors contributing to observed variance across countries, the MSEM framework that we introduce here could be used to answer such critical questions. Therefore, this study lays the methodological foundation for future research into cultural patterns of car consumption and serves as a cautionary tale for researchers and practitioners looking to translate attitude-behavior relations from one cultural context to another.

6.6.2 Limitations and Future Work

In this chapter, we complement the in-depth exploration of car pride and its bidirectional relations with car consumption in two U.S. cities presented in Chapter 5 with a broad exploration of variation in car pride and its association with car consumption across 41,932 individuals and 51 countries. While this chapter greatly expands previous work by providing breadth of cross-cultural understanding, the results are limited by the non-representativeness of the countries sampled, the small sample size at the country-level, and the cross-sectional nature of the data. Here we discuss these limitations and potential for future research to address them.

Generalizability across Countries

Given the implications of sampling design on inference in multilevel models, we must be careful to draw any generalized inference from our study not supported by the sampling design (see Chapter 2). Given that the individuals in our international sample are representative of their national populations in terms of age and gender and a reasonable set of sociodemographic covariates are included in the models to control for other individual sociodemographics, we can be reasonably confident in our parameter estimates and their standard errors for our large sample of individuals. This suggests that our results are likely to generalize to a large portion of the global population.

On the other hand, the countries included in the survey were a convenience sample and are not necessarily representative of all countries in the world. Most notably, our sample of 51 countries contained none of the world's lowest income countries (see Chapter 2). Therefore, without further post-stratification, we cannot attribute the results of our analysis to countries outside of our sample and future research would be needed to explore whether the findings from this study generalize to other national contexts.

Explaining Variation across Countries

In this chapter, we employ MSEM to properly address the hierarchical nature of our international data. We use this multilevel framework to estimate attitude-behavior relations at the individual-level and to visualize how these relations differ across countries. However, we do not try to explain

the variation we observe across countries in our model. In theory, since MSEM allows specification of relations among variables at both the individual and country levels, we could use country-level covariates, such as national economic and motorization indicators, to try to explain observed country-level variation. However, in practice, our international sample includes only 51 countries, which post-hoc power analysis suggests is an insufficient sample size to detect statistically meaningful relations at the country level. Therefore, we are unable to include country-level covariates in our models and we are limited to demonstrating, but not explaining variation across countries.

Limited by our sample size at the country-level, we are unable to use the MSEM framework to its fullest potential. However, research equipped with data from more countries (or cities) can build on the modeling framework that we present here to not only demonstrate, but also explain higher-level variations in car pride and its relation to car consumption. In order to perform such an analysis, researchers would need survey data from individuals and a set of country (or city) covariates that are standardized and consistent. Unavailability of comparable data on economic activity, urbanization, and transportation across countries (or cities) may be a barrier to this promising line of future research. This quantitative approach should also be complemented by qualitative methods that explore further the mechanisms by which these attitudes (and associated behaviors) form across people and places (Ashmore et al., 2018b; Sheller, 2004).

Endogeneity from Reciprocal Relations

In this chapter, we explore the associations between car pride and car consumption using cross-sectional data. While we expect that bidirectional relations exist, our data do not contain the information necessary to simultaneously estimate both attitude-to-behavior and behavior-to-attitude relations as we did in Chapter 5.

In the absence of such information, we specify directed paths between individual car pride and car ownership and use based on the in-depth modeling results from our U.S. sample in Chapter 5. In doing so, we generalize results from a relatively homogeneous population of commuters in two U.S. cities to a sample of individuals and countries far beyond the original population of interest and which demonstrates significant country-to-country variation. Therefore, future research is needed to check the validity of this generalization of the relative strengths of bidirectional relations between car pride and car consumption from the U.S. to a global context.

While the models from the U.S. inform the directed paths specified in the model, we do not correct for the endogeneity that may be introduced by the presence of an unmodeled bidirectional relation. Therefore, it is likely that the relations between car pride and car consumption estimated in this chapter are biased by this endogeneity. Therefore, the exact magnitude of the relations between car pride and car consumption estimated here should not be overly interpreted. Future research could employ longitudinal data or other econometric techniques (such as the use of instrumental variables) to correct for this endogeneity and make causal claims on the relations between car pride and car consumption in our international sample.

Chapter 7

Findings, Recommendations, and Implications

The transportation sector is a significant and fast-growing contributor to CO₂ emissions globally (EIA, 2016; IEA, 2012; SLoCaT, 2015). Furthermore, projections suggest that the sector will be an even more substantial problem in the future. Many countries that currently have very low transport emissions per capita are showing significant growth in this sector, and will have to take immediate action to keep transport emissions in check in the coming decades (SLoCaT, 2015). In addition to CO₂ emissions, private fossil fuel-based vehicles are also significant contributors to local air pollution, road safety issues, and social exclusion (Sum4All, 2017).

As global incomes continue to rise, demand for new car purchases and the number of personal vehicle miles traveled will continue to grow, often at the expense of more sustainable transit and active travel modes. Road travel is projected to double by 2050 with most of this growth coming from developing countries (EIA, 2016). While expanding individual mobility, car consumption comes with too many negative externalities. As we are becoming increasingly aware of the unsustainability of our current (and future) car-reliant transportation systems, understanding how to avoid new car ownership growth and shift current users towards more efficient, environmentally-friendly, safe, and inclusive alternatives is a critical vision for meeting sustainable (transportation) development goals (IEA, 2012; Sum4All, 2017; UN General Assembly, 2015). While technology, infrastructure, and service development will play a role in providing sustainable alternatives, symbolic and affective values (attitudes) also influence an individual's travel decisions to own or use a car. Therefore, a thorough understanding of these attitudes is critical in formulating strategies to promote sustainable transportation systems.

The car not only fulfills instrumental transportation functions, but also holds important symbolic and affective meaning for its owners and users. However, existing studies in the transportation domain share three critical limitations that make it difficult to compare findings across studies and draw general conclusions regarding attitude-behavior relations:

1. Lack of specific, well-validated measures for symbolic and affective motives
2. Failure to account for the bidirectionality of attitude-behavior relations
3. Little exploration across contexts

This dissertation addresses each of these limitations by investigating, in depth, one specific symbolic value of owning and using a car: pride. We design and deploy two purpose-built surveys, collecting cross-sectional data for a U.S. city sample of 1,236 individuals in New York City and Houston and an international sample of 41,932 individuals across 51 countries (see Chapter 2). Through a series of empirical analyses on these data, we evaluate how to measure car pride (Chapters 3 and 4), model its relations with car-related behaviors (Chapter 5), and compare it across countries with different social and cultural contexts (Chapter 6). Thus this dissertation builds the first systematic knowledge base on car pride and its relations to car consumption across individuals, cities, and countries.

This final chapter synthesizes the findings from our multiple empirical investigations, makes recommendations for future research, and discusses their implications for policy. Section 7.1 summarizes the main findings and contributions of this dissertation on car pride and car consumption. Section 7.2 discusses general limitations of our empirical approach and lays out how future studies can expand on and complement the knowledge we have generated here. Section 7.3 discusses key lessons-learned for researchers and highlights the greater methodological rigor in studying attitude-behavior relations in transportation. Finally, Section 7.4 discusses how these findings regarding car pride and car consumption (as well as our understanding of attitude-behavior relations in transportation more broadly) might inform sustainable transportation policy. It discusses the interplay between policy interventions that directly target car ownership or use and marketing interventions that reshape attitudes related to these behaviors.

7.1 Main Findings

In this section, we summarize the main findings from our empirical investigations into car pride and its relations with car consumption (Chapters 3-6). While each of these chapters includes more in-depth discussions of its results, here we summarize the key findings from across the different chapters. While we cannot directly compare model estimates between our two survey measures of car pride and our two samples, we do identify overarching findings that are supported by both cases. Therefore, here we integrate findings from across our chapters, synthesizing what we have learned generally about car pride and its relations with car ownership and use.

7.1.1 Measuring Car Pride

In this dissertation, we develop and test multiple ways of measuring car pride. In a sample of commuters from the New York City and Houston metropolitan areas, we investigate the reliability, validity, and invariance of an explicit measure of car pride derived from a polytomous survey scale (see Chapter 3) using a series of confirmatory factor analysis (CFA) models. Based on these results, we propose our 12-item, 7-point Likert-scale measure of the attribution of social status and personal image to driving and owning a vehicle as a new, standard measure for car pride that is reliable, valid, and invariant between cities and across individuals with different car consumption.

For the U.S. cities sample, we also derive an implicit measure from a car vs. bus social status Implicit Association Test (IAT; see Chapter 4). Comparing the psychometric properties of our explicit and

implicit measures of car pride in our U.S. sample, we find that our explicit measure is a more valid measure. Comparing their correlations with actual car ownership and use, we further find that our explicit measure of car pride is more interpretable and useful than our implicit measure derived from the IAT. These results might suggest that explicit rather than implicit cognitive pathways dominate car consumption, including decisions of car ownership and use. The results also suggest that traditional (explicit) survey scales, if carefully developed and well-validated, are likely adequate for probing many attitude-behavior relations.

In our international sample of 41,932 individuals in 51 countries, we test a dichotomous version of the car pride scale, composed of 9 agree-disagree survey items designed for mobile phone-based data collection. Using multilevel CFA, we find that this measure also exhibits reasonable convergent validity, reliability, and invariance across countries and propose it as an alternative, standard measure particularly useful for cross-cultural comparison. However, the dichotomous version of the car pride scale is less able to differentiate among individuals who disagree with statements associating social status and personal image to owning and using a car. Therefore, the polytomous version of the car pride scale should be preferred unless, as in our international survey, data collection will be done via small-screen devices that make display of Likert-format scales difficult.

Together this measurement development and validation provides standard, quantifiable survey scales of car pride that can be compared across people, providing consistent, specific, and actionable information for future transportation planning and policymaking. It also provides the foundation needed for the empirical explorations of car pride and its relations with car ownership and use in Chapters 5 and 6.

7.1.2 Variations in Car Pride

Equipped with well-validated survey measures of car pride, we can visualize and model variations in car pride across individuals, cities, and countries. For individuals in our U.S. cities, we find higher car pride among those who are younger, male, white, students, and from higher-income households. For individuals in our international sample, we find that those who are younger, male, highly educated, full-time employed, who live in larger towns or cities, and from higher-income households have higher car pride, no matter the country they live in. Therefore, across both samples we identify age, gender, and income as significant sociodemographic predictors of car pride. However, we also find that individual sociodemographics are limited in their capacity to explain observed variation in car pride, suggesting that many other factors not explored in this dissertation contribute to the formation of different levels of car pride among different individuals.

Next, we compare car pride across cities and countries. Using multigroup and multilevel modeling techniques, we first control for any differences in car pride related to the individuals in the subsamples. Comparing between cities in the U.S., we find that an equivalent individual living in New York City is likely to have lower car pride than one from Houston. While future work would be needed to explore what characteristics of these cities contribute to observed differences, we speculate that car pride may be related to car dependency; individuals living in cities like Houston—where urban form and transportation infrastructure provide little alternative to owning and using a car—may form greater symbolic attachment to their vehicles.

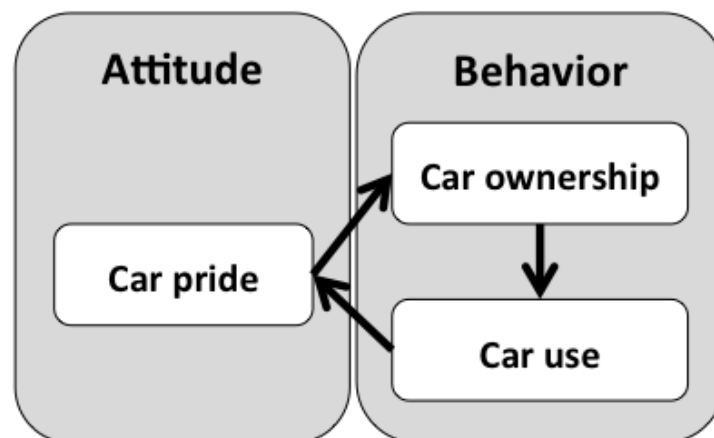
Similarly, after controlling for the types of people living in different countries, we find that developing countries—with lower national wealth, greater income inequality, and lower rates of car ownership and use—report higher values of car pride. This suggests that the effect of national context on car pride is related to the stage of economic development and motorization of a given country. Again, explaining this observed variation across countries is left for future research.

7.1.3 Car Pride and Car Consumption

Next, we explore how car pride relates to car consumption. We begin by comparing car pride between car-owners and non-car owners and car-users and non-car-users. In almost every city and country examined, we find that individuals who own and use cars have significantly higher car pride than others. Applying multivariate structural equation modeling techniques, we find that these observed relations between car pride and car consumption remain significant after controlling for sociodemographics of the individuals in our U.S. and international samples.

Unlike much of the literature that assumes attitudes influence behavior, we explore bidirectional relations between car pride and car ownership and use in our U.S. sample. We find that bidirectional relations exist between car pride and car ownership as well as between car pride and car use. However, the relative strengths of these bidirectional attitude-behavior relations depend on the dimension of car consumption. We find that car pride strongly predicts car ownership, which in turn predicts car use; in the reverse direction, car use strongly reinforces car pride (see Figure 7.1). In other words, an individual with higher car pride is more likely to own a vehicle, and, enabled with this ownership, use it more frequently. In the reverse direction, we find that owning a car has no statistically significant impact on car pride, but using a car more (in terms of frequency or miles driven) contributes to greater car pride. All together, these relations create a feedback loop among car pride, car ownership, and car use.

Figure 7.1: Relations among car pride, car ownership, and car use



We find that the directions of car pride-car consumption relations depicted in Figure 7.1 hold on average across a diverse set of individuals living in different cities in the U.S. In fact, between New York City and Houston, we do not find a statistically significant difference in the strength of

these relations. We then impose these same directions when modeling car pride-car consumption relations across individuals in different countries around the world. In our international sample, we see significant variation across contexts. In particular, we find that the per-unit impact of an individual's car pride on the likelihood of owning a vehicle varies by country. Therefore, our work emphasizes the importance of taking the social and cultural context into account when measuring and interpreting symbolic and affective motivations for car consumption.

7.2 Areas for Future Research

This dissertation uses large-scale, cross-sectional data collection and the application of quantitative techniques that combine methods from psychometrics and econometrics to explore attitude-behavior relations in transportation. From primary data collection through measurement development and evaluation to behavioral analysis, this dissertation represents a significant step forward in quantifying and understanding car pride and its relations with car consumption. However, many questions still remain unanswered.

While each chapter in this dissertation concludes with a discussion of the limitations and immediate extensions of its empirical exercise, here we reflect more generally on the limitations of our approach, providing suggestions for how future research can expand on and complement the knowledge we have generated here. In particular, we highlight the need for future studies that use longitudinal data to explore the dynamics of car pride and its relation with car ownership and use over time; explore car pride as part of a broader set of symbolic and affective motivations of car consumption; consider car pride's relations with other dimensions of car consumption and travel behaviors; and explain differences in the car pride-car consumption relations that we observe in this dissertation across individuals and countries.

Attitude-Behavior Dynamics over Time

While our study makes a substantial contribution to the literature by using instrumental variables to estimate bidirectional relations using cross-sectional data of car pride, car ownership, and use, these results are based on only a single snapshot in time. We are able to compare the strength and direction of the bidirectional relations between car pride and car consumption, but we are unable to explore how these relations form or change over time. Investigations using panel data (consisting of repeated measures from the same individuals over time) could reinforce the directional and causal claims suggested in this dissertation by adding time precedence. Using cross lagged panel models or other similar longitudinal SEM techniques, researchers could reproduce and extend results similar to those presented in Chapter 5.

Panel data could also be used to probe individual dynamics of car pride and its relations with car consumption that we cannot capture using our cross-sectional data. One such application would be to study how car pride is formed, ebbs, and flows at an individual level according to different life stages and external influences. However, use of our car pride scale in these panel studies would require additional evaluation of the measure's psychometric properties (particularly test-retest reliability) to ensure that it is consistent across repeated measures.

Longitudinal cross-sections (consisting of multiple waves of random, representative samples over time), such as many regional and national household travel surveys, could also be used to look at aggregate dynamics in attitude-behavior relations. These surveys could look at changes in the average relations between car pride and car consumption over time and explain these dynamics with changes in economic, political, environmental, and social development. This type of study could help policymakers understand and predict how car pride and its relations with car ownership and use might evolve as cities and nations develop. Such investigations over time are an important extension of this work and could build from the existing measure development and behavioral modeling that we have laid out in this dissertation.

Other Symbolic and Affective Values of the Car

In this dissertation, we deliberately narrow the focus of our investigation to one specific symbolic motive of car consumption: car pride. This allows us to clearly define our construct, develop and evaluate how to measure it, model its relations with specific car-related behaviors, and compare it across cultures. However, with its narrowed scope, this research is not able to capture car pride's interactions with other symbolic and affective values of cars. Future research could define and measure other symbolic and affective values of car consumption and how they relate to car pride. For example, one could study whether individuals with greater car pride also experience greater feelings of freedom, control, or excitement about owning or using a car.

Additionally, research could explore how these other symbolic and affective motives relate to car ownership and use. When it comes to the relations between car pride and car consumption measured in this dissertation, other symbolic and affective values may be important omitted variables that could amplify or dampen the attitude-behavior relations that we measure throughout this work.

Other Dimensions of Car Consumption and Travel Behavior

Future research could also explore the impact of car pride on other dimensions of car consumption and travel behavior. When it comes to car consumption, this dissertation is limited in how it operationalizes car ownership and use. Car ownership decisions are not just binary decisions of whether or not a household owns a vehicle, but also involves multiple, interdependent decisions such as how many cars to own, what type(s) of vehicle(s) to purchase, when to purchase, and how much to spend. Similarly, car use is not limited to deciding how frequently to drive alone when commuting, but involves the choice of using a car over other modes as well as the frequency and distance of car travel for all different types of trips.

Beyond car ownership and use, research might also consider whether car pride is related to intended or actual use of emerging transportation technologies and services. We might reasonably hypothesize that car pride relates to an individuals' willingness to adopt vehicle electrification, automation, and sharing (and their different combinations). As policymakers look to encourage the joint development of these "three revolutions," future research can help by understanding how car pride may affect or be affected by the changing role and form of the car in our (urban) transportation systems.

Explaining Observed Variations across Cities and Countries

While informed by qualitative findings and theory regarding symbolic and affective values and their relations to car consumption, this dissertation is largely quantitative in its investigation of car pride and car consumption. While it demonstrates significant variations in car pride across individuals, cities, and countries, our multivariate modeling approach is limited in how much of the variation it can actually explain. Sociodemographic characteristics are significantly predictive of car pride, but much of the variation in car pride scores we see across individuals in cities in the U.S. and across countries remains unexplained. In our international sample, low statistical power from the small number of countries does not allow us to probe how and why we see cross-cultural differences in car pride and its relations with car consumption.

Future studies looking to explain, rather than simply demonstrate, cross-cultural variation in attitude-behavior relations should recognize the potential limits of quantitative modeling in exploring such questions and embrace mixed methods approaches that supplement quantitative analysis with qualitative understanding (Teddlie and Tashakkori, 2012). While our multivariate and multi-group or multilevel structural equation modeling techniques can incorporate additional predictors to provide even greater breadth of understanding, they may be most informative when combined with qualitative investigations of car pride and car consumption in key sociodemographic groups and case study cities or countries (Ashmore et al., 2017). Our empirical research could help to identify who and where in-depth interviews, focus groups, or other follow-up studies could be carried out. Such a mixed methods approaches would provide a much more nuanced picture of how individuals attribute their social status and personal image to owning and using a car than we can get using a quantitative approach alone.

7.3 Recommendations for Transportation Research

In measuring car pride and its relations with car consumption, this dissertation summarizes and applies state-of-the art methodological approaches that blend insights and tools from psychometrics, econometrics, and social psychology. This work extends the confirmatory factor analysis (CFA) and structural equation modeling (SEM) techniques commonly applied in the transportation literature by rigorously examining the psychometric properties of the measures used, incorporating instrumental variables to tease out bidirectional effects, and using multigroup and multilevel analyses to compare across individuals, cities, and countries.

From this experience, we make three important recommendations for how to improve the methodological rigor of empirical research into attitude-behavior relations in transportation:

1. Pay greater attention to validating and standardizing measures of symbolic and affective constructs;
2. Recognize that bidirectional relations are likely to exist between attitudes and behavior and model these relations accordingly; and
3. Expand the breadth of samples investigated and appropriately address their social and cultural context.

These three recommendations, each discussed in more detail below, urge transportation researchers studying attitude-behavior relations to engage more actively in the technical literature surrounding their work and to be more timely in learning from and applying methodological innovations from other disciplines. Blending knowledge and tools from psychometrics, econometrics, and social psychology, this dissertation serves as a reference for how to combine and more rigorously apply existing methods to further our understanding of attitude-behavior relations in transportation.

1. Pay greater attention to validating and standardizing measures of symbolic and affective constructs.

First, the transportation discipline must pay greater attention to the measurement of symbolic and affective constructs. The validity (accuracy), reliability (precision), and invariance (lack of bias across groups) of measures must be established if these measures are to be interpreted or used in further modeling (of travel behavior, for example). Good measure development starts from careful and systematic survey design, informed by existing theory and empirical evidence. Then measurement evaluation is carried out in a CFA framework, but it goes far beyond the current practice of citing established thresholds for factor loadings and overall model fit.

Because good measure development and validation requires significant due diligence, efforts should be streamlined and measures should be standardized and shared across studies, where possible. While this approach is a significant departure from the use of ad-hoc surveys that continues to dominate the literature, it enables the comparison of attitudes and their relations to travel behavior across people, between places, and over time. This approach would enable more collaboration and cumulative knowledge-building across studies and research groups.

In sharing measurement scales, it is important to remember that reliability, validity, and invariance are attributes of measures (scores) rather than immutable properties of the measurement scale (test). Therefore psychometric properties are determined by the sample being assessed and the purpose of the assessment (intended inference) as well as the underlying construct being measured and the scale itself. Therefore, even when conducting replication studies using established scales, measures must be re-evaluated for each new sample and research question.

Only with a more systematic and transparent approach to measurement development and evaluation, as demonstrated in this dissertation, can the transportation discipline begin to build comprehensive theories of the interrelations between attitudes and travel behaviors. With good measures of attitudes we can begin to understand their interrelations with one another and their implications for travel behavior in a way that is consistent, specific, and actionable for future transportation planning and policymaking.

2. Recognize that bidirectional relations are likely to exist between attitudes and behavior and model them accordingly.

Once equipped with well-validated and standard measures of attitudes, researchers will be able to explore their relations with travel behavior. In any such exercise, researchers must acknowledge that bidirectional relations exist between attitudes and travel behavior and that the relative

strengths of the attitude-to-behavior and behavior-to-attitude relations depend on the specific behavior in question. Given the bidirectionality of attitude-behavior relations (no matter their relative magnitudes), models that assume only one direction are plagued by endogeneity that can lead to erroneous conclusions. This calls into question the current practice of estimating single-directional models, even if the directional assumption is made based on Random Utility Theory or a general theory of human behavior, such as the Theory of Planned Behavior.

Researchers should anticipate this bidirectionality from the outset of research design. If limited to cross-sectional data collection, instrumental variables should be identified from complementary data sources or created through additional survey questions. These instrumental variables can then be incorporated into traditional SEM approaches. This can be sufficient for understanding attitude-behavior relations that have reached equilibrium or are slow to change. However, if working with attitudes and/or behaviors that exist in a dynamic environment, longitudinal data may be required. In such cases, time-series SEM approaches—such as cross-lagged panel models—should be applied.

3. Expand the breadth of samples investigated and appropriately address their social and cultural context.

Finally, our research highlights the importance of social and cultural contexts when it comes to attitude-behavior studies. While our findings regarding the general strength and direction of relations among car pride, car ownership, and car use hold, on average, across a broad range of individuals, cities, and countries, the per-unit impact of attitude on behavior shows significant variation based on social and cultural context. This should serve as a cautionary tale for researchers and policymakers wanting to generalize the findings from existing studies—generally conducted on samples from single cities or regions in developed countries—to broader populations.

Future research into attitude-behavior relations in transportation must expand the breadth of samples investigated and use multigroup or multilevel analysis to compare across contexts. Multigroup analysis is recommended for in-depth case studies that compare many multivariate relations across a small number of groups (defined by similar sociodemographics, attitudes, or geographic locations). These types of studies usually require minimum sample sizes of 200 individuals within each of 2-10 groups. Multilevel analysis is most useful for broad cross-cultural comparisons of a few, key relations. These types of studies compare relations across a much larger number of groups (minimum of 50, but often more than 100), usually with as few as 10 individuals representing each group. No matter the chosen modeling technique, the study must be designed and data collected from the outset to support it. This should include a pre-study power analysis to determine the sample size needed for the complexity of the model being tested and the hypothesized magnitude of the effects being measured.

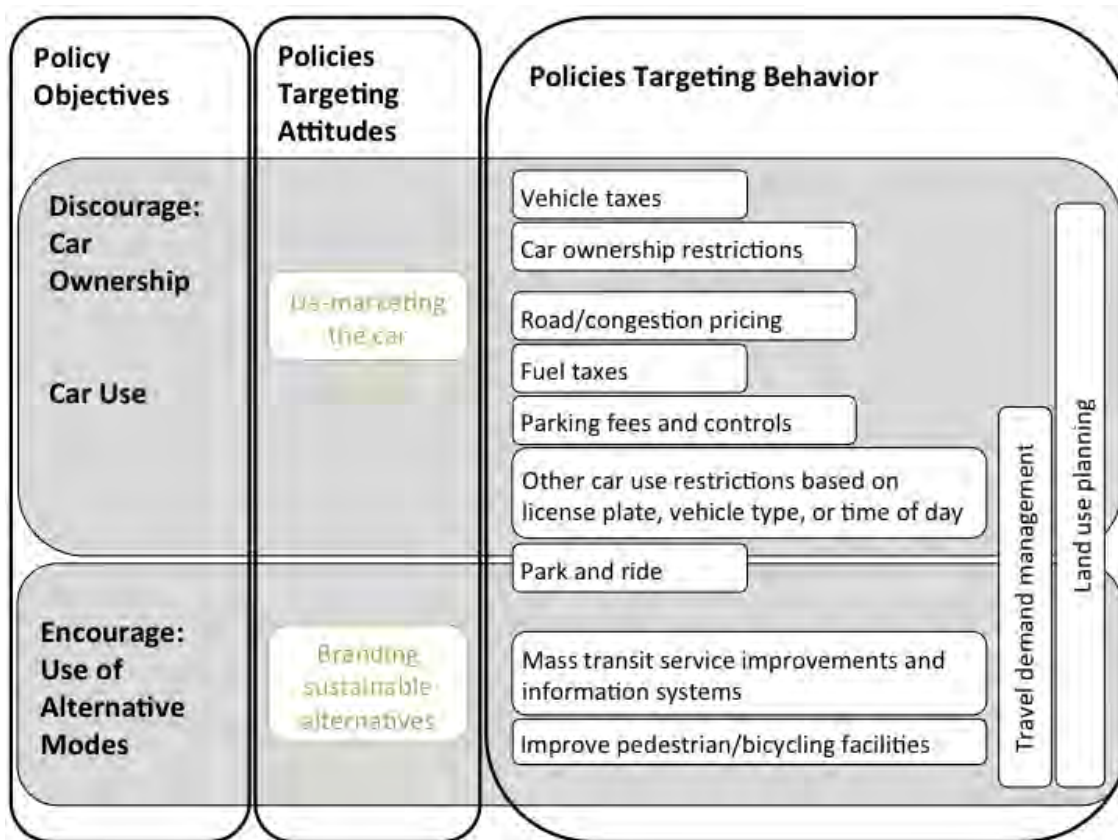
Appropriately designing data collection and modeling to capture social and cultural contexts not only allow us to generalize existing findings to different populations, they also open up possibilities for new research questions. By capturing variation in attitudes and behaviors attributable not to the individual but to the environment surrounding the individual, we can move beyond visualizing variations. We can begin to hypothesize and test what environmental factors—whether they are aspects of the built environment, social networks, or stages of economic development and motorization—contribute to this variation across cities and countries.

7.4 Implications for Sustainable Transportation Policy

Throughout this dissertation, we claim that an improved understanding of car pride and its relations with car consumption has important implications for the formulation of sustainable transportation policy. In this section, we discuss how practitioners might use the findings from this dissertation and similar studies of attitude-behavior relations in transportation to inform policy. We begin by making the distinction between policy interventions that target travel behaviors directly and those that target the attitudes that relate to these behaviors.

When it comes to sustainable transportation policy, practitioners can enact a variety of interventions. These interventions can come in the form of “push” measures meant to discourage the ownership and use of private, gasoline-powered vehicles, or in the form of “pull” measures meant to encourage the use of other, more sustainable modes (Steg and Vlek, 1997). In the pursuit of either of these policy objectives, interventions can take the form of conventional measures that target travel behaviors directly or marketing measures that target the attitudes related to these travel behaviors (see Figure 7.2) (Wright and Egan, 2000).

Figure 7.2: The role of branding sustainable alternatives and de-marketing the car among transportation policy interventions



With the framework presented in Figure 7.2 in mind, the following sections discuss how marketing interventions that discourage car use or encourage use of sustainable alternatives can complement more conventional interventions addressing transportation infrastructure, service, pricing, and regulation. We highlight how our findings can help policymakers identify the right audience for these marketing interventions. Throughout these sections, we illustrate a few key points with real-world examples. These examples are not meant to be taken as “best practice,” but are chosen only to highlight that some of this understanding is already being put into practice. Finally, we discuss the importance of understanding local context when it comes to learning and adapting the experience of other marketing campaigns.

The discussion that follows is speculative and should be read with the understanding that the author of this dissertation is neither a policymaker nor a creative marketer. Rather than lay out concrete recommendations, this section is meant to illustrate how policymakers might learn from and put into practice the growing knowledge of attitude-behavior relations in transportation. This section may also serve as a guide for researchers looking to better connect their work with the on-the-ground challenges faced by city- and national-level policymakers trying to support more sustainable transportation systems around the world.

7.4.1 Policies Targeting Behavior

Transportation policymaking most often employs interventions that directly target behavior, such as the provision of infrastructure and service, as well as pricing and regulation of travel by different modes. Among these policies targeting behavior, conventional “push” measures discourage car ownership and use by making car consumption more difficult or expensive. Examples of such interventions include car ownership restrictions through the allocation of new vehicle license plates as seen in Singapore and megacities in China or car use fees such as congestion pricing, fuel taxes, or parking fees. Alternatively, policymakers can adopt “pull” measures that target behavior. These types of policies improve the alternatives to car ownership and use to encourage mode shift, such as improving public transit service and expanding infrastructure for cycling and walking.

However, transportation policymaking has yet to embrace the fact that travel modes hold symbolic and affective value as well as instrumental value and that these personal connections and collective social norms continue to drive unsustainable travel behaviors. Policies could also tackle attitudinal, social, and cultural factors, such as car pride, that present additional obstacles to the adoption of more sustainable transportation alternatives at both the individual and national levels.

7.4.2 Policies Targeting Attitudes

Often times, so many resources are focused on policies directly targeting behavior—the provision, funding, and regulation of transportation infrastructure and services—that policies targeting attitudes (such as marketing and branding) become an afterthought. However, our improved understanding of how attitudes and behaviors are strongly interrelated suggests there is significant, untapped potential for sustainable transportation policies that nudge travel behavior indirectly by targeting attitudes.

It is important to recognize that the symbolic and affective values of the car are not instinctual: they have been shaped by decades of marketing and social norms. Major automobile companies spend billions of dollars annually to advertise their products to customers. In 2016, *Advertising Age* published a list of the top 100 advertisement spenders worldwide. The automotive category—consisting of fifteen automakers and one tire maker—spent more than any other category on the list. The auto industry’s combined spending of \$47 billion in 2015 accounted for about 20 percent of the top 100 companies’ total advertisement spending of \$240.5 billion (Hernandez McGavin, 2016; Johnson, 2016). In fact, seven automakers made the top 25 companies in terms of global advertising expenditure in 2015.¹

Policymakers interested in promoting sustainable transportation are losing a marketing war with the car by default. While governments may not be able to compete on a dollar-to-dollar basis with the advertising spending of auto manufacturers, current understanding of the attitude-behavior relations underlying unsustainable travel choices demands a more concerted and sustained effort to reshape attitudes and behavior through marketing interventions and the clear setting of new social expectations. Thus, marketing can be seen as a core investment in any sustainable transportation system.

In contrast with other public information campaigns, sustainable transportation marketing should focus on people’s self-image rather than their sense of public duty (Wright and Egan, 2000). Public welfare arguments are often not successful because individuals often do not picture their own travel consumption as a problem. When crafting the intervention, people must be left in no doubt that the message applies to them as individuals, not collectively.

In this section, we explore the potential for changing attitudes towards the car and alternative modes through targeted information and branding. Just as with conventional policy interventions targeting behavior, these marketing interventions can be either “push” measures—de-marketing or discouraging demand for car ownership and use—or “pull” measures—building a brand for more sustainable, alternative modes such as public transit, walking, and biking. These marketing interventions have the potential to achieve modest shifts away from unsustainable car consumption and towards the use of more sustainable modes. While the shifts are likely to be modest, these interventions that target attitudes come at a relatively lower cost than policies directly targeting behaviors, providing the potential for significant returns on investment.²

¹Volkswagen ranked No. 4, with its advertisement spending totaling \$6.6 billion. General Motors ranked No. 7 with advertisement spending of \$5.1 billion; Daimler AG ranked No. 7 with \$5 billion; Ford Motor Company ranked No. 11 with \$4.3 billion; Toyota Motor Corporation followed at No. 12 with \$4.1 billion; Fiat Chrysler Automobiles ranked No. 14 with \$3.9 billion; and BMW Group ranked No. 25 with \$3.1 billion. Furthermore, the target for an increasing percentage of this spending is emerging markets, where auto companies see huge growth prospects (Hernandez McGavin, 2016).

²For example, fuel-efficiency labeling schemes have been shown to have moderate impacts on car purchasing decisions and overall fleet fuel-economy (e.g., Fickl and Raimund, 1999). While these impacts are generally lower than those seen for gasoline taxes and other interventions directly targeting car use (e.g., Li et al., 2014), they can be relatively less costly and easier politically to implement. Therefore, many governments find them well worth the investment (Asia-Pacific Economic Cooperation, Energy Working Group, 2015).

De-Marketing the Car

One type of marketing intervention might discourage demand for car consumption by undermining existing symbolic and affective motivations for car ownership and use. It is important to distinguish between de-marketing strategies targeting car ownership and those targeting car use. Some have claimed that campaigns to de-market car ownership would likely involve a greater challenge than de-marketing car use because a car user might be prepared to forego a proportion of car trips at the margin, but the decision to forego car purchase altogether would entail a radical change in life style (Wright and Egan, 2000). Thus, an appeal to forego car ownership may be unlikely to engage the consumer's attention, and it might provoke resistance or outright antagonism (Wright and Egan, 2000). Therefore, such claims that de-marketing car use may actually be more effective than de-marketing car ownership rely on the assumption that attitudes cause behavior (rather than the reverse).

Our new understanding of car pride and its relations with car ownership and use tell a different story. While potentially more difficult, our research suggests that de-marketing strategies targeting symbolic and affective values of car ownership may be more effective than those targeting use. This is because car pride directly predicts car ownership, but only indirectly predicts car use. Therefore, reducing symbolic attachments to the car reduces the likelihood of car ownership, and only through this reduction of car ownership can it affect frequency of car use.

For private car owners, the most effective approach might be to promote a less appealing image of cars and those who own them. Advertising campaigns could portray cars as clumsy, old-fashioned machines that take up space and spend most of the time depreciating without being used (Wright and Egan, 2000). In addition, it might be effective to target specific types of car, such as those that most heavily pollute, diverting demand towards vehicles that are quieter and more fuel-efficient and thus reduce the environmental impact of car traffic (Wright and Egan, 2000). Advertisement could also repaint car-owners not as successful and rich, but as arrogant, selfish, wasteful, or lazy.³

However, de-marketing the car is difficult. There is no market incentive for devaluing car ownership and use, and in fact, there is a cost (in terms of utility) to individuals who have already formed these symbolic connections with the car. Attacking the car is likely to cause significant pushback if symbolic attachments are already established. In such cases, it may be more effective to adopt a "pull" marketing approach by rebranding sustainable alternatives to the car to appear more attractive. With such an approach, policymakers can provide individuals with symbolic and affective motivations for choosing sustainable transportation, potentially replacing existing attachments to owning and using a car.

Branding Sustainable Transportation Alternatives

Interventions could also shape more positive attitudes and social norms around sustainable alternatives through informational campaigns and better branding of public transit services. Many public transit agencies have proven that creating a strong identity through branding, graphic design, and signage improves the perceived total customer experience and increases ridership, when coupled

³However, such messages should be carefully communicated so as not to alienate people who are car-dependent, such as the elderly or those with mobility impairments.

with well-managed service (Hess and Bitterman, 2008, 2016). A better public image attracts riders, leading to higher revenue and greater demand for public transit service. In turn, higher revenue and greater demand increase the likelihood of service expansion and improvements, making public transit even more attractive to riders. In short, marketing can lead to a virtuous cycle of ever growing demand and service (Embarq, 2011).

Many existing marketing efforts among public transit agencies focus on clear and cohesive communication of services provided. Rather than try to create a symbolic or affective connection with users, these information campaigns simply make public transit easier to use. Initial evidence suggests that this approach may be the most effective. Recent research suggests that use of travel modes is more strongly reinforcing of attitudes rather than attitudes influencing behavior (Kroesen et al., 2017). This dissertation corroborates that finding for cars specifically. This means that “pull” measures that encourage use of more sustainable alternatives—through both conventional and marketing interventions—may be the best way to promote new, sustainable attitude-behavior relations.

Additionally, advertising campaigns for sustainable transportation alternatives can grab attention by combining both “pull” and “push” marketing measures, branding the positive aspects of public transit as a foil to the negative externalities of car consumption (see Example 1).

Example 1: Los Angeles Metro’s “Opposites” Campaign

The “Opposites” campaign from L.A. Metro is an award-winning example of an intervention that positioned transit as the solution to the problems caused by car consumption. This campaign was also successful because it was specifically tailored to the concerns of local residents. Through surveys, focus groups, and other public participation processes, L.A. Metro knew that residents were most concerned with congestion and high gas prices. Therefore, they highlighted the related stress, pollution, and expense of driving as opposed to taking public transit (see Image E.1).

This campaign helped secure new riders and greatly contributed to the victory of a ballot proposition to increase sales tax to fund major capital projects for the public transit system in Los Angeles (Arpi, 2009; Embarq, 2011).

Image E.1: L.A. Metro’s “Opposites” advertisement campaign (Los Angeles Metro, 2009)



However, it is important to remember that marketing is not a substitute for high-quality public transit service and infrastructure. Marketing is most powerful when it builds on a reality or truth. Therefore, in many places, policymakers may need to improve public transit service before branding it. Only then is the incremental increase in cost to brand the system likely to see significant returns in terms of ridership.

7.4.3 Identifying the Right Audience

Regardless of whether a push or pull marketing strategy is adopted, policymakers must consider the audience of their informational campaign and tailor the message to those individuals for which it is most likely to be effective. Knowing the audience means conducting surveys, focus groups, and other forms of stakeholder engagement to understand the needs, identities, and emotions of local residents (see Example 1). Messaging can be targeted to certain sociodemographic groups or to users or non-users of different modes.

In defining both the audience and the message, governments have the luxury of being able to take a long-term view, with the potential to build new and self-sustaining social expectations. In fact, when behavior is easily observable—like driving a car or, conversely, walking, biking, or taking public transit—marketing can more easily create tipping points that change social norms and conforming behaviors (Nyborg et al., 2016). In other words, the very visibility of travel behavior provides potential for social feedback that can alter social norms.

Whether de-marketing the car or branding sustainable transportation alternatives, it may be more productive to concentrate not on the car owners and drivers of today, but on those of tomorrow. Most successful campaigns concentrate on shaping the attitudes of those at the opinion-forming stage. This is because the attitudes (and behavior) of younger individuals are often more malleable and are influenced more strongly by social norms, such as the approval of their peers. When it comes to car consumption, children and adolescents are not yet committed to a car-based lifestyle in the way that their parents are, and they are more open to arguments relating to health and the environment (Stradling et al., 1999). Furthermore, younger family members can actually influence the decisions of their parents and peers, in particular, decisions about what make and model of car to buy (Wright and Egan, 2000). There is also growing evidence that educating children about public transit boosts long-term ridership (Embarq, 2011).

Our research suggests that targeting individuals who are not yet car owners or users may be the most successful strategy. Comparing car pride across individuals in our U.S. and international samples, we find that non-car-owning and non-car-using individuals have substantially lower car pride than car-owning and car-using individuals in almost every context. Therefore, rather than attack already entrenched symbolic values tied to long-term car ownership decisions and habitual patterns of car use, marketing campaigns could focus on reshaping existing narratives to prevent these symbolic connections with the car from forming among newer generations or providing them with an alternative norm that focuses on sustainable transportation (see Example 2). However, we should also acknowledge that, on average, younger individuals in our samples actually report higher car pride than older individuals.

Example 2: Building Awareness of and Excitement for Public Transit among Children in South Africa

In Johannesburg, South Africa, policymakers tapped into the idea that educating and exciting children about the public transit system could have wide-ranging impacts, as children share what they learn with their friends and family. In 2010, the operator of the Johannesburg bus rapid transit system—Rea Vaya, meaning “we are going” in Sotho—hired a theatre production company to travel around local primary schools to teach children how to use the system. Using song and dance, the theater group helped children understand the color scheme for the new system—red for the trunk buses, blue for the complementary buses, and purple for the feeder buses (Embarq, 2011; Rea Vaya, 2010). By targeting children, these types of informational campaigns can help form lasting social norms and attitudes that favor sustainable transportation among younger generations.

7.4.4 Transferring Policies

Rapidly rising incomes and the mass local manufacture of vehicles in many developing nations have led to an exponential rise in car acquisition within recent years (Dargay et al., 2007; Pucher et al., 2007). This rapid growth in car consumption has given rise to new and acute issues such as urban air pollution and congestion. While governments in these nations may develop their own tailored transport policies that respond to their unique circumstances, it is currently common practice for transport policies and forecasting tools to be exported from one country to another—usually from

developed countries to developing countries (Marsden and Stead, 2011; Wang, 2010). This may be problematic, since a policy or model developed and implemented in one nation may be unsuccessful in another, not merely for practical reasons (such as different fiscal, governance, technological, urban, and transportation environments), but also cultural reasons (Ashmore et al., 2017; Shukla, 2010, 2011).

Our research clearly demonstrates that national culture can affect the symbolic motivations of transport choices in different countries for those of a similar social level. This suggests that policies targeting attitudes, even in the same sociodemographic audience, can vary in their effectiveness by location. For example, our research suggests that an intervention de-marketing the car among young people in India may be more effective than the same campaign in Argentina. This should serve as a cautionary tale for practitioners looking to translate policies targeting attitude (or even behavior) from one cultural context to another.

7.4.5 Packaging Policies

While there are significant, untapped opportunities for marketing interventions to help promote sustainable transportation goals, the success and impact of these marketing interventions will depend on the extent to which conventional measures that target behavior are applied in parallel. Our research highlights that feedback loops exist between attitudes and travel behavior (see Figure 7.1). Therefore, any intervention, whether it is targeted at the behavior or the attitude, will influence the other. This creates potential for synergistic packages of policies, in which interventions that target attitudes can complement conventional measures that target behavior.

Governments, at the national and local levels, can align their funding and infrastructure investment decisions to clearly and transparently prioritize more sustainable transportation modes. This means making the unpopular and hard decisions to reorganize institutions and funding away from road building towards the construction of dedicated infrastructure for pedestrians, cyclists, and public transit on a network scale. This also means rethinking and reallocating existing street and curb space traditionally reserved for car throughput and parking towards more sustainable modes. Governments can combine these infrastructure investments with road use charges that clearly price the environmental and social externalities of car use. Collectively, such policies can provide reasons for people to change their expectations and their behavior.

In fact, targeting use may be the best way to enter the attitude-behavior feedback loop depicted in Figure 7.1. This dissertation suggests that the more an individual uses a car, the more symbolic value he/she ascribes to it. Therefore, it is likely to be more difficult to shift people from cars once they are users. By discouraging use of cars and encouraging use of sustainable alternatives, particularly among individuals who do not yet own or use cars, policymakers may stop symbolic connections with the car from being formed in the first place. This presents a strong case for advancing economic travel demand management measures, particularly in countries with low car ownership and use.

However, economic incentives are often not enough to modify collective behavior. Governments can complement these conventional interventions with normative information that alters an individual's understanding of values, attitudes, and social expectations (Miller and Prentice, 2016).

Governments can do more to establish the social norm that using more sustainable transportation alternatives (and not the car) is what everyone is doing and is the right thing to do (see Example 3).

Sustainable transportation policymaking must be holistic and systematic, combining behavioral as well as attitudinal interventions. As countries consider policies that modify existing utilitarian incentives (travel time and travel cost) through taxes, subsidies, and infrastructure and service investments toward more sustainable alternatives, governments should also consider the power of normative information to encourage individual consumers and car manufacturers to rethink the value of the car, and of mobility generally, in a more sustainable future. What matters for ultimately changing behavior on a large scale is the combined effect of both conventional and marketing interventions (Nyborg et al., 2016).

Example 3: Setting a New, Sustainable Social Norm in London, United Kingdom

London, United Kingdom provides a clear example of how city governments and public transit agencies can combine “push” and “pull” and conventional and marketing measures to create a holistic policy package to promote sustainable transportation. In 2003, London introduced congestion charging to reduce traffic and air pollution in the city center. The revenue from this “push” measure was then reinvested into improved and expanded service of the mass transport system to provide quality alternatives to driving (a strong “pull”). In addition, policymakers in London accompanied these conventional measures targeting travel behavior with clear and sustained rebranding of sustainable transportation alternatives.

Adding to the strong brand recognition of the Underground (or ‘Tube’), the government of London actively created a brand of inclusion and unique city character around its local, red double-decker buses. By heavily publicizing Mayor Sadiq Khan commuting to work by bus on his first day in office, they sent the message that, whether rich or poor, successful or unsuccessful, the bus is the true “Londoner’s mode” (see Image E.3, top). By sending a double decker bus to pick up the Olympic torch from Beijing, the government reinforced the bus as a symbol of the city and its vibrancy (see Image E.3, bottom).

Image E.3: The red double-decker bus as a symbol of modern and inclusive London (Allegretti, 2016; Peet, 2016; SINA News, 2008)



7.5 Conclusion

This dissertation builds a systematic understanding of car pride and its relations with car consumption across individuals, cities, and countries. We design and deploy two surveys to gather data in two U.S. cities and in 51 countries around the world, then employ a series of empirical analyses on these data to evaluate how to measure car pride (Chapters 3 and 4) and model its relations with car-related behaviors across cultures (Chapters 5 and 6).

We develop and evaluate two survey measures for car pride. A polytomous version—a collection of 12, 7-point Likert-format statements—is shown to be valid, reliable, and invariant across a sample of individuals in New York City and Houston. A dichotomous version—9 agree-disagree statements—is shown to be valid, reliable, and invariant across our international sample. These measures are proposed as new standards for quantifying car pride, to be used to compare across individuals and cultures.

Equipped with well-validated survey measures of car pride, we explore variations in car pride across individuals, cities, and countries. Across individuals, we find that those who are younger, male, and have higher incomes generally have higher car pride. Between cities, we find that an individual living in Houston (a more car-dependent city) has significantly higher car pride than a similar individual living in New York City. Similarly, after controlling for the types of people living in different countries, we find that developing countries—with lower national wealth, greater income inequality, and lower rates of car ownership and use—report higher values of car pride.

On average across all individuals, cities, and countries, we find a clear feedback loop between car pride and car consumption. We find that car pride strongly predicts car ownership, which in turn predicts car use. In the reverse direction, car use strongly reinforces car pride. While these general relations appear universal, their strengths differ by country, emphasizing the importance of taking the social and cultural context into account when measuring and interpreting symbolic and affective motivations for car consumption.

In addition to these substantive contributions, this dissertation also synthesizes methodological good-practice when it comes to the study of attitude-behavior relations in transportation. Drawing on this experience, we provide recommendations for transportation researchers on how to best develop and validate new measures of attitudes, model their bidirectional relations with travel behavior, and properly address social and cultural context that varies across individuals, cities, and countries.

Finally, our understanding of attitude-behavior relations in transportation can inform sustainable transportation policy. Despite growing empirical evidence, transportation policymaking has yet to embrace the fact that travel modes hold attitudinal value as well as utilitarian value and that social norms continue to drive unsustainable travel behaviors. While many countries and cities are considering new sustainable transportation investments, policies must also tackle attitudinal, social, and cultural factors, such as car pride, that present additional obstacles to the adoption of more sustainable transportation alternatives at both the individual and national levels. Future collaborations between researchers and policymakers can leverage the measures of car pride developed in this dissertation in experimental studies that quantify the impact of different marketing interventions on attitudes and car consumption.

Appendix A

U.S. City Survey

This Appendix includes all questions from the U.S. city survey as it was implemented in New York City and Houston. The first part of the survey involved an Implicit Association Test (IAT)—a series of computer based matching exercises—which was hosted on a separate, secure server and included as an iFrame in the questionnaire. All respondents were asked to complete the IAT, enter the code they receive at the end, and then proceed to the rest of the survey questions. This IAT code was used to match their IAT score to their survey responses in post-processing. For more details on the experimental design of the IAT, we refer the reader to Chapter 4.

For ease of legibility of this appendix, the questions have been broken up into sections, but these headings were not displayed to respondents. Furthermore, the order of questions as they appear here may not directly match that experienced by respondents. Multiple choice questions were presented either as drop-down menus or lists (as displayed here). Questions with circular radio buttons allow only one response category to be selected. Questions with square radio buttons allow multiple responses to be selected. Shaded blocks are used here to indicate questions that are displayed only for some respondents (based on their answers to previous questions). Instructions and a consent form preceded all the questions outlined here.

Screening Questions

I maintain that I am at least 18 years of age and am a commuter (travel to work 3 or more days a week).

- Yes
- No

Please indicate your age:

_____ *[entry must be numeric; 18 - 100]*

With which gender do you most identify?

- Male
- Female

What is your total annual household income?

- Less than \$10,00
- \$10,000 - \$14,999
- \$15,000 - \$24,999
- \$25,000 - \$34,999
- \$35,000 - \$49,999
- \$50,000 - \$74,999
- \$75,000 - \$99,999
- \$100,000 - \$149,999
- \$150,000 - \$199,999
- \$200,000 or more

In which greater metropolitan area do you live and work?

- New York City Metro Area
- Houston Metro Area
- None of the above

Implicit Association Test

Complete this series of IAT matching exercises to receive your 10-digit alpha-numeric code. Please expand your browser window so that the entire test frame is visible. While this has been optimized for default browser settings, if the IAT does not display or advance, please open your browser settings/preferences and check “search for text when I start typing” or similar advanced accessibility setting.

IAT Matching Exercise

The first part of this study is a simple series of matching exercises. Your task is to sort the words and pictures that appear at the center of the screen into categories (at the top right or left) as quickly as possible. You should be able to complete the tasks in less than 10 minutes total. When you finish, you will receive a 10-digit alpha-numeric code, which will allow you to proceed to the survey questions.

After completing the above IAT exercise, copy and paste your 10-digit alphanumeric code to proceed to the rest of the survey.

Home and Work Locations

Please fill in your HOME zip code

_____ *[entry must be numeric; 6 digits]*

Please open the map and select your HOME census block.

Please indicate the names of the two streets of the intersection that is closest to your HOME address.

Name of the first street: _____

Name of the second street: _____

Please fill in your WORK zip code

_____ *[entry must be numeric; 6 digits]*

Please open the map and select your **WORK** census block.

Please indicate the names of the two streets of the intersection that is closest to your **WORK** address.

Name of the first street: _____

Name of the second street: _____

Commute Travel Diary

Please tell us about your travel behavior from home to work.

Do you have a drivers license?

- Yes
- No

How many years of driving experience do you have?

If you're not sure, please provide an estimate. If you have never driven, enter "0."

Please specify how you get from home to work in the most typical commute trip (choose all that apply):

For example, if you walk from home to a bus station, take the bus, transfer to a train, then walk from the trains station to work then select walk, bus, and train.

- Car - drive alone
- Car - shared ride
- Rail/Subway
- Bus
- Bicycle
- Walk

How often do you take this most typical commute trip (above)?

- 6 or 7 days a week
- 5 days a week
- 3 or 4 days a week
- 1-3 days a week
- Once every 2 weeks
- Once every month

On an average work day, what time do you leave home to get to work via the above routine? (example: 7:30AM)

On other days, do you use a different routine than the one specified above?

For example: choose “yes” if you drive directly from home to work a few times a month rather than taking the most typical transit trip above.

- Yes
- No

If “yes,” respondent does use a different routine on other days:

Please specify how you get from home to work in your second most typical commute trip (choose all that apply):

For example, if you walk from home to a bus station, take the bus, transfer to a train, then walk from the trains station to work then select walk, bus, and train.

- Car - drive alone
- Car - shared ride
- Rail/Subway
- Bus
- Bicycle
- Walk

How often do you take this second most typical commute trip (above)?

- 6 or 7 days a week
- 5 days a week
- 3 or 4 days a week
- 1-3 days a week
- Once every 2 weeks
- Once every month

On an average work day, what time do you leave home to get to work via the above routine? (example: 7:30AM)

What is (or would be) your daily parking cost for your commute by car?

- \$0.00 (Free)
- \$0.01 - \$4.99
- \$5.00 to \$9.99
- \$10.00 to \$19.99
- \$20.00 or more
- Not applicable/don't know

What is (or would be) the round trip toll costs for your commute by car?

- \$0.00 (Free)
- \$0.01 - \$4.99
- \$5.00 to \$9.99
- \$10.00 to \$19.99
- \$20.00 or more
- Not applicable/don't know

Do you purchase a weekly, monthly, or seasonal bus and/or rail pass?

- Yes
- No

How long would it take (in minutes) for you to walk:

From home to your nearest bus stop: _____

From the bus stop to work: _____

How long would it take (in minutes) for you to walk:

From home to your nearest rail/subway station: _____

From the rail/subway station to work: _____

How many cars does your household own?

- 0
- 1
- 2
- 3 or more

If respondent's household has at least 1 car:

To the best of your knowledge, please tell us the following about your household car(s):

Car 1: In what year was the car purchased? (YYYY): _____

Car 1: What is the car model year? (YYYY): _____

Car 1: Was the car purchased "pre-owned" or "new"?: _____

Car 1: What is the make/model?: _____

Car 1: What was the purchase price?: _____

Car 2: In what year was the car purchased? (YYYY): _____

Car 2: What is the car model year? (YYYY): _____

Car 2: Was the car purchased "pre-owned" or "new"?: _____

Car 2: What is the make/model?: _____

Car 2: What was the purchase price?: _____

Car Pride and Bus Shame

Please indicate your attitudes towards driving a car now and in the future. If you do not drive a car now, please answer the questions about general and future car usage, but indicate "not applicable" or "N/A" where appropriate.

	Strongly agree	Agree	Partially agree	Neither agree nor disagree	Partially disagree	Disagree	Strongly disagree	x N/A
I feel more accepted in my community when I drive a car	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Driving meets my self esteem or personal image	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Driving a car makes me feel superior to those who don't	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel like I don't belong driving a car	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Driving a car positively affects my perception of myself	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Driving to work suits my job/position	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
If I could, I would choose not to drive a car now or in the future.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please continue to indicate your attitudes towards driving a car now and in the future. If you do not drive a car now, please answer the questions about general and future car usage, but indicate “not applicable” or “N/A” where appropriate.

	Strongly agree	Agree	Partially agree	Neither agree nor disagree	Partially disagree	Disagree	Strongly disagree	x N/A
I would be ashamed if future financial circumstances prevented me from driving.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would love to be seen more often driving.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
If more people saw me in/with my car, I would drive more.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I gain respect from my peers because I drive a car.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Please choose "disagree"	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would feel better about myself if I drove less	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
A car is a sign of social status	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I need a car for my job/work	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate your attitudes about owning a car now and in the future. If you do not own a car now, please answer the questions about general and future car ownership, but indicate “not applicable” or “N/A” where appropriate.

	Strongly agree	Agree	Partially agree	Neither agree nor disagree	Partially disagree	Disagree	Strongly disagree	x N/A
Having a car is connected with one's social image	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I deserve to own and express myself with a great car	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Others would see me as more successful if I owned a better car or more cars.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have achieved in life and therefore I deserve a good car	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Please choose "partially agree."	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel proud of owning my car	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please continue to indicate your attitudes towards owning a car now and in the future. If you do not own a car now, please answer the questions about general and future car ownership, but indicate “not applicable” or “N/A” where appropriate.

	Strongly agree	Agree	Partially agree	Neither agree nor disagree	Partially disagree	Disagree	Strongly disagree	x N/A
I feel owning a car is a positive component of my identity	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Having a car makes me feel superior to those who don't	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have a sense of accomplishment after buying a car.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I want to have a successful life and that includes owning a nicer car or more cars.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
If I could, I would prefer not to own a car now or in the future	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please tell us how you feel about riding the bus now and in the future. If you do not ride the bus, please answer the questions about general and future bus usage, but indicate “not applicable” or “N/A” where appropriate.

	Strongly agree	Agree	Partially agree	Neither agree nor disagree	Partially disagree	Disagree	Strongly disagree	x N/A
I am proud of riding the bus.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel that riding the bus positively impacts my social image.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Only poor people ride the bus.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I gain respect from my peers when I ride the bus.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel successful riding the bus.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel like a loser if I ride the bus.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I should not ride the bus if I have achieved a certain level of success in my life/career.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
People who ride the bus should be ashamed.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Sociodemographics

Please tell us a little bit more about yourself and your household.

How many people are there in your household (including yourself)?

How many working adults are there in your household (including yourself)?

To what extent do you agree with the following statements about yourself and your accomplishments in life?

	Strongly agree	Agree	Partially agree	Neither agree nor disagree	Partially disagree	Disagree	Strongly disagree
I am proud of myself and what I have achieved	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I feel a sense of self-worth	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I have accomplished a degree of greatness in my life and career	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am not ashamed of who I am and what I will become	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My peers would say that I am successful	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am confident in my abilities	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I would consider myself superior to the majority of my peers	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

What is your race or origin?

- White or Caucasian
- Black or African American
- Hispanic, Latino, or Spanish origin
- Native American or Alaska Native
- Asian
- Native Hawaiian or other Pacific Islander
- Other

Please indicate the highest level of education you have attained/completed:

- Less than high school degree
- High school diploma or equivalent (GED)
- Trade/technical/vocational training
- Some college, no degree
- 2-year college/Associates degree
- 4-year college/Bachelors degree
- Master's degree
- Doctoral or professional degree (PhD, M.D., J.D., etc.)

What most closely indicates your employment status?

- Full-time employed
- Full-time self-employed
- Part-time employed
- Part-time self-employed
- Student
- Military
- Other

That's all! Thanks so much for participating!

Appendix B

International Survey

This Appendix includes the full international survey as administered. This survey represents a collaboration among multiple researchers as part of the MIT Energy Initiative Mobility of the Future study and only a subset of the questions are analyzed for the purpose of this thesis. In addition to the sociodemographic information collected in the survey, the Dalia research system profiles of each respondent also include age, gender, education level (as low, medium, or high), urban vs. rural, and location information—country code, city name, latitude and longitude.

For ease of legibility of this appendix, the questions have been broken up into sections, but these headings were not displayed to respondents. Furthermore, the order of questions as they appear here may not directly match that experienced by respondents. Due to the mobile-phone based platform, all questions were presented in multiple choice format. Questions with circular radio buttons allow only one response category to be selected. Questions with square radio buttons allow multiple responses to be selected. Shaded blocks are used here to indicate questions that are displayed only for some respondents (based on their answers to previous questions). Simple instructions, registration on the Dalia platform (for new respondents), and a consent question preceded all the questions outlined here.

Sociodemographics

Which best describes the place where you live?

- Countryside
- Town with fewer than 1,000 people
- Town with 1,000 - 50,000 people
- City with 50,000 - 250,000 people
- City with 250,000 - 1 million people
- City with 1 million - 5 million people
- City with 5 million - 10 million people
- City with more than 10 million people

What is your household's monthly income after taxes?

[Ranges were specified in U.S. dollars, but were automatically converted into local currency for respondents based on current market exchange rates and rounded to the nearest whole number.]

- Under 250
- 250 - 500
- 500 - 1,000
- 1,000 - 2,000
- 2,000 - 3,000
- 3,000 - 4,000
- 4,000 - 6,000
- 6,000 - 8,000
- 8,000 - 10,000
- 10,000 - 12,000
- 12,000 - 15,000
- More than 15,000
- Prefer not to say

Which of the following categories best describes your employment status?

- In school, university or practical training
- Employed, working 1 to 29 hours per week
- Employed, working 30 or more hours per week
- Self-employed / Freelancer
- Entrepreneur / Employer
- Not employed, currently looking for work
- Not employed, currently NOT looking for work
- Disabled / not able to work
- Retired
- None of the above

While in school, university or practical training, are you...?

- ...not employed, currently NOT looking for work
- ...not employed, currently looking for work
- ...employed

Mobility Patterns

Do you own a car?

('Own' includes cars that are on long-term lease / financing plans)

- No, I don't
- No, but I have regular access to one
- Yes, I do

Which of the following do you take to get to work / school / other regular journey on a weekday?

- Car: driver
- Car: passenger
- Bicycle
- Electric bicycle
- Motorbike/scooter
- Boat / ferry
- Walking
- Bus or minibus
- Rickshaw
- Tram
- Train
- Underground / metro / subway
- Other public transport
- Taxi or other hired vehicle
- Other private vehicle

How many hours do you spend on transportation/commuting/trips per weekday?

- Less than 30 minutes
- 30 minutes - 1 hour
- 1 - 2 hours
- 2 - 3 hours
- 3 - 4 hours
- More than 4 hours

What would roughly be the value (purchase price) of the next car you buy / lease?
[Ranges were again specified in U.S. dollars, but were automatically converted into local currency.]

- Under 5,000
- 5,000 - 10,000
- 10,000 - 20,000
- 20,000 - 30,000
- 30,000 - 40,000
- 40,000 - 50,000
- 50,000 - 60,000
- 60,000 - 70,000
- 70,000 - 80,000
- More than 80,000
- No idea

Among your peers, what proportion of them do you think drive regularly?

- All / Almost all
- Most of them
- Some of them
- Few of them
- None / Almost none

If the respondent owns or has regular access to a car:

On days when you drive, how many miles do you drive typically?

- None / not applicable
- Up to 10 mi (16 km)
- More than 10 mi (16 km) and up to 50 mi (80 km)
- More than 50 mi (80 km) and up to 100 mi (160 km)
- More than 100 mi (160 km)

Where are your car(s) usually parked overnight?

- In a private garage
- In a public garage
- In a driveway
- Other off-street parking
- On the street / some other public location

For which of the following reasons do you use a car instead of other transport options?

Please select all that apply.

- I don't have access to public transportation
- The public transportation isn't good enough
- I prefer to be independent
- I like owning something valuable
- It is more comfortable / relaxing
- I need it for long-distance travel
- I need it for transporting equipment and heavy objects
- I need it to drive my kids
- I prefer the privacy
- I can control my own schedule
- It is faster
- It is safer
- It is cheaper
- None of the above

Policy Support

If the government decides to improve overall transportation conditions in your location, which of the following policies would you support? Please select up to three.

- Build additional roads
- Discourage the use of private automobiles in the city center
- Expand bike lanes
- Expand public transportation services (bus/train)
- Improve pedestrian facilities (sidewalks, street crossings etc.)
- Introduce car-free pedestrian zones in the city center
- Lower public transportation fares
- Prioritize public bus lanes and/or bus rapid transit
- Provide clean energy-based public transportation options
- Provide more parking spaces
- Subsidize clean energy vehicles

Car Pride and Car Dependence

Which of these statements reflect your feelings about driving / using a car (now or in the future)? Select all that apply

- Driving meets my self esteem or personal image.
- I would be ashamed if future financial circumstances prevented me from driving.
- If more people saw me in / with my car, I would drive more.
- I gain respect from my peers because I drive a car.
- I would feel better about myself if I drove less.
- A car is a sign of social status.
- My lifestyle is dependent on having a car.
- I don't have time to think about how I travel; I just get in my car and go.
- I would like to reduce my car use, but there are no practical alternatives.
- I am actively trying to use my car less.
- I am not interested in reducing my car use.
- I need a car for my job/work.
- None of the above

Which of these statements reflect your feelings about owning a car (now or in the future)? Select all that apply

- Having a car is connected with my social image.
- Others would see me as more successful if I owned a better car or more cars.
- I have achieved in life and therefore I deserve to own a good car.
- I feel proud of owning a car.
- I have a sense of accomplishment after buying a car.
- If I could, I would prefer not to own a car now or in the future.
- None of the above

Electric Vehicles

Which of the following is true of your experience with electric vehicles? Select all that apply.

- I know someone who has one
- I have seen one in person
- I have seen an image of one
- I have been in one
- I own one
- None of these

Next time you buy / lease a car, how likely are you to buy an all-electric car?

- Very likely
- Somewhat likely
- Not very likely
- Not at all likely

If you were to buy an electric vehicle, what would be the minimum acceptable range for you on a full charge?

- 10 mi (16 km)
- 50 mi (80 km)
- 100 mi (160 km)
- 200 mi (320 km)
- 300 mi (480 km)
- More than 300 mi (480 km)
- Don't know

Autonomous Vehicles

Have you seen, heard or read anything about self-driving cars?

- Yes, a lot
- Yes, a bit
- No

How safe do you think self-driving cars are, as of now?

- Very safe
- Somewhat safe
- Not very safe
- Not safe at all
- Not sure

If respondent does not select "very safe" above:

How soon, if at all, do you think self-driving cars will be safe enough for you to consider using one?

- Within the next 2 years
- Within the next 5 years
- Within the next 10 years
- Within the next 20 years
- More than 20 years
- Never (50)
- Don't know

Bibliography

- Henk Aarts and A. P. Dijksterhuis. The automatic activation of goal-oriented behaviour: The case of travel habit. *Journal of Environmental Psychology*, 20(1):75–82, 2000. doi: 10.1006/jev.1999.0156.
- Veronique Van Acker and Frank Witlox. Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. *Journal of Transport Geography*, 18:65–74, 2010. doi: 10.1016/j.jtrangeo.2009.05.006.
- Icek Ajzen. The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2):179–211, 1991. doi: 10.1016/0749-5978(91)90020-T.
- Icek Ajzen. *Attitudes, Personality, and Behavior*. Open University Press, New York, NY, 2 edition, 2005.
- Icek Ajzen. The theory of planned behaviour is alive and well, and not ready to retire: a commentary on sniehotta, presseau, and aráujo-soares. *Health Psychology Review*, 9(2):131–137, 2015. doi: 10.1080/17437199.2014.883474.
- Icek Ajzen and Martin Fishbein. *Understanding attitudes and predicting social behavior*. Prentice Hall, 1980.
- Icek Ajzen and Martin Fishbein. The influence of attitudes on behavior. In Dolores Albarracín, Blair T. Johnson, and Mark P. Zanna, editors, *The Handbook of Attitudes*, pages 173–221. Erlbaum, Mahwah, NJ, 2005.
- Aubrey Allegretti. Sadiq Khan took the bus into work on his first day as London mayor: The ‘mayor for all Londoners’ hit the ground ‘riding’. *Huffington Post*, September 5 2016. https://www.huffingtonpost.co.uk/entry/sadiq-khan-took-the-bus-into-work-on-his-first-day-as-london-mayor_uk_57306080e4b0ade291a21a85?
- Paul D. Allison. Instrumental variables in structural equation models, June 26 2018. <https://statisticalhorizons.com/iv-in-sem>.
- Jillian Anable and Birgitta Gatersleben. All work and no play? the role of instrumental and affective factors in work and leisure journeys by different travel modes. *Transportation Research Part A: Planning and Practice*, 39(2-3):163–181, 2005. doi: 10.1016/j.tra.2004.09.008.
- Sabreena Anowar, Shamsunnahar Yasmin, Naveen Eluru, and Luis F. Miranda-Moreno. Analyzing car ownership in quebec city: a comparison of traditional and latent class ordered and unordered models. *Transportation*, 41:1013–1039, 2014. doi: 10.1007/s11116-014-9522-9.

John Antonakis, Samuel Bendahan, Philippe Jacquart, and Rafael Lalive. On making causal claims: A review and recommendations. *The Leadership Quarterly*, 21(6):1086–1120, 2010. doi: 10.1016/j.leaqua.2010.10.010.

John Antonakis, Samuel Bendahan, Philippe Jacquart, and Rafael Lalive. Causality and endogeneity: Problems and solutions. In David V. Day, editor, *The Oxford Handbook of Leadership and Organizations*, chapter 6, pages 93–117. Oxford University Press, 2014.

American Public Transportation Association APTA. Transit ridership report: Fourth quarter 2017. <https://www.apta.com/resources/statistics/Pages/RidershipArchives.aspx>, March 13 2018.

Ethan Arpi. Transit agencies need to invest in marketing: A lesson from Los Angeles. *The City Fix*, December 8 2009. <http://thecityfix.com/transit-agencies-need-to-invest-in-marketing-a-lesson-from-los-angeles/>.

David P. Ashmore, Nicola Christie, and Nicholas A. Tyler. Symbolic transport choices across national cultures: theoretical considerations for research design. *Transportation Planning and Technology*, 40(8):875–900, 2017. doi: 10.1080/03081060.2017.1355882.

David P. Ashmore, Dorina Pojani, Roselle Thoreau, Nicola Christie, and Nicholas A. Tyler. The symbolism of ‘eco cars’ across national cultures: Potential implications for policy formulation and transfer. *Transportation Research Part D: Transport and Environment*, 63:560–575, 2018a. doi: 10.1016/j.trd.2018.06.024.

David P. Ashmore, Roselle Thoreau, Corina Kwami, Nicola Christie, and Nicholas A. Tyler. Using thematic analysis to explore symbolism in transport choice across national cultures. *Transportation*, 2018b. doi: 10.1007/s11116-018-9902-7.

Asia-Pacific Economic Cooperation, Energy Working Group. A review and evaluation of vehicle fuel efficiency labeling and consumer information programs. <https://apec.org/Publications/2015/12/A-Review-and-Evaluation-of-Vehicle-Fuel-Efficiency-Labeling-and-Consumer-Information-Program> November 2015.

Tihomir Asparouhov. Bidirectional association. <https://www.statmodel.com/download/Rec.pdf>, 2016.

Tihomir Asparouhov and Bengt Muthén. Computationally efficient estimation of multilevel high-dimensional latent variable models. *Proceedings of the Joint Statistical Meeting*, pages 2531–2535, 2007. <https://www.statmodel.com/download/JSM2007000746.pdf>.

Tihomir Asparouhov and Bengt Muthén. Bayesian analysis using Mplus: Technical implementation, 2010a. <https://www.statmodel.com/download/Bayes3.pdf>.

Tihomir Asparouhov and Bengt Muthén. Bayesian analysis of latent variable models using Mplus, September, 29 2010b. <http://www.statmodel.com/download/BayesAdvantages18.pdf>.

Tihomir Asparouhov and Bengt Muthén. General random effect latent variable modeling: random subjects, items, contexts, and parameters, November, 19 2014. https://www.statmodel.com/download/NCME_revision2.pdf.

- Michael N. Bagley and Patricia L. Mokhtarian. The impact of residential neighborhood type in travel behavior: a structural equation modeling approach. *Annals of Regional Science*, 36(2): 279–297, 2002. doi: 10.1007/s001680200083.
- George Baltas and Charalampos Saridakis. An empirical investigation of the impact of behavioural and psychographic consumer characteristics on car preferences: An integrated model of car type choice. *Transportation Research Part A: Policy and Practice*, 54:92–110, 2013. doi: 10.1016/j.tra.2013.07.007.
- Sebastian Bamberg. Is a residential relocation a good opportunity to change people’s travel behavior? results from a theory-driven intervention study. *Environment and Behavior*, 38(6):820–840, 2006. doi: 10.1177/0013916505285091.
- Sebastian Bamberg and Peter Schmidt. Incentives, morality, or habit? predicting students’ car use for university routes with the models of ajzen, schwartz, and triandis. *Environment and Behavior*, 35(2):264–285, 2003. doi: 10.1177/0013916502250134.
- Sebastian Bamberg, Icek Ajzen, and Peter Schmidt. Choice of travel mode in the theory of planned behavior: the roles of past behavior, habit, and reasoned action. *Basic and Applied Social Psychology*, 25(3):175–187, 2003. doi: 10.1207/S15324834BASP2503_01.
- Sebastian Bamberg, Marcel Hunecke, and Anke Blöbaum. Social context, personal norms and the use of public transportation: two field studies. *Journal of Environmental Psychology*, 27(3): 190–203, 2007. doi: 10.1016/j.jenvp.2007.04.001.
- Mahzarin R. Banaji and Anthony G. Greenwald. *Blind Spot: Hidden Biases of Good People*. Bantam Books, 2013.
- Raoul Baron and David A. Kenny. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6):1173–1182, 1986.
- Andre Beauducel and Philipp Yorck Herzberg. On the performance of maximum likelihood versus means and variance adjusted weighted least squares estimation in cfa. *Structural Equation Modeling: A Multidisciplinary Journal*, 13(2):186–203, 2006. doi: 10.1207/s15328007sem1302_2.
- Gabriela Beirão and J.A. Sarsfield Cabral. Understanding attitudes towards public transport and private car: A qualitative study. *Transport Policy*, 14(6):478–489, 2007. doi: 10.1016/j.tranpol.2007.04.009.
- Prawira Fajarindra Belgiawan, Jan-Dirk Schmöcker, Maya Abou-Zeid, Joan Walker, Tzu-Chang Lee, Dick F. Ettema, and Satoshi Fujii. Car ownership motivations among undergraduate students in china, indonesia, japan, lebanon, netherlands, taiwan, and usa. *Transportation*, 41(6): 1127–1244, 2014. doi: 10.1007/s11116-014-9548-z.
- Moshe Ben-Akiva and Steven R. Lerman. *Discrete Choice Analysis: Theory and Applications to Travel Demand*. MIT Press, 1985.
- Moshe Ben-Akiva, Daniel Mcfadden, Kenneth Train, Joan Walker, Chandra Bhat, Michel Bierlaire, Denis Bolduc, Axel Boersch-Supan, David Brownstone, David S. Bunch, Andrew Daly, Andre de Palma, Dinesh Gopinath, Anders Karlstrom, and Marcela A. Munizaga. Hybrid choice models: progress and challenges. *Marketing Letters*, 13(3):163–175, 2002. doi: 10.1023/A:1020254301302.

- Peter M. Bentler. Comparative fit indices in structural equation models. *Psychological Bulletin*, 107(2):238–246, 1990. doi: 10.1037/0033-2909.107.2.238.
- Peter M. Bentler. Covariance structure models for maximal reliability of unit-weighted composites. In Sik-Yum Lee, editor, *Handbook of Computing and Statistics with Applications*, volume 1. Handbook of Latent Variable and Related Models, chapter 1, pages 1–19. Elsevier, New York, NY, 2007. doi: 10.1016/B978-044452044-9/50004-5.
- Peter M. Bentler and Chih-Ping Chou. Practical issues in structural modeling. *Sociological Methods & Research*, 16(1):78–117.
- Cecilia Jakobsson Bergstad, Amelie Gamble, Olle Hagman, Merritt Polk, Tommy Gärling, and Lars E. Olsson. Affective-symbolic and instrumental-independence psychological motives mediating effects of socio-demographic variables on daily car use. *Journal of Transport Geography*, 19(1):33–38, 2011. doi: 10.1016/j.jtrangeo.2009.11.006.
- Hart Blanton and James Jaccard. Arbitrary metrics in psychology. *American Psychologist*, 61(1):27–41, 2006. doi: 10.1037/0003-066X.61.1.27.
- Hart Blanton, James Jaccard, Patricia M. Gonzales, and Charlene Christie. Decoding the Implicit Association Test: Implications for criterion prediction. *Journal of Experimental Social Psychology*, 42(2):192–212, 2006. doi: 10.1016/j.jesp.2005.07.003.
- Paul D. Bliese. Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In Katherine J. Klein and Steve W. J. Kozlowski, editors, *Multilevel Theory, Research, and Methods in Organization*, chapter 8, pages 349–381. Jossey-Bass, San Francisco, CA, 2000.
- Matthias Bluemke and Malte Friese. Reliability and validity of the Single-Target IAT (ST-IAT): Assessing automatic affect towards multiple attitude objects. *European Journal of Social Psychology*, 38(6):977–997, 2008. doi: 10.1002/ejsp.487.
- Kenneth A. Bollen. *Structural Equations with Latent Variables*. Wiley, New York, NY, 1989.
- Kenneth A. Bollen. An alternative two stage least squares (2SLS) estimator for latent variable equations. *Psychometrika*, 61(1):109–121, 1996. doi: 10.1007/BF02296961.
- Kenneth A. Bollen. Instrumental variables in sociology and the social sciences. *Annual Review of Sociology*, 38(1):37–72, 2012. doi: 10.1146/annurev-soc-081309-150141.
- Kenneth A. Bollen and Mark D. Noble. Structural equation models and the quantification of behavior. *Proceedings of the National Academy of Science*, 108(3):15639–15646, 2011. doi: 10.1073/pnas.1010661108.
- Kenneth A. Bollen and Judea Pearl. Eight myths about causality and structural equation models. In Stephen L. Morgan, editor, *Handbook of Causal Analysis for Social Research*, chapter 15, pages 301–328. Springer, The Netherlands, 2013. doi: 10.1007/978-94-007-6094-3_15.
- Kenneth A. Bollen, James B. Kirby, Patrick J. Curran, Pamela M. Paxton, and Feinian N. Chen. Latent variable models under misspecification - two-stage least squares (2SLS) and maximum likelihood (ML) estimators. *Sociological Methods & Research*, 36(1):48–86, 2007. doi: 10.1177/0049124107301947.

- Anne E. Brown. *Ridehail Revolution: Ridehail Travel and Equity in Los Angeles*. PhD thesis, University of California Los Angeles, 2018.
- Michael W. Browne and Robert Cudeck. Alternative ways of assessing model fit. *Sociological Methods & Research*, 21(2):230–258, 1992. doi: 10.1177/0049124192021002005.
- Isabel Buil, Leslie de Chernatony, and Eva Martínez. Methodological issues in cross-cultural research: An overview and recommendations. *Journal of Targeting, Measurement and Analysis for Marketing*, 20(3-4):223–234, 2012. doi: 10.1057/jt.2012.18.
- Stephen Burgess, Rhian M. Daniel, Adam S. Butterworth, Simon G. Thompson, and the EPIC-InterAct Consortium. Network mendelian randomization: using genetic variants as instrumental variables to investigate mediation in causal pathways. *International Journal of Epidemiology*, 44(2):484–495, 2014. doi: 10.1093/ije/dyu176.
- Barbara M. Byrne and Fons J. R. van de Vijver. Testing for measurement and structural equivalence in large-scale cross-cultural studies: Addressing the issue of nonequivalence. *International Journal of Testing*, 10(2):107–132, 2010. doi: 10.1080/15305051003637306.
- Barbara M. Byrne, Richard J. Shavelson, and Bengt O. Múthen. Testing for the equivalence of factor covariance and mean structures: the issue of partial measurement invariance. *Psychological Bulletin*, 105(3):456–466, 1989. doi: 0.1037/0033-2909.105.3.456.
- Huajian Cai, Natarajan Sriram, Anthony G. Greenwald, and Sam G. McFarland. The Implicit Association Test’s D measure can minimize a cognitive skill confound: Comment on McFarland and Crouch (2002). *Social Cognition*, 22(6):673–684, 2004. doi: 10.1521/soco.22.6.673.54821.
- Fang Fang Chen. Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, 14(3):464–504, 2007. doi: 10.1080/10705510701301834.
- George W. Cheung and Roger B. Rensvold. Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, 9(2):233–255, 2002. doi: 10.1207/S15328007SEM0902_5.
- Guillaume Chevance, Nelly Héraud, Agata Guerrieri, Amanda Rebar, and Julie Boiché. Measuring implicit attitudes toward physical activity and sedentary behaviors: Test-retest reliability of three scoring algorithms of the Implicit Association Test and Single Category-Implicit Association Test. *Psychology of Sport and Exercise*, 31:70–78, 2017. doi: 10.1016/j.psychsport.2017.04.007.
- Sangho Choo and Patricia L. Mokhtarian. What type of vehicle do people drive? the role of attitude and lifestyle in influencing vehicle type choice. *Transportation Research Part A: Policy and Practice*, 38:201–222, 2004. doi: 10.1016/j.tra.2003.10.005.
- Caspar G. Chorus and Maarten Kroesen. On the (im-)possibility of deriving transport policy implications from hybrid choice models. *Transport Policy*, 36:217–222, 2014. doi: 10.1016/j.tranpol.2014.09.001.
- CIA World Factbook. “Age structure”. <https://www.cia.gov/library/publications/the-world-factbook/fields/341.html#AS>, 2017.

- Mark T. Conner, Marco Perugini, Rick O’Gorman, Karen Ayres, and Andrew Prestwich. Relations between implicit and explicit measures of attitudes and measures of behavior: evidence of moderation by individual difference variables. *Personality and Social Psychology Bulletin*, 33(12): 1727–1740, 2007. doi: 10.1177/0146167207309194.
- Lee J. Cronbach. Coefficient alpha and the internal structure of tests. *Psychometrika*, 16:297–334, 1951. doi: 10.1007/BF02310555.
- Dario Cvencek, Anthony G. Greenwald, Anthony S. Brown, and Nicola S. Gray and Robert J. Snowden. Faking of the Implicit Association Test is statistically detectable and partly correctable. *Basic and Applied Social Psychology*, 32(4):302–314, 2010. doi: 10.1080/01973533.2010.519236.
- Sandor Czellar. Self-presentational effects in the Implicit Association Test. *Journal of Consumer Psychology*, 16(1):92–100, 2006. doi: 10.1207/s15327663jcp1601_11.
- Joyce Dargay, Dermot Gately, and Martin Sommer. Vehicle ownership and income growth, worldwide: 1960-2030. *The Energy Journal*, 28(4):143–170, 2007.
- Joyce M. Dargay. The effect of income on car ownership: Evidence of asymmetry. *Transportation Research Part A: Policy and Practice*, 32(9):807–821, 2001. doi: 10.1016/S0965-8564(00)00018-5.
- Data USA. Houston-The Woodlands-Sugar Land, TX Metro Area: “Car ownership” and “Commuter transportation”. <https://datausa.io/profile/geo/houston-sugar-land-baytown-tx-metro-area/>, 2018a.
- Data USA. New York-Newark-Jersey City, NY-NJ-PA Metro Area: “Car ownership” and “Commuter transportation”. <https://datausa.io/profile/geo/new-york-northern-new-jersey-long-island-ny-nj-pa-metro-area/>, 2018b.
- Jan de Houwer and Els de Bruycker. The Implicit Association Test outperforms the Extrinsic Affective Simon Task as an implicit measure of inter-individual differences in attitudes. *British Journal of Social Psychology*, 46(2):401–421, 2007. doi: 10.1348/014466606X130346.
- Jan de Houwer, Tanja Geldof, and Els De Bruycker. The Implicit Association Test as a general measure of similarity. *Canadian Journal of Experimental Psychology*, 59(4):228–239, 2005. doi: 10.1037/h0087478.
- André de Palma and Denis Rochat. Mode choices for trips to work in geneva: An empirical analysis. *Journal of Transport Geography*, 8(1):43–52, 2000. doi: 10.1016/S0966-6923(99)00026-5.
- Sarah Depaoli and James P. Clifton. A bayesian approach to multilevel structural equation modeling with continuous and dichotomous outcomes. *Structural Equation Modeling: A Multidisciplinary Journal*, 22(3):327–351, 2015. doi: 10.1080/10705511.2014.937849.
- René F.W. Diekstra and Martin Kroon. Cars and behaviour: Psychological barriers to car restraint and sustainable urban transport. In Rodney Tolley, editor, *Sustainable transport: Planning for walking and cycling in urban environments*, pages 252–264. Woodland Publishing, Cambridge, UK, 2003. doi: 10.1016/B978-1-85573-614-6.50025-2.
- Helga Dittmar. *The Social Psychology of Material Possessions: to have is to be*. St. Martin’s Press, Havester Wheatsheaf, UK, 1992.

- Ricardo Dobson, Frederick Dunbar, Caroline J. Smith, David Reibstein, and Christopher Lovelock. Structural models for the analysis of traveler attitude-behavior relationships. *Transportation*, 7(4):351–363, 1978. doi: 10.1007/BF00168036.
- Conor V. Dolan. Factor analysis of variables with 2, 3, 5, and 7 response categories: A comparison of categorical variable estimators using simulated data. *British Journal of Mathematical and Statistical Psychology*, 47(2):309–326, 1994. doi: 10.1111/j.2044-8317.1994.tb01039.x.
- Christian Domarchi, Alejandro Tudela, and Angélica González. Effect of attitudes, habit and affective appraisal on mode choice: An application to university workers. *Transportation*, 35(5):585–599, 2008. doi: 10.1007/s11116-008-9168-6.
- Ian J. Donald, Simon R. Cooper, and Stacy M. Conchie. An extended theory of planned behavior model of the psychological factors affecting commuters’ transport mode use. *Journal of Environmental Psychology*, 40:39–48, 2014. doi: 10.1016/j.jenvp.2014.03.003.
- Yarrow Dunham, Andrew Scott Baron, and Mahzarin R. Banaji. From american city to japanese village: A cross-cultural investigation of implicit race attitudes. *Child Development*, 77(5):1268–1281, 2006. doi: 10.1057/jt.2012.18.
- David Eagleman. *Incognito: the secret lives of the brain*. Pantheon Books, New York, NY, 2011.
- Paul W. Eastwick, Alice H. Eagly, Eli J. Finkel, and Sarah E. Johnson. Implicit and explicit preferences for physical attractiveness in a romantic partner: A double dissociation in predictive validity. *Journal of Personality and Social Psychology*, 101(5):993–1011, 2011. doi: 10.1037/a0024061.
- U.S. Energy Information Association EIA. Transportation sector energy consumption. In *International Energy Outlook 2016*, chapter 8, pages 127–137. International Energy Agency, Washington, D.C., 2016. <https://www.eia.gov/outlooks/ieo/pdf/transportation.pdf>.
- Embarq. From here to there: A creative guide to making public transport the way to go, 2011. www.wrirosscities.org/sites/default/files/From-Here-to-There-EMBARQ.pdf.
- Craig K. Enders and Davood Tofghi. Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods*, 12(2):121–138, 2007. doi: 10.1037/1082-989X.12.2.121.
- Russell H. Fazio. Multiple processes by which attitudes guide behavior: The mode model as an integrative framework. *Advances in Experimental Social Psychology*, 23:75–109, 1990. doi: 10.1016/S0065-2601(08)60318-4.
- Stefan Fickl and Wilfried Raimund. Fuel economy labelling of cars and its impacts on buying behaviour, fuel efficiency and co2 reduction. <https://p2infohouse.org/ref/17/16366.pdf> and related work at https://www.eceee.org/library/conference_proceedings/eceee_Summer_Studies/1999/Panel_5/p5_5/, 1999.
- Klaus Fiedler and Matthias Bluemke. Faking the IAT: Aided and unaided response control on the Implicit Association Tests. *Basic and Applied Social Psychology*, 27(4):307–316, 2005. doi: 10.1207/s15324834basp2704_3.

- Klaus Fiedler, Claude Messner, and Matthias Bluemke. Unresolved problems with the “T”, the “A”, and the “I”: A logical and psychometric critique of the Implicit Association Test (IAT). *European Review of Social Psychology*, 17:74–147, 2006. doi: 10.1080/10463280600681248.
- Robert J. Fisher. Social desirability bias and the value of indirect questioning. *Journal of Consumer Research*, 20:303–315, 1993. doi: 10.2307/2489277.
- Zachary Fisher, Kenneth A. Bollen, Kathleen Gates, and Mikko Rönkkö. R package ‘miivsem’: Model implied instrumental variable (miiv) estimation of structural equation models. <https://github.com/zackfisher/MIIVsem>, 2019.
- Geraldine Fulcher, Graham Parkhurst, Chris Alford, and Charles Musselwhite. The role of implicit data collection techniques in traffic and transport psychology, 2014. citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.723.6085&rep=rep1&type=pdf.
- Silvia Galdi, Luciano Arcuri, and Bertram Gawronski. Automatic mental associations predict future choices of undecided decision-makers. *Science*, 321(5892):1100–1102, 2008. doi: 10.1126/science.1160769.
- Matthew W. Gallagher and Timothy A. Brown. Introduction to confirmatory factor analysis and structural equation modeling. In Timothy Teo, editor, *Handbook of Quantitative Methods for Educational Research*, chapter 14, pages 289–314. Sense Publishers, Rotterdam, 2013. doi: 10.1007/978-94-6209-404-8_14.
- Benjamin Gardner. Modelling motivation and habit in stable travel mode contexts. *Transportation Research Part F: Traffic Psychology and Behaviour*, 12(1):68–71, 2009. doi: 10.1016/j.trf.2008.08.001.
- Benjamin Gardner and Charles Abraham. Psychological correlates of car use: A meta-analysis. *Transportation Research Part F: Traffic Psychology and Behaviour*, 11(4):300–311, 2008. doi: 10.1016/j.trf.2008.01.004.
- Tommy Gärling and Peter Loukopoulos. Economic and psychological determinants of car ownership and use. In Alan Lewis, editor, *The Cambridge Handbook of Psychology and Economic Behavior*, chapter 16, pages 383–405. Cambridge University Press, Cambridge, U.K., 2008. 10.1017/CBO9780511490118.016.
- Tommy Gärling, Robert Gillholm, and Anita Gärling. Reintroducing attitude theory in travel behavior research: the validity of an interactive interview procedure to predict car use. *Transportation*, 25(2):129–146, 1998. doi: 10.1023/A:1005004311776.
- Birgitta Gatersleben. Affective and symbolic aspects of car use. In Tommy Gärling and Linda Steg, editors, *Threats to the Quality of Urban Life from Car Traffic: Problems, Causes, and Solutions*, chapter 16, pages 219–233. Elsevier, Amsterdam, Netherlands, 2007.
- Birgitta Gatersleben. The car as a material possession: Exploring the link between materialism and car ownership and use. In Karen Lucas, Evelyn Blumenberg, and Rachel Weinberger, editors, *Auto Motives: Understanding Car Use Behaviours*, chapter 7, pages 137–148. Emerald Group Publishing, Ltd., Bingley, UK, 2011.

- Bertram Gawronski. Ten frequently asked questions about implicit measures and their frequently supposed, but not entirely correct answers. *Canadian Psychology*, 50(3):141–150, 2009. doi: 10.1037/a0013848.
- Bertram Gawronski and Galen V. Bodenhausen. Associative and propositional processes in evaluation: An integrative review of implicit and explicit attitude change. *Psychological Bulletin*, 132(5):692–731, 2006. doi: 10.1037/0033-2909.132.5.692.
- G. John Geldhof, Kristopher J. Preacher, and Michael J. Zyphur. Reliability estimation in a multilevel confirmatory factor analysis framework. *Psychological Methods*, 19(1):72–91, 2014. doi: 10.1037/a0032138.
- Andrew Gelman and Donald B. Rubin. Inference from iterative simulation using multiple sequences (with discussion). *Statistical Science*, 7(4):457–511, 1992. doi: 10.1214/ss/1177011136.
- Andrew Gelman, John B. Carlin, Hal S. Stern, and Donald B. Rubin. *Bayesian Data Analysis*. Chapman & Hall, New York, NY, 2 edition, 2004.
- German Agency for International Cooperation (GIZ). “Pump price for diesel fuel (US\$ per liter)”. <https://data.worldbank.org/indicator/EP.PMP.SGAS.CD?view=map>.
- Daniel T. Gilbert. How mental systems believe. *American Psychologist*, 46(2):107–119, 1991. doi: 10.1037/0003-066X.46.2.107.
- Klaske A. Glashouwer, Fren T. Y. Smulders, Peter J. de Jong, Anne Roefs, and Reinout W. H. J. Wiers. Measuring automatic associations: Validation of algorithms for the Implicit Association Test (IAT) in a laboratory setting. *Journal of Behavior Therapy and Experimental Psychology*, 44(1):105–113, 2013. doi: 10.1016/j.jbtep.2012.07.015.
- Paul D. Glennie and Nigel J. Thrift. Modernity, urbanism, and modern consumption. *Environment and Planning D: Society and Space*, 10(4):423–443, 1992. doi: 10.1068/d100423.
- Tara B. Goddard. *Drivers’ Attitudes and Behaviors Toward Bicyclists: Intermodal Interactions and Implications for Road Safety*. PhD thesis, Portland State University, 2017.
- Tara B. Goddard, Kimberly Barsamian Kahn, and Arlie Adkins. Racial bias in driver yielding behavior at crosswalks. *Transportation Research Part F: Traffic Psychology and Behaviour*, 33: 1–6, 2015. doi: 10.1016/j.trf.2015.06.002.
- Jennifer L. Goetz, Julie Spencer-Rodgers, and Kaiping Peng. Dialectical emotions: How cultural epistemologies influence the experience and regulation of emotional complexity. In Richard M. Sorrentino and Susumu Yamaguchi, editors, *Handbook of motivation and cognition across cultures*, chapter 22, page 517–540. Elsevier, New York, NY, 2008.
- Thomas F. Golob. Structural equation modeling for travel behavior research. *Transportation Research Part B: Methodological*, 37(1):1–25, 2003. doi: 10.1016/S0191-2615(01)00046-7.
- Stefan Gössling. *The Psychology of the Car: Automobile Admiration, Attachment, and Addiction*. Elsevier, Amsterdam, Netherlands, 2017.
- Anthony G. Greenwald. The totalitarian ego: Fabrication and revision of personal history. *American Psychologist*, 35(7):603–618, 1980. doi: 10.1037/0003-066X.35.7.603.

- Anthony G. Greenwald and Mahzarin R. Banaji. Implicit social cognition: Attitudes, self-esteem, and stereotypes. *Psychological Review*, 102(1):4–27, 1995. doi: 10.1037//0033-295X.102.1.4.
- Anthony G. Greenwald, Brian A. Nosek, and Mahzarin R. Banaji. Understanding and using the Implicit Association Test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology*, 85(2):197–216, 2003. doi: 10.1037/0022-3514.85.2.197.
- Anthony G. Greenwald, Brian A. Nosek, Mahzarin R. Banaji, and Karl Christoph Klauer. Validity of the salience asymmetry interpretation of the IAT: Comment on Rothermund and Wentura (2004). *Journal of Experimental Psychology: General*, 134(3):420–425, 2005. doi: 10.31234/osf.io/bkvsp.
- Anthony G. Greenwald, Brian A. Nosek, and Natarajan Sriram. Consequential validity of the Implicit Association Test: Comment on the article by Blanton and Jaccard (2006). *American Psychologist*, 61(1):56–61, 2006. doi: 10.1037/0003-066X.61.1.56.
- Anthony G. Greenwald, T. Andrew Poehlman, Eric Luis Uhlmann, and Mahzarin R. Bamaji. Understanding and using the Implicit Association Test: III. Meta-analysis of predictive validity. *Journal of Personality and Social Psychology*, 97(1):17–41, 2009. doi: 10.1037/a0015575.
- Alden P. Gregg and James Klymowsky. The Implicit Association Test in market research: Potentials and pitfalls. *Psychology & Marketing*, 30(7):588–601, 2013. doi: 10.1002/mar.20630.
- Alden P. Gregg, Beate Seibt, and Mahzarin R. Banaji. Easier done than undone: Asymmetry in the malleability of automatic preferences. *Journal of Personality and Social Psychology*, 90(1):1–20, 2006. doi: 10.1037/0022-3514.90.1.1.
- Vladas Griskevicius, Joshua M. Tybur, and Bram Van den Bergh. Going green to be seen: status, reputation, and conspicuous conservation. *Journal of Personality and Social Psychology*, 98(3):392–404, 2010. doi: 10.1037/a0017346.
- Judith De Groot and Linda Steg. General beliefs and the theory of planned behavior: the role of environmental concerns in the tpb. *Journal of Applied Social Psychology*, 37(8):1817–1836, 2007. doi: 10.1111/j.1559-1816.2007.00239.x.
- Nigel Guenole. Reconsidering cluster bias in multilevel data: A monte carlo comparison of free and constrained baseline approaches. *Frontiers in Psychology*, 9, 2018. doi: 10.3389/fpsyg.2018.00255.
- H. Anna Han, Michael A. Olson, and Russell H. Fazio. The influence of experimentally-created extrapersonal associations on the Implicit Association Test. *Journal of Experimental Social Psychology*, 42(3):259–272, 2006. doi: 10.1016/j.jesp.2005.04.006.
- Gregory R. Hancock and Ralph O. Mueller. Rethinking construct reliability with latent variable systems. In Robert Cudeck, Stephen du Toit, and Dag Sörbom, editors, *Structural Equation Modeling: Present and Future—A festschrift in honor of Karl Jöreskog*, chapter 10, pages 195–216. Scientific Software International, Inc., Lincolnwood, IL, 2001.
- Paul Harland, Henk Staats, and Henk A. M. Wilke. Explaining proenvironmental intention and behavior by personal norms and the theory of planned behavior. *Journal of Applied Social Psychology*, 29(12):2505–2528, 1999. doi: 10.1111/j.1559-1816.1999.tb00123.x.

- Niki Harré and Chris G. Sibley. Explicit and implicit self-enhancement biases in drivers and their relationship to driving violations and crash-risk optimism. *Accident Analysis and Prevention*, 39(6):1155–1161, 2007. doi: 10.1016/j.aap.2007.03.001.
- Ran R. Hassin, James S. Uleman, and John A. Bargh. *The new unconscious*. Oxford University Press, New York, NY, 2005.
- Julie Hatfield, Ralston Fernandes, Gavin Faunce, and R. F. Soames Job. An implicit non-self-report measure of attitudes to speeding: Development and validation. *Accident Analysis and Prevention*, 40(2):616–627, 2008. doi: 10.1016/j.aap.2007.08.020.
- Sonja Haustein and Marcel Hunecke. Reduced use of environmentally friendly modes of transportation caused by perceived mobility necessities: An extension of the theory of planned behavior. *Journal of Applied Social Psychology*, 37(8):1856–1883, 2007. doi: 10.1111/j.1559-1816.2007.00241.x.
- Sylvia Y. He and John Thøgersen. The impact of attitudes and perceptions on travel mode choice and car ownership in a chinese megacity: The case of guangzhou. *Research in Transportation Economics*, 62:57–67, 2017. doi: 10.1016/j.retrec.2017.03.004.
- Yuko Heath and Robert Gifford. Extending the theory of planned behavior: predicting the use of public transportation. *Journal of Applied Social Psychology*, 32(10):2154–2189, 2002. doi: 10.1111/j.1559-1816.2002.tb02068.x.
- Ronald H. Heck and Scott L. Thomas. *An introduction to multilevel modeling techniques*. Routledge, New York, NY, 2 edition, 2009.
- Stephanie Hernandez McGavin. Automakers rank high on annual ad-spending list. *Automotive News*, June 28 2016. <https://www.autonews.com/article/20160628/RETAIL03/160629852/automakers-rank-high-on-annual-ad-spending-list>.
- Daniel Baldwin Hess and Alex Bitterman. Bus rapid transit identity: An overview of current “branding” practice. *Journal of Public Transportation*, 11(2):19–42, 2008. doi: 10.5038/2375-0901.11.2.2.
- Daniel Baldwin Hess and Alex Bitterman. Branding and selling public transit in north america: An analysis of recent messages and methods. *Research in Transportation Business & Management*, 18:49–56, 2016. doi: 10.1016/j.rtbm.2016.01.001.
- Rosemary Hiscock, Sally Macintyre, Ade Kearns, and Anne Ellaway. Means of transport and ontological security: do cars provide psychosocial benefits to their users? *Transportation Research Part D: Transport and Environment*, 7(2):119–135, 2002. doi: 10.1016/S1361-9209(01)00015-3.
- Wilhelm Hofmann, Bertram Gawronski, Tobias Gschwendner, Huy Hoàng Lê, and Manfred Schmitt. A meta-analysis on the correlation between the Implicit Association Test and explicit self-report measures. *Personality and Social Psychology Bulletin*, 31(10):1369–1385, 2005. doi: 10.1177/0146167205275613.
- Wilhelm Hofmann, Wolfgang Rauch, and Bertram Gawronski. And deplete us not into temptation: Automatic attitudes, dietary restraint, and self-regulatory resources as determinants of eating behavior. *Journal of Experimental Social Psychology*, 43(3):497–504, 2007. doi: 10.1016/j.jesp.2006.05.004.

- Jana Holtmann, Tobias Koch, Katharina Lochner, and Michael Eid. A comparison of ML, WLSMV, and Bayesian methods for multilevel structural equation models in small samples: A simulation study. *Multivariate Behavioral Research*, 51(5):661–680, 2016. doi: 10.1080/00273171.2016.1208074.
- Oliver Horeni, Theo A. Arentze, Benedict G. C. Dellaert, and Harry J. P. Timmermans. Online measurement of mental representations of complex spatial decision problems: Comparison of cnet and hard laddering. *Transportation Research Part F: Traffic Psychology and Behaviour*, 22: 170–183, 2014. doi: 10.1016/j.trf.2013.12.002.
- Joop J. Hox. *Multilevel analysis techniques and applications*. Routledge, New York, NY, 2 edition, 2010.
- Joop J. Hox and Cora J. M. Maas. The accuracy of multilevel structural equation modeling with pseudobalanced groups and small sample sizes. *Structural Equation Modeling*, 8(2):157–174, 2001. doi: 10.1207/S15328007SEM0802_1.
- Hsien-Yuan Hsu, Jr-Hung Lin, Oi-Man Kwok, Sandra Acosta, and Victor Willson. The impact of intraclass correlation on the effectiveness of level-specific fit indices in multilevel structural equation modeling: A monte carlo study. *Educational and Psychological Measurement*, 77(1): 5–31, 2016. doi: 10.1177/0013164416642823.
- Li-Tze Hu and Peter M. Bentler. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6(1):1–55, 1999. doi: 10.1080/10705519909540118.
- Stephen Hudson. Here are the most popular forms of transit in different cities. <https://ggwash.org/view/65488/see-the-most-popular-forms-of-transit-in-different-cities>, November 9 2017.
- Marcel Hunecke, Sonja Haustein, Sylvie Grischkat, and Susanne Böhler. Psychological, socio-demographic, and infrastructure factors as determinants of ecological impact caused by mobility behavior. *Journal of Environmental Psychology*, 27(4):277–292, 2007. doi: 10.1016/j.jenvp.2007.08.001.
- John E. Hunter and David W. Gerbing. Unidimensional measurement, second order factor analysis, and causal models. *Research in Organizational Behavior*, 4:267–320, 1982.
- International Energy Agency IEA. Energy technology perspectives 2012: Pathways to a clean-energy system. In *Transport*, chapter 13, pages 195–216. International Energy Agency, Paris, France, 2012. https://www.iea.org/publications/freepublications/publication/ETP2012_free.pdf.
- International Organization of Motor Vehicle Manufacturers (OICA). “Vehicles in use 2005-2015, by country and type”, howpublished = <http://www.oica.net/category/vehicles-in-use/>.
- International Transport Forum (ITF). “Transport infrastructure investment and maintenance spending”. https://stats.oecd.org/Index.aspx?DataSetCode=ITF_INV-MTN_DATA.
- Suzanne Jak and Terrence D. Jorgensen. Relating measurement invariance, cross-level invariance, and multilevel reliability. *Frontiers in Psychology*, 8, 2017. doi: 10.3389/fpsyg.2017.01640.

- Suzanne Jak, Frans J. Oort, and Conor V. Dolan. A test for cluster bias: Detecting violations of measurement invariance across clusters in multilevel data. *Structural Equation Modeling*, 20: 265–282, 2013. doi: 10.1080/10705511.2013.769392.
- Maria Vredin Johansson, Tobias Heldt, and Per Johansson. The effects of attitudes and personality traits on mode choice. *Transportation Research Part A: Policy and Practice*, 40(6):507–525, 2006. doi: 10.1016/j.tra.2005.09.001.
- Bradley Johnson. What you need to know about the world’s largest advertisers, from Adidas to Yili. *Ad Age*, December 4 2016. <https://adage.com/article/advertising/world-s-largest-advertisers/306983/>.
- Marc W. Julian. The consequences of ignoring multilevel data structures in nonhierarchical covariance modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, 8(3):325–352, 2001. doi: 10.1207/S15328007SEM0803_1.
- Daniel Kahneman. *Thinking, fast and slow*. Farrar, Strauss, Giroux, New York, NY, 2011.
- Michael T. Kane. Validating the interpretations and uses of test scores. *Journal of Educational Measurement*, 50(1):1–73, 2013. doi: 10.1111/jedm.12000.
- David Kaplan and Sarah Depaoli. Bayesian structural equation modeling. In Rick H. Hoyle, editor, *Handbook of Structural Equation Modeling*, chapter 38, pages 650–673. Guilford Press, New York, NY, 2012.
- David Kaplan, Polina Harik, and Lawrence Hotchkiss. Cross-sectional estimation of dynamic structural equation models in disequilibrium. In Robert Cudeck, Stephen du Toit, and Dag Sörbom, editors, *Structural Equation Modeling: Present and Future—A festschrift in honor of Karl Jöreskog*, chapter 15, pages 315–339. Scientific Software International, Inc., Lincolnwood, IL, 2001.
- Andrew Karpinski and Ross B. Steinman. The Single Category Implicit Association Test as a measure of implicit social cognition. *Journal of Personal and Social Psychology*, 91(1):16–32, 2006. doi: 10.1037/0022-3514.91.1.16.
- Do-Yeong Kim. Voluntary controllability of the Implicit Association Test (IAT). *Social Psychology Quarterly*, 66(1):83–96, 2003. doi: 10.2307/3090143.
- Eun Sook Kim, Oi man Kwok, and Myeongsun Yoon. Testing factorial invariance in multilevel data: A monte carlo study. *Structural Equation Modeling*, 19(2):250–267, 2012. doi: 10.1080/10705511.2012.659623.
- Eun Sook Kim, Robert F. Dedrick, Chunhua Cao, and John M. Ferron. Multilevel factor analysis: Reporting guidelines and a review of reporting practices. *Multivariate Behavioral Research*, 51(6):881–898, 2016. doi: 10.1080/00273171/2016.1228042.
- Young-Hoon Kim, Siqing Peng, and Chi-Yue Chiu. Explaining self-esteem differences between Chinese and North Americans: Dialectical self (vs. self-consistency) or lack of positive self-regard. *Self and Identity*, 7(11):113–128, 2008. doi: 10.1080/15298860601063437.

- Maryon F. King and Gordon C. Bruner. Social desirability bias: A neglected aspect of validity testing. *Psychology & Marketing*, 17(2):79–103, 2000. doi: 10.1002/(SICI)1520-6793(200002)17:2<79::AID-MAR2>3.0.CO;2-0.
- Rex B. Kline. *Principles and Practice of Structural Equation Modeling*. Guilford Press, New York, NY, 4 edition, 2016.
- Tobias Koch, Martin Schultze, Michael Eid, and Christian Geiser. A longitudinal multilevel cfa-mtmm model for interchangeable and structurally different methods. *Frontiers in Psychology*, 5, 2014. doi: 10.3389/fpsyg.2014.00311.
- Frank S. Koppelman and Patricia K. Lyon. Attitudinal analysis of work/school travel. *Transportation Science*, 15(3):233–254, 1981. doi: 10.1287/trsc.15.3.233.
- Maarten Kroesen, Susan Handy, and Caspar Chorus. Do attitudes cause behavior or vice versa? An alternative conceptualization of the attitude-behavior relationship in travel behavior modeling. *Transportation Research Part A: Policy and Practice*, 101:190–202, 2017. doi: 10.1016/j.tra.2017.05.013.
- Mark H. C. Lai and Oi man Kwok. Estimating the rule of thumb of not using multilevel modeling: The “design effect smaller than two” rule. *Journal of Experimental Education*, 83(3):423–438, 2015. doi: 10.1080/00220973.2014.907229.
- Kristin A. Lane, Mahzarin R. Banaji, Brian A. Nosek, and Anthony G. Greenwald. Understand and using the Implicit Association Test: What we know (so far) about the method. In Bernd Wittenbrink and Norbert Schwarz, editors, *Implicit Measures of Attitudes*, chapter 3, pages 59–102. Guilford Press, New York, NY, 2007. <http://faculty.washington.edu/agg/pdf/Lane%20et%20al.UUIAT4.2007.pdf>.
- Jeff T. Larsen, A. Peter McGraw, and John T. Cacioppo. Can people feel happy and sad at the same time? *Journal of Personality and Social Psychology*, 81(4):684–696, 2001. doi: 10.1037/0022-3514.81.4.684.
- Jeff T. Larsen, A. Peter McGraw, Barbara A. Mellers, and John T. Cacioppo. The agony of victory and thrill of defeat: Mixed emotional reactions to disappointing wins and relieving losses. *Psychological Science*, 15(5):325–330, 2004. doi: 10.1111/j.0956-7976.2004.00677.x.
- A. Nicole LeBarr and Judith M. Shedden. Psychological ownership: The implicit association between self and already-owned versus newly-owned objects. *Consciousness and Cognition*, 48:190–197, 2017. doi: 10.1016/j.concog.2016.11.012.
- Rubén D. Ledesma, Jeremías Tosi, Fernando M. Poó, Silvana A. Montes, and Soledad S. López. Implicit attitudes and road safety behaviors. the helmet-use case. *Accident Analysis and Prevention*, 79:190–197, 2015. doi: 10.1016/j.aap.2015.03.030.
- Sik-Yum Lee, Xin-Yuan Song, and Jing-Heng Cai. A bayesian approach for nonlinear structural equation models with dichotomous variables using logit and probit links. *Structural Equation Modeling: A Multidisciplinary Journal*, 17(2):280–302, 2010. doi: 10.1080/10705511003659425.

- Won-Chan Lee and Guemin Lee. Irt linking and equating. In Paul Irwing, Tom Booth, and David J. Hughes, editors, *The Wiley Handbook of Psychometric Testing: A Multidisciplinary Reference on Survey, Scale and Test Development*, chapter 21, pages 639–673. John Wiley & Sons Ltd, Hoboken, NJ, 2018. doi: 10.1002/9781118489772.ch21.
- Pui-Wa Lei and Qiong Wu. Introduction to structural equation modeling: Issues and practical considerations. *Educational Measurement: Issues and Practice*, 26(3):33–43, 2007. doi: 10.1111/j.1745-3992.2007.00099.x.
- Gerty J. Lensvelt-Mulders, Joop J. Hox, Peter G. M. van der Heijden, and Cora J. M. Maas. Meta-analysis of randomized response research. *Sociological Methods and Research*, 33(3):319–348, 2005. doi: 10.1177/0049124104268664.
- Shanjun Li, Joshua Linn, and Erich Muehlegger. Gasoline taxes and consumer behavior. <https://www.nber.org/papers/w17891>, 2014.
- Todd Litman. Mobility as a positional good: Implications for transport policy and planning, 2011. <http://www.vtppi.org/prestige.pdf>.
- Todd D. Little, Ulman Lindenberger, and John R. Nesselroade. On selecting indicators for multivariate measurement and modeling with latent variables: When “good” indicators are bad and “bad” indicators are good. *Psychological Methods*, 4(2):192–211, 1999. doi: 10.1037/1082-989X.4.2.192.
- David Lois and Mercedes López-Sáez. The relationship between instrumental, symbolic and affective factors as predictors of car use: A structural equation modeling approach. *Transportation Research Part A: Policy and Practice*, 43(9-10):790–799, 2009. doi: 10.1016/j.tra.2009.07.008.
- Frederic M. Lord and Melvin Robert Novick. *Statistical Theories of Mental Test Scores*. Addison-Wesley, Reading, MA, 1968.
- Los Angeles Metro. Opposites campaign summary. libraryarchives.metro.net/DB_Attachments/141013_msc_Opposites_booklet_r4.pdf, July 2009.
- Samuel R. Lucas. An inconvenient dataset: bias and inappropriate inference with the multilevel model. *Quality & Quantity*, 48(3):1619–1649, 2014. doi: 10.1007/s11135-013-9865-x.
- Oliver Lüdtke, Herbert W. Marsh, Alexander Robitzsch, Ulrich Trautwein, Tihomir Asparouhov, and Bengt Muthén. The multilevel latent covariate model: A new more reliable approach to group-level effects in contextual studies. *Psychological Methods*, 13(3):203–229, 2008. doi: 10.1037/a0012869.
- Robert C. MacCallum, Michael W. Browne, and Hazuki M. Sugawara. Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, 1(2):130–149, 1996. doi: 10.1037//1082-989X.1.2.130.
- Steven Manson, Jonathan Schroeder, David Van Riper, , and Steven Ruggles. IPUMS National Historical Geographic Information System: Version 13.0 [Database]. Minneapolis: University of Minnesota. <http://doi.org/10.18128/D050.V13.0>, 2018.
- Hy Mariampolski. *Qualitative market research: A comprehensive guide*. Sage, Thousand Oaks, CA, 2001.

- Greg Marsden and Dominic Stead. Policy transfer and learning in the field of transport: A review of concepts and evidence. *Transport Policy*, 18(3):492–500, 2011. doi: 10.1016/j.tranpol.2010.10.007.
- Herbert W. Marsh, Oliver Lüdtke, Benjamin Nagengast, Ulrich Trautwein, Alexandre J. S. Morin, Adel S. Abduljabbar, and Olaf Köller. Classroom climate and contextual effects: Conceptual and methodological issues in the evaluation of group-level effects. *Educational Psychologist*, 47(2):106–124, 2012. doi: 10.1080/00461520.2012.670488.
- Laila M. Martinussen, Mikael J. Sømhovd, Mette Møller, and Frank Siebler. A go/no-go approach to uncovering implicit attitudes toward safe and risky driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, 30:74–83, 2015. doi: 10.1016/j.trf.2015.02.005.
- Laila M. Martinussen, Laura Petranca, and Mikael J. Sømhovd. The relationship between explicit and implicit attitudes towards drunk driving. *PLoS ONE*, 13(10):e0206124, 2018. doi: 10.1371/journal.pone.0206124.
- Winter Mason, Steven Allon, and Pinar Ozturk. Open source, web-based iat. stevens institute of technology. <https://github.com/winteram/IAT>, 2014.
- Roderick P. McDonald. *Test Theory: A Unified Treatment*. Erlbaum, Mahwah, NJ, 1999.
- Daniel McFadden. Economic choices. *The American Economic Review*, 91(3):351–378, 2001. doi: 10.1257/aer.91.3.351.
- Gideon J. Mellenbergh. Item bias and item response theory. *International Journal of Educational Statistics*, 13(2):127–143, 1989. doi: 10.1016/0883-0355(89)90002-5.
- Gideon J. Mellenbergh. A unidimensional latent trait model for continuous item responses. *Multivariate Behavioral Research*, 29(3):223–236, 1994. doi: 10.1207/s15327906mbr2903_2.
- William Meredith. Measurement invariance, factor analysis, and factorial invariance. *Psychometrika*, 58(4):525–543, 1993. doi: 10.1007/BF02294825.
- William Meredith and Jeanne A. Teresi. An essay on measurement and factorial invariance. *Medical Care*, 44(11. Measurement in a Multi-Ethnic Society):69–77, 2006. doi: 10.1097/01.mlr.0000245438.73837.89.
- Dale T. Miller and Deborah A. Prentice. Changing norms to change behavior. *Annual Review of Psychology*, 67:339–361, 2016. doi: 10.1146/annurev-psych-010814-015013.
- Roger E. Millsap and Jenn Yun-Tein. Assessing factorial invariance in ordered-categorical measures. *Multivariate Behavioral Research*, 39(3):479–515, 2004. doi: 10.1207/S15327906MBR3903_4.
- Carme Miralles-Guasch, Montserrat Martínez Melo, and Oriol Marquet Sarda. On user perception of private transport in barcelona metropolitan area: an experience in an academic suburban space. *Journal of Transport Geography*, 36:24–31, 2014. doi: 10.1016/j.jtrangeo.2014.02.009.
- Brett R. C. Molesworth and Betty Chang. Predicting pilots’ risk-taking behavior through an Implicit Association Test. *Human Factors*, 51(6):845–857, 2009. doi: 10.1177/0018720809357756.

- Metropolitan Transportation Authority MTA. “The MTA network: Public transportation for the New York region”. <http://web.mta.info/mta/network.htm>. Accessed: March 12, 2019.
- Stanley A. Mulaik. *Linear causal modeling with structural equations*. CRC Press, New York, NY, 2009.
- Bengt Muthén. Bayesian analysis in Mplus: A brief introduction, May, 17 2010. [Incomplete Draft, Version 3] <https://www.statmodel.com/download/IntroBayesVersion%203.pdf>.
- Bengt O. Muthén. Multilevel covariance structure analysis. *Sociological Methods & Research*, 22: 376–398, 1994. doi: 10.1177/0049124194022003006.
- Bengt O. Muthén and Tihomir Asparouhov. Beyond multilevel regression modeling: Multilevel analysis in a general latent variable framework. In Joop J. Hox and J. Kyle Roberts, editors, *The Handbook of Advanced Multilevel Analysis*, chapter 10, pages 15–40. Taylor and Francis, New York, NY, 2011. <https://www.statmodel.com/download/multilevelVersion2.pdf>.
- Linda K. Muthén and Bengt O. Muthén. *Mplus User’s Guide*. Muthén & Muthén, 8 edition, 1998-2018.
- Linda K. Muthén and Bengt O. Muthén. How to use a Monte Carlo study to decide on sample size and determine power. *Structural Equation Modeling: A Multidisciplinary Journal*, 9(4):599–620, 2009. doi: 10.1207/S15328007SEM0904_8.
- Alim Nayum and Christian A. Klöckner. A comprehensive socio-psychological approach to car type choice. *Journal of Environmental Psychology*, 40:401–411, 2014. doi: 10.1016/j.jenvp.2014.10.001.
- Kenneth Bo Nielsen and Harold Wilhite. The rise and fall of the ‘people’s car’: Middle-class aspirations, status, and mobile symbolism in ‘new india’. In Arve Hansen and Kenneth Bo Nielsen, editors, *Cars, Automobility and Development in Asia: Wheels of Change*, pages 171–190. Routledge, New York, NY, 2014.
- Maria Nilsson and Rikard Küller. Travel behavior and environmental concern. *Transportation Research Part D: Transport and Environment*, 5(3):211–234, 2000. doi: 10.1016/S1361-9209(99)00034-6.
- Brian A. Nosek. Implicit-explicit relations. *Current Directions in Psychological Science*, 16(2): 65–69, 2007. doi: 10.1111/j.1467-8721.2007.00477.x.
- Brian A. Nosek and Mahzarin R. Banaji. The go/no-go association task. *Social Cognition*, 19(6): 625–666, 2001. doi: 10.1521/soco.19.6.625.20886.
- Brian A. Nosek and Jeffrey J. Hansen. The associations in our heads belong to us: Searching for attitudes and knowledge in implicit evaluation. *Cognition and Emotion*, 22(4):553–594, 2008a. doi: 10.1080/02699930701438186.
- Brian A. Nosek and Jeffrey J. Hansen. Personalizing the Implicit Association Test increases explicit evaluation of the target concepts. *European Journal of Psychological Assessment*, 25(4):226–236, 2008b. doi: 10.1027/1015-5759.24.4.226.

- Brian A. Nosek and Natarajan Sriram. Faulty assumptions: A comment on blanton, jaccard, gonzales, and christie (2006). *Journal of Experimental Social Psychology*, 43(3):393–398, 2007. doi: 0.1016/j.jesp.2006.10.018.
- Brian A. Nosek, Anthony G. Greenwald, and Mahzarin R. Banaji. Understanding and using the Implicit Association Test: II. Method variables and construct validity. *Personality and Social Psychology Bulletin*, 31(2):166–180, 2005. doi: 10.1177/0146167204271418.
- Brian A. Nosek, Anthony G. Greenwald, and Mahzarin R. Banaji. The Implicit Association Test at age 7: A methodological and conceptual review. In John A. Bargh, editor, *Social Psychology and the Unconscious: The automaticity of higher mental processes*, chapter 6, pages 265–292. Psychology Press, New York, NY, 2007. <https://faculty.washington.edu/agg/pdf/Nosek%20&%20a1.IATatage7.2007.pdf>.
- Melvin Robert Novick and Charles Lewis. Coefficient alpha and the reliability of composite measurements. *Psychometrika*, 32:1–13, 1967. doi: 10.1007/BF02289400.
- Karine Nyborg, John M. Anderies, Astrid Dannenberg, Therese Lindahl, Caroline Schill, Maja Schlüter, W. Neil Adger, Kenneth J. Arrow, Scott Barrett, Stephen Carpenter, F. Stuart Chapin III, Anne-Sophie Crépin, Gretchen Daily, Paul Ehrlich, Carl Folke, Wander Jager, Nils Kautsky, Simon A. Levin, Ole Jacob Madsen, Stephen Polasky, Marten Scheffer, Brian Walker, Elke U. Weber, James Wilen, Anastasios Xepapadeas, and Aart de Zeeuw. Social norms as solutions: Policies may influence large-scale behavioral tipping. *Science Policy Forum*, 354(6308):42–43, 2016. doi: 10.1126/science.aaf8317.
- Organization for Economic Co-Operation and Development (OECD). “Indicators: Traffic”. https://stats.oecd.org/Index.aspx?DataSetCode=ITF_INV-MTN_DATA.
- Judea Pearl. *Causality: Models, reasoning, and inference*. Cambridge University Press, Cambridge, UK, 2000.
- William Gadsby Peet. Interview: Sadiq Khan, Tooting MP and mayoral candidate. *Essential Surrey & SW London*, April 12 2016. <https://www.essentialssurrey.co.uk/home/interview-sadiq-khan/>.
- Pew Research Center. Car, bike or motorcycle? Depends on where you live. <http://www.pewresearch.org/fact-tank/2015/04/16/car-bike-or-motorcycle-depends-on-where-you-live/>, April 16 2015.
- Brad Pinter and Anthony Greenwald. Clarifying the role of the ‘other’ category in the self-esteem IAT. *Experimental Psychology*, 52(1):74–79, 2005. doi: 10.1027/1618-3169.52.1.74.
- Elona Pojani, Veronique Van Acker, and Dorina Pojani. Cars as a status symbol: Youth attitudes towards sustainable transport in a post-socialist city. *Transportation Research Part F: Traffic Psychology and Behaviour*, 58:210–227, 2018. doi: 10.1016/j.trf.2018.06.003.
- Kristopher J. Preacher, Zhen Zhang, and Michael J. Zyphur. Alternative methods for assessing mediation in multilevel data: The advantages of multilevel sem. *Structural Equation Modeling*, 18(2):161–182, 2011. doi: 10.1080/10705511.2011.557329.

- John Pucher, Zhong-ren Peng, Neha Mittal, Yi Zhu, and Nisha Korattyswaroopam. Urban transport trends and policies in China and India: Impacts of rapid economic growth. *Transport Reviews*, 27(4):379–410, 2007. doi: 10.1080/01441640601089988.
- Diane L. Putnick and Marc H. Bornstein. Measurement invariance conventions and reporting: the state of the art and future directions for psychological research. *Developmental Review*, 41:71–90, 2016. doi: 10.1016/j.dr.2016.06.004.
- Tenko Raykov and Stephen H. C. Du Toit. Estimation of reliability for multiple-component measuring instruments in hierarchical designs. *Structural Equation Modeling*, 12(4):536–550, 2005. doi: 10.1207/s15328007sem1204_2.
- Rea Vaya. Song and dance teaches kids. <https://www.reavaya.org.za/news-archive/march-2010/483-song-and-dance-teaches-kids>, March 2010.
- David J. Reibstein, Christopher H. Lovelock, and Ricardo Dobson. The direction of causality between perceptions, affect, and behavior: an application to travel behavior. *Journal of Consumer Research*, 6(4):370–376, 1980. doi: 10.1086/208780.
- Steven P. Reise, Keith F. Widaman, and Robin H. Pugh. Confirmatory factor analysis and item response theory: Two approaches for exploring measurement invariance. *Psychological Bulletin*, 114(3):552–566, 1993. doi: 10.1037/0033-2909.114.3.552.
- Juliette Richetin, Marco Perugini, Andrew Prestwich, and Rick O’Gorman. The IAT as a predictor of spontaneous food choice: The case of fruits versus snacks. *International Journal of Psychology*, 42(3):166–173, 2007. doi: 10.1080/00207590601067078.
- Juliette Richetin, Giulio Costantini, Marco Perugini, and Felix Schönbrodt. Should we stop looking for a better scoring algorithm for handling Implicit Association Test data? test of the role of errors, extreme latencies treatment, scoring formula, and practice trials on reliability and validity. *PLoS ONE*, 10(6):e0129601, 2015. doi: 10.1371/journal.pone.0129601.
- Yves Rosseel. R package ‘lavaan’: Latent variable analysis. <http://lavaan.org>, 2018.
- Klaus Rothermund, Dirk Wentura, and Jan De Houwer. Validity of the salience asymmetry account of the Implicit Association Test: Reply to Greenwald, Nosek, Banaji, and Klauer (2005). *Journal of Experimental Psychology: General*, 134(3):426–430, 2005. doi: 10.1037/0096-3445.134.3.426.
- Ehri Ryu. Effects of skewness and kurtosis on normal-theory based maximum likelihood test statistics in multilevel structural equation modeling. *Behavioral Research Methods*, 43(4):1066–1074, 2011. doi: <https://doi.org/10.3758/s13428-011-0115-7>.
- Ehri Ryu. Model fit evaluation in multilevel structural equation models. *Frontiers in Psychology*, 5, 2014. doi: 10.3389/fpsyg.2014.00081.
- Ehri Ryu. The role of centering for interaction of level 1 variables in multilevel structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, 22(4):617–630, 2015. doi: 10.1080/10705511.2014.936491.
- Ehri Ryu and Stephen G. West. Level-specific evaluation of model fit in multilevel structural equation modeling. *Structural Equation Modeling*, 16(4):583–601, 2009. doi: 10.1080/10705510903203466.

- Albert Satorra and Peter M. Bentler. A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika*, 66(4):507–514, 2001. doi: 10.1007/BF02296192.
- Albert Satorra and Peter M. Bentler. Ensuring positiveness of the scaled difference chi-square test statistic. *Psychometrika*, 75(2):243–248, 2011. doi: 10.1007/s11336-009-9135-y.
- Paul L. Sauer and Alan Dick. Using moderator variables in structural equation models. In Leigh McAlister and Michael L. Rothschild, editors, *NA - Advances in Consumer Research*, volume 20, pages 636–640. Association for Consumer Research, Provo, UT, 1993. <http://www.acrwebsite.org/volumes/7532/volumes/v20/NA-20>.
- Karin Schermelleh-Engel, Martin Kerwer, and Andreas G. Klein. Evaluation of model fit in non-linear multilevel structural equation modeling. *Frontiers in Psychology*, 5:1–11, 2014. doi: 10.3389/fpsyg.2014.00181.
- Konrad Schnabel, Jens B. Asendorpf, and Anthony G. Greenwald. Using Implicit Association Tests for the assessment of implicit personality self-concept. In Gregory J. Boyle, Gerald Matthews, and Donald H. Saklofske, editors, *The SAGE Handbook of Personality Theory and Assessment*, volume 2. Personality Measurement and Testing, chapter 24, pages 508–528. SAGE Publications, Inc., Thousand Oaks, CA, 2008. https://faculty.washington.edu/agg/pdf/Schnabel%20&%20al.Hbk_2008.proofs.pdf.
- Randall E. Schumacker and Richard G. Lomax. *A Beginner’s Guide to Structural Equation Modeling*. Routledge, New York, NY, 3 edition, 2010.
- Tim Schwanen and Karen Lucas. Understanding auto motives. In Karen Lucas, Evelyn Blumenberg, and Rachel Weinberger, editors, *Auto Motives: Understanding Car Use Behaviors*, chapter 1, pages 3–38. Emerald Group Publishing, Ltd., Bingley, UK, 2011.
- Tim Schwanen and Patricia L. Mokhtarian. What affects commute mode choice: Physical neighborhood structure or preferences toward neighborhoods? *Journal of Transport Geography*, 13(1):83–99, 2005. doi: 10.1016/j.jtrangeo.2004.11.001.
- Jonathan Schweig. Multilevel factor analysis by model segregation: New applications for robust test statistics. *Journal of Educational and Behavioral Statistics*, 39(5):394–422, 2014. doi: 10.3102/1076998614544784.
- John Searle. *The rediscovery of the mind*. MIT Press, Cambridge, MA, 1992.
- Constantine Sedikides and Aiden P. Gregg. Self-enhancement: Food for thought. *Perspectives on Psychological Science*, 3(2):102–116, 2008. doi: 10.1111/j.1745-6916.2008.00068.x.
- Mimi Sheller. Automotive emotions: Feeling the car. *Theory, Culture & Society*, 21(4):221–242, 2004. doi: 10.1177/0263276404046068.
- Baba Shiv and Alexander Fedorikhin. Spontaneous versus controlled influences of stimulus-based affect on choice behavior. *Organizational Behavior and Human Decision Processes*, 87(2):342–370, 2002. doi: 10.1006/obhd.2001.2977.
- Paurav Shukla. Status consumption in cross-national context: Socio-psychological, brand and situational antecedents. *International Marketing Review*, 27(1):108–129, 2010. doi: 10.1108/02651331011020429.

- Paurav Shukla. Impact of interpersonal influences, brand origin and brand image on luxury purchase intentions: measuring interfunctional interactions and a cross-national comparison. *Journal of World Business*, 46(2, Managerial Decision Making in International Business):242–252, 2011. doi: 10.1016/j.jwb.2010.11.002.
- Chris G. Sibley and Niki Harré. Gender role socialization model of explicit and implicit biases in driving self-enhancement. *Transportation Research Part F: Traffic Psychology and Behaviour*, 12(6):452–461, 2009a. doi: 10.1016/j.trf.2009.08.006.
- Chris G. Sibley and Niki Harré. The impact of different styles of traffic safety advertisement on young drivers’ explicit and implicit self-enhancement biases. *Transportation Research Part F: Traffic Psychology and Behaviour*, 12(2):159–167, 2009b. doi: 10.1016/j.trf.2008.11.001.
- SINA News. Photo: A London double decker bus. <http://2008.sina.com.cn/en/photo/2008-08-24/22038232.html>, August 24 2008.
- Partnership for Sustainable Low Carbon Transportation SLoCaT. *Differentiating National Transport Sector Emissions Trends to Better Inform National Targets and Implementation Strategies*. Eschborn, Germany, 2015. http://slocat.net/sites/default/files/u13/slocat_transport_emission_trends_analysis_-_25may_0.pdf.
- Tom A. B. Snijders. Power and sample size in multilevel linear models. In Brian S. Everitt and David C. Howell, editors, *Encyclopedia of Statistics in Behavioral Science*, volume 3, pages 1570–1573. Wiley, Chichester, UK, 2005.
- Tom A. B. Snijders and Roel J. Bosker. *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. Sage, Thousand Oaks, CA, 2 edition, 2012.
- Julie Spencer-Rodgers, Kaiping Peng, Lei Wang, and Yubo Hou. Dialectical self-esteem and East-West differences in psychological well-being. *Personality and Social Psychology Bulletin*, 30(11): 1416–1432, 2004. doi: 10.1177/0146167204264243.
- David J. Spiegelhalter, Nicola G. Best, Bradley P. Carlin, and Angelika van der Linde. Bayesian measures of model complexity and fit (with discussion). *Journal of the Royal Statistical Society, Series B (Statistical Methodology)*, 64(4):583–639, 2002. doi: 10.1111/1467-9868.02022.
- Laura M. Stapleton, Ji Seung Yang, and Gregory R. Hancock. Construct meaning in multilevel settings. *Journal of Educational and Behavioral Statistics*, 41(5):481–520, 2016. doi: 10.3102/1076998616646200.
- Statista.com. “Percentage of all global web pages served to mobile phones from 2009 to 2018”. <https://www.statista.com/statistics/241462/global-mobile-phone-website-traffic-share/>, a.
- Statista.com. “Mobile internet traffic as percentage of total web traffic as of january 2018, by country”. <https://www.statista.com/statistics/430830/share-of-mobile-internet-traffic-countries/>, b.
- Jan-Benedict E. M. Steenkamp, Martijn G. de Jong, and Hans Baumgartner. Socially desirable response tendencies in survey research. *Journal of Marketing Research*, 47(2):199–214, 2010. doi: 10.1509/jmkr.47.2.199.

- Melanie C. Steffens. Is the Implicit Association Test immune to faking? *Experimental Psychology*, 51(3):165–179, 2004. doi: 10.1027/1618-3169.51.3.165.
- Linda Steg. Car use: Lust and must. instrumental, symbolic, and affective motives for car use. *Transportation Research Part A: Policy and Practice*, 39(2-3):147–162, 2005. doi: 10.1016/j.tra.2004.07.001.
- Linda Steg and Charles Vlek. The role of problem awareness in willingness-to-change car use and in evaluating relevant policy measures. In *Traffic and Transport Psychology: Theory and Application*, chapter 48, pages 465–475. Emerald Group Publishing, Ltd., Bingley, UK, 1997.
- Linda Steg, Karst Geurs, and Michiel Ras. The effects of motivational factors on car use: A multidisciplinary modelling approach. *Transportation Research Part A: Policy and Practice*, 35(9):789–806, 2001a. doi: 10.1016/S0965-8564(00)00017-3.
- Linda Steg, Charles Vlek, and Goos Slotegraaf. Instrumental-reasoned and symbolic-affective motives for using a motor car. *Transportation Research Part F: Traffic Psychology and Behaviour*, 4(3):151–169, 2001b. doi: 10.1016/S1369-8478(01)00020-1.
- James H. Steiger. Structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research*, 25(2):173–180, 1990. doi: 10.1207/s15327906mbr2502.4.
- Stefan Steiger, Anja S. Göritz, Andreas Hergovich, and Martin Voracek. Intentional faking of the Single Category Implicit Association Test and the Implicit Association Test. *Psychological Reports*, 109(1):219–230, 1990. doi: 10.2466/03.09.22.28.PR0.109.4.219-230.
- Stephen G. Stradling, M. L. Meadows, and S. Beatty. Factors affecting car use choices, 1999.
- Sustainable Mobility for All Sum4All. Global mobility report 2017: tracking sector performance. <https://sum4all.org/publications/global-mobility-report-2017>, 2017.
- Andrew C. H. Szeto, Richard M. Sorrentino, Satoru Yasunaga, Yasunao Otsubo, Sadafusa Kouhara, and Ikuo Sasayama. Using the Implicit Association Test across cultures: A case of implicit self-esteem in Japan and Canada. *Asian Journal of Social Psychology*, 12(3):211–220, 2009. doi: 10.1111/j.1467-839X.2009.01286.x.
- Daniel Sznycer, Laith Al-Shawaf, Yoella Bereby-Meyer, Oliver Scott Curry, Delphine De Smet, Elsa Ermer, Sangin Kim, Sunhwa Kim, Norman P. Li, Maria Florencia Lopez Seal, Jennifer McClung, Jiaqing O, Yohsuke Ohtsubo, Tadeq Quillien, Max Schaub, Aaron Sell, Florian van Leeuwen, Leda Cosmides, and John Tooby. Cross-cultural regularities in the cognitive architecture of pride. *Proceedings of the National Academy of Sciences (PNAS)*, 114(8):1874–1879, 2017. doi: 10.1073/pnas.1614389114.
- Timothy J. Tardiff. Causal inferences involving transportation attitudes and behavior. *Transportation Research*, 11(6):397–404, 1977. doi: 10.1016/0041-1647(77)90004-1.
- Louis Tay, Sang Eun Woo, and Jeroen K. Vermunt. A conceptual and methodological framework for psychometric isomorphism validation of multilevel construct measures. *Organizational Research Methods*, 17(1):77–106, 2014. doi: 10.1177/1094428113517008.

- Charles Teddlie and Abbas Tashakkori. Mixed methods research: Contemporary issues in an emerging field. In Norman K. Denzin and Yvonna S. Lincoln, editors, *Strategies of Qualitative Inquiry*, chapter 4. SAGE Publications, Inc., 4 edition, 2012.
- John Thøgersen. Understanding repetitive travel mode choices in a stable context: a panel study approach. *Transportation Research Part A: Policy and Practice*, 40(8):621–638, 2006. doi: 10.1016/j.tra.2005.11.004.
- Louis Leon Thurstone. *Multiple-Factor Analysis*. University of Chicago Press, Chicago, IL, 1947.
- Mary Lynn Tischer and Robert V. Phillips. The relationship between transportation perceptions and behavior over time. *Transportation*, 8(1):21–36, 1979. doi: 10.1007/BF00149849.
- Roger Tourangeau and Ting Yan. Sensitive questions in surveys. *Psychological Bulletin*, 133(5): 859–883, 2007. doi: 10.1037/0033-2909.133.5.859.
- Roger Tourangeau, Tom W. Smith, and Kenneth A. Rasinski. Motivation to report sensitive behaviors in surveys: Evidence from a bogus pipeline experiment. *Journal of Applied Social Psychology*, 27(3):209–222, 1997. doi: 10.1111/j.1559-1816.1997.tb00629.x.
- Jessica L. Tracy and Richard W. Robins. The psychological structure of pride: A tale of two facets. *Journal of Personality and Social Psychology*, 92(3):537–547, 2007a. doi: 10.1037/0022-3514.92.3.506.
- Jessica L. Tracy and Richard W. Robins. Emerging insights into the nature and function of pride. *Current Directions in Psychological Science*, 16:147–150, 2007b. doi: 10.1111/j.1467-8721.2007.00493.x.
- Kenneth Train. A structured logit model of auto ownership and mode choice. *The Review of Economic Studies*, 47(2):357–370, 1980. doi: 10.2307/2296997.
- Harry C. Triandis. *Interpersonal behavior*. Brooks/Cole, Monterey, CA, 1977.
- Ledyard R. Tucker and Charles Lewis. A reliability coefficient for maximum likelihood factor analysis. *Psychometrika*, 38(1):1–10, 1973. doi: 10.1007/BF02291170.
- United Nations UN General Assembly. *Transforming our world: the 2030 Agenda for Sustainable Development*. New York, NY, 2015. http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E.
- United Nations. Statistical annex: Country classification. In *World Economic Situation and Prospects 2017*, pages 151–159. United Nations, New York, NY, 2017. https://sustainabledevelopment.un.org/content/documents/25012017wesp_full_en.pdf.
- United Nations Department of Economic and Social Affairs, Statistics Division. “Passenger volume (passenger kilometers), by mode of transport IS_RDP_PFVOL”. <https://unstats.un.org/sdgs/indicators/database>, 2016.
- United Nations Population Division, et al. “Population, total”. World Bank Open Data. <https://data.worldbank.org/indicator/SP.POP.TOTL>.

- United Nations, World Urbanization Prospects. “Population in urban agglomerations of more than 1 million (% of total population)”. World Bank Open Data. data.worldbank.org/indicator/EN.URB.MCTY.TL.ZS, 2017.
- John Urry. The ‘system’ of automobility. *Theory, Culture & Society*, 21(4-5):25–39, 2004. doi: 10.1177/0263276404046059.
- Hong Tan Van, Kasem Choocharukul, and Satoshi Fujii. The effect of attitudes toward cars and public transportation on behavioral intention in commuting mode choice - a comparison across six asian countries. *Transportation Research Part A: Policy and Practice*, 69:36–44, 2014. doi: 10.1016/j.tra.2014.08.008.
- Fons J. R. van de Vijver and Ype H. Poortinga. Structural equivalence in multilevel research. *Journal of Cross-Cultural Psychology*, 33(2):141–156, 2002. doi: 10.1177/0022022102033002002.
- Robert J. Vandenberg and Charles E. Lance. A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, 2:4–69, 2000. doi: 10.1177/109442810031002.
- Bas Verplanken, Henk Aarts, Ad van Kippenberg, and Carina van Kippenberg. Attitude versus general habit: Antecedents of travel mode choice. *Journal of Applied Social Psychology*, 24(4): 285–300, 1994. doi: 10.1111/j.1559-1816.1994.tb00583.x.
- Kathleen D. Vohs and Ronald J. Faber. Spent resources: Self-regulatory resource availability affects impulse buying. *Journal of Consumer Research*, 33(4):537–547, 2007. doi: 10.1086/510228.
- Rob Wall, Patrick Devine-Wright, and Greig A. Mill. Comparing and combining theories to explain proenvironmental intentions: The case of commuting-mode choice. *Environment and Behavior*, 39(6):731–753, 2007. doi: 10.1177/0013916506294594.
- Rui Wang. Shaping urban transport policies in China: Will copying foreign policies work? *Transport Policy*, 17(3):147–152, 2010. doi: 10.1016/j.tranpol.2010.01.001.
- Lee V. White and Nicole D. Sintov. You are what you drive: environmentalist and social innovator symbolism drives electric vehicle adoption intentions. *Transportation Research Part A: Policy and Practice*, 99:94–113, 2017. doi: 10.1016/j.tra.2017.03.008.
- Timothy D. Wilson. *Strangers to ourselves: Discovering the adaptive unconscious*. Harvard University Press, Cambridge, MA, 2002.
- Chi-Sum Wong and Kenneth S. Law. Testing reciprocal relations by nonrecursive structural equation models using cross-sectional data. *Organizational Research Methods*, 2(1):69–87, 1999. doi: 10.1177/109442819921005.
- World Bank. “Population, female (% of total)”. World Bank Open Data. <https://data.worldbank.org/indicator/SP.POP.TOTL.FE.ZS>, 2016.
- World Bank. “World Bank country and lending groups”. <https://datahelpdesk.worldbank.org/knowledgebase/articles/906519>, 2017.
- World Bank and OECD national accounts data. “GDP per capita (current US\$)”. World Bank Open Data. <https://data.worldbank.org/indicator/NY.GDP.PCAP.CD>, a.

- World Bank and OECD national accounts data. “GDP per capita growth (annual %)” . World Bank Open Data. <https://data.worldbank.org/indicator/NY.GDP.PCAP.KD.ZG>, b.
- World Bank Development Research Group. “GINI index (World Bank estimate)” . World Bank Open Data. <https://data.worldbank.org/indicator/SI.POV.GINI>.
- World Bank International Comparison Program database. “GDP per capita, PPP (current international \$)” . World Bank Open Data. <https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD>.
- World Bank International Comparison Program database. “GDP per capita, PPP (constant 2011 international \$)” . World Bank Open Data. <https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.KD>, 2016.
- World Health Organization. “Registered vehicles: Data by country” . <http://apps.who.int/gho/data/node.main.A995?lang=en>.
- Benjamin D. Wright. Fundamental measurement for psychology. In Susan E. Embretson and Scott L. Hershberger, editors, *The new rules of measurement: What every psychologist and educator should know*, chapter 4, pages 65–104. Lawrence Erlbaum Associates, Mahwah, NJ, 1999.
- Chris Wright and John Egan. De-marketing the car. *Transport Policy*, 7(4):287–294, 2000. doi: 10.1016/S0967-070X(00)00029-9.
- Ge Wu, Toshiyuki Yamamoto, and Ryuichi Kitamura. Vehicle ownership model that incorporates the causal structure underlying attitudes toward vehicle ownership. *Transportation Research Record: Journal of the Transportation Research Board*, 1676, 1999. doi: 10.3141/1676-08.
- Ke-Hai Yuan and Peter M. Bentler. Three likelihood-based methods for mean and covariance structure analysis with nonnormal missing data. *Sociological Methodology*, 30(1):165–200, 2000. doi: 10.1111/0081-1750.00078.
- Ke-Hai Yuan and Peter M. Bentler. Multilevel covariance structure analysis by fitting multiple single-level models. *Sociological Methodology*, 37(1):53–82, 2007. doi: 10.1111/j.1467-9531.2007.00182.x.
- Zhan Zhao and Jinhua Zhao. Car pride and its behavioral implications: An initial exploration in Shanghai. *Transportation*, 2018. doi: 10.1007/s11116-018-9917-0.
- Charles Zhu, Yiliang Zhu, Rongzhu Lu, Ren He, and Zhaolin Xia. Perceptions and aspirations for car ownership among chinese students attending two universities in the yangtze delta, china. *Journal of Transport Geography*, 24:315–323, 2012. doi: 10.1016/j.jtrangeo.2012.03.011.